An Integrated Framework for Balancing Contractor's Workload versus Capacity using System Dynamics

by

Ahmed Abdelrady Okasha Mohamed Elnady

A thesis submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Construction Engineering and Management

Department of Civil and Environmental Engineering
University of Alberta

ABSTRACT

Workload fluctuation is one of the major challenges facing contracting (project-based) organizations because of the rational decision-making model applied to manage it in current practice. The rational model balances the workload with the capacity required at the level of activity, ignoring the influence of other factors. It also fails to consider the nondeterministic nature of these factors. Hence, there is a need for a decision support system that considers holistically the factors influencing workload fluctuation, their interactions, and their nondeterministic nature.

Although the system dynamics approach is capable of filling the previously mentioned gaps, previous studies in this area have overlooked the organization-to-industry relationship. One of the important aspects of this relationship is industry demand. Previous studies have typically focused on predicting the organization's demand, which is not representative of industry demand. While some studies have endeavored to project industry demand by monitoring economic and political variables, these variables are very difficult to track. Hence, there is a need to accurately predict industry demand and integrate its characteristics with a robust decision support system.

To fill these gaps, the present study pursues three objectives. The first is to comprehensively identify the factors affecting workload fluctuation in project-based organizations. The second is to identify the characteristics of industry demand in construction and devise a method for predicting future demand. The third is to develop an integrated dynamic model that considers the inherent uncertainties of, and interactions among, variables.

To achieve these objectives, a multi-step approach is applied. First, a systematic literature review is conducted to identify the factors affecting the contractor's workload, and these factors are analyzed using relative usage index and social network analysis. Second, the number of building permits issued is used as the metric to represent construction industry demand. It is analyzed using statistical tools to measure its characteristics such as mean, range, variability, and distribution. Also, the future demand is predicted using various machine learning algorithms such as neural network, Facebook prophet, and gaussian with kernels. Third, the system dynamics approach is applied to link the identified factors with demand features. The proposed model is analyzed using social network and sensitivity analysis by applying Monte Carlo simulation and other statistical tools.

The results reveal a gap with respect to the factors used by the expert mental model in managing the organization's workload and by the dynamic decision support model that is typically employed. For instance, the cycle of owner bid selection, holistic integration, and the effect of both on organizational performance have received relatively little attention considering their importance. Another notable finding is that industry demand behaviour is found to be cyclic and stable and thus can be considered a low- to medium-variability market condition. Seasonality, on the other hand, it found to have a significant effect on demand. Moreover, the results demonstrate that the cyclical structure of historical data can be leveraged to predict future demand with an average error of 10% for stationary, normally distributed and corelated data type, although the error ranges from 7% to 30% in a few cases for this type of data. Finally, the analysis of the integrated model reveals a tight structure in which one variable variation propagates easily and rapidly to other factors. The hub of these propagations is workload, as it is closely connected to the causes and effects of variations, either directly or indirectly through one or more variables. Hence, the analysis provides an influence matrix for workload fluctuations.

This research contributes to the body of knowledge in several respects by providing a robust decision support system. First, it takes into consideration the significant causal factors affecting an organization's performance that are often overlooked in existing approaches. Moreover, the organization-to-industry relationship that is overlooked in existing approaches is considered in this model. Finally, this model considers the nondeterministic characteristics of the factors influencing management decisions.

PREFACE

This thesis is an original work by *Ahmed Abdelrady Okasha Moham Elnady* under the supervision of Dr. Ahmed Hammad, Associate Professor of Construction Engineering and Management, Department of Civil and Environmental Engineering, Faculty of Engineering, University of Alberta. No part of this thesis has been previously published. There are three journal papers related to this thesis have already been submitted to the journals and one accepted conference paper.

Journal papers:

Ahmed Elnady and Ahmed Hammad, 2022. Performance Modeling and Analysis of Project-Based Organizations using System dynamic. Canadian Journal of Civil Engineering (under review).

Ahmed Elnady and Ahmed Hammad, 2022. Identification of factors affecting workload fluctuations in PBO, Journal of engineering science and military technologies (ESMT) (Submitted).

Ahmed Elnady and Ahmed Hammad, 2022. Analysis and prediction of construction industry demand. International Journal of Construction Management (Submitted).

Conference paper:

Ahmed Elnady and Ahmed Hammad, 2022. PBO Workload Fluctuation Analysis Using System Dynamic Simulation. Canadian Journal of Civil Engineering (Accepted).

Other published conference papers:

Ahmed A. Okasha, Parastoo Eivazi Ziaei, And Ahmed Hammad, “Optimizing Productivity Rate To Minimize Overdraft Interest Payment In Infrastructure Construction Projects”. Proceedings of the Eleventh International Structural Engineering And Construction Society (ISEC) Conference in Cairo, Egypt.doi: 10.14455/ISEC.2021.8(1).CPM-04

Elnady, A., Broda, Y., Hammad, A., Golabchi, H. and Mohamed, Y. (2022) "Utilizing Simulation to Predict Optimum number of Projects", Proceedings of the European Conference on Computing in Construction (ECCC) in Rhodes, Greece.

DEDICATION

I dedicate this thesis to the Egyptian Armed Forces, which I am honored to join, and they have offered me this great opportunity and funded my research. To my professors at Military Technical College who supported me in the preparation process. To my family, who with love and effort have accompanied me in this journey without hesitating at any moment of seeing my dreams come true, which are also their dreams.

ACKNOWLEDGEMENT

Accomplishing a thesis is by no means an easy endeavor. Completing it without the unswerving support of the supervisor, academic and industry experts, university staff, family, and friends was a next-to-impossible task. Hence, I wish to register my heartfelt appreciation to a few individuals who have played a pivotal role in my completing this assignment. Firstly, my appreciation goes out to my supervisor, Dr. Ahmed Hammad; without his guidance, I would have been lost on this long road to my thesis: thank you for all the meetings, so many emails, for answering my many queries, and for all your valuable insight. Second, I would like to thank my father, Abdelrady Okasha, who supported me along the Ph.D. journey and contributes to building me. Thanks to my mother, Hoda Elnady, my wife, Youmna Abdullah, and my daughters, Lucinda and Loreen, whose contribution is not directly visible from the outcome but who consistently supported me while I worked: without your patience, love, and support, I could not have completed this. Third, my appreciation goes out to Dr. Evan Davies, Dr. Osmar Zaiane, and Dr. Yasser Mohamed from the University of Alberta: your knowledge and time have been most valuable in preparing my thesis. Fourth, I would like to thank Eng. Trevor Harrington and Eng. Brandon Pratt for finding time out of their busy schedules to sit in on meetings and participate in my research: without your input, my research would have remained incomplete. Finally, I would like to extend my gratitude to my team members Eng. Negar Mansouri Asl, Eng. Houssam Matar, Eng. Cristhian Laura Portugal, Eng. Mai Ghazal, Eng. Olabode Babalola, Eng. Mohammad Masfiqul, Eng. Denisse Diaz Merino, Eng. Fatemeh Parvaneh, and Eng. Sridhar Kidambi for supporting me in developing the causal loop diagram for the model: your expertise, time, and feedback are highly appreciated.

Table of Contents

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

PBO	Project-based organization
RBV	Resource-based view
DC	Dynamic capabilities
AC	Absorptive capacity
SD	System dynamics
WBS	Work-breakdown-structure
EVM	Earned value management
GA	Genetic algorithm
LPS	Last planner system
BM	Business model
FBL	Feedback loop
CLDs	Causal loop diagrams
SNA	Social network analysis
RUI	Relative usage index
TS	Time series
CV	Coefficient of variation
MAE	Mean absolute error
MAPE	Mean absolute error percentage
Log	Logarithmic transformation
HW	Holt-winter
SARIMA	Seasonal auto-regression integrated moving average
ACF	Auto-correlation function
PACF	Partial auto-correlation function
FBP	Facebook prophet
LSTM	Long-short-term-memory
ETS	Exponential smoothing
MAPE	Mean absolute percentage error
ANOVA	Analysis of variance

CHAPTER 1 INTRODUCTION

1.1 BACKGROUND

The construction sector is subject to market fluctuations that may alter the way construction projects are approached. Globally, significant levels of economic uncertainty exist, and the construction industry is substantially more volatile than other sectors of the economy (Ribeirinho et al. 2020). This volatility directly affects contracting organizations, since they rely on a continuous supply of projects in order to make a profit. Due to this dependency on a steady supply of projects, construction contracting organizations are considered project-based organizations (PBOs). In terms of organizational structure, PBOs must create a temporary system for managing the activities of each given project to ensure project success (Turner, R. and Miterev 2019, 487-498).

Market features such as high unpredictability and cyclicality affect a PBO's long-term plans. Moreover, due to the inherent uncertainty of the internal and external environments, the long-term plans developed often perform poorly in terms of the outcomes yielded (Wolf and Floyd 2017, 1754-1788). Another factor that adds to uncertainty in long-term planning has to do with the deficiencies of the management models traditionally used in strategic planning. The main assumption of such models is that, if elements are understood, then the project/program/portfolio can be controlled. However, experience suggests that the interrelationships among elements are more complex than what is reflected in the traditional work breakdown structures of project networks (Wang, Lin, Kunc, and Bai 2017, 341-352).

Several studies have endeavored to enhance the planning process and address operational-level performance issues by seeking a local optimum solution (i.e., at the project level) (Killen et al. 2012, 525-538). However, such solutions typically focus on project performance and do not consider the effect one project may have on other projects operated by the same contractor (Martinsuo 2013, 794-803). Such an approach can have a “butterfly effect” with long-term, often adverse, implications (Mahdavi et al. 2019, 1200-1217). In specific, such a static, one-dimensional approach is not capable of representing the dynamic complexities of the business and market landscape (Cosenz 2017, 57-80), and focuses on the logical top-down structural characteristics of strategy that overlook the underlying practices generated by the strategy, as well as how these practices may affect the implementation of the strategy (Clegg et al. 2018, 762-772).

Many theories have been proposed for strategic management, such as the Resource-Based View (RBV) (Killen et al. 2012, 525-538). RBV, which is considered the foundational and most popular theory for addressing the inherent challenges of strategic planning in construction contracting, proceeds from the premise that competing organizations' resources and competencies are not uniform. This concept of heterogeneity is used to explain variances in organizational success. RBV theory also considers that intangible resources (e.g., patents, trademarks, reputation, experience, practices) are more likely than material ones to provide a competitive advantage.

The successful application of RBV theory, though, requires relative stability of both the organization and the external environment. In this context, Dynamic Capabilities (DC) theory endeavors to build on RBV and fill this gap by defining a set of organizational capabilities and systematic procedures or operational routines that enable businesses to successfully adjust to dynamic changes in the environment in which they compete.

DC theory cannot provide value as a standalone approach, though, as the existing resource base must be reconfigured to obtain value. In this regard, Absorptive Capacity (AC) theory seeks to build on the foundation of RBV and DC while addressing this shortcoming. The key to AC theory is the notion that the internal process of learning from previous experience and present activities strengthens the imperative to acquire information from the external environment. Broadly speaking, AC theory can be understood as a holistic perspective that considers an organization's dynamic capacity as something inextricably linked to its systems, processes, and structures (Killen et al. 2012, 525-538). This perspective requires an approach capable of holistically addressing the systems and facilitating the analysis and understanding of the emergent behaviours from the linked structures and accumulation of effects. Emergent behaviours can be considered the huge consequences from the simple rules governing the system, i.e., the whole is not equal to the sum of its parts (Checkland 1999, 45-56). The analysis and understanding of this behaviour can be achieved by the system dynamics (SD) approach.

The SD approach allows for the holistic study of PBOs. SD links core cause-and-effect interactions among key business variables to gain understanding of how a company operates and what may be the keys to its future success (Kenefic 2020). In recent years, the SD approach has been integrated with strategic management to support the PBO framework, given its effectiveness in promoting strategic learning, facilitating decision-making, and enhancing performance based on a systemic perspective (Cosenz 2017, 57-80). A notable deficiency of this approach, though, is that selecting model boundaries by focusing on the project may isolate the internal dynamics of the project from the organization and external dynamics related to the market.

1.2 PROBLEM STATEMENT

For PBOs, strategic planning is inherently challenging due to the influence of stochastic workload fluctuations. Many factors, such as market conditions, owners' decisions and priorities, project characteristics, and contractors' business models, shape these fluctuations. In turn, the uncertainty tied to such factors limits the strategic planner's ability to develop a reliable long-term plan. Moreover, operating multiple projects simultaneously makes it particularly challenging for a PBO to manage its workload and resources. In addressing these issues, previous studies have tended to focus on just one perspective and apply it at the project level. Hence, the primary gap in the body of knowledge is the distinct lack of research identifying and analyzing the variables affecting the PBO's workload cycle. Also, there is a gap with respect to the factors used by the expert mental model in managing the organization's workload and by the dynamic decision support model that is typically employed

One of these factors is market variation. Strategic planners tend to attribute the unreliability of long-term plans to market dynamics (e.g., volatile demand), which increase uncertainty in the organization's upstream operations and make it difficult to maintain a stable workforce or a balanced workload. In such circumstances, monitoring the economic variables (e.g., oil prices, inflation rates, raw material prices) and using projections to shape expectations of future demand is the most common approach. However, tracking and predicting all economic variables is an extremely difficult process, particularly when there is not sufficient data available. Hence, the second gap identified is the need for a reliable method of predicting demand that considers economic variability, is precise, and that delivers critical information to planners to aid in planning and decision making.

Contractors make strategic decisions to adapt to local dynamics, and they are able to do so with a reasonable amount of confidence. However, they often fail to account for what unforeseen circumstances may emerge from the complicated linkages among known local behaviours. The cumulative and delayed effect of their decisions is not considered, nor is the interaction with the organization's structure, or how behaviour dynamics may deviate from the optimum behaviour, accounted for. Hence, the third gap identified is the lack of support systems and holistic analysis that could aid PBOs in enhancing their decision-making and better understanding the holistic effect of their decisions.

1.3 RESEARCH OBJECTIVES

The overall research goal is to gain understanding of workload fluctuations and the effect of interacting dynamic factors on PBOs at the organizational level. Toward this goal, the following research objectives are pursued:

- identify the factors affecting workload fluctuations in PBOs (Chapter 3);
- extract the characteristics and devise a method for predicting future demand with an acceptable level of error (Chapter 4); and
- build an SD model that supports strategic decision making by analyzing workload and the strategic factors influencing PBOs (Chapters 5–7).

1.4 RESEARCH METHODS

In this research, a multistep approach is adopted to define and achieve the objectives, as shown in Figure 1.1. A review of the literature in the area of project planning and control is conducted by drawing upon source material from various databases, such as Scopus, Google Scholar, and Web of Science. The literature review consists of a series of iterations of identifying preliminary gaps and searching for their solutions in order to definitively identify the gaps in the current body of knowledge that have yet to be addressed. Based on the literature review and as noted in Section 1.2 above, the gaps identified are (1) the lack of research identifying the variables affecting the PBO workload cycle; (2) the need for a method of predicting demand that considers economic variability, is precise, and that delivers critical information to aid planners in planning and decision making; and (3) the lack of support systems and holistic analysis that could aid managers in enhancing their decision making and in better understanding the holistic effect of their decisions.

To fill these gaps, first, a systematic literature review of the available body of knowledge is conducted. A comprehensive list of dynamic factors is identified accordingly. Analysis of these factors using both a conventional approach and social network analysis (SNA) is conducted. The purpose of the conventional analysis is to define the gap in the frequency of modelling the dynamic factors and their identifications in the literature. While the purpose of SNA is to define the gap between the expert mental models used to link these variables and the dynamic models applied to support the decision makers. The relations among the factors identified are then used as the basis for proposing a conceptual framework linking these variables.

Second, market variations are investigated, where the key metric is the monthly number of building permits issued for different provinces, and the case jurisdiction considered in Canada, the data used having been obtained from Statistics Canada (https://www150.statcan.gc.ca/). The data are explored and cleaned from duplication, entry errors, and missing values using Python codes. This analysis is performed to extract the construction industry demand features, such as range, variability, mean, and distribution. Then, various statistical and machine-learning algorithms are applied in devising a method to predict future demand.

Finally, an SD model is built using the variables identified. The developed model is validated using the soft data available, consideration of extreme-case scenarios, and reality checks of the behaviour of the variables. Moreover, sensitivity analysis is performed to identify areas of future investment that contracting organizations should consider. The research methods employed are described in a detailed step-by-step manner in chapters three, four, and five.

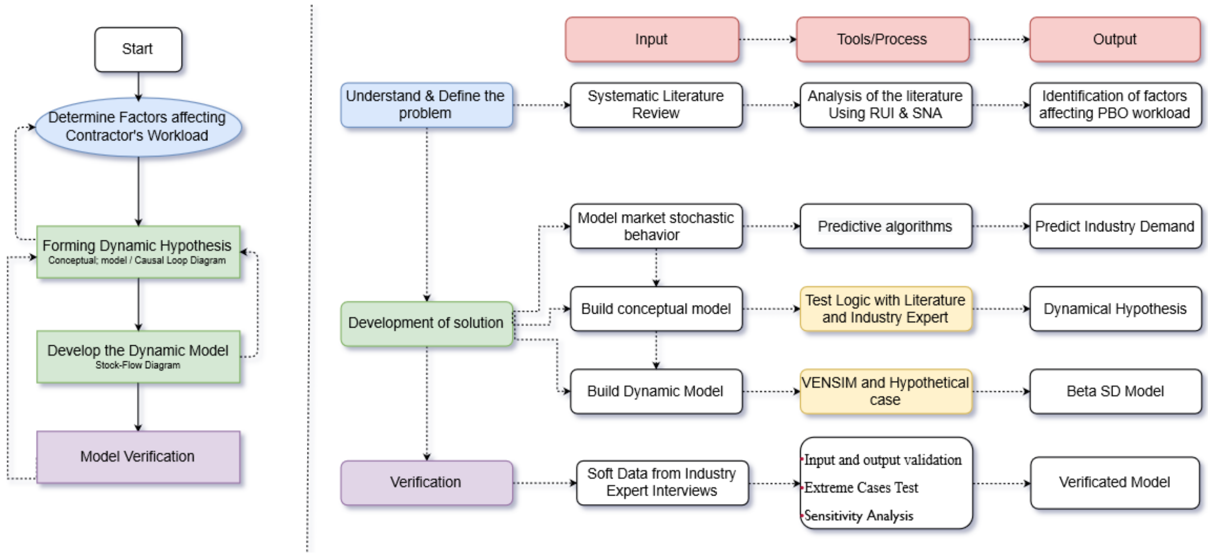


Figure 1.1 Research methods

1.5 .CONTRIBUTIONS

1.5.1 Academic contributions:

- This study develops a decision support system that links the dynamics of project, organization, and market, which are typically considered separately in a piecemeal and fragmented manner in existing approaches. This aids decision-makers in taking into account the nondeterministic nature of variables and thereby enhances the reliability of decisions.
- This study provides a comprehensive list of factors affecting workload fluctuation at the organizational level, linking together previously disparate knowledge sources and niche research topics such as project management, contractor selection, and portfolio optimization. This enhances knowledge management and provides a point of departure for future research in this area by defining the problem boundaries holistically.
- This study provides a simple representation of unconstrained demand that considers the variability of economic and political factors. As such, it aids in the understanding of the characteristics of demand, the assessment of demand fluctuations, and the prediction of future demand.

- This study provides a list of significant factors influencing organizational performance, as well as an influence matrix for workload fluctuation. This assists scholars to define the optimum strategic boundaries in order to enhance workload management decisions.

1.5.2 Contributions to industry practice:

- This study provides tools to aid contractors in strategic decision making to achieve stable resource management at the level of the organization.
- This study aids contractors in better understanding what overall behaviours may emerge from the complicated linkages among known local behaviours.
- This study allows contractors to better understand demand fluctuations and their characteristics to support them in market-related decision making.

1.6 THESIS ORGANIZATION

Chapter 1 presents a concise overview and background of the research problem addressed in this thesis. The research goal and objectives to be achieved, as well as the expected contributions, are also discussed.

Chapter 2 presents a review of the literature on the topic of project planning and control. The key findings of the literature review discussed in this chapter are the lack of attention given to workload (scope) management in the current body of knowledge, the mismatch between traditional planning tools and the PBO business model, and the need for an SD application to enhance strategic planning on the part of PBOs.

The gaps in the body of knowledge having been identified in Chapter 2, Chapter 3 presents the detailed literature review conducted specifically for the purpose of identifying the key factors affecting the workload fluctuations PBOs face. The SD approach is discussed in general terms, and an analysis of the identified factors is presented. Both conventional and SNA methods are employed in the analysis in order to define the gap between expert mental models in the analysis of workload fluctuations and the dynamic models developed to model workload variations.

Chapter 4 presents the analysis of market fluctuations in the construction industry, where market fluctuations are represented via a univariant time series of building permits issued, and the analysis is performed using qualitative and quantitative statistical tests. Statistical and machine-learning algorithms are used to devise a method of predicting future demand and thereby reduce uncertainty in strategic planning.

Chapter 5 describes the development of a conceptual SD model, including the dynamic hypothesis and assumptions underlying the development of the model.

Chapter 6 describes in detail the computerized SD model developed to represent a PBO's business model. It presents the hard relations between activities and workflow, as well as the soft logic embedded in the model's decision rules.

Chapter 7 presents the analysis of the conceptual and computerized models using SNA and sensitivity analysis. It describes how the assessment of the variables based on their positions in the network structure is achieved using SNA, as well as how the sensitivity analysis is performed using three different methods: screening, ANOVA, and linear regression. Finally, analysis of organization performance and policy selection is performed.

Chapter 8 presents the conclusions and limitations of this study, as well as recommendations for future work in this area.

CHAPTER 2 LITERATURE REVIEW

2.1 INTRODUCTION

Project-based organizations (PBOs), as mentioned earlier, rely on a continuous supply of projects to make a profit from their successful delivery. Each project is unique because of its features and its special nature which can be summarized according to (Zhu and Mostafavi 2014a, 0):

- Construction projects include highly dynamic processes, such as hiring and training, that are unfolded during the project.
- Construction projects are composed of multiple feedback processes, such as hiring resources that affect the subsystem of work execution, the organization's financial system, and the competitiveness in the market.
- Construction projects contain nonlinear relationships, i.e., increasing for example the productivity to double does not guarantee the excepted work is doubled too.
- Construction projects consist of both "hard" and "soft" data.

The interactions among those properties give rise to different behaviors, which attract researchers' attention. Some research classified them into intended and unintended behaviors related to cost, time, quality, environment, and safety (Zou, Zhang, and Wang 2006). Other studies categorized them into technological, political, economic, social, environmental, and legal (Rastogi and Trivedi 2016).

The unintended behaviors of construction projects negatively impact the schedule and budget (Love et al. 2002, 425-436). Incorporating these effects in the plan under contingency reduces the competitiveness of the company because it is highly affected by the project scale (Moshood et al. 2020, 100064). This dilemma makes construction projects suffer from imperfect symptoms, despite the great efforts of researchers.

The area of planning and control in construction projects has received attention from previous studies and the application of various state-of-the-art tools, such as artificial intelligence (AI) and applications of computer vision (Darko et al. 2020, 103081), building information modeling (BIM) in construction management and performance analysis (Sacks, Girolami, and Brilakis 2020, 100011), risk internally such as uncertainties within the project itself and externally such as environmental risk (Yaseen et al. 2020, 1514).

Applications of AI tools in general require a huge amount of clean data to train the model and achieve a reasonable error margin. This amount of data might not be available for various problems. In such cases an approach that allows the usage of soft or qualitative data is required.

Visualization tools help designers and planners to reduce errors by visualizing the output of each process. This process enhances the communication of various stakeholders and provides data for further analysis. This approach requires to be integration with other decision support systems to provide the management team with required alternative decisions.

To fully understand the project planning symptoms and map the tools utilized in this process, this chapter systematically reviews construction planning and control. It collects the used tools, dimensions of interest, and potential for future research in construction planning and control. This chapter focuses on the period from 2000 to the end of 2019 to collect available studies by utilizing a clearly defined methodology mentioned in the next section. This is specific period is chosen 4to capture the full picture of tools' evolution and ensure continuity of knowledge.

2.2 LITERATURE REVIEW METHODOLOGY

The review process was divided into two rounds. The first round focused on construction planning and control. Results from this round reveal the need to have a holistic methodology to deal with construction projects, which will be discussed later in detail. Hence, a second round of searching for a holistic approach was initiated. The second round of review searched for SD as a methodology that fulfills this need. Figure 2.1 represents the research methodology which consists of:

1. Searching Scopus, Web of Science, IEEE Xplore, ScienceDirect, ASCE, JSTOR, and Google Scholar to ensure reaching the largest related published articles.
2. Selecting journals in the Engineering domain related to the topic of research, as well as other journals with more than five related articles.
3. Selecting keywords related to the topic of research to be: “construction+ projects + planning + control + system + dynamics”

4. Limiting the time frame between 2000–2019
5. Limiting the type of published articles to be "Review papers", and "Article".
6. Limiting the type of publication to published, not in progress.
7. Reviewing the abstract and conclusion of all articles to select the most relevant articles.
8. Ensuring that content is related to Construction planning and control, in addition to System dynamics applications in construction projects with a model and case applied.
9. Analyzing the body, structure, methodology, tools used, and sample project applied in selected articles

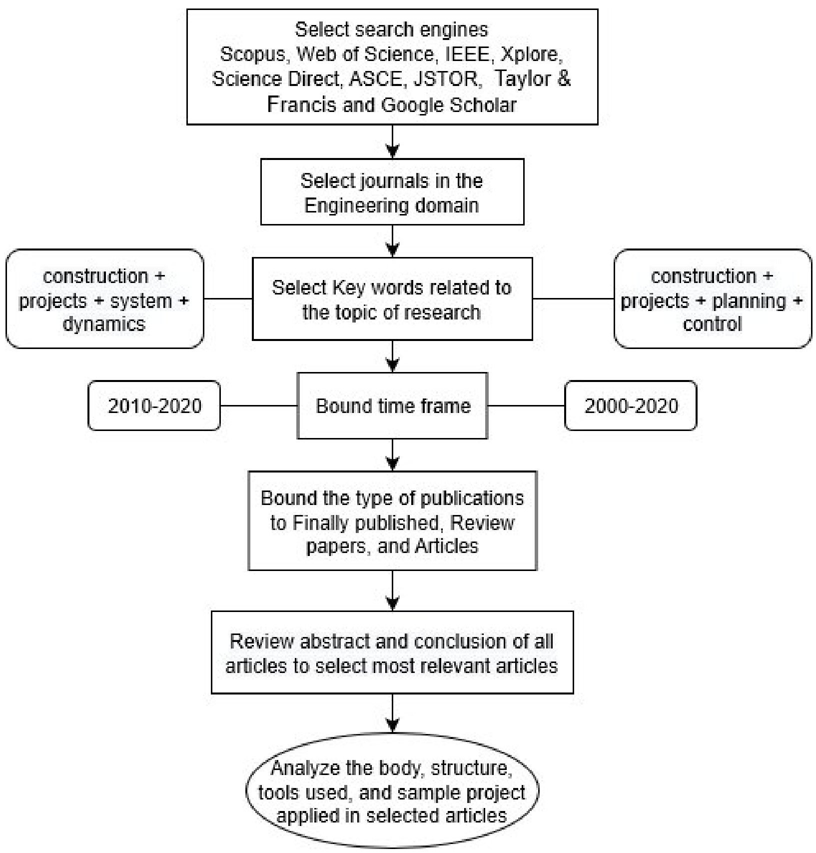


Figure 2.1 Literature review methodology

This methodology was applied in rounds, as mentioned above. The first round was for the keywords "construction+ projects + planning + control" with the time frame "2000–2019". In this round, review papers on the topic were reviewed. Then, research results were refined by type "Article". This led to articles related to the topic of research. The same methodology was applied again for the keywords "construction+ projects + system + dynamics" with bounded time "2010–2019" because search results with time frame "2000–2020" revealed multiple reviews papers of

SD till 2015. The number of articles resulting from the search with keywords “planning + control” was 728 articles, which were filtered by hand to 135 relevant articles based on the criteria mentioned earlier. While, the number of articles that resulted from the search with keywords “system + dynamics” was 529 articles, which were filtered by hand to 112 relevant articles. All these articles were thoroughly reviewed and will be discussed in the following sections.

2.3 CONSTRUCTION PROJECT PLANNING AND WORKLOAD

Meta-analysis of the 135 selected articles revealed that construction planning and control has received increasing attention in the past two decades, as shown in Figure 2.2, and this attention is increasing. The list of the articles used in this analysis is mentioned in Appendix I

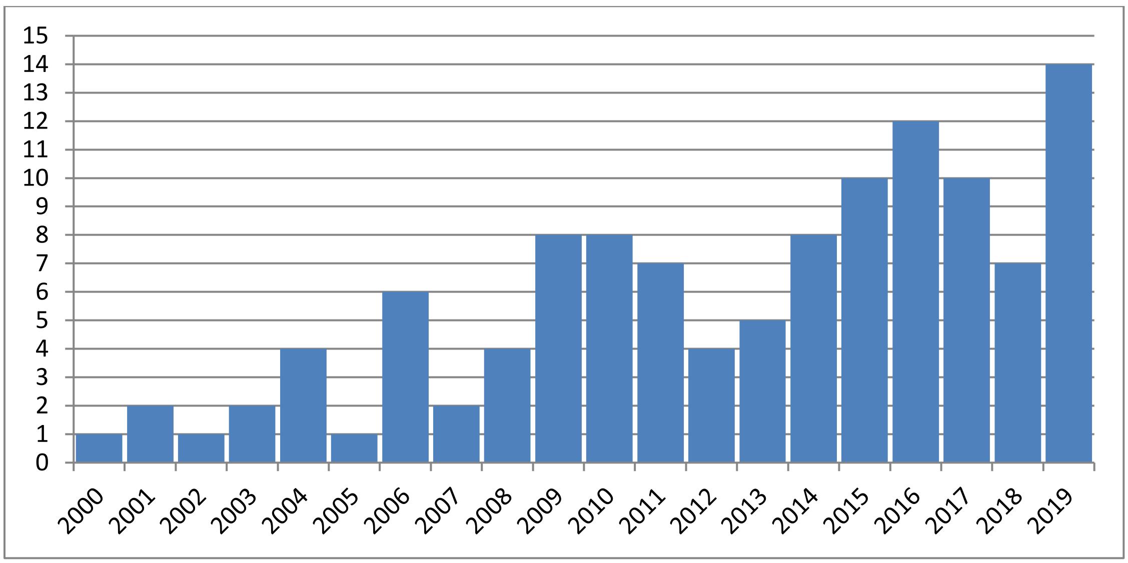


Figure 2.2Distribution of construction planning and control in the past two decades

According to the Project Management Body of Knowledge (PMBOK), time, risk, scope, human resources, integration, quality, communications, cost, and procurement analysis are all important knowledge areas for project success (PMI 2017). Their relative importance is different by the goal of measure (Zwikael 2009, 94-103). Table 2.1 shows the knowledge areas with different rankings relative to their extent of use, contribution to project success, and the construction industry. Interestingly, the integration knowledge area represents the number one ranking in the extent of use and the construction industry, yet Figure 2.3 shows that the integration knowledge area is not receiving the appropriate attention. Unfortunately, the scope is ranked the last important knowledge area in the construction industry (shown in Table 2.1) and from the academic perspective (shown in Figure 2.3).

Table 2.1 Ranking of the knowledge areas based on relative importance (Zwikael 2009, 94-103)

Knowledge Area	Extent of Use	Contribution to Project Success	Construction and Engineering
Integration	1	5	1
Time	2	1	7
Scope	3	3	9
Human Resource	4	4	3
Cost	5	8	2
Risk	6	2	4
Quality	7	6	6
Communication	8	7	5
Procurement	9	9	8

However, the time knowledge area is ranked the 7th for the construction industry (Table 2.1), and it received the highest attention from the previous studies (Figure 2.3). This might be because the research focused on project success, which agrees with the PMBOK analysis shown in Table 2.1 (ranked the most important knowledge area for project success) (Zwikael 2009, 94-103). Comparing Table 2.1 and Figure 2.3 shows that cost is ranked as the second most important knowledge area in the construction industry. Quality, human resources, risk, communications, quality, and communication knowledge areas are the next successively studied factors, as presented in Figure 2.3.

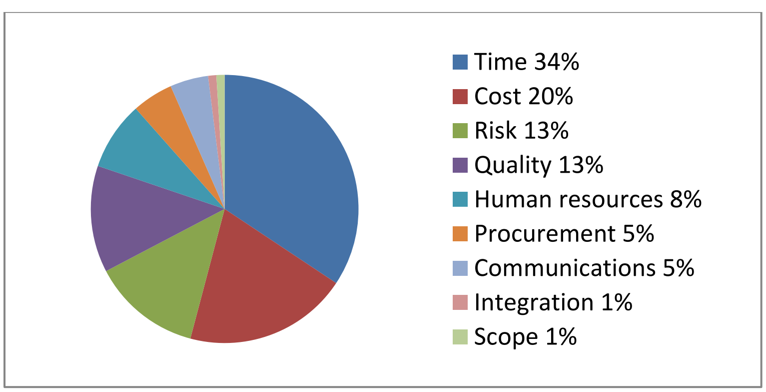


Figure 2.3 Knowledge areas of planning and control according to PMBOK from 2000–2019

The PMBOK Guide comprehensively describes project planning from the standpoint of several knowledge domains. The planning processes are divided into two categories: basic (fundamentals) processes and supporting processes. The primary activities are scope identification, task identification, resource prediction, resource allocation, tasks' relations, calculating the task's length, estimating the activity's cost, schedule preparation, project budgeting, and the creation of various plans. The project plans, which are the result of these procedures, are input to the process execution (Turner, J. R. 2009), (PMBOK guide).

The domination of the classical delivery technique of Design-Bid-Build (DBB), makes the starting of the execution phase preceded by phases where the scope of the project is fully defined (Shrestha, P. P. et al. 2007, 17-25). Hence during the project, the scope is fixed, and any change to it is defined as a symptom (Yu, Shen, and Shi 2017). Researchers in construction projects define changes of scope as change management and include it under the risk knowledge area, i.e. negative risks impact the project. This delivery method is not efficiently compatible with the increasing complexity and size of projects, in addition to the increasing demand for fast delivery and parallelism of project phases (Xue 2020). While in Design-Build (DB) delivery method and Turn Key, the scope is not well defined; the contractor starts the project with a conceptual design. It has a single point of responsibility and could improve performance but it lacks industry interest (Alleman and Tran 2020). Hence in DB projects, the overall performance is more influenced by design-builder contractors, i.e., prime contractors (Gransberg and Molenaar 2004, 162). That increases the need for modification of researchers' perspectives from the traditional view of construction projects that have a well-defined scope.

There are two important issues related to the delivery method of a construction project, procurement, and communication. In DBB, contractors seek to start projects with a definite quantity and delivery time contract with the supplier. These efforts to eliminate uncertainties with a fully defined project and almost fully known work steps lead to successful projects. However, these efforts are becoming sources of complexity and risk in the DB delivery method. However, DB overcomes the communication cons in DBB but DB as a delivery method still has cons (Alleman and Tran 2020). In addition, it stresses the need for integration of all the knowledge areas to have a successfully delivered project, which is mentioned as an area for improvement in the discussion of the integration knowledge area.

Integration, as mentioned earlier, appears at the lower level of researchers' attention by 1%. To be even-handed, this percentage depicts the full integration of the knowledge areas, and if we consider the partial integration of the knowledge areas, this percentage will increase to 74%. Full integration means all knowledge areas are covered in the research, while partial integration means that research focuses on specific knowledge areas. The partial integration of two knowledge areas is performed in 38.5% of studies. While the partial integration of five knowledge areas is performed in 5.2% of the articles reviewed. The partial integration details are shown in Figure 2.4.

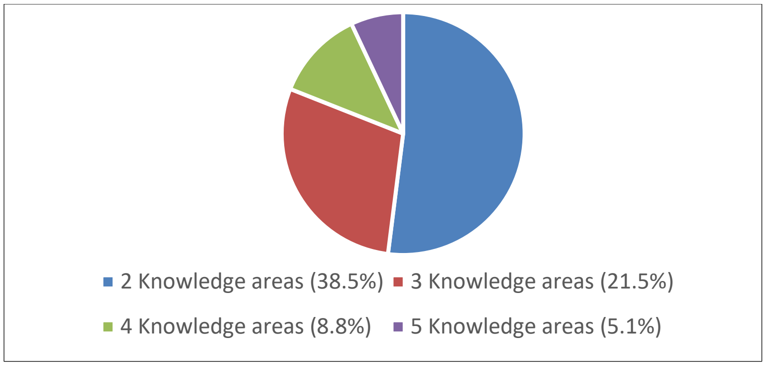


Figure 2.4 Partial integration of knowledge areas from 2000–2019

2.3.1 Clustering of tools used from 2000–2020

It is very important to enhance the control process in the execution phase to meet the plan. This concept implicitly assumed that the plan is flawless and the errors in execution to meet the plan can be handled through the thermostat theory. This principle is rooted in the philosophy of PMBOK, which makes a feedback loop connecting planning, execution, controlling, and re-planning again (Koskela and Howell 2002, 293-302). The domination of the management as planned theory, (Johnston and Brennan 1996, 367-384), and the design-bid-build delivery method drive research to apply various tools to control the project execution.

For the last two decades, the researchers used various tools in the planning and control of construction projects, which appear in the 135 articles surveyed. These tools are clustered into three general categories: traditional 45.39%, mathematical/statistical tools 33.69%, and artificial intelligence (AI) 20.92%. Samples of these tools are presented in Table 2.2. The most frequently used tool is earned value management (EVM), which is time and cost-oriented. EVM compares planned and actual quantities (Kim, B. 2015, 04014077). The project workload is cut down into time-based pieces with assigned budgets; aggregating the separate pieces results in total elapsed time and cost (Christensen 1998, 1-16). Despite the wide use of this tool, researchers have described weaknesses and efforts to overcome its limitations. For example, control charts are used with EVM to determine adequate levels of divergence from the plan (Votto, Lee Ho, and Berssaneti 2020, 04020001), and the last planner system (LPS) is used to assess plan accuracy, and with a dynamic threshold can overcome the fake alarms of risk signals (Kim 2015, 04014077). Besides, different tools are used with EVM to enhance its ability to measure risks in modern complex projects (Ibrahim, Thorpe, and Mahmood 2019), (Nadafi, Moosavirad, and Ariafar 2019), and predict a realistic production rate with consideration of ripple effects (Lee 2015, 222-232).

Table 2.2 Clustering of planning and control tools

Traditional Tools	Resource	Artificial Intelligent Tools	Resource	Mathematical/ Statistical Tools	Resource
Earned Value Management	(Bortolini, Núria, and Matheu 2018)	Genetic algorithm	(Abd Elrehim, Eid, and Sayed 2019, 507-516)	Statistical analysis	(Tennant, Langford, and Murray 2011, 220)
Interviews/ meetings/ questionnaires	(Wu, D. et al. 2018, 282-295)	Robotic Total Station (RTS)	(Cheng, Venugopal, Teizer, and Vela 2011b, 1173-1184) (Zhou et al. 2020, 107251)	Bayesian inference and the Bayesian model averaging technique/ Bayesian beta S-curve method	(Kim, B. and Reinschmidt 2011, 958)
Last Planner/ Line-of-balance System	(Tayeh et al. 2019, 1424-1436),	Artificial neural network	(Li, Yan-Wen and Cao 2020, 382-389), (Ayhan and Tokdemir 2020)	Monte Carlo simulation	(Tokdemir, Erol, and Dikmen 2019a, 04018132)
Network scheduling approach	(Araújo and	Smartphone	(Umer et al. 2018, 438-448)	Fuzzy random parameters	(Song et al. 2018, 138-157)

Traditional Tools	Resource	Artificial Intelligent Tools	Resource	Mathematical/ Statistical Tools	Resource
	Lucko 2016)				
Work breakdown structure/ Critical Path Method	(Li, Duanshun and Lu 2017)			Game theory	(Khanzadi, Eshtehardian, and Chalekaee 2016, 1066-1077)

The second most popular set of tools are interviews, meetings, questionnaires, and surveys. These tools are used in two contexts, collecting data from the field (Adafin, Rotimi, and Wilkinson 2016), (Sacks et al. 2017, 45-63), and validating the output results of the developed model or hypotheses (Mahalingam, Kashyap, and Mahajan 2010, 148-159), (Lin et al. 2017). The third most frequently used tool is LPS. Many researchers use this tool to benefit from its privilege of engaging laborers in the plan to be more accurate, e.g, (González et al.) developed a decision-making tool to measure the accuracy of the executed plan.

Another category of tools is AI tools, such as genetic algorithm (GA), which are utilized with the critical path method to help project managers experiment with different scenarios for allocating available crews based on operation and crew characteristics (East and Liu 2006, 1294-1305). GA is applied, also, in material handling and stockpiling on the site (Said and El-Rayes 2011, 421-431).

Construction projects also adopted smartphones as a proactive defense against laborers falling out of balance through activity execution (Umer et al. 2018, 438-448). Moreover, (Cheng, Venugopal, Teizer, and Vela 2011a, 1173-1184) utilized robotic total stations to track the used resources and to investigate ongoing operations at the site in harsh sites.

2.3.2 Insights of surveyed articles

The projects used as cases in the surveyed literature varied among infrastructure (Nguyen et al. 2019, 384-399), building (Xiao et al. 2018), heavy industrial (Mccabe and 2017, 25), power and energy projects (Sacco et al. 2019, 269-281), and combination of more than one category (Zhao et al. 2019, 52-65), as shown in Figure 2.5. Projects are fairly evenly distributed among categories, except for projects related to power and energy. The combination of projects is widely observed in articles that surveyed the industry or in applied cases for generic models. However, most researchers preferred to use one project or different projects of the same category as applications of their models.

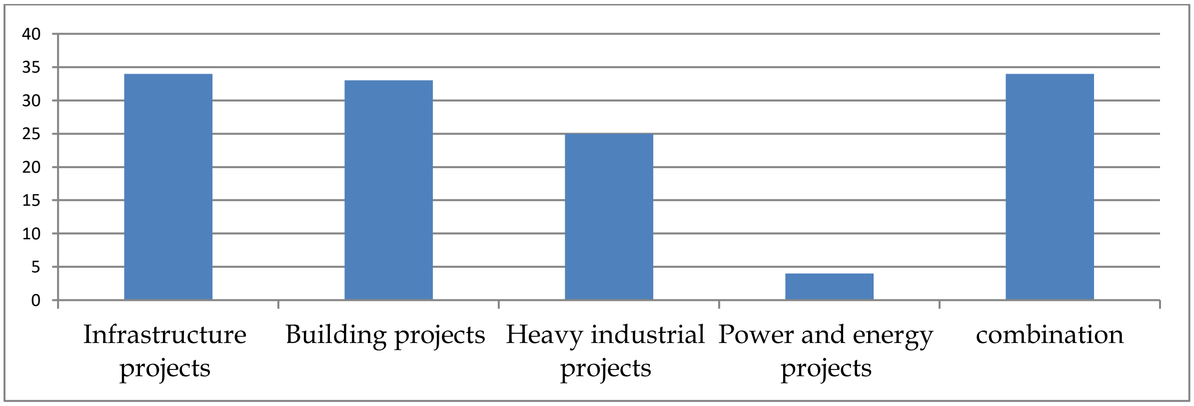


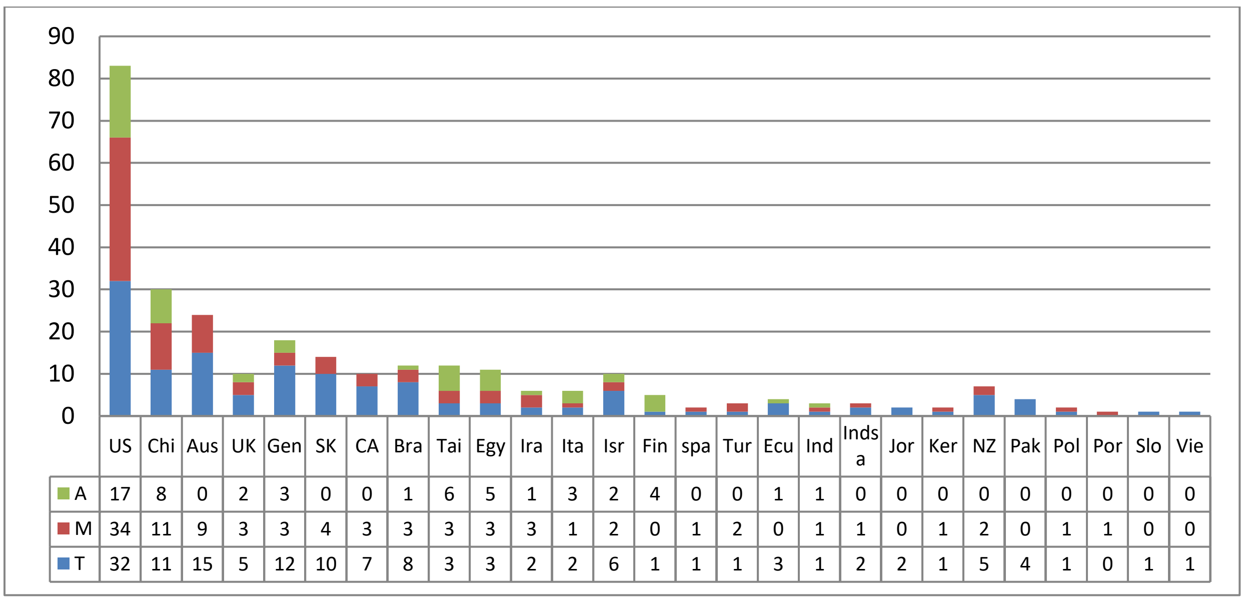
Figure 2.5 Frequency of projects analyzed in the research

Another key aspect in the analysis of articles is extracting the countries where the projects take place. Table 2.3 represents these countries and the number of articles mentioning them. The United States accounts for the majority of projects and research (Shrestha, K. J., Jeong, and Gransberg 2017), followed by China (Deng et al. 2020). Those two countries have the greatest share of using AI and mathematical tools compared to other countries. Figure 2.6 sums up the frequency of tools used by the country. This chart depicts increasing interest to integrate traditional tools with mathematical and AI tools, producing more reliable plans and tools in the construction industry.

Table 2.3 Countries of projects and their frequency

Country	Number of articles	Country	Number of articles	Country	Number of articles	Country	Number of articles
USA	39	Brazil (Bra)	5	Finland (Fin)	2	Jordan (Jor)	1
China (Chi)	15	Taiwan (Tai)	4	Spain (Spa)	2	Kerman (Ker)	1
Australia (Aus)	11	Egypt (Egy)	3	Turkey (Tur)	2	New Zealand (NZ)	1
UK	9	Iran (Ira)	3	Ecuador (Ecu)	1	Pakistan (Pak)	1

Country	Number of articles	Country	Number of articles	Country	Number of articles	Country	Number of articles
South Korea (SK)	8	Italy (Ita)	3	India (Ind)	1	Poland (Pol)	1
Canada (CA)	6	Israel (Isr)	3	Indonesian (Indsa)	1	Portugal (Por)	1
General (Gen)	9	Projects Locations are not stated or have different locations.		Vietnam (Vie)	1	Slovenia (Slo)	1



	US	Chi	Aus	UK	Gen	SK	CA	Bra	Tai	Egy	Ira	Ita	Isr	Fin	spa	Tur	Ecu	Ind	Indsa	Jor	Ker	NZ	Pak	Pol	Por	Slo	Vie
A	17	8	0	2	3	0	0	1	6	5	1	3	2	4	0	0	1	1	0	0	0	0	0	0	0	0	0
M	34	11	9	3	3	4	3	3	3	3	3	1	2	0	1	2	0	1	1	0	1	2	0	1	1	0	0
T	32	11	15	5	12	10	7	8	3	3	2	2	6	1	1	1	3	1	2	2	1	5	4	1	0	1	1

A: Artificial intelligence. M: Mathematics. T: Traditional

Figure 2.6 Countries and frequency of using tools in construction planning and control research

The previously mentioned tools helped in partially solving the problems of planning and control in the construction industry. These partial solutions encourage the integration of these efforts to bridge the planning symptoms. One of the powerful approaches that have a holistic view in dealing with problems is SD. It analyzes the structure that generates the unwanted behaviors and then makes changes to the structure to finally tackle the events (Sterman, J. D. 1994, 291-330). This approach and its use in the construction management field will be discussed in the next section.

2.3.3 Need for a holistic approach

PBO applies the previously mentioned tools and theories in its business model (BM). BM is a general overview of a company framework and how it operates to achieve its objectives, and it encompasses sustainability, growth, creativity, social influence, and value development. BM has emerged as a central process for characterizing business strategy by modeling how a company operates to achieve its objectives (Cosenz and Noto 2018, 127-140).

BM in such circumstances focuses on the operational issues and usage of traditional tools in strategic planning. This makes PBO decisions focus on one issue. Ignoring the feedback effect of decisions on other subsystems makes it difficult to take the optimum decision for the organization.

Indeed, planning and management in PBO is a dynamic process affected by the sequential decisions applied, where “the actual sequence of decisions is determined not only by planning, but also by emergent variables, or decisions and actions that arise within an enterprise that adds to the pattern but are not expected in the strategy” (Wolf and Floyd 2017, 1754-1788). This means each decision has a butterfly effect on other subsystems that need to be addressed. These perspectives are technical and tactical planning oriented, and miss the feedback between interacting subsystems and integration between them (Swei 2020). Hence, there is a need for a holistic approach to enhance the PBO strategic planning process.

Moreover, the characteristics of construction projects, (Sterman and John 2002, 42-42.), and PBO require a dynamic approach that can consider the PBO as a system of systems made of projects, can examine the non-linear relations between subsystems, can cope with the highly dynamic environment of the PBO, can involve “soft” & “hard” data, can capture responses that exhibit time delays from actions.

2.4 SYSTEM DYNAMICS

Dynamic business modeling, in turn, is capable of representing emergent behavioral patterns based on sequences of decisions and feedback. The system Dynamic (SD) approach evolved from systems thinking, which not only considers components but also the holistic view, and focuses on reliably projecting behavior based on the underlying structure (Richmond 1993, 113-133). SD considers the lag between an action and its consequences, as well as the nonlinear relationships between attributes (Sweeney and Sterman 2000, 249-286). From this perspective, SD is used to capture the causality relationships and feedback loops in the system (Stave and Hopper 2007, 1-22), and to adopt multiple perspectives as subsystems in a single model (Squires et al. 2011, 10).

SD modeling can generate macro dynamics from microstructure (Sterman, J. D. 1989, 321-339) because it is a white box modeling. This means it is a causal driven (based on theory) model, not a data-driven (based on correlation) model (Barlas and Carpenter 1990, 148-166). SD employs techniques from the field of feedback control to set up the problem factors into a causes feedback loop (Forrester 1993, 199-240). The construction project is not a unidirectional system. Each decision contributes to the system status which in turn affects the upcoming decision. In such systems, SD helps to understand that problems are mainly attributed to internal factors, despite a widespread and deceptive inclination to blame problems on external factors (Sterman 1989, 321-339). The structure of the organization can be simulated and interplay with management decisions might result in accumulated dynamics that consistently deviate from the optimum behavior. Moreover, it is capable of integrating the company strategies and resources (Kim, S., Chang, and Castro-Lacouture 2020a). These capabilities provide incentives to choose this approach as an integrated tool to help eliminate the gaps in the aforementioned studies.

2.4.1 Philosophical perspective of SD

SD makes use of the feedback control theory's principles and mathematics (Richmond 1993, 113-133). It has two main sorts of variables based on accumulations and flows, i.e. levels and rates. Auxiliaries are a third category that is utilized for additional context and modeling. The volume of an accumulation can be altered by the in-flows and out-flows. It can be modified by their fluxes. i.e, it is impossible to regulate the level directly (Sweeney and Sterman 2000, 249-286). This includes the delays between the actions and consequences, and nonlinear relations between attributes (Sterman, J. D. 2001, 8-25). Time delays and other variables can be represented by auxiliaries. Generally, the type of variable is determined by the procedure that produces its value.

SD projects a trustworthy behavior generated from the underlying structure (Richmond 1993, 113-133). This is in the form of patterns of change rather than static snapshots (Senge 1990). The temporal patterns (trends and oscillations) are created by the architecture of the feedback loop (FBL) working across time, considering the values and delays of the causal effects. From this perspective, SD is used to capture the causality relationships (Stave and Hopper 2007, 1-22), and can adopt multiple perspectives in one model as subsystems (Squires et al. 2011, 10).

Because the patterns are created by the full system mechanism, decisions centered on one variable using the open system cannot successfully change the required variable to the desired value. Hence, the entire structure should be examined across time. Computer simulation is utilized by SD to explain why processes act the way they do, based on the information we already have about the problem under investigation (Ramage and Shipp 2009, 99-108). SD's graphical tools facilitate the sketching of causal loops that enables communication and understanding of mental models (Sterman 2001, 8-25). Causal loop diagrams (CLDs) consist of variables linked with arrows that have a positive sign for causes directly proportional to the effect and a negative sign for causes that are inversely proportional to the effect. This depicted conceptual relation is transformed into a numerical integration model using the stock and flow tool. The stock is similar to a box or level that elucidates the behavioral response, while the flow is the rate that changes the stock (Sterman and John 2002, 42-42.). Two equations at least are required to express the simplest basic feedback relationship mathematically between a stock and flow. The first equation must depict the formula in which the flows alter the level. The second equation must depict how the buildup stock alters the flow patterns. The simulation of the mathematical model employs algebra and logic functions.

2.4.2 SD in the construction planning and control

SD is essential to understanding and depicting the casual and internal relationships at different levels of construction projects in planning and control, effectiveness and performance, strategic management, sustainability, and other areas (Liu, M. et al. 2019, 730-741). SD is utilized to examine the effects of the skilled labor shortage. Results provide a better understanding of the effects of wages and their effect on project cost and schedule (Kim, Chang, and Castro-Lacouture 2020).

Various construction applications utilized the SD approach (Liu et al. 2019, 730-741). It is used to investigate the owner characteristics on market price (Lo, Lin, and Yan 2007, 409-416). It is used to represent project cash flow feedback loops (Cui, Hastak, and Halpin 2010, 361-376), and to optimize the Net Present Value of a big portfolio (Ali 2017). It is used to investigate the output of projects under different working conditions and productivity changes at the project level (Alvanchi, Lee, and AbouRizk 2012, 66-77), and portfolio level (Salehizadeh and Mahmudi 2019, 12-22).

Attention on SD is growing as shown in Figure 2.7, the full list of articles used to build this figure and upcoming analysis is mentioned in Appendix III. Researchers have completed several literature surveys on its use and importance such as (Shafieezadeh et al. 2020a, 201-216; Pagoni and Georgiadis 2020, 277-291; Kim, Chang, and Castro-Lacouture 2020), the full list of surveyed literature articles is mentioned in Appendix II. SD methodology has two unique tools: causal loop diagrams (CLDs) and stock and flow models (Sterman 1994, 291-330). Those tools enable system modelers to capture the cause-and-effect relationships and numerically simulate them. CLDs consist of variables linked with arrows that have a positive sign for causes directly proportional to the effect, and a negative sign for causes that are inversely proportional to the effect (Sterman and John 2002, 42-42.). This depicted conceptual relation can be transformed into a numerical integration model using the stock and flow tool. The stock is similar to a box or level that elucidates the behavioral response, while the flow is the rate changing the stock (Zhu and Mostafavi 2014, 0), (Zhu and Mostafavi 2014b, 213-219). The CLD and stock and flow improve SD's ability to manage complex systems and capture feedback processes and delays. Also, they help in the evaluation of new strategies and decisions (Sterman and John 2002, 42-42.).

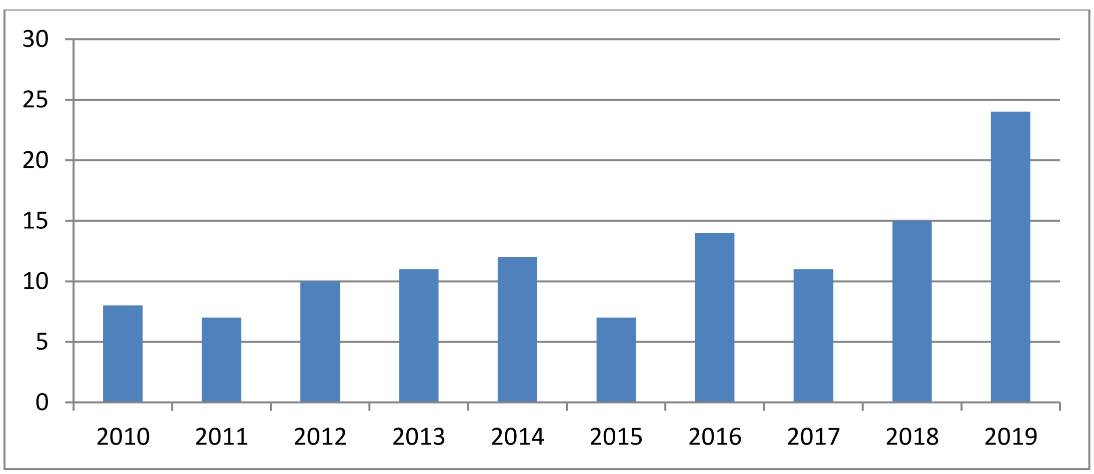


Figure 2.7 Studies using SD in the construction industry from the last decade

The analysis of 112 papers from 2010 to 2020 revealed that researchers' main application of SD is in the time knowledge area, with 19.2% as shown in Figure 2.8. The main cause of this high percentage is that researchers use time as a tool to synchronize the workflow of a system and as a tool to measure the system's response to changes and decisions.

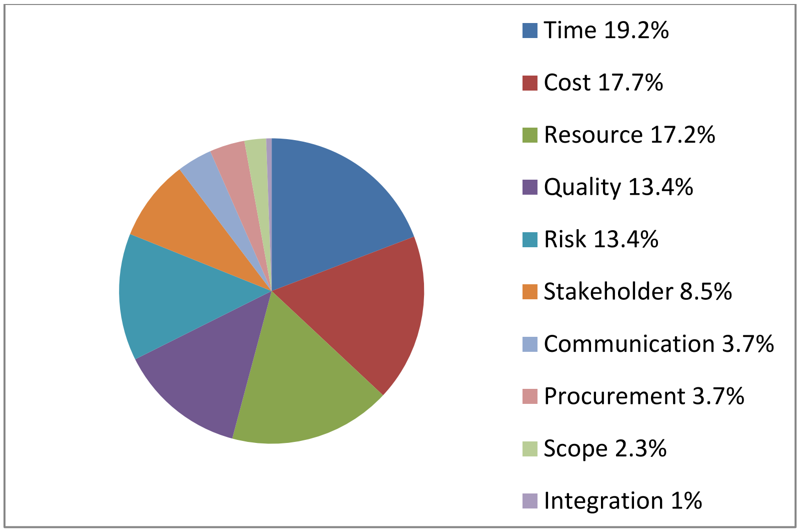


Figure 2.8 Use of SD in knowledge areas

The next most frequent applications are cost and resource knowledge areas, with approximately the same percentage of 17.7% and 17.2%, respectively. The high frequency of using cost because it measures consequences, in addition to its importance to all stakeholders. Resources have the same attention in research due to their limitations. Much of the research published in the resource area is interested in minimizing the waste of resources or recycling construction waste.

Labor resources take more attention in the SD approach than traditional methods (Kim, S., Chang, and Castro-Lacouture 2020b). This is related to the capabilities of SD tools that could abstract the behavior of the social interaction and uncertainties using cause and effect with syngeneic relations (Al-Kofahi, Mahdavian, and Oloufa 2020a, 1-12). (Nasirzadeh and Nojedehi 2013, 903-911), their study provided a worker productivity dynamic model that describes the synergetic factors that contribute to labor productivity using causal loops and feedback relations. This model helps managers determine the main causes of productivity losses as shown in Figure 2.8. In their study, the focus was on the project level and the operational detail of the project which provides a valuable feedback model. Integrating the project level into the organizational level could enhance the organization's performance and allocation of resources for better productivity. Also, (Cosenz and Bianchi 2014) provide an SD model to depict the relationship between labor productivity and motivation, including the linear and nonlinear relations and factors. The results highlight incentives, rewards, career promotions, and burnout as the main factors that contribute to motivation and productivity. Other SD models depict the synergetic relations between causes and effects using the tools of causal loop and feedback relations (Nasirzadeh, Khanzadi, and Mir 2018, 132-143), (Kim, S., Chang, and Castro-Lacouture 2020c, 04019035).

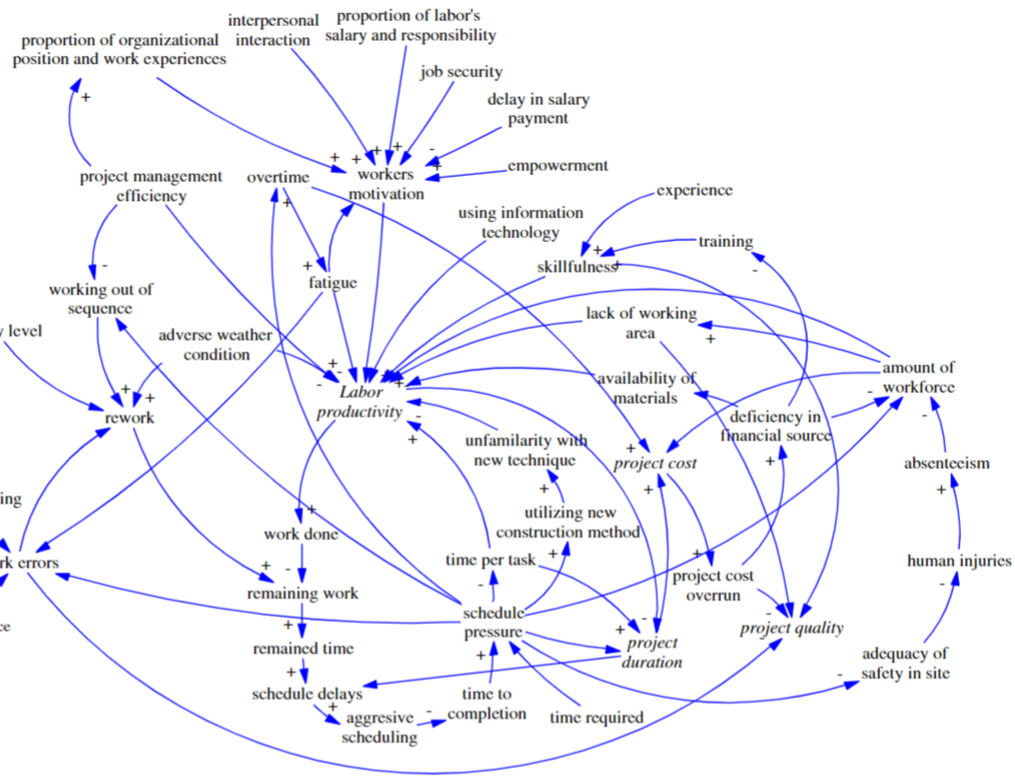


Figure 2.9 Labor productivity model (Nasirzadeh and Nojedehi 2013, 903-911)

Quality and risk come at the third level, with a percentage of 13.4%. The knowledge areas of stakeholders, communication, and procurement still require more attention as they participate in project success. Owner satisfaction and engagement in project processes are essential. Likewise, in surveys conducted by researchers, communication among contractors, subcontractors, and the owner is frequently mentioned as one cause of project delay (Amarkhil et al. 2020). But communication still lacks the appropriate attention in the literature. Finally, as mentioned in the previous section, scope and integration knowledge areas have much concern from a dynamic perspective. This becomes essential in the increasing complexity of construction projects and the dynamic environment.

2.4.3 Tools and programs used with system dynamics

Almost all of the articles surveyed integrate SD with other tools in hybrid models to make the most of it, as shown in Figure 2.10. Questionnaires, interviews, and case studies have been used with

SD to predict the impact of the owner and contractor-related variables on the legislation stages (Jing et al. 2019, 677), to determine delays in Indian construction projects (Das, Dillip Kumar and Emuze 2017, 21-39), or to identify sources of rework in Nigerian construction projects (Aiyetan and Das 2015, 1266-1295). SD has also been integrated with neural networks and regression analysis to model construction project behavior using management, employee, equipment, and environment system sub-systems (Wu, X. et al. 2019, 221).

Discreet Event Simulation (DES) has been integrated with SD to confine strategies with operational variables to determine more reliable plans (Alzraiee, Moselhi, and Zayed 2012, 1063-1073). Another study shows that integrating traditional tools like CPM and activity-on-node (AON) networks with SD is more beneficial in dealing with schedule issues and project control (Gonzalez, Kalenatic, and Moreno 2012, 21-32).

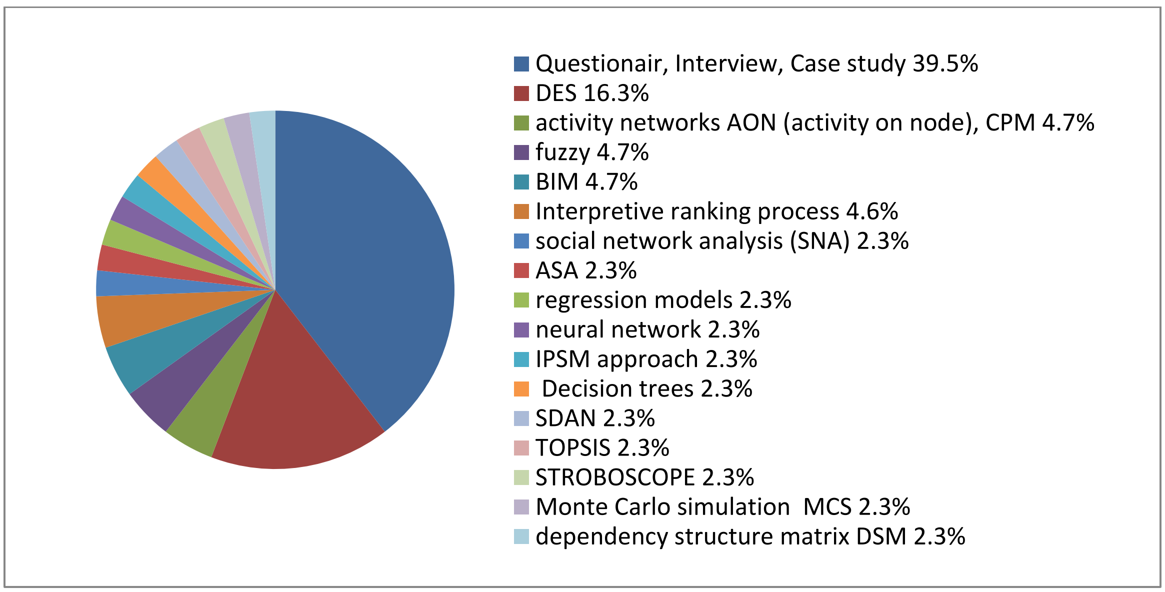


Figure 2.10 Utilized tools with system dynamics

Fuzzy models have used SD to picture the complex, synergistic nature of construction projects, and address uncertain relations that are not easy to quantify or quantitatively allocate risks (Akbari et al. 2020, 545-567). In most cases, these values are determined by the judgment of the field experts. For example, (Nasirzadeh, Khanzadi, and Mir 2018, 132-143) used this methodology in a highway project to predict the values of factors affecting the concession period. Also, BIM has been connected with SD models to help in quantifying risk allocations (Thompson and Bank 2010, 1006-1015).

Regression models have been used with SD to measure the impact of lacking skilled laborers on labor wages, project time, and budget (Kim, Chang, and Castro-Lacouture 2020, 04019035). Monte Carlo simulation simulates stochastic and probabilistic changes in construction projects, while the dependency structure matrix models the estimated effects of these changes (Tokdemir, Erol, and Dikmen 2019b, 4018132). The interpretive ranking was also used with SD to identify construction risk variables. The main function of interpretive ranking is to define, evaluate, and rank the risk relationships. These values were then fed into SD models to quantify their impacts (Mhatre, Thakkar, and Maiti 2017).

Other tools used with SD include decision trees and Integrated Participatory Systems Modeling (IPSM) to facilitate the decision-making process in a complex stochastic environment like construction projects (Suprun et al. 2019, 1-23). They utilized an integrated methodology to collect data from stockholders and model the collected data into a causal loop diagram. They analyzed the conceptual model built and finally simulation of this model. This technique is different from the group model building because it allows collecting data from stack holders for model conceptualization and analysis of policies explicitly from the modeling process by volunteering, which means the stakeholders might be not familiar with the SD tools such as stock and flow (Suprun et al. 2018, 33). In their study, they ranked the decision tree to quantify the range of values that the project manager can perform. Also, the Technique of Order Preference Similarity to the Ideal Solution (TOPSIS) was integrated with SD to facilitate selecting projects based on their portfolios for the projectized organizations. This methodology increases the flexibility of high-level planning adaptation in a shared resources environment (Rad and Rowzan 2018, 175-194). This enables portfolio alignment but is limited to the linear relationship between variables in the application of the SD approach. The application of the hybrid model is valuable and the nonlinear relations could provide more utilization for the SD capabilities.

Finally, the literature indicates five software packages used with system dynamics, VENSIM (Shafieezadeh et al. 2020b, 201-216), STELLA (Das, Dilip Kumar and Emuze 2017, 21-39), POWERSIM (Azhari et al. 2014, 65-86), SIMULINK (White 2011, 696-705), iThink (Chritamara, Ogunlana, and Bach 2002, 269-295). At the top of those programs, with a 76.4% acquisition rate of articles is VENSIM, followed by STELLA with a percentage of 14.7%. The other programs equally share the remainder. The widespread use of VENSIM is due to its reality check feature available in the PLE version. In addition, VENSIM is free while the other software is not.

2.5 TIME SERIES

Contracting companies face problems in capacity/workload prediction either in short-term or long-term planning. Contractors blame the complexity, inherent nonlinear relations of the construction market, and its sensitivity to economic and political fluctuations, to have a volatile demand. This volatility affects various operational and strategic decisions on the project and organization levels (Christopher and Holweg 2017). Understanding such fluctuations in demand helps in reducing uncertainty and enhance performance. There are indices to measure the uncertainty (volatility) in the demand time series. The coefficient of variation (CV), one of these indices, can measure the volatility of a demand pattern. This is determined by calculating the standard deviation divided over the average for a certain period (Gilliland 2010), (Abolghasemi et al. 2020, 106380). Time series with higher CV are normally related to higher levels of uncertainty and are harder to forecast (Huang, Chang, and Chou 2008, 3223-3239).

It is critical to include and foresee these uncertainties to minimize the harmful repercussions of variable demand, which makes forecasting difficult (Syntetos et al. 2016, 1-26). Inaccurate estimates may result in wasteful expenditures in terms of labor, equipment, and other resources. There are approaches to mitigate these uncertainties; for instance, increasing organization capacity, which works as an inventory of capabilities to face fluctuations in demand. This will aid in reducing demand volatility, but it will come at a high cost to businesses (costly proposition) (Hope and Fraser 2003).

This represents a need for demand forecasting to reduce market uncertainty. Several models have been employed to anticipate demand forecasting during the last few decades. For instance, in Hong Kong, grey forecasting is utilized to predict the local construction industry demand (Tan et al. 2015, 219-228). Findings show that the local construction industry is about to begin another boom era (assuming no big external shocks to the economy), with substantial growth projected in the structures and facilities sector. In Australia, multivariant TS prediction is used in predicting the construction industry demand and comparing it with the vector error correction (VEC) with dummy variables (Jiang and Liu 2011, 969-979). The effect of global economic events was considered, and the results show that it has a greater forecast accuracy than the conventional VEC model. Findings show, also, that population growth, changes in national income, interest rate fluctuations, and changes in household expenditure all play important roles in predicting variations in construction demand. Another study in Singapore utilized Machine learning, especially Artificial Neural Networks (ANN), and compared it with Multiple Regression (MR) in predicting the demand for new projects based on economic variables (Hua 1996, 25-34). Results revealed that 12 economic factors have a strong relationship with residential building demand. These factors are national income per capita, general demand for construction, size of the population, rate of household formation, interest rate, property price, levels of supply of residential property, disposable income, economic growth, level of unemployment, existing housing stock, rate of inflation, construction cost, mortgage credit availability, and household personal savings.

2.6 SUMMARY

This chapter provides systematic literature reviews of the area of construction project planning and control in the last two decades. The analysis revealed that time management attracts the most attention from researchers in both planning and control. Cost management comes at the second level of interest, and others follow successively (i.e. quality, risk, labor resources, equipment, material, safety, and communication management). There is great interest reflected in the tools used in this process; the most commonly used tool is EVM, which relates plan achievement to time and cost. The workload (scope) and integration receive little attention.

Various tools were used to enhance the accuracy and consistency of planning and improve control performance in construction projects. These tools are divided into three main groups: traditional, AI, and mathematical tools. Besides, researchers' efforts provide a clear picture of the lack of feedback among different variables.

The need for a holistic approach that matches the characteristics of project executions in the PBOs. SD is the best match for these characteristics. The value added from the integration (hybrid modeling) of SD with different tools is reviewed. This highlights the potential for enhancing the PBO's strategic planning by linking its subsystems together e.g, resources, finances, workloads, etc. The characteristics of SD will enable the visualization of the interaction between the whole subsystems. The feedback mechanism will illustrate the effects either intended or unintended on the different levels of the system. Also, it will help to find the optimal strategy for the contracting company and how to adapt to market conditions.

CHAPTER 3 IDENTIFICATION OF FACTORS AFFECTING WORKLOAD FLUCTUATIONS IN PBO

3.1 INTRODUCTION

Project-based organizations (PBOs) are companies that rely on a continuous supply of projects to make a profit. Their structure evolves to develop a temporary system leading to the project's success. Through this system, the organization's workload is managed (Turner and Miterev 2019, 487-498). PBO strives to achieve harmony between project and portfolio workload management to provide tangible value to stakeholders.

PBO is composed of five main dimensions: strategy, structure, human resource, behavior, and process (Miterev, Turner, and Mancini 2017, 527-549). Previous work has mostly focused on one of these dimensions or the interaction between two dimensions. Relatively little attention—15 of the 177 articles analyzed in a study by Miterev et al. (2017)—has been given to studying the effect of three or four of these dimensions on one another (Miterev, Turner, and Mancini 2017, 527-549), despite the significant effect of these interactions on an organization's strategic planning.

3.1.1 Planning in PBO

Strategic planning is widely used, but few managers are satisfied with the outcomes it yields, particularly when it comes to the role of uncertainty in the internal and external environments (Wolf and Floyd 2017, 1754-1788). Several factors affect plans' reliability, one of them is dealing with strategic planning using the traditional operational project management models (Too and Weaver 2014, 1382-1394). This can give rise to project schedule delays and budget overruns. This stems from the traditional management model's main assumption that is, if elements are understood, then the project/program/portfolio can be controlled. However, experience suggests that the interrelationships among elements are more complex than has been stated in the traditional work breakdown structure of project networks (Wang, Kunc, and Bai 2017, 341-352).

To enhance the planning process, several studies have endeavored to address operational-level performance issues by seeking a local optimum solution (i.e., at the project level) (Killen et al. 2012, 525-538). This results from using the traditional approach. The application of project planning traditional tools has typically focused on project performance, but without consideration for the effect, one project's performance may have on other projects operated by the same contractor (Martinsuo 2013, 794-803). This can have a butterfly effect with long-term implications (Mahdavi et al. 2019, 1200-1217). As such, it is crucial to link the performance of all projects operated by a given organization (i.e. the portfolio level).

The cycle of workload management could be considered generally as two phases interacting together, workload acquisition and workload execution. Previous studies considered workload acquisition studies from the perspective of the contractor and owner. The contractor perspective studies focused on Bidding decisions using different tools such as the Logistic regression model (Lowe and Parvar 2004, 643-653), Adaptive Neuro-Fuzzy Inference System (Polat, Bingol, and Uysalol 2014, 1083-1092), Fuzzy TOPSIS method (Al-Humaidi 2016, 04016068), Multi-criteria decision analysis (van der Meer et al. 2020, 172-188). These studies centered around the application of a process system to aid project selection and portfolio design to have a consistent characteristic of workload (Jerbrant 2014, 33-51). These processes hypothesize that optimizing the portfolio of PBO workload will help in achieving stable planning and management of workload. Also, other studies focused on competition and increasing the probability of winning in the bidding process. These studies utilized different tools to define the markup percent such as Bayesian statistics and correlation between bid items (Yuan 2011, 1101-1119), surveys and statistical tools to define the competitive tender price (Aje, Oladinrin, and Nwaole 2016a, 19), (Ye et al. 2014, 461-472), a hybrid Bayesian-fuzzy to optimize the bid price in the negotiation phase (Leu, Hong Son, and Hong Nhung 2015, 1566-1572).

Previous studies from the owner's perspective were focused on contractor selection and linked it with project success. (Nasir and Hadikusumo 2019, 04018052) utilized a hybrid system dynamic and agent-based model to study the relationship between owner and contractor. They found that the pre-award policies have a greater effect on project performance. (Semaan and Salem 2017) developed a multi-criteria decision support system to evaluate and select contractors in the bidding phase. Other models utilized the fuzzy technique (Singh and Tiong 2005, 62-70), and a hybrid fuzzy-AHP model (Jaskowski, Biruk, and Bucon 2010, 120-126).

Previous studies considered the after-award phase was oriented toward contractor project management. Several studies have endeavored to address operational-level performance issues by seeking a local optimum solution (i.e., at the project level) (Killen et al. 2012, 525-538). This results from using the traditional approach. The application of project planning traditional tools has typically focused on project performance, but without consideration for the effect, one project's performance may have on other projects operated by the same contractor (Martinsuo 2013, 794-803). This can have a butterfly effect with long-term implications (Mahdavi et al. 2019, 1200-1217). As such, it is crucial to link the performance of all projects operated by a given organization (i.e. the portfolio level).

3.1.2 Gaps in the PBO planning regime

At the project/portfolio level, the most widely adopted management approach is open systems (Martinsuo and Geraldi 2020, 441-453). However, the open system considers the flow of actions without considering their feedback. This static approach is not capable of representing the dynamic complexities of the business and market landscape (Cosenz 2017, 57-80). Open system tools focus on the logical, top-down, and structural characteristics of strategy. As a result, this approach tends to overlook the underlying practices generated by the strategy, as well as how these practices may affect strategy implementation (Clegg et al. 2018, 762-772). Successful project management, in contrast, requires integration among the various dimensions of PBO (i.e. strategy, structure, human resource, behavior, and process).

Using traditional BM with dynamic financial constraints, during the bidding process, to decide the size of markups could have a bias, either downward or upward, that is positively associated with the financial stability of the organization (Beker and Hernando-Veciana 2015, 234-261). Owner characteristics and the method of selecting the contractor directly affect the contractor's behavior during and after the bidding process. This could lead the contractor to change the markup percent (bidding price) or tend to manipulate during project execution to overcome the reduction in the bidding price to award the project. Previous studies utilized different tools such as Fuzzy Decision Framework (Singh and Tiong 2005, 62-70), Data Mining Framework (Art Chaovalitwongse et al. 2012, 277-286), and Multi-Criteria Decision Support System (Semaan and Salem 2017) to optimize the contractor selection. In contrast, there is a lack of research that studied the effect of these decisions on contractor behavior and project performance.

3.1.3 Value added from SD fills the current gap

SD is significantly different from the open system. SD allows for the study of the core cause-and-effect interactions among key business variables, this allows one to learn how a company operates and what may be the keys to its future success (Kenefic 2020). In recent years the SD approach has been integrated with strategic management to support the PBO, given its effectiveness in promoting strategic learning, thereby facilitating decision-making and performance enhancement from a systemic viewpoint (Cosenz 2017, 57-80). However, selecting model boundaries by focusing on the project, might isolate the internal dynamics of the project from external dynamics related to the market and organization.

3.1.4 Chapter goal

This chapter focuses on identifying and analyzing the factors affecting PBO's workload fluctuation using traditional and social network techniques, which is the first objective of this research. This highlights the gap in identifying the factors and their dynamic modeling. Then, a conceptual framework using the SD approach is proposed to address the previously mentioned limitations in the current body of knowledge (the focus on operational issues, the use of limited traditional tools in strategic planning, and the separation of internal dynamics from external dynamics).

3.2 METHODOLOGY

The literature on dynamic modeling of PBO/contracting organizations and construction projects is studied to gain an understanding of the direct and indirect effects of various project and portfolio variables in a holistic manner. The identification of these variables is achieved through multiple steps executed in rolling cycles as shown in Figure 3.1. The process starts by selecting a suitable search engine platform. Google Scholar is selected to have a general overview and because it is more inclusive that cover diversity of researches included in other databases such as Scopus and Web of Science (Martín-Martín et al. 2021, 871-906). Also, Scopus and Web of Science are screened with the same keywords to make sure that most of the sources are reviewed. A suitable search engine having been identified, a systematic review is conducted using predefined keywords: dynamic/modeling of contracting organization performance, dynamic/modeling of construction project performance, dynamic/modeling of contracting organization workload, and dynamic/modeling of contracting organization bidding process. The keywords are carefully selected to cover the entire process of workload generation and execution on the part of the contracting organization. The title, abstract, and conclusion of each article returned in the search are then screened.

The second step is to review the full papers based on whether their content is sufficient for mathematical analysis and for characterizing the relationships among variables. Then, analyze the content of the selected articles (see Table 3.1) to identify the variables responsible for the dynamics of how a contracting organization adds to its workload and executes its operations to earn profit. These articles, listed in Table 3.1, are classified into three categories: survey, non-dynamic modeling, and SD modeling. Survey studies focus mainly on defining variables affecting a specific problem using surveys, questionnaires, and interviews and carrying out statistical analysis of the results. Non-dynamic modeling studies use modeling tools (e.g., fuzzy modeling, equation modeling, neural networks) to analyze the surveyed variables. SD modeling studies apply SD theory to model the surveyed variables.

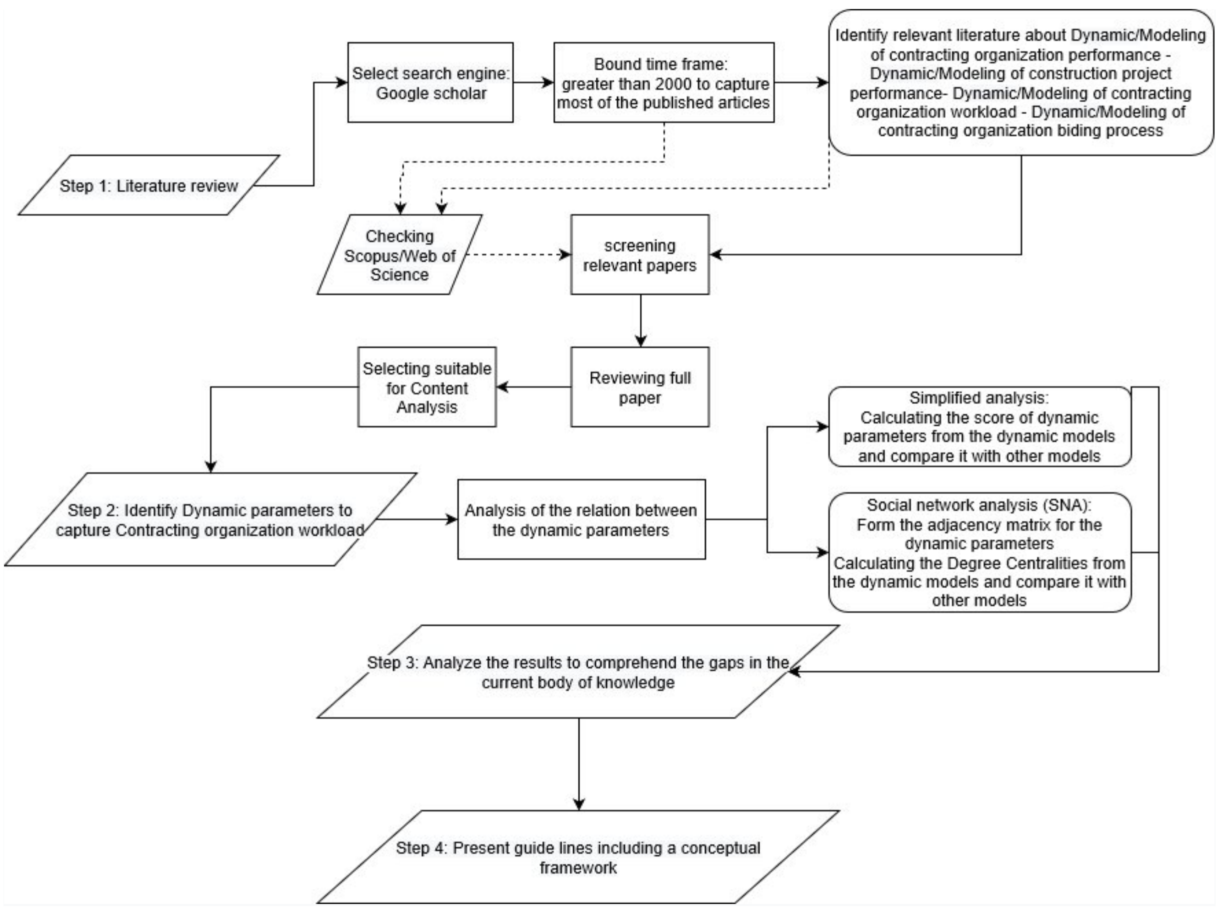


Figure 3.1 Research methodology (adapted from (Abotaleb and El-adaway 2018b, 04018033))

Table 3.1 Papers studied

Item	Source	Survey	Non-dynamic modeling	SD model
S1	(Bajracharya, Ogunlana, and Bach 2000, 91-112)			✓
S2	(Tang and Ogunlana 2003a, 127-136)			✓
S3	(Lo, Lin, and Yan 2007, 409-416)			✓
S4	(Taylor and Ford 2008, 421-431)			✓
S5	(Egemen and Mohamed 2008, 864-872)		✓	
S6	(Bageis and Fortune 2009, 53-71)	✓		
S7	(Cui, Hastak, and Halpin 2010, 361-376)			✓
S8	(Dangerfield, Green, and Austin 2010, 408-420)			✓
S9	(Enshassi and Mohamed 2010, 118-142)	✓		
S10	(Alvanchi, Lee, and AbouRizk 2011, 77-91)			✓
S11	(Lisse and Student 2012)			✓
S12	(Alvanchi, Lee, and AbouRizk 2012, 66-77)			✓
S13	(El-Mashaleh 2013, 200-205)	✓		
S14	(Jarkas 2013, 53-75)	✓		
S15	(Li, Ying and Taylor 2014, 04014044)			✓
S16	(Jarkas, Mubarak, and Kadri 2014, 05014007)	✓		
S17	(Polat, Bingol, and Uysalol 2014, 1083-1092)		✓	
S18	(Ye et al. 2014, 461-472)	✓		
S19	(Yan 2015, 15423-15448)			✓
S20	(Leśniak and Plebankiewicz 2015, 04014032)		✓	
S21	(Shokri-Ghasabeh and Chileshe 2016, 127-157)	✓		
S22	(Aje, Oladinrin, and Nwaole 2016, 19)	✓		
S23	(Wibowo, Astana, and Rusdi 2017, 341-347)			✓
S24	(Chisala 2017, 04017088)		✓	
S25	(Aznar et al. 2017, 880-889)	✓		
S26	(Olatunji, Aje, and Makanjuola 2017, 378-392)	✓		
S27	(Li, Ying et al. 2018, 605-618)			✓
S28	(Nasirzadeh, Khanzadi, and Mir 2018, 132-143)			✓
S29	(Abotaleb and El-adaway 2018a, 04018084)			✓
S30	(Marzouk and Mohamed 2018, 90-108)		✓	
S31	(Abbaspour and Dabirian 2019)			✓
S32	(Oke, Omoraka, and Olatunbode 2020, 169-175)	✓		
S33	(Li, Guanghua et al. 2020, 04020050)		✓	
S34	(Shafieezadeh et al. 2020c, 201-216)			✓
S35	(Al-Kofahi, Mahdavian, and Oloufa 2020b, 1-12)			✓

The body of knowledge was studied and analyzed using both a conventional method (relative usage index-RUI) and social network analysis (SNA) to define the gaps. Each analysis encompasses two clusters of previous studies: dynamic modeling studies and non-dynamic modeling studies. In comparing the results from each cluster using SNA, the difference between expert mental models and actual dynamic models represents a gap that should be addressed in future holistic studies. Also, the variation between the non-dynamic models and dynamic models—identified using RUI—helps to determine which variables still warrant further investigation from the dynamic perspective. All of these results are described further in the analysis section below.

A conceptual framework is then developed by applying the SD approach to mitigate the three weaknesses mentioned above—the focus on operational issues, the use of limited traditional tools in strategic planning, and the separation of internal dynamics from external dynamics—. This framework abstracts the cycle of seeking workload (new projects) until its successful execution for the PBO. The proposed framework draws upon the relationships described and discussions presented in previous studies and consist of three subsystems: the pre-award stage, the post-award stage, and the financial system underlying the PBO. Each subsystem includes variables related to the organization, market, owner, and project (identified in the variable identification subsection). This is fully explained in the description of the conceptual framework later in this paper.

It is worth mentioning that, Abotaleb and El-Adaway (El-Adaway, Abotaleb, and Vechan 2018, 353-374) utilized this approach to identify the parameters affecting the project performance. In contrast, this work focuses on the contracting organization dynamics including projects and their interaction with each other.

3.3 DYNAMIC VARIABLES AFFECTING PBO WORKLOAD CYCLE

A review of the selected articles (shown in Table 3.1) reveals that 28 dynamic variables are affecting the PBO workload cycle. These variables are defined and categorized in Table 3.2. The categorization reveals that the majority of the variables investigated are related to the contractor, whereas other categories of variables require further investigation from the perspective of dynamic modeling. These categories will help researchers to define selected variables based on the model boundaries to be included in the study. It is worth mentioning that the present study is, to the best of the authors' knowledge, the first attempt to describe the dynamic variables that influence the PBO workload cycle for strategic planning. This method helps to understand holistically the effect of variations in one variable on other variables in the short and long terms. The applied decisions and strategies to be applied can be tested before implementation to support, facilitate, and enhance decision-making.

Table 3.2 Identification of dynamic variables

Category	Item	Variable	Identification
Contractor	V1	Organization Cash	This variable indicates the cash balance of the organization, the financial capacity of the contractor, and the available cash for running projects and upcoming projects.
	V2	Organization experience	This variable indicates the experience of the organization with this type of project, management competency, work quality, the percentage of errors in work, and the rework percentage. It is measured by the previous workload performed by the organization.
	V3	Resources	This variable indicates the availability and capacity of the contractor's equipment, qualified staff, booked value, and assets. This is measured by the man hours available.
	V4	Bid price	This variable indicates the size of the project, the contract price, or the awarded price.
	V5	Productivity	This variable includes labor productivity, equipment productivity, and crew productivity.
	V6	Debit	This variable indicates the number of contractors' loans from financial institutions, interest rate, and payment terms.
	V7	Bid manipulation	This variable includes overbidding, low tender sum, and beyond contractual reword or abnormal claims for contractor behavior.
	V8	Markup	This variable indicates the profit margin in similar projects and the expected return on investment.
	V9	Organization utilization	This variable indicates the utilization of resources, their allocation, and organizational capacity relative to workload.
	V10	Overhead cost /organization overheads	This variable indicates the indirect costs incurred, such as the cost of measures to satisfy the safety level required.
	V11	Tender preparation cost	This variable indicates the cost for an organization to prepare a plan and estimate the bidding price of the potential project.
	V12	Winning percent	This variable indicates the probability of winning the tender based on the tendering method, evaluation criteria, and contractor's history.
Owner	V13	Owner strictness	This variable indicates owner auditing or leniency of the owner in reviews, the quality level required, the required level of supervision, the owner's reputation, and the type. This is measured by the tolerance level accepted.
	V14	Payment	This variable indicates the terms of payment, advanced payment, and payment delay.

Category	Item	Variable	Identification
	V15	Tender document purchasing fees	This variable indicates the purchasing price of contract documents and other administrative fees to participate in the bidding phase.
	V16	Compensation	This variable includes the value of liquidated damage, penalties for non-completion, and the bonus for early completion.
	V17	Bonds value	This variable indicates the size of the contractor in the market, its running financial power, and the size and validity of the bonds required.
	V18	Bid time	This variable indicates the time allowed for bid preparation and tendering duration.
Market	V19	Projects availability	This variable indicates the market conditions and severity/intensity of competition in the industry.
	V20	Market share	This variable includes the current and expected market share based on the expected awarded projects.
	V21	Outsource quality	This variable refers to the output quality of the available qualified subcontractors and material suppliers
	V22	Number of bidders	This variable indicates the level of interest in the project.
	V23	Price feasibility	This variable indicates the efficiency of the costing method, uncertainty in cost estimation, and the feasibility of cost to market. This is identified by comparing the bidding price to the market price.
Project	V24	Outsource percent	This variable indicates the amount of work that is allowed to be subcontracted according to the contract.
	V25	Project schedule	This variable indicates planned/approved contract duration.
	V26	Risk	This variable indicates safety incidents, safety hazards, the possibility of environmental issues during execution, resource price fluctuations, schedule pressure or delays, and change in scope.
	V27	Design complexity	This variable indicates the design difficulty, clarity of requirements, quality, and potential for design rework.
	V28	Project scope	This variable indicates the workload required and the project type of work.

3.4 ANALYSIS OF DYNAMIC VARIABLES

A reference matrix (Table 3.3) is created using the 28 variables in Table 3.2 as rows and the 35 sources as columns. Then, for each cell (i.e., the intersection between row and column), if the variable is mentioned in this source, the value of the cell will be 1; otherwise, it will be 0, as shown in Table 3.3. The purpose of this matrix is to illustrate what the consensus is among academics and professionals regarding the variables in general. The matrix is then split into two matrices, one for SD modeling and the other for non-dynamic modeling.

Table 3.3 Reference matrix

	SD Sources																		Non-SD Sources																
	S1	**S2**	**S3**	**S4**	**S7**	**S8**	**S10**	**S11**	**S12**	**S15**	**S19**	**S23**	**S27**	**S28**	**S29**	**S31**	**S34**	**S35**	**S5**	**S6**	**S9**	**S13**	**S14**	**S16**	**S17**	**S18**	**S20**	**S21**	**S22**	**S24**	**S25**	**S26**	**S30**	**S32**	**S33**
V01	1				1	1					1	1					1		1	1	1	1	1	1	1	1		1		1		1	1		1
V02		1		1	1			1	1	1	1	1	1		1	1	1	1	1	1	1	1	1	1	1		1			1		1	1		1
V03		1			1	1	1	1	1			1	1		1	1	1	1	1	1	1	1	1	1	1		1	1	1	1		1	1	1	1
V04			1			1						1									1	1	1	1		1	1	1	1	1	1	1	1		1
V05				1	1		1	1	1				1	1	1	1	1	1											1						
V06		1			1															1	1			1											
V07			1								1																							1	
V08												1								1		1	1	1	1		1	1	1	1	1	1	1		1
V09		1					1	1							1				1	1	1	1	1	1		1	1	1		1		1	1		1
V10																					1		1	1									1	1	
V11																										1									
V12																					1		1	1		1			1					1	
V13											1								1	1	1	1	1	1		1	1	1		1		1	1	1	1
V14					1	1				1						1	1	1		1	1	1	1	1	1	1		1	1	1			1		1
V15																					1		1	1									1		
V16																					1	1	1	1								1			1
V17																					1		1	1	1	1	1			1		1	1		1
V18																				1	1	1	1	1	1	1	1			1		1	1		1
V19			1			1					1	1							1	1	1	1	1	1				1		1		1	1		1
V20		1				1					1								1	1	1	1	1	1	1	1				1			1		
V21								1									1		1	1	1	1	1	1	1		1	1	1			1	1	1	1
V22		1	1			1					1	1								1	1	1	1	1				1		1	1		1		1
V23											1												1			1									
V24								1									1		1	1		1	1									1	1		1
V25		1		1	1			1	1	1		1	1		1	1	1	1		1	1	1	1	1	1		1	1	1	1	1	1	1	1	1
V26		1		1		1	1	1	1				1	1	1		1	1		1	1	1	1	1	1		1	1	1	1	1	1	1		1
V27								1		1										1	1	1	1	1	1	1	1	1				1	1		1
V28		1						1	1			1	1		1	1	1	1			1	1	1	1		1	1	1		1	1	1	1	1	1

Note: S1 means Sours number 1, and V1 means Variable number 1. The details of each source and variable are mentioned in Table 3.1and Table 3.2 respectively.

3.4.1 Conventional analysis (RUI)

The conventional analysis begins with calculating the sum of each row of the reference matrix (both dynamic and non-dynamic sources). This summation is then normalized for the calculated matrix to compare the ranking of variables for both matrices (since the number of sources varies between the two matrices). The normalized value is calculated by dividing the total value of each row by the maximum total value for the analyzed matrix. Hence, the score of each variable ranges between 0 and 1.

To this point, the interconnections among the various variables have not been factored into the analysis. Accordingly, another technique is required to determine how the variables relate to one another and thereby provide a more accurate picture of their relevance and gaps. SNA is utilized for this purpose.

3.4.2 Social network analysis

SNA represents people or variables as nodes and their relations as lines. SNA is used to investigate how variables are connected and organized (Marin and Wellman 2011, 25). In the present study, to build the network, the previously built matrices (SD and non-SD) are used. Each variable is considered a node in the network, where two variables being mentioned in the same source is indicative of a relation (edge) between them. This network is considered undirected because it considers the study of two variables simultaneously, not the effect of one variable on another.

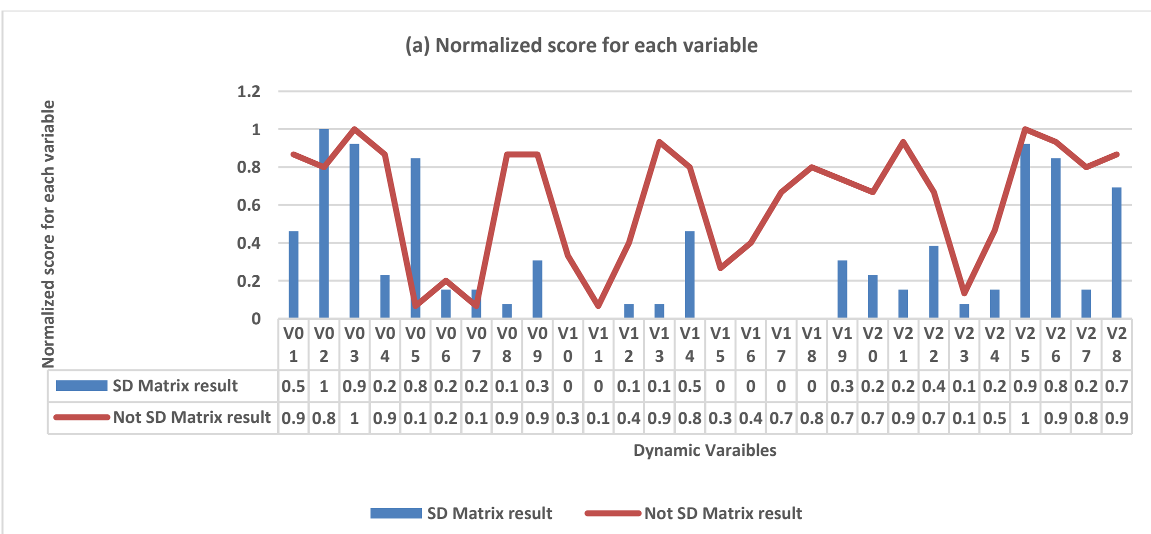
Gephi is used to analyze the networks built. Gephi is software for visual analytics and investigation of networks, dynamics, and relational graphs (Marin and Wellman 2011, 25). The measures used for social networks are divided into two categories: those that provide information about individual positions and interactions between nodes, and those that provide information about the SN's overall structure (Hanneman and Riddle 2005). For this research, the first category is adopted. The prestige measurement used for undirected networks is centrality.

The main assumption to build the network of variables from the previous studies states that the link/connection between these variables is the mention of these variables in one study. Hence, some SNA measures cannot provide a real reflection of the value generated from the measurements. For example, the degree to which a node is between other nodes in the network is measured by node betweenness. The variables with a higher degree of betweenness (gatekeepers) might function as an interface between closely knit groups. They are vital pieces in the connection between distinct parts of the network because they tend to regulate data flow across variables. Yet, based on the assumption the network is not mimicking the data flow between variables. The same concept is applied to the closeness measure as well. Hence, both are not calculated.

3.5 RESULTS AND DISCUSSION

3.5.1 Conventional analysis (RUI)

The results of the normalized score (RUI) are shown in Figure 3.2, where this score is reflective of the frequency of variables used in the studied articles. The frequency with which a variable has been mentioned in previous studies may be indicative of its relevance. Moreover, Figure 3.2 indicates that the most used variables are V3 (Resources), V2 (Organization experience), V25 (Project schedule), and V26 (Risk). This indicates that these are, theoretically, the most prevalent variables mentioned in the literature, and as such, they are incorporated in the SD models that analyze project management elements. The differences between scores allow for the detection of discrepancies between theoretical and simulation models that have been developed to date. These variables are V13 (Owner strictness), V18 (Bid time), V8 (Markup), V21 (Outsource quality), V17 (Bonds value), V27 (Design complexity), V4 (Bid price), V9 (Organization utilization). The discrepancies concerning these variables indicate that these variables have received less research attention than what may be warranted. In other words, there is a lack of dynamic models for studying and simulating these variables. It is worth mentioning that variables such as V18 (Bid time) and V17 (Bonds value), despite their importance, have not been studied using SD models in any previous study.



	V01	V02	V03	V04	V05	V06	V07	V08	V09	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22	V23	V24	V25	V26	V27	V28
SD Matrix result	0.5	1	0.9	0.2	0.8	0.2	0.2	0.1	0.3	0	0	0.1	0.1	0.5	0	0	0	0	0.3	0.2	0.2	0.4	0.1	0.2	0.9	0.8	0.2	0.7
Not SD Matrix result	0.9	0.8	1	0.9	0.1	0.2	0.1	0.9	0.9	0.3	0.1	0.4	0.9	0.8	0.3	0.4	0.7	0.8	0.7	0.7	0.9	0.7	0.1	0.5	1	0.9	0.8	0.9

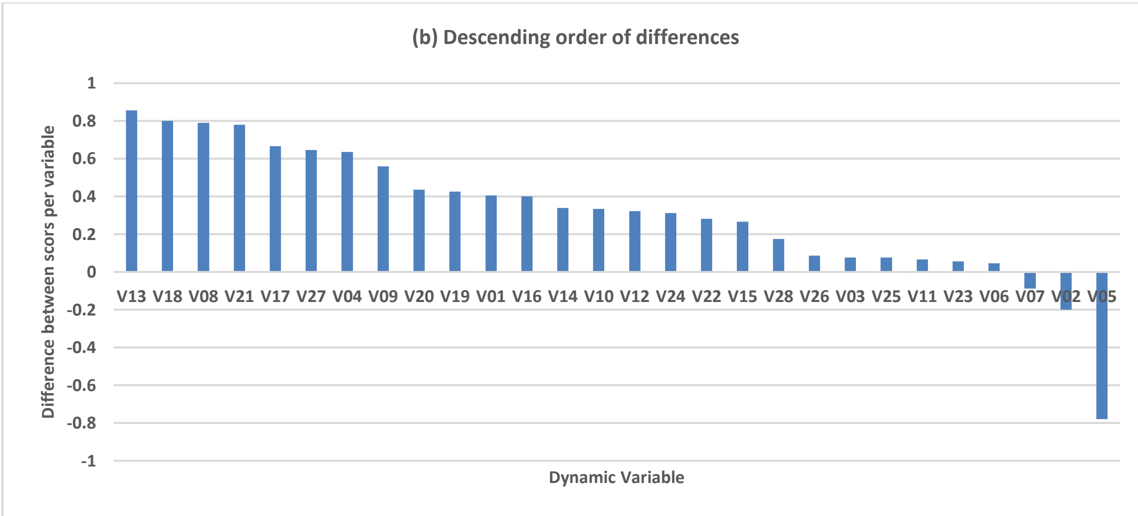
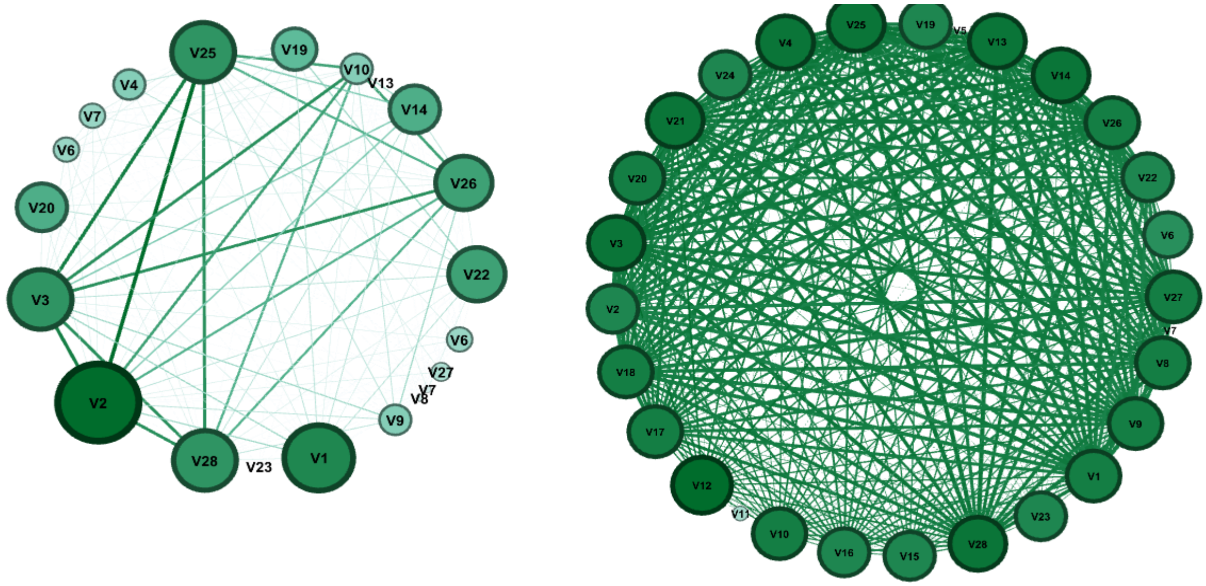


Figure 3.2 Normalized score for each variable as per the matrix

3.5.2 Social network analysis

Figure 3.3 reveals that the non-SD network has a higher degree of centrality than the SD network. This indicates that, while the literature emphasizes the importance of investigating dynamic variables in conjunction rather than separately, the simulation models developed have tended to focus on specific variables. Figure 3.4 quantifies this observation, where the variables with the highest normalized score in both networks can be considered the most prominent variables in construction project management. These variables are V1 (Organization Cash), V3 (Resources), V22 (Number of bidders), V25 (Project schedule), and V26 (Risk). In both networks, these variables have a normalized degree greater than 0.8, meaning that, concerning these variables, the simulation models developed are in agreement with what has been advocated theoretically in the literature.

Both the conventional analysis and the SNA show that the greatest disparity is about variable V13 (Owner strictness). From this, it can be inferred that, although "Owner strictness" is a critical variable influencing project success, it has been underrepresented in the simulation models developed to date. The second-largest gap is V23 (Price feasibility). This variable has not received sufficient attention from the dynamic analysis perspective, as shown in Figure 3.4. Moreover, the difference in density between the two networks shown in Figure 3.3 indicates that the variables are linked and have been considered in expert mental models, but have not garnered a sufficient amount of attention in terms of modeling analysis. Finally, the analysis reveals that no model among the studies reviewed accounts for all 28 dynamic variables. Among the models reviewed, none is capable of modeling more than 10 variables at once.



(a) Social Network for Dynamic studies

(b) Social Network for NOT Dynamic studies

Figure 3.3 Social network for SD and non-SD studies

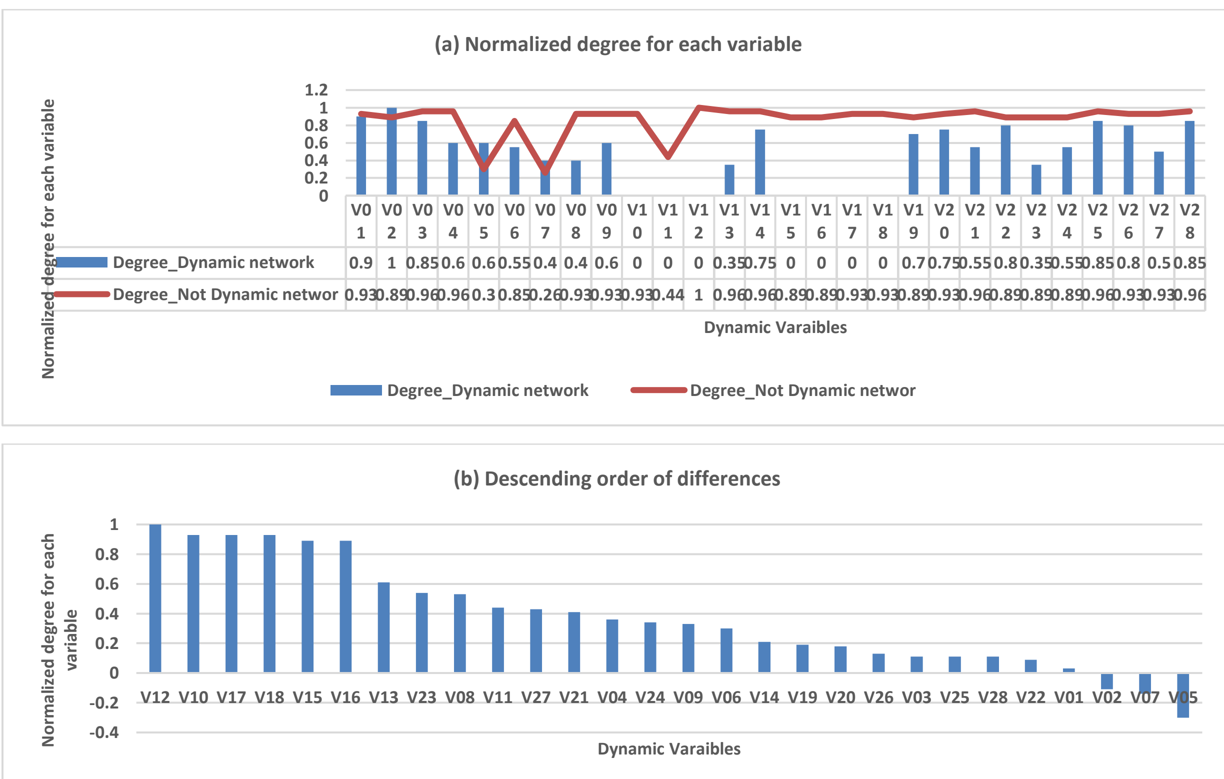
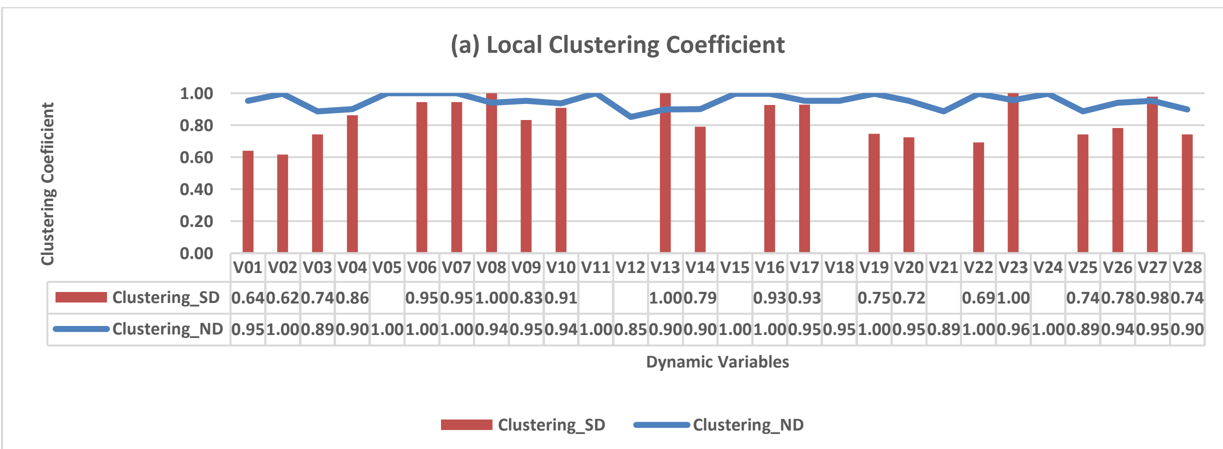


Figure 3.4 Normalized degree score per variable for each network

The identified 28 dynamic variables can cover a wide range of project aspects such as risk, productivity, resources, outsourcing, project scope changes, and others as mentioned in Table 3.2. Moreover, these variables can represent safety using the variables: overhead cost, rework, and risk. The organization's technology level can be represented by the productivity, and rework variables. The schedule pressure can be represented by the difference between the project schedule and the project time. Overtime can be represented by productivity and cost. In other words, the 28 dynamic variables can be reconfigurable to represent almost the project aspects.

Because social networks are inherently transitive, a particular node's connections are probably to be connected. i.e. in the current case how the mental models of experts link one variable to other variables and other variables to the connection of this variable. A clustering coefficient is used to measure this attribute of transitivity. Transitivity is a local attribute of a node's neighborhood that reflects the amount of cohesiveness amongst the node's neighbors. The local clustering coefficient is calculated for each node and is shown in Figure 3.5



	V01	V02	V03	V04	V05	V06	V07	V08	V09	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22	V23	V24	V25	V26	V27	V28
Clustering_SD	0.64	0.62	0.74	0.86		0.95	0.95	1.00	0.83	0.91			1.00	0.79		0.93	0.93		0.75	0.72		0.69	1.00		0.74	0.78	0.98	0.74
Clustering_ND	0.95	1.00	0.89	0.90	1.00	1.00	1.00	0.94	0.95	0.94	1.00	0.85	0.90	0.90	1.00	1.00	0.95	0.95	1.00	0.95	0.89	1.00	0.96	1.00	0.89	0.94	0.95	0.90

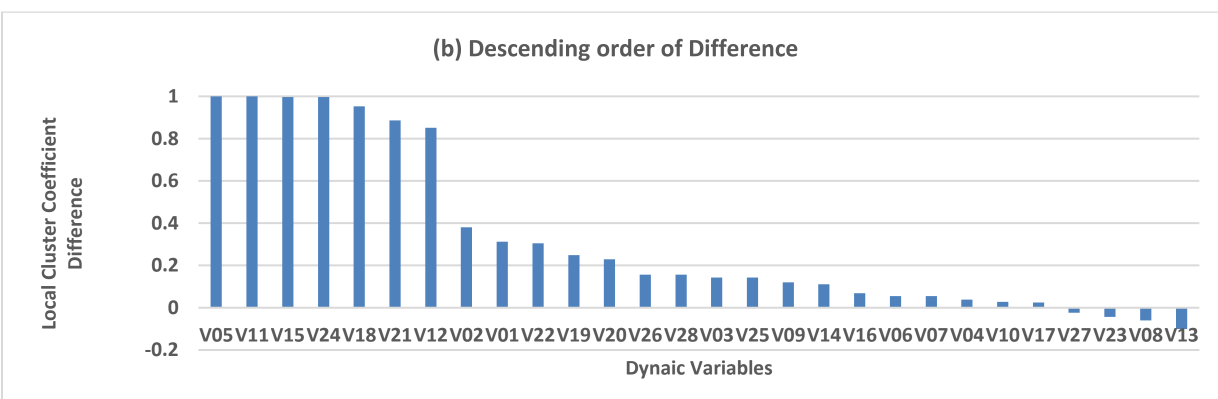


Figure 3.5 Normalized local clustering coefficient per variable for each network

The difference between the local clustering coefficient calculated from the Dynamic network and the Non-Dynamic network highlights the gap between what is required as represented by experts' suggestions and the dynamic models available. It also stresses the same variables identified by the degree of node measurements.

To sum up, V13 (Owner strictness), V18 (Bid time), V10 (Overheads), V5 (Productivity), V11 (Tender preparation cost), and V12 (Winning percent) are the most important factors. These factors exhibit the highest difference between their importance in the expert mental models and the applied dynamic model to assess them. These variables require further investigation to quantify their impact and position among other variables in the expert mental management system of the PBO. It is worth mentioning that variables analysis is discussed with industry experts to validate these results and they emphasize the importance of the variables.

3.6 SUMMARY

This chapter utilized the systematic literature review approach to identify causes that affect the PBO workload fluctuation and understand their interaction. The need for this study was highlighted in multiple industrial reports and increased this need in the transformation of the construction industry to digitalization and modularity.

The goal of this chapter was threefold. The first goal was to address the absence of a systematic evaluation and content analysis of existing studies on workload changes in construction, identify research gaps, and recommend future research possibilities. The second goal was to conduct a critical analysis of common components used in construction management procedures. The third goal was to identify factors influencing construction projects and contracting organizations.

The available literature on PBO business modeling and construction project management was analyzed using dynamic modeling. Two project phases that have typically been studied separately in the literature (pre-award and post-award) were linked in this study. Accordingly, a systematic analysis of prior studies was carried out and identified the dynamic variables that affect the project and the PBO's performance. Then, conventional analysis and SNA were utilized to quantify any variable that has received little to no attention in the available literature.

The analysis revealed that no model among the articles reviewed was capable of accounting for all 28 dynamic variables. The available models were capable of modeling simultaneously 10 variables. This established a compelling argument for the development of an SD model that incorporates all 28 variables to realize more holistic PBO and project management. This step filled the gap between mental models linking these variables and the applied dynamic models revealed from SNA.

CHAPTER 4 ANALYSIS AND PREDICTION OF CONSTRUCTION INDUSTRY DEMAND

4.1 INTRODUCTION:

The construction industry is a dynamic environment that is affected by multiple economic factors. In such dynamics, a contracting organization's strategic planners depend on monitoring economic variables such as oil prices, inflation rates, and raw material prices. Then use their mental projection to get expectations for future construction industry demand (Asamoah et al. 2019). (Asamoah et al. 2019) in their review study identified 59 cited variables used in the construction industry to predict demand. The most five cited variables are growth domestic product, inflation, exchange rate, interest rate, and consumer price index. Tracking and predicting all economic variables is a super hard process and the data is not available (Christopher and Holweg 2017)

Demand prediction is very important for strategic decisions because it affects other upstream operations of the organization. The demand prediction is required to consider the economic variability, be precise, and grant critical information to capacity planners (Gilliland 2010). This is a challenging process because of the underlying volatility and various uncertainties (Nazaripouya et al. 2016, 1-5).

Demand has two types, constrained and unconstrained. The unconstrained demand is the total customer demand that represents the industry demand. Constrained demand is the one that considers the organization's ability and limitations to fulfill the unconstrained demand. Forecasting using constrained demand will not reflect the real market need for a service. This explains why the previously awarded projects for contracting organizations are not used to predict the future demand for its services. In other words, the true demand is unique for each organization and is not reflected by the historical data of its orders (Gilliland 2010).

Strategic planners blame the unreliability of long-term plans on the market dynamics, which reduce their ability to maintain a stable workforce and a balanced workload. Volatile demand is being blamed to increase uncertainty in the organization's upstream operations. Tracking and predicting all economic variables is a super hard process and the data is not available (Christopher and Holweg 2017).

Building permits can work as an indicator of the construction industry demand that includes the effect of economic variations. The number of building permits issued at a time can be used as a univariate time series (TS) to represent the fluctuation in the demand of the construction industry in a specific area. This local variant includes the effect of interrelated industrial parameters influencing the market. Univariate analysis is very helpful because prediction algorithms do not require a lot of inputs and provide an understanding of the fundamental structure of past data (Lazzeri 2020). This is helpful for the context of understanding the behavior of the SD model variable's pattern input in the following chapters.

4.1.1 Time series analysis

A time series is a collection of raw data points that are arranged chronologically. It could be either univariate that have a single variable, or multivariate (Adhikari and Agrawal 2013). TS consists of short and long-term, and variations (errors). The short-term is the seasonal (cyclic changes), while the long-term one is the trend (Lazzeri 2020). The components of TS are (Gilliland 2010):

- Level, which is the series' arithmetic mean.
- Trend, which is the series' growing or falling value.
- Seasonality, which is the series' recurring short-term cycle.
- Noise, which is the series' unpredictable fluctuation.

Analysis of TS is separating the previously mentioned components from the raw data to make it ready for model feeding and future projections. The analysis includes the use of statistical parameters, such as mean and standard deviation, to provide information about the dependency of the data on time and the volatility inherent in the data. If the series is dependent on time then it is called non-stationary, stationary otherwise (Lazzeri 2020). The uncertainty (volatility) in the demand time series can be represented by the coefficient of variation (CV). That is determined by calculating the standard deviation and dividing it over the average for a certain period as shown in Equation 4.1 (Gilliland 2010), (Abolghasemi et al. 2020, 106380).

$$CV = \frac{\sigma}{\mu} \qquad (4.1)$$

Where: σ is the standard deviation of the variable for a specific period and μ is the average of this variable for the same period.

A high CV value means a high level of uncertainty (Huang, Chang, and Chou 2008, 3223-3239). It is critical to include and foresee these uncertainties to minimize the harmful repercussions of variable demand, which makes forecasting difficult (Syntetos et al. 2016, 1-26).

4.1.2 Prediction algorithm selection

Although no particular model can be said to work well with all types of time series, the time series characteristics can be used to select the best prediction models (Wang, Xiaozhe, Smith-Miles, and Hyndman 2009, 2581-2594).

The algorithms predict the future values of the TS assuming that values are a mixture of the level, trend, seasonality, and noise factors. This combination could be in the form of addition or multiplication. In the addition form, the TS value is the summation of the components. In the multiplication form, the TS value is the multiplication of the components. Additive models are great in short projections, but not working perfectly in long-term projections. This weak point comes from the assumption of existing patterns are the future ones. Another weak point is it cannot predict turning points, which are points when a significant change of trend occurs. However, the additive model is used when the variations in trend are linear. Other than that, the multiplicative model is used and is considered more stable than the additive one in predicting demand (Montgomery, Jennings, and Kulahci 2015). In this study, multiple additive and multiplicative models are utilized in predicting future demand and testing their ability relative to time series patterns.

4.1.3 Chapter goal

This chapter focuses on the research's second objective. This will be achieved through two subgoals. The first goal is to help contractors understand the construction industry's demand for stochastic variation. This is achieved through the analysis of 65 univariant time series of building permits from various Canadian provinces. The number of projects is used as an indicator of the demand. The statistical analysis extracts the construction industry demand features, such as range, variability, mean, and distribution. These features help to identify demand as stable or not, have low or high variability, and extract its pattern across the years. Also, find if seasonality affects the demand or if the trend is the dominant feature.

The second goal is to find an easy reliable tool to forecast the local construction industry demand. That can consider the uncertainties and volatility in such a market and can consider the economic variables without explicitly mentioning their values. This is achieved through the application of multiple prediction algorithms. Such as Seasonal Naïve (SNAIVE), Holt-Winter (HW), Seasonal Auto Regression Integrating Moving Average (SARIMA), FaceBook Prophet, Exponential smoothing (ETS), Neural network (NN), and Gaussian with kernels as the most common and successful techniques for demand forecasting. The characteristics of these techniques and results help to prove if the historical structure of the data is replicated in the future and can be predicted or if there is a need for other techniques.

4.2 METHODOLOGY

This work utilizes a multi-step methodology, as shown in Figure 4.1 to achieve the goals mentioned in the previous section. It starts by defining the problem through discussion with a collaborative industry partner. They reveal that the construction industry is very dynamic and has a volatile demand. This continuous variation makes it hard for contractors to maintain stable long-term planning. Hence, the problem is identified to understand the demand uncertainty in the construction industry and evaluate the ability to forecast its future demand. The market variation is investigated by studying the number of building permits in the Canadian construction industry. The source of the data used in this analysis is the Statistics Canada Government Agency Website (https://www150.statcan.gc.ca/). An example of the raw data is shown in Figure 4.2.

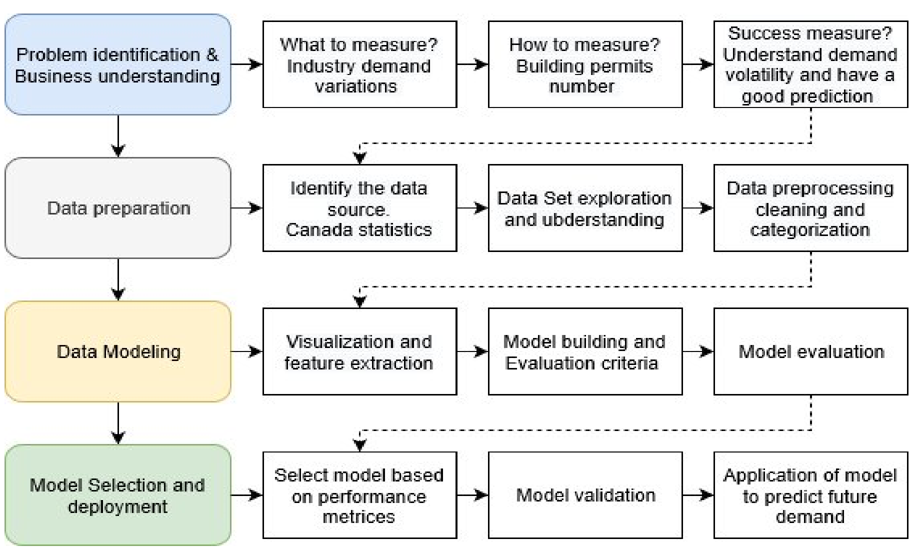


Figure 4.1 Multi-step methodology outlines

The second step is preparing the data for analysis. The number of building permits is downloaded from the Canada statistics website. Then, they are checked for missing data points and duplicates. The data available consists of different provinces and territories, each including six categories. The provinces and territories included in the analysis are Quebec, Alberta, British Columbia, Manitoba, New Brunswick, Northwest territories, Newfoundland and Labrador, Nova Scotia, Ontario, Prince Edward Island, Saskatchewan, and Yukon. The categories of each province dataset are Residential, Non-residential, Industrial, Commercial, Institutional, and governmental, and the total Canadian building permits. The data is monthly permits from January 2018 till December 2021. This means 48 data points that consist of 4 consecutive years for 65 time series.

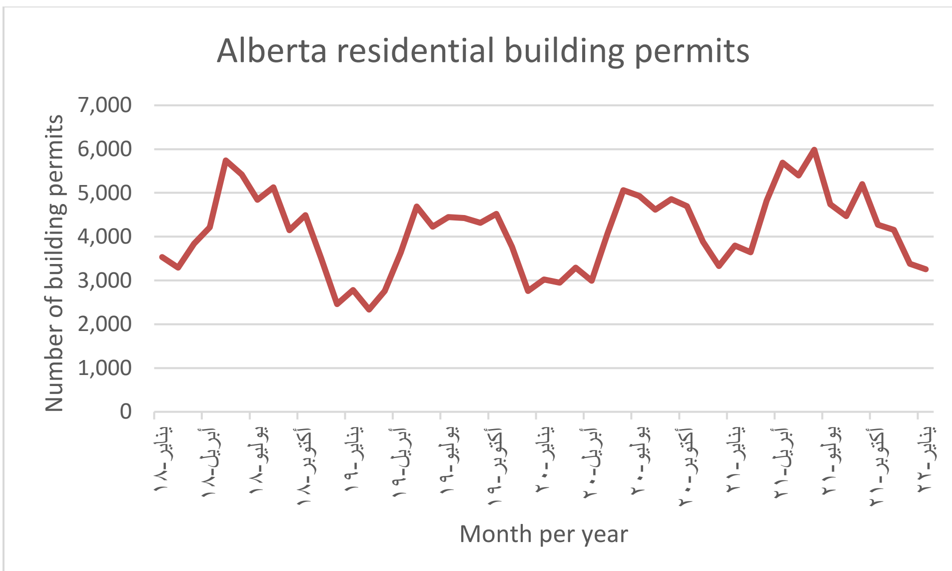


Figure 4.2 Alberta monthly building permits

The third step is data modeling. The data are explored and cleaned using Python codes to test their integrity and quality. It is found that the data has neither missing values nor duplicates. Each year and month have one unique observation and the data are continuous. Then the data points are sub-plotted to show how the TS behave after splitting them into train, test, and validation sets. The training set is selected to be the first 23 data points in each TS, the testing set is the last three months of the first three years and the validation set is selected to be the last year.

Finally, the best model is selected. There are various criteria for selecting the best-performing algorithm. Assessments are used to measure prediction performance using various metrics to determine how well the model reflects the data structure. Mean absolute error (MAE) is not used because it has the drawback of dependency on the series scale. They cannot be used to compare performance across models that are trained with various data scales. Mean absolute error percentage (MAPE) overcomes this issue by calculating a percentage of error relative to the real data, this means it scales all the models' performance between 0 and 100% to be compared. Also, the distribution of error and its characteristics are used to assure model suitability for the data structure. It is calculated as shown in Equation 4.2.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n} |\frac{e_i}{y_i}| * 100 \qquad (4.2)$$

Where (y) is the actual value and e is the difference between the actual and predicted value.

MAPE can be used to compare the results from different scales of data series, and the positive and negative error percentages do not cancel each other (Adhikari and Agrawal 2013).

The main assumption in most time series prediction algorithms is a systematic pattern in the data and the future behavior will replicate the past pattern. The crucial problem for model selection should not be model fit, but model suitability to the type of behavior present in the data. To evaluate prediction results, there are advanced approaches including testing the performance over a test data set. The model should take into consideration the pattern's genuine underlying structure or systematic behavior. Moreover, there should be a value added by using a specific forecast algorithm. This value is typically calculated by the difference between the used predictive algorithm and the naïve approach (Gilliland 2010).

The mean absolute percentage error (MAPE) is used to measure the algorithm performance. MAPE is calculated using Equation 4.2.

The residual analysis is used to measure the algorithm performance in representing the structure and behavior of the data series. The Ljung-Box test is utilized to test if the residuals are independent and are identically distributed (i.e. uncorrelated) as a group. If the residuals have a pattern then there is still some structured information about the data series that are not captured yet. The optimum case is residuals do not show any pattern.

4.2.1 Qualitative analysis of time series

The TS is sub-plotted for each year, both monthly and quarterly, to show and understand how the series behave seasonally. The box plot is, also, sub-plotted yearly to visualize the range distribution of the building permit numbers. Then, the percent of change for the industry demand is calculated to explore how the total demand is changing from the previous year. The behavior of each quarter over the years is then plotted to understand the trend and seasonality of the TS. The density distribution is plotted for each TS yearly to the overall distribution to visualize the range of box plots for each year. Then quarterly industry demand is plotted as a percentage of each year to understand the contribution of each quarter to the entire year. Finally, the data series is decomposed into its original components to check the trend, seasonality, and residuals to make sure that all characteristics of the series are extracted.

4.2.2 Quantitative analysis of time series

Statistical tests are utilized to confirm observations from the qualitative analysis. First, the coefficient of variation (CV) is determined by calculating the standard deviation and dividing it by the average. The range of medium variability is between 0.75 and 1.3 for CV value. low variability is for a CV less than 0.75, and high variability is for a CV greater than 1.3.

Autocorrelation and partial autocorrelation of the data are plotted to check the data momentum. Then, test the series to be stationary using the Augmented Dicky Fuller (ADF) test. ADF examines the null hypothesis that there is no unit root in a data series. The alternative hypothesis varies based on the version of the test employed, but it is often stationarity (Paparoditis and Politis 2018, 955-973), (Cheung and Lai 1995, 277-280). The function used is the “adfuller” function from the “Statsmodels” package in python. If the result (p-value) is less than 0.05, then the series is stationary, otherwise non-stationary.

Finally, check if the series is normally distributed. i.e. it does not have a long tail that will affect the performance of the models that will be used to predict future demand. The “Jarque Bera” test for normality is conducted. This is a goodness-of-fit test that determines if data exhibits the skewness and kurtosis of a normal distribution (Thadewald and Büning 2007, 87-105). The “Jarque–Bera” function from the "statsmodels” in python is used to test the data points.

4.3 FORECASTING THE FUTURE DEMAND

The characteristics of data are used to filter the candidate models to a narrow set that could handle its features, such as SARIMA, Facebook Prophet, S-Naïve, and Exponential smoothing. The description for each model will be discussed in the following subsections. These models are trained using the data in either its raw condition or after transformation using Box-Cox, Log function, scaling, or differencing. This transformation can deseasonalize and-or detrend the dataset for efficient model training. The model training starts by feeding the training set to the algorithm. The feature selection process is done at this step to provide helpful information that enhances the algorithm learning process. The model is, then, tested using a different set of data called a testing set. Finally, the best-performing model is selected and compared with other selected algorithms.

4.3.1 Box-Cox transformation

The Box-Cox transformation is used to make the data as normally distributed as possible. This step aims to get a normal distribution residual using Equation 4.3. In other words, help the algorithm to get a good prediction by removing the white noise from this transformation.

$$w = \begin{cases} \log(y) & if\ \lambda = 0 \\ (y^{\lambda} - 1)/\lambda & otherwise \end{cases} \qquad (4.3)$$

Where:

y and w are the original and transformed data.

λ is a parameter calculated to maximize the log-likelihood function.

The confidence interval is calculated using Equation 4.4.

$$llf(\hat{\lambda}) - llf(\lambda) < 0.5\,\chi\,2\,(1-\alpha, 1) \qquad (4.4)$$

llf is the log-likelihood function and χ 2 is the chi-square function. If the optimal value for λ is 1 then the data has a normal distribution, and in this case, the original data will only be shifted down.

α is the error percent and is set to 0.05 for confidence interval calculations.

4.3.2 Log transformation

The most widespread conversion in time series analysis is the logarithmic (Log) transformation. It is used frequently to stabilize a series' variation and reduce the skewness using Equation 4.5. If a steady variance is not maintained, then, the log transformation might be detrimental to prediction precision (Lütkepohl and Xu 2012, 619-638), (Hassani et al. 2020, 4-25). The transformation is done using the "log" function from "NumPy" in python.

$$y_t = \log(x_t) \quad (4.5)$$

Where: x_t and y_t are the original and transformed data points at time t.

4.3.3 Difference transformation

Any algorithm's prediction is influenced by trends and random patterns in time series. One of the most common practices to remove seasonality and trend is to differentiate the series with the specific lags using Equation 4.6.

$$y_t = x_t - x_{t-n} \quad (4.6)$$

Where: y_t is the value of the data point after removing the seasonality and x_t is the raw data point.

n is the significant lag value. i.e. if n =1 then x_t-n = x_t-1 which is the previous value of x_t

4.3.4 Seasonal Naïve

The tendency of the series to display behavior that replicates again every number of intervals is known as seasonality. There are two types of seasonality, additive and multiplicative. The series exhibits consistent seasonal variations independent of its average level in additive seasonality. While in the multiplicative situation, the seasonal variation depends on the average level. The overall level of the TS is called a trend. It can be increasing, linear, exponential, or damping (Kalekar 2004, 1-13).

The seasonal naïve (s-naïve) model is used as a base case to compare other models' results with its results (Anđelić and Rakićević 2020, 10), (Mamula 2015, 102), (Silvestre, dos Santos, and de Carvalho 2021, 1-7), (Joshi and Tyagi 2021). The reason to pick s-naïve is that the data series exhibit strong seasonality as mentioned in the understanding and visualization of data. The forecast using this method does not consider the trend in the calculations as it assigns the last similar seasonal value to the same season in the prediction. For example, to predict the future demand for January, it assigns the demand in the last January as a predicted value.

4.3.5 Holt Winter

Exponential smoothing is a method that assigned exponential weights to the data points. The current data are assigned a higher weight than older ones. Holt-Winter (HW) model is the third exponential smoothing. It is suitable for data that exhibits seasonality and trend components and has two models depending on seasonality, additive and multiplicative. The multiplicative Holt Winter is suitable for data that shows a multiplicative seasonality component and assumes that data can be represented using Equation 4.7, (Kalekar 2004, 1-13):

$$y_t = (b_1 + b_2)S_t + \varepsilon_t \tag{4.7}$$

The additive model is used when data shows additive seasonality, and assumes that data can be presented using Equation 4.8, (Kalekar 2004, 1-13):

$$y_t = b_1 + b_2 t + S_t + \varepsilon_t \tag{4.8}$$

Where: b_1 is the base component. b_2 is the trend component. S_t is the seasonal component (additive factor in the case of additive equation and multiplicative factor in the other case). ε_t is the error component

The additive model is not adaptive, where parameters are calculated once and the history of data is not used in the forecasting, but it is simpler and easy. The multiplicative model is adaptive and the parameters are changed using the historical data to adapt to changes.

4.3.6 SARIMA

Because the data series demonstrates seasonality, the seasonal auto-regression integrated moving average (SARIMA) model is preferred to the normal ARIMA model. It may be defined as the product of two ARIMA models (p,d,q) and (P, D, Q). The non-seasonal auto-regression order, no seasonal differencing, and non-seasonal moving average order are represented by the model parameters p, d, and q, respectively. The seasonal auto-regression order, seasonal differencing, seasonal moving average order, and repeating seasonal pattern time duration are represented by the model parameters P, D, Q, and S, respectively (Tseng and Tzeng 2002, 367-376).

This approach has been used successfully in anticipating economic, marketing, and social difficulties, among other things. The algorithm does not consider the dataset measurement errors (uncertainties) (Wang, Yuanyuan et al. 2012, 284-294), (Chen and Wang 2007, 254-264)

The prediction using the SARIMA model is started by utilizing the auto-correlation function (ACF) and partial auto-correlation function (PACF). These calculations enhance the identification of the model parameters and estimate the unknown variables. Then, tests the performance of the algorithm through analysis of the calculated residuals. Finally, select the best fit model and predict the future data points. The residuals (prediction errors) should be statistically independent and normally distributed with zero means (Liu, X., Lin, and Feng 2021, 120492).

One of the limitations of using the SARIMA model is it requires the data points to be normally distributed which is very hard to prove in real data, because of the data availability and value uncertainty (Tseng and Tzeng 2002, 367-376).

4.3.7 Facebook prophet

Facebook Prophet (FBP) is a method for forecasting TS. It uses an additive model to fit non-linear patterns to annual, monthly, and daily seasonality. FBP considers the impact of holidays and performs effectively with time series that have substantial seasonal effects. FBP is resilient to missing data and trend alterations. It usually handles outliers as well (Sulasikin et al. 2021, 1-5). It was designed to handle high-frequency data such as daily, hourly, minute, and so on. It may or may not work well with monthly or quarterly data. It provides changepoints, anomalies, and forecasts in addition to forecasting. This is useful for spotting rapid changes in time series.

The FBP model was developed by Facebook in 2017 (Vishwas and Patel 2020). It employs a decomposable model with three key components: trend, seasonality, and holidays as in Equation 4.9.

$$y(t) = T(t) + s(t) + j(t) + \varepsilon_t \tag{4.9}$$

Where T(t) is the trend function for irregular variations, s(t) is the seasonality , j(t) is the impact of the holiday or non-periodic seasonality, and ε_t is the error term.

4.3.8 Neural network forecasting

In this approach, the model is trained to get the right rules. This tool differs from statistical methods. A good machine learning model requires data points to feed the model with, examples to train the model, and an evaluation technique. The model takes the input data then try to get the rules using the examples and then evaluates the progress using the given evaluation mechanism.

Long-Short-Term-Memory (LSTM) is utilized in this study because it overcomes the drawbacks of missing the feedback in the feed-forward neural network and the vanishing gradient of the recurrent neural network (Bengio, Simard, and Frasconi 1994, 157-166), (Toharudin et al. 2020, 1-24). The LSTM does this with three gates: a forget gate to determine the amount of information that must be deleted, an input gateway to regulate the number of neurons that must be collected, and an output gateway to regulate the number of neurons that must be transferred to the next cell (Hochreiter and Schmidhuber 1997, 1735-1780).

The learning step is performed on the training set using various network setups and selects the least error among the different training models. This is performed by computing the operator's value up to the max-epoch or stop if the goal error is achieved (Toharudin et al. 2020, 1-24).

In general, deep learning approaches cannot be used to do grid searching; grid searching is multiple combinations of different factors' values and selecting the best performing combination. This is because deep learning approaches frequently need vast quantities of data and complex models, leading to models that consume hours or days to learn. In circumstances when the data sources are tiny, such as univariate time series, a grid search may be used to modify the parameters of the model.

4.3.9 Exponential smoothing

Exponential Smoothing (ETS) is capable of dealing with discrete data with trend and seasonality. It also adheres to the Robustness condition and is used as a model of Bayesian Extrapolation. The principle behind the exponential Smoothing technique is that the predictions produced by this method are the weighted average of previous observations, and the weight decays exponentially with time, such that current data have bigger weights than previous ones. As a result, smarter projections are produced (Jain and Mallick 2017).

ETS contains three key components: error, trend, and seasonality that might be additive, multiplicative, or none. The automated ETS model selection procedure is used to adapt exponential structures with multiplying elements and assessed different versions before choosing the optimum framework for predicting the data. The best model was determined by minimizing the corrected Akaike information criterion (Liu, H. et al. 2020, 287-294).

4.3.10 Gaussian with kernels

Kernels are used because of their ability to handle nonlinear issues. They've been used successfully for pattern recognition, regression, and density estimation (Richard, Bermudez, and Honeine 2008, 1058-1067), (Williams and Rasmussen 2006). The Gaussian technique utilizes the Bayesian concept of P(x2|x1=known) to represent the effect of the previous data point in the series on future values (Gelman and others 1995). It utilizes the kernel covariance to define the covariance function for the independent variable (x or t variable in the regression problem between time or location and value of the data point) (Roberts et al. 2013, 20110550). Then, predict the probability for future value using Equation 4.10.

$$p\big(y(x)\big) = \mathcal{N}(\mu(x), K(x,x)) \qquad (4.10)$$

Where:

Y(x) is the dependent variable. i.e. the data point value. x is the location. i.e. the time of the value of y. M(x) is the mean function. K(x,x) is the kernel covariance of the x.

For the application on python, the GaussianProcessRegressor is imported from the sklearn.gaussian_process module. Also, different kernels such as WhiteKernel, ExpSineSquared, ConstantKernel, and RBF kernels are imported to represent the noise in data, seasonality, and trend.

4.4 ANALYSIS OF RESULTS AND DISCUSSION

4.4.1 Results from qualitative analysis

From the qualitative analysis of the data series, it is obvious that the market goes up and down each year as shown in Figure 4.3, which represents a seasonal pattern. Typically, the market goes up from the first quarter to the second quarter, which is the peak of the market, and almost steady to the third quarter, then drops in the fourth quarter. Comparing the second quarter's peak demand shows that the industry demand exhibits a trend.

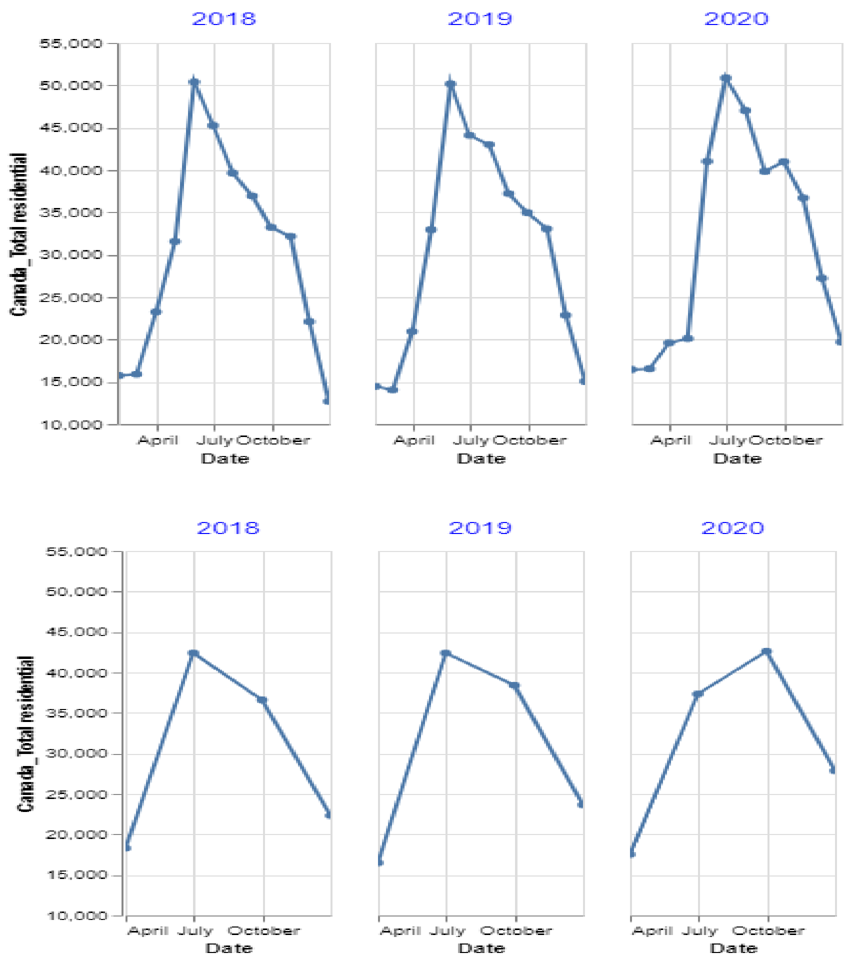


Figure 4.3 Monthly and Quarterly plot of building permits for three years

The overall data is clean and a few data points are outside of the interquartile range of the box plot as shown in Figure 4.4, this means that the data has no or little outliers. The TS has no structure breaks. However, the length of the bar in the box plot is relatively stable from 2018 to 2019, it shrinks in 2020 (this might be because of the CovId19). This change in the mean and variance of the data will require stabilization. Also, the model will be used to predict the industry's future demand should capture both trend and seasonality, and can handle outliers.

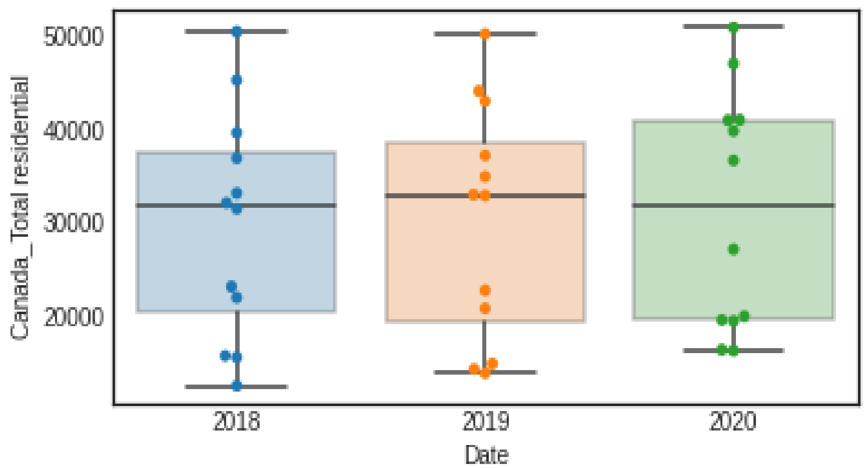


Figure 4.4 Box-plot of building permits numbers in the yearly distribution

From the calculations of quarter contribution relative to average demand, the quarter plot and heat map (Figure 4.5) confirm that the industry peak is in the second quarter and drops in the fourth quarter. In each quarter over the years, a little distortion from this trend appears in the third and fourth quarters of the residential series. It has an upward trend, while others (the majority) observe cyclic seasonality. Although demand peaks in the second quarter of each year, all quarters contribute almost the same to the yearly industry demand. The seasonal factor analysis shows that market demand increases in the second and third quarters by 5 to 30% depending on the project category relative to average, while the demand drops in the first and fourth quarters by 20 to 40% depending on the project category relative to average.

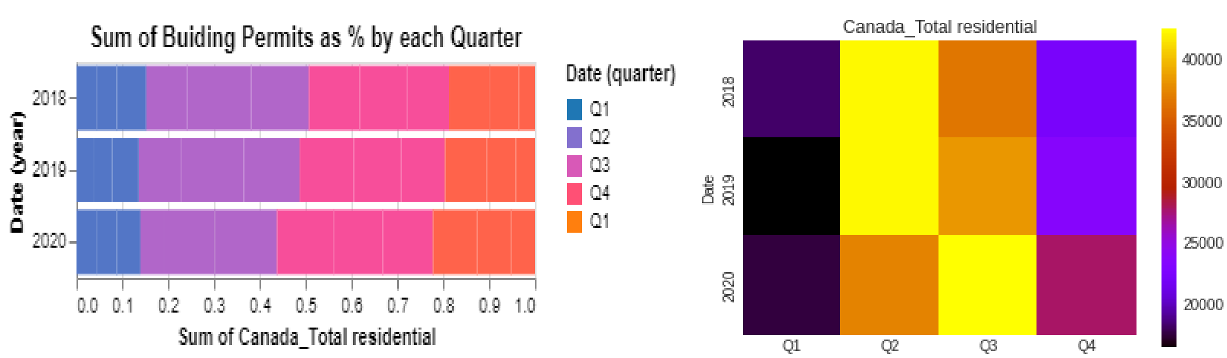


Figure 4.5 Quarter percent plot and heat map plot

The Kennel Density plot shows data look normally distributed with a bimodal distribution as shown in Figure 4.6. This indicates the sinusoidal distribution of the series. Also, bimodal distribution reflects the peak and valley of the demand along the quarters. The beaks are almost stable over the years, which indicates the demand average is slightly changing. This indicates a sinusoidal wave or fluctuation in demand throughout the year. The average demand is almost the same between years. i.e. the market demand could be considered balanced around the average. The distribution is not flattened as years progress, indicating no or little spread/ variation, which confirms the results from the Box plot (except in 2020 because of CovId-19 the box plot indicates shrinkage in the market size).

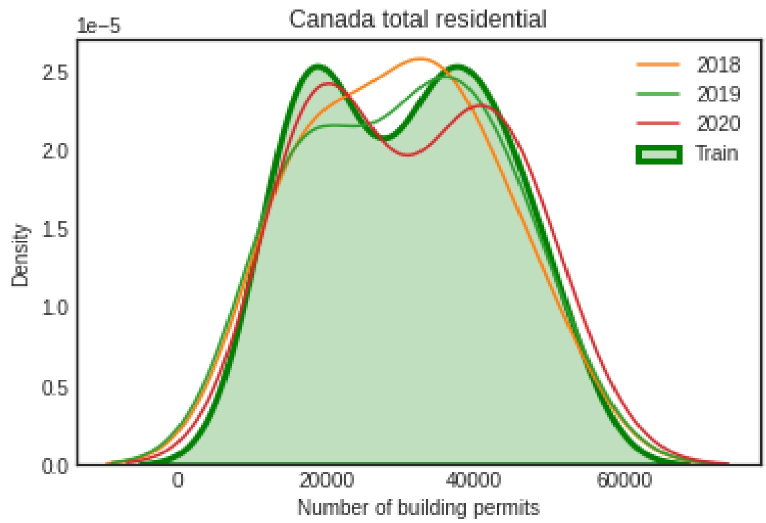


Figure 4.6 Bimodal distribution of the data with a little distortion

The histogram plot (Figure 4.7) shows that data are normally distributed with a little distortion. This misshape is represented in the Q-Q plot (Figure 4.8) around the 45-degree line. To confirm these observations, statistical tests are conducted as presented in the next subsection.

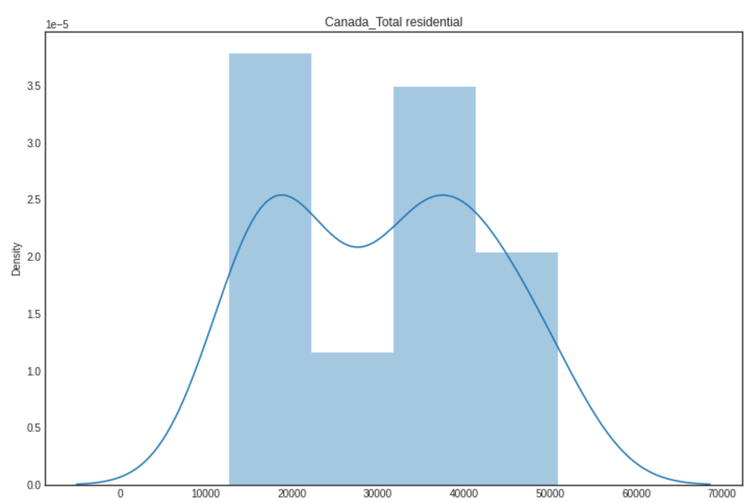


Figure 4.7 Histogram distribution of data

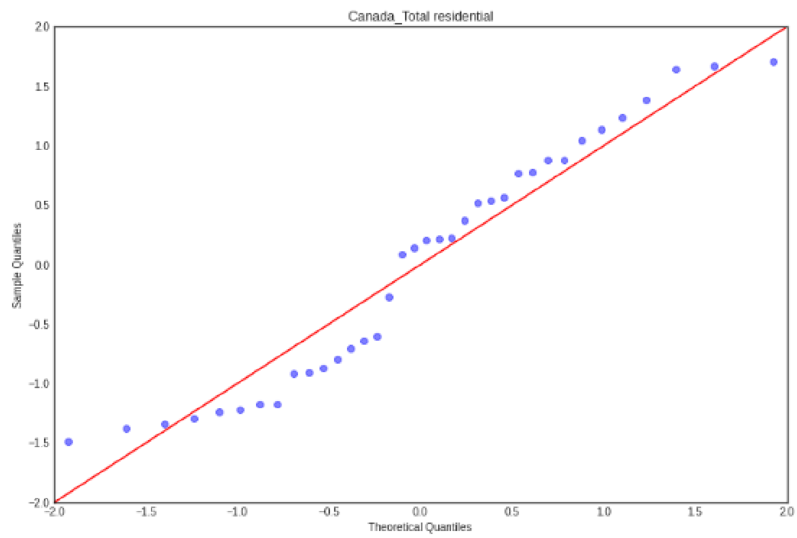


Figure 4.8 Q-Q plot of data

4.4.2 Results from quantitative analysis

Coefficient of Variance (CV) test results show that the demand has a low to medium variability. The Autocorrelation (ACF), as shown in Figure 4.9, results indicate that the autocorrelation coefficient is insignificant at all lag values as they appear within 95% of the correlation index except for the first leg and this indicates that the last demand value directly affects the nearest future value. Also, there are some series indicating a long memory effect (barely significant) from last year's value (fifth and sixth lag value). On the other hand, the partial autocorrelation function (PACF) shows that the partial autocorrelation coefficient is insignificant at various values of lags, which indicates long-term memory of data series. The fluctuations of the bar lengths show a repeating pattern that indicates seasonality has many effects on the data structure and there is no momentum as the length varies from positive to negative.

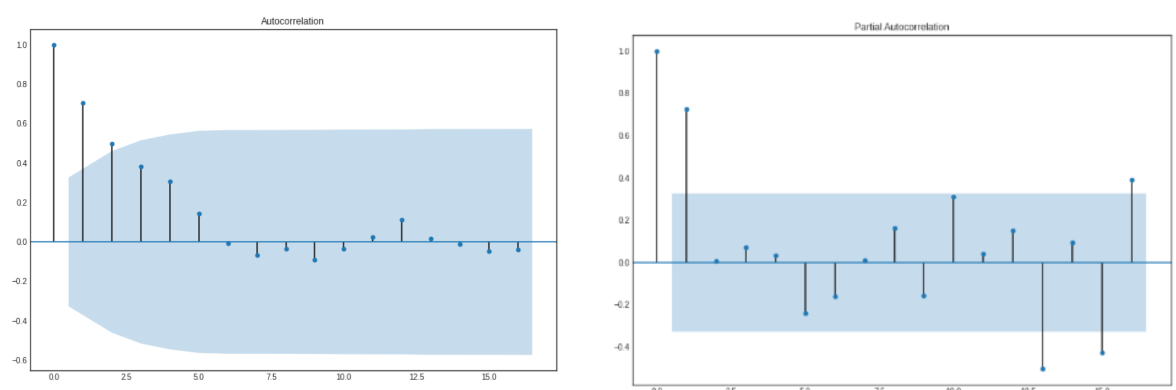


Figure 4.9 Autocorrelation and Partial autocorrelation plots

Results from Augmented Dicky Fuller (ADF) test show that the demand series is non-stationary (random walk) at the aggregate level, i.e. Canada total data series, that requires further calculations to detrend the series (differencing method). Otherwise, almost all data series are stationary.

Jarque Bera's test revealed that data are normally distributed, except for a little data series. Jarque Bera's test for normality is conducted to test the goodness-of-fit and determines if the data exhibits the skewness and kurtosis of a normal distribution (Thadewald and Büning 2007, 87-105).

Generally, after visualizing the data series and extracting its features, the datasets can be categorized into nine categories. The categories are a combination of the basic characteristics of data as shown in Figure 4.10. Data are not uniformly distributed to the nine categories. Most of the data are correlated, normally distributed, stationary, and with low variability. 85% of the data are categorized into the first four types. The data does not include a high variability data series. A little percentage of data is uncorrelated or non-normally distributed. The nine data categories are:

- C1 = correlated + normal + stationary + low variability. Represents 43.08% of the data
- C2 = correlated + normal + non-stationary + low variability. Represents 23.08% of the data
- C3 = uncorrelated + normal + stationary + low variability. Represents 9.23% of the data
- C4 = correlated + not normal + stationary + low variability. Represents 9.23% of the data
- C5 = uncorrelated + not normal + stationary + medium variability. Represents 6.15% of the data
- C6 = uncorrelated + not normal + stationary + low variability. Represents 3.08% of the data
- C7 = correlated + not normal + stationary + medium variability. Represents 3.08% of the data
- C8 = uncorrelated + normal + non-stationary + low variability. Represents 1.54% of the data
- C9 = correlated + normal + stationary + medium variability. Represents 1.54% of the data

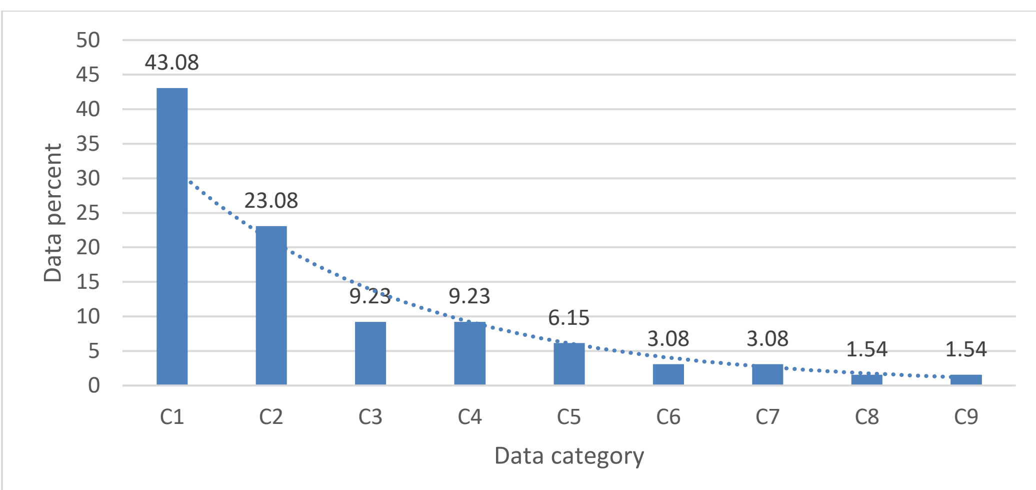


Figure 4.10 Data characteristics distribution

4.5 PREDICTION RESULTS

The collected data mentioned in the previous section are fed to different prediction algorithms (ETS, HW, SARIMA, FBP, LSTM) to test their ability to predict future demand. The best prediction model for each category of data and the assessment of prediction algorithms are presented in the following subsections.

4.5.1 Seasonal Naïve results

Seasonal naïve forecasting works admirably given that it is only a logical forecasting approach with no statistical process. The model does a good job of capturing seasonality and overall trend, although it has a big error margin, an example of prediction results is shown in Figure 4.11. The residual analysis reveals that the residuals are not stationary and have a non-zero mean. i.e. The model did not capture the trend and seasonal behavior as effectively as it would be liked.

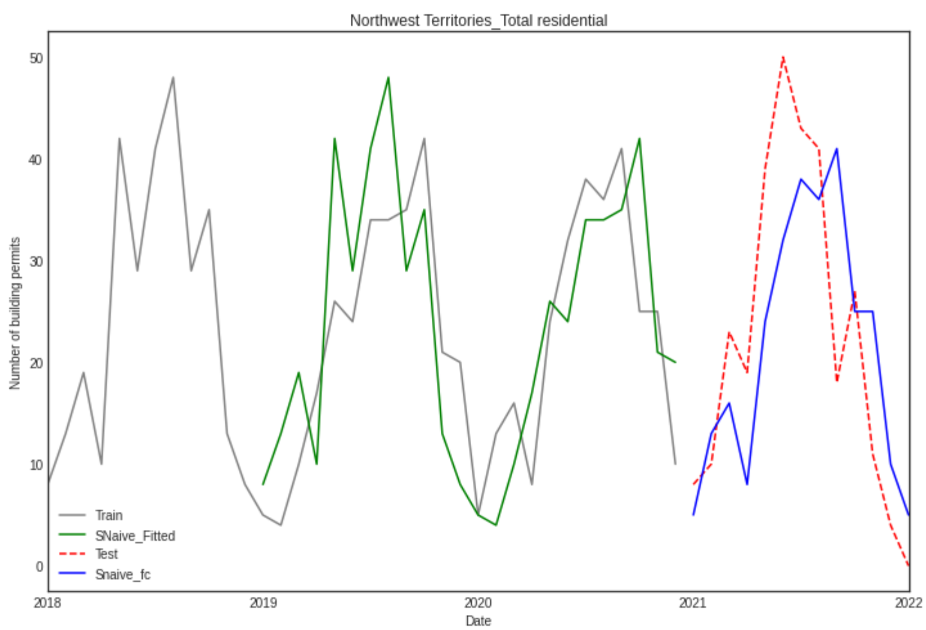


Figure 4.11 Example of SNAIVE prediction results

4.5.2 HW results

The model is applied for the data with different combinations of additive and multiplicative seasonality, and with data transformation using Cox-Box, differencing, scaling, and log operator. Then all these combinations are compared to get the best model from these alternatives. Results reveal that there is no specific best combination that fits all datatypes. But each series has its best-fit combination. The algorithm of HW cannot handle zero values and require the dataset to have a positive value. In 44% of the results, HW performs better on the training set than on the testing set. Most of the residuals are uncorrelated and stationery. But some are not normal and almost all of them have a non-zero mean with a very small value. i.e. the bias can be considered minor. However, the algorithm did CoxBox and Log transformation for some series on the original values to get the best results. Using the data at its original values without differencing or scaling is better. Example of prediction results using HW is shown in Figure 4.12.

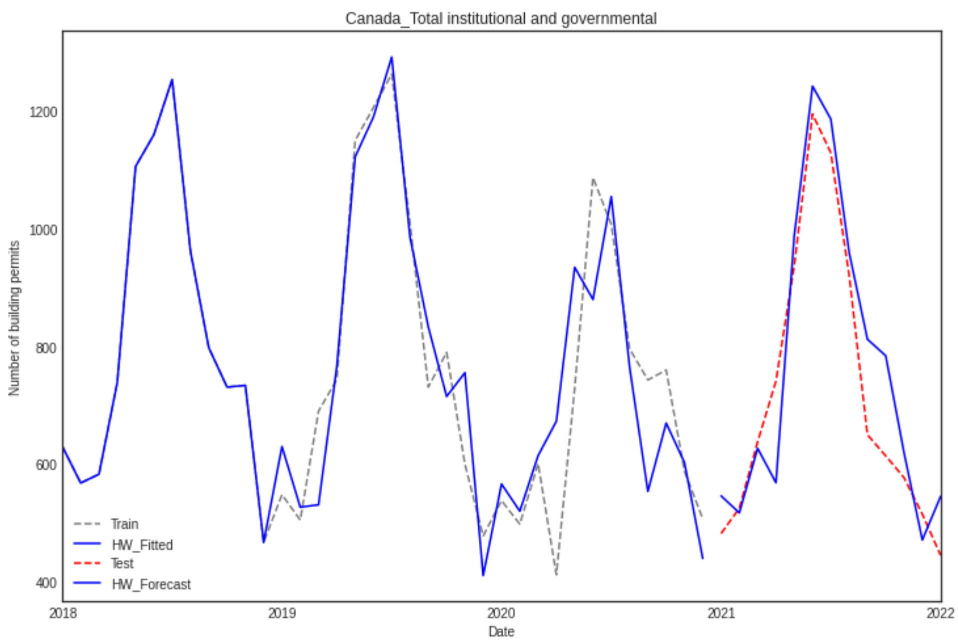


Figure 4.12 Example of HW prediction results

4.5.3 SARIMA Results

First, the best fit model for the data series was searched using different data transformations like Box-Cox, Log, differencing, and scaling. Then, the best model is trained using the training set and then test using the test set. The results of the model vary relative to the data type and transformation of the data. Overall the SARIMA performs better for data C1, C2, C7, C8, and C9. i.e. the correlated and stationary data. An example of prediction results using SARIMA is shown in Figure 4.13. The majority of error percent is within 10% and a maximum of 28% for these categories. The algorithm results are biased as the residual mean is not zero. Most of the residuals are stationary but they swing between the correlation and normality. The overall prediction accuracy and results were not better than the HW model and the performance is getting worse.

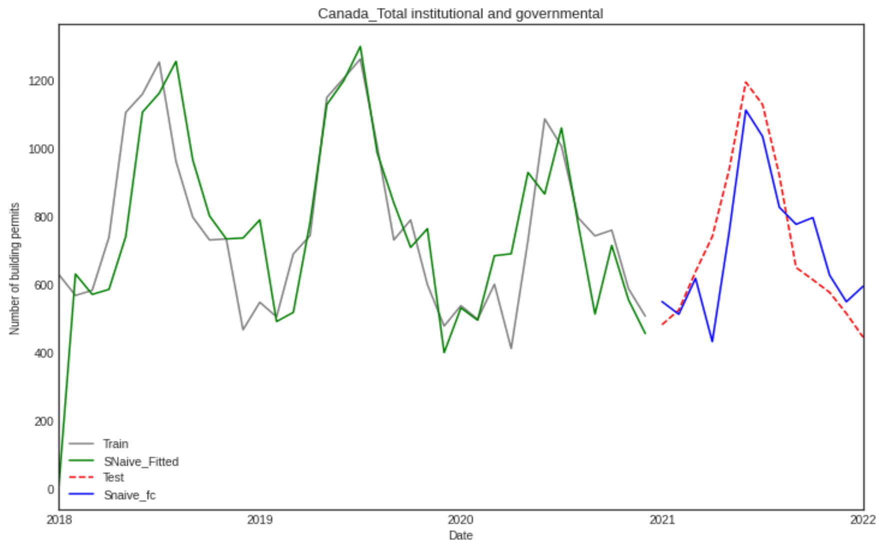


Figure 4.13 Example of SARIMA prediction results

4.5.4 FBP results

The FBP model is applied to the data with multiplicative and additive seasonality and various data transformation, such as differencing, scaling (normalization), CoxBox, and Log transformation. Results for most combinations reveal that multiplicative seasonality is the best fit for data characteristics. Except for the differencing data transformation, the additive model is the best fit. Unfortunately, the FBP algorithm does not perform better than the previous models as it is suitable for high-frequency data. Furthermore, the trend and seasonality were captured well by the model. An example of prediction results using FBP is shown in Figure 4.14.

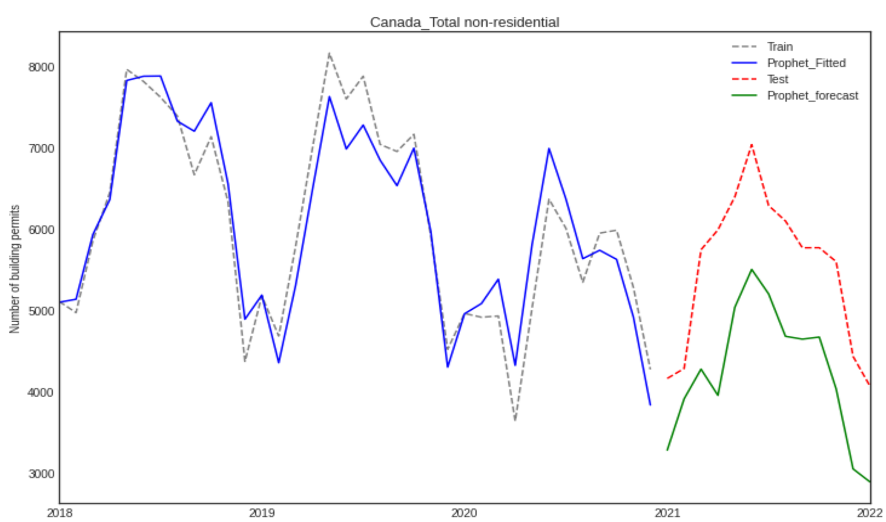


Figure 4.14 Example of FBP prediction results

4.5.5 Neural network results

The neural network model (LSTM algorithm) didn't perform well along the different kinds of datasets. The error percentage is higher than the other algorithms. This is might be because of the limited amount of data to train the algorithm, i.e., the parameters of the algorithm did not adjust properly because of the lack of data to enhance its values. Furthermore, it takes so long time relative to other algorithms in training and grid search. For example, LSTM consumes 19 minutes and 36 seconds doing the grid search for one data set and consumes 1 minute and 34 seconds in training the algorithm for the best parameter selection. Finally, the error percent ranges from 11.08, for the Alberta commercial dataset which has an error percent of 7.6 using the HW model, and 108 percent error for the Yukon commercial which has a 20.2 percent error using HW. So, it is not recommended for this limited amount of training set.

4.5.6 ETS results

Even though ETS and HW both use exponential smoothing, the ETS model outperformed the HW model substantially. This is because ETS has an enhanced parameter setup and optimization. ETS, also, maximizes the likelihood whereas HW lowers the residual error. The residuals resulting from ETS are uncorrelated, normally distributed, and have a mean of almost zero, like 1.2 and -2.3. An example of prediction results using ETS is shown in Figure 4.15

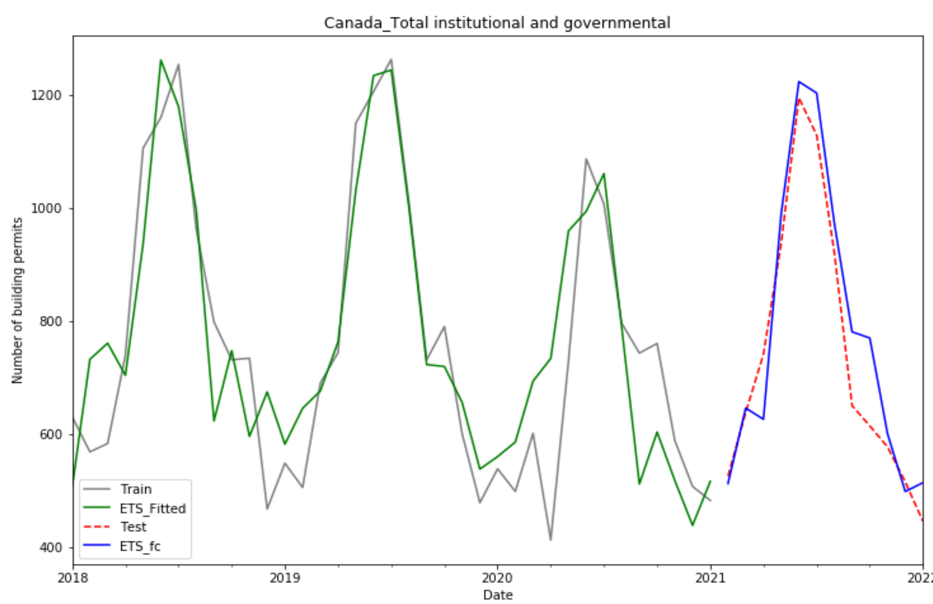


Figure 4.15 Example of ETS prediction results

4.5.7 Gaussian with kernels

Different combinations of kernels were made. Then, a grid search was applied to find the best-fit combination of these kernels. The model performed well for the first three types of data. i.e. normal and low variability data sets, and worse otherwise as shown in Figure 4.16. The error margin for the majority of the first three types of data is within 30%. Example of prediction results using gaussian with kernels for other data types is shown in Figure 4.17

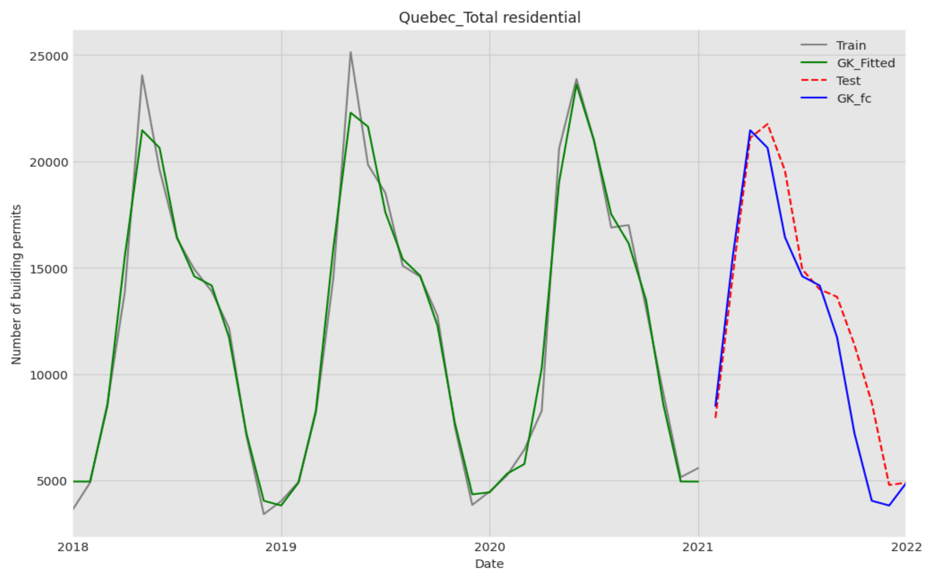


Figure 4.16 Example of Gaussian with kernels prediction results for the first three types of data

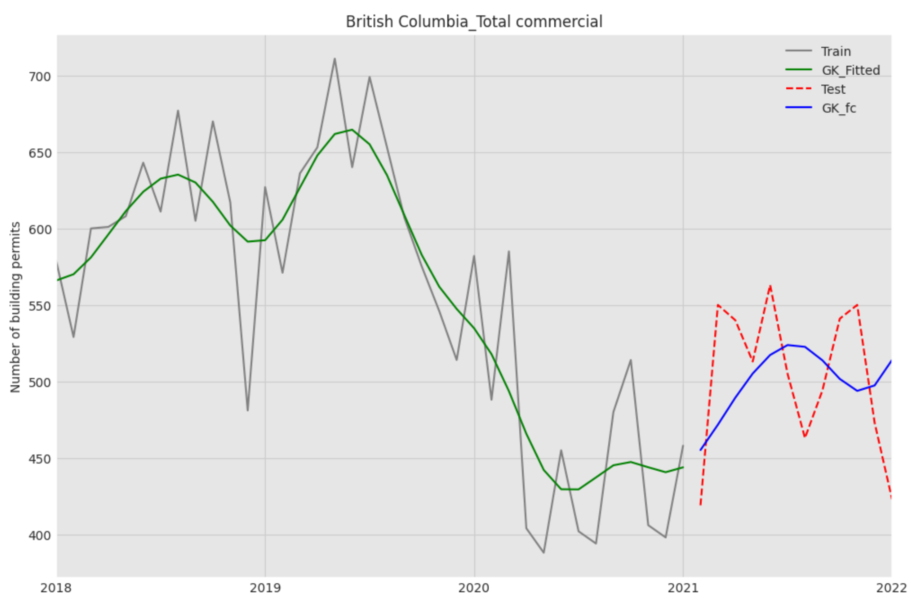


Figure 4.17 Example of Gaussian with kernels prediction results for the rest of the data

4.6 FORECASTING TECHNIQUE SELECTION

Each dataset is fed to 23 algorithms including transformations. This is to train the algorithms with the first 33 data points (the first three years except for the last quarter) and predict the last three months of the third year. Table 4.1 shows the ranges of error for the best prediction algorithms for the first four datatypes. The reason to present the first four datatypes is that they represent 85% of the used data. Results revealed that exponential smoothing (ETS and HW) with different data transformations performs very well, with a maximum error of 27.4% and an average of 8.75%. SARIMA performs well for data types C1, C2, and C3. SARIMA has a higher average error (9.66%) than exponential smoothing and a higher maximum error (36.3%). LSTM, SNAIVE, and Gaussian with kernel algorithms perform well for a minor percent of the dataset. These results revealed that market demand can be predicted and the historical structure of the data can represent its future. On the other hand, the test set is small to get high confidence in the prediction accuracy of the selected algorithms. It might be better to collect more data to be able for a better assessment of the algorithm's prediction accuracy.

Table 4.1 Prediction results on the test set

Model		ETS			HW		SARIMA			GS	SNAIVE	LSTM
Transformation		Box-Cox	Log	--	--	Diff+ Scale	--	scale	Box-Cox			
Error Percent	**C1**	1.4-4.8	5.1-27.4	1.5-2.9	1.5-13.7	5.4	9		4-4.6	4.3-4.9		
	C2	3.2-9		2.4-13.7	4.3-11.6		11.3		3.6-7.1		3.9-7.6	
	C3		17.8	11.2-17.8				36.3	1.4		7.7	9.01
	C4	3.5	4.1	4.9-16	20.2						2.6-16	
residual check		NZ - NC - N - S	Z - NC - N - S	Z - NC - N - S	NZ - NC - NN - NS	Z - NC - N - S	NZ - NC - NN - S	NZ - NC - N - S	NZ - NC - NN - NS	Z - C - N - S	NZ - NC - N - S	NZ - NC - N - S

Zero mean: Z, Correlated: C, Normally distributed: N, Stationary: S, Add N before the symbol for indicating opposite

4.7 PREDICTION VALIDATION

In the validation process, not only test the best models on the validation set but test the effect of the increasing train set on the algorithm prediction as shown in Table 4.2. Exponential smoothing (HW and ETS) is still the best algorithm. HW has an average error of 18.57 % with a minimum of 7.1% and a maximum of 43.4%, while ETS has an average error of 10.1 % with a minimum of 6.2% and a maximum of 16.3%. SARIMA has a high average error percentage of 30.2%. the neural network performs better as the training set has increased with an average error of 13.8% and ranges from 6.79 to 20.34%. However, Gaussian with kernels and FBP algorithm has a 30% of error, they do a good forecast for the limited amount of data.

The prediction algorithms captured the data behavior and the Pearson correlation coefficient between the predicted demand and actual values range from 0.7448 to 0.9626, which is considered a strong positive correlation. Even though these results are plausible, the prediction of 2021 makes this accuracy unpleasable. This is because the construction demand is highly affected by COVID-19 in the year 2021 and after. So, it is recommended to test these algorithms after collecting a few years past COVID and retest the prediction accuracy. Unfortunately, now this data does not exist.

Table 4.2 Prediction results on the validation set

Model		ETS			HW		SARIMA			GS	FBP	LSTM
Transformation		Box-Cox	Log	--	--	Difference	--	Box-Cox	Log			
Error Percent	**C1**	6.2-11.8	10.7-17.9	8.1-27.2	7.1-16.5	7.1	14.5	35.4-38.7	15.6		30.4	11.83
	C2	6.5-16.3	14.8	6.8-16.7	8.1-26.5							
	C3			6.8	24-37.1		25.3		25.3			6.79-17.54
	C4			13.7-32.2	43.4					30.6		10.77-11.68
residual check		NZ - NC - N - S	Z - NC - N - S	Z - NC - N - S	NZ - NC - NN - S	Z - NC - N - S	NZ - NC - NN - NS	NZ - NC - NN - S	NZ - NC - NN - NS	Z - C - NN - S	NZ - C- NN- NS	NZ - NC - NN - S

Zero mean: Z, Correlated: C, Normally distributed: N, Stationary: S, Add N before the symbol for indicating opposite

Overall, the used algorithms could capture the pattern of the market demand with some errors and can replicate the seasonality and trend very well as shown in Figure 4.18. This might be because of the data characteristics, i.e., the pattern is stable and regular. Qualitatively, this valuable piece of information will reduce the uncertainty for the strategic planner by predicting the unconstrained demand, i.e. market demand behavior. Quantitively, ETS works better for the majority of data (85% of the data). This will allow the strategic planner to quantify the risk and profit margin for each quarter.

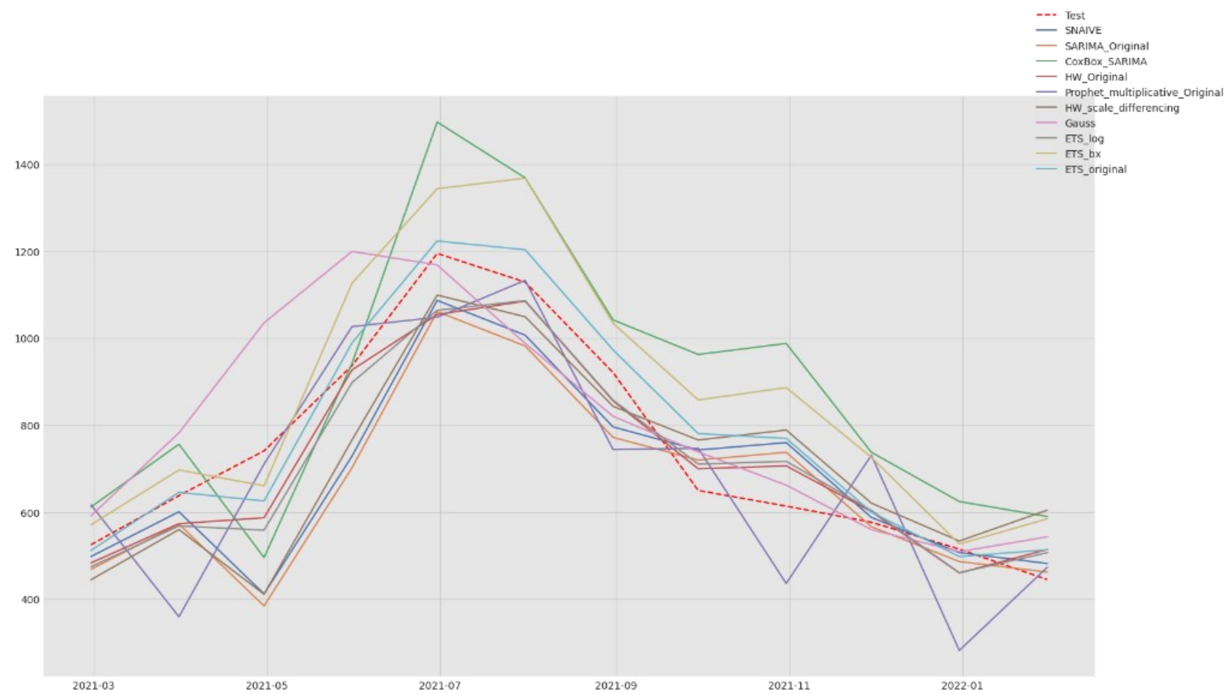


Figure 4.18 Multiple algorithms prediction for construction demand for the year 2021

4.8 SUMMARY

Construction demand in Canada may be divided into two categories: short or medium-seasonality (due to weather seasons) and long-term trends (due to economic situations). Because of the variability in construction demand, it is hard for contractors to estimate correctly the required capacity. This work utilized the number of building permits issued as a new representative for the industry demand. Statistical analysis of the market behavior reveals that construction industry demand in Canada has a one-year cycle that started in January and ends in December. The peak of this cycle is in the second and third quarter of the year and the valley happens in the fourth and first quarter of the year. This piece of information allows planners to quantify the risk and profit margin for each quarter to maintain a competitive pricing strategy. The analysis reveals, also, that construction demand is stationary, normally distributed, relatively stable, fluctuates around the average, and has low variability in terms of the number of projects issued.

This work tests the ability of the demand volume to be predicted using statistical and machine learning methods. The statistical tools, especially exponential smoothing, excel machine learning algorithms in the case of limited available data for training. SARIMA is best for correlated and stationary data. HW is better than SARIMA for 85% of the data. Gaussian with Kernels is better for normal and low variability data.

This work recommends the exponential smoothing algorithm for demand prediction. Because it does not require sophisticated calculations, a relatively short training time, and the error margin is acceptable. However, there is still uncertainty in the prediction due to errors, this work helps strategic planners to reduce market uncertainty, quantify the risk, and optimize markup percent for profit and competitiveness. Another advantage of this work is the methodology used in this study can be applied to different industries and markets to support contracting organizations in their strategic decision to expand and invade a new market. Finally, this work reflects the voice of the market in demand prediction so the organization could have an unbiased and unconstrained demand prediction.

On the other hand, time-series analysis fails short to explain why behaviors occur. It does not explain why the demand has a seasonal cycle and exponential or damped trend. So, it is recommended to utilize a causal-driven approach to analyze the construction industry demand. For the purpose of this study the level of analysis performed is suitable to be integrated with the next chapter (model building) as input for the model to represent the industry demand behavior (pattern). Also, this work could be integrated with other models to reflect the organization's constraints to predict market share for future work.

CHAPTER 5 CONCEPTUAL MODEL

5.1 INTRODUCTION

One of the challenges facing project-based organizations (PBOs) is workload fluctuation. This problem accumulates at the organizational level and affects its performance. It also affects various upstream and downstream decisions, such as optimum resource level (Gębczyńska 2019). Maintaining low capacity could be an economical decision but it reduces the competitiveness of the organization. On the other hand, a higher capacity level comes with a lot of drawbacks, such as high overheads. Also, workload fluctuations will stress the utilization of resources either over or underutilization. This might lead to a high turnover rate and loss of cash and experience (Xie, Liu, and Zhang 2021, 012047).

Previous researches tend to segment the chronic problem of workload fluctuation into different causes related to market, owner, contractor, and project. First are market-related causes, such as dynamics and competition. For example, (Dorée, Holmen, and Caerteling 2003, 817-826) analyzed the trend of firms cooperating and competing in the construction industry. Also, (Tan, Shen, and Langston 2012, 352-360) analyzed the impact of competing strategies on contractor performance. Moreover, (Beker and Hernando-Veciana 2015, 234-261) focused on the dynamics of bidding markets with financial constraints. Furthermore, (Wang, Jidong, Wu, and Che 2019, 444-456) improved the competitiveness of agents participating in bidding (electricity market) using agent-based and SD.

The second is owner-related causes. Previous studies focused on contractor-bid selection methods. They tried different tools such as Fuzzy Decision Framework (Singh and Tiong 2005, 62-70), Data Mining Framework to Optimize the Bid Selection (Art Chaovalitwongse et al. 2012, 277-286), and Multi-Criteria Decision Support System (Semaan and Salem 2017). The third is the contractor. Previous studies relate the contractor with the bidding decision. This decision is either to bid or not for a project, or how to select the suitable project to bid for. They used different tools to support this decision such as the Logistic regression model (Lowe and Parvar 2004, 643-653), Adaptive Neuro-Fuzzy Inference System (Polat, Bingol, and Uysalol 2014, 1083-1092), Fuzzy TOPSIS method (Al-Humaidi 2016, 04016068), Multi-criteria decision analysis (van der Meer et al. 2020, 172-188), and questionnaire surveys to collect data and bidding factors (Aje, Oladinrin, and Nwaole 2016b, 19), (Olatunji, Aje, and Makanjuola 2017, 378-392), (Oke, Omoraka, and Olatunbode 2020, 169-175). Finally, previous studies focused on project performance such as studies by (Habibi, Kermanshachi, and Rouhanizadeh 2019, 14), (Mansour et al. 2020, 1-10).

Management of workload is considered a prevalent dynamic decision-making problem (Forrester 1985, 133-134). In such cases, the decision maker's goal is to keep the workload at a relatively stable targeted value. The complexity of this task is that workload cannot be regulated directly. Instead, the flow effect can be managed by controlling its causing factors. The controlling decisions exhibit delays to establish their outcomes. This lag might last longer and can affect other management decisions. Workload management issues arise at a variety of accumulative degrees such as project and portfolio levels. At the project level, project managers face workload fluctuations due to variations in productivity, material availability, change orders, and other contributing factors. variations of one project accumulated at the portfolio level. This requires the manager to have a stock of cash and resources to avoid drawbacks from these changes. Policies to decide on the amount of required cash and resources affected by aggregations and delays, i.e., the "bullwhip effect" (Metters 1997, 89-100), makes it very expensive to mitigate these risks using the traditional percent of contingency.

In such an environment, the impacts on the organization depend on how the organization responds to such changes (Forrester 1985, 133-134). Generally, managers are adequately aware and accurate about the information for local decision-making. On the other hand, they frequently misunderstand the complicated linkages of known local behaviors on the overall behavior (Sterman 1989, 321-339). Holistic modeling is capable of integrating organization portfolio and project dynamics. This can be achieved via the application of the System dynamics (SD) approach.

5.1.1 Holistic modeling

Holistic modeling is capable of integrating organization portfolio and project dynamics. This can be achieved via the application of the System dynamics (SD) approach. SD is a causal-driven approach (based on theory), that enables having a white model based on causes not just correlation between variables (Barlas and Carpenter 1990, 148-166). SD employs techniques from the field of feedback control to set up the problem factors into a causal feedback loop for the best understanding of the problem under investigation (Forrester 1993, 199-240), which is used to generate macrodynamic from this microstructure (Sterman 1989, 321-339). SD considers the delayed effect between cause and effect. The structure of such models has a significant added value from considering the network effect and system inertia in studying the problem under investigation.

5.1.2 Controlling workload dilemma

From a system thinking perspective, workload management can be considered a problem of stock management which has two main parts. First, the workload level (stock) and the flows affecting it. Second, the management decisions to avoid and mitigate the variations (Sterman 1989, 321-339). In the stock problem, the management needs to set the ordering frequency over time to maintain the inventory levels near the target. In the case of PBO, both inflow and outflow affecting the workload management decisions are beyond the manager's control. Inflow and outflow are determined by the interaction among the market, project, owner, and organization. Bidding strategy is one of the inflow factors, that affects the organization's workload and project performance (Wibowo, Astana, and Rusdi 2017, 341-347). The bidding price is the most influential factor in such strategies, and the project is awarded the lowest bid price. This awarding process can lead to the winner curse (Elsayegh, Dagli, and El-Adaway 2020, 147-153). Ignoring the effect of the lowest bid on the long-term performance of the organization reduces its competitiveness. Also, the effect of these strategies on the organization's capabilities is required to be addressed.

Market landscape and competition mechanism affect the contractor’s behavior. Owner characteristics are one of the parameters that shape the competition mechanism, e.g. if the owner is not strict (permissive) about the project deliverables. This could drive the contractor to optimistic pricing of the project and intentionally offer a low price to award the project (Yan 2015, 15423-15448). This affects the market balance prices and competition landscape.

Contractor competitiveness is very important to sustain in the market. This competitiveness is usually computed based on the organization's capabilities and competition strategies. The aggressive strategies in the competition are not the best for the organization. These strategies make an organization's profit unstable and have high swings (Dangerfield, Green, and Austin 2010, 408-420). In such cases, market demand has a great effect on the markup percentage. This effect is required to be reflected in the applied strategies.

Moreover, the project's profit is the main source of the organization's income that drives the cash flow (Turner and Miterev 2019, 487-498). Income delays affect the organization's financial stability and could lead to overdrafts. One of the widely used strategies to reduce overdrafts is overbilling and credit trade. They can reduce the overdraft by 11% to 30% (Cui, Hastak, and Halpin 2010, 361-376).

Not only does cash flow management affects the project and organization performance, the operational aspects of projects such as motivation and working hours affect the project performance (Alvanchi, Lee, and AbouRizk 2012, 66-77). It's found that work-hours arrangements can enhance productivity and benefit the project performance for cost and time. (Li et al. 2018, 605-618) found that hiring laborers for long periods improve the project performance but increases the organization's overheads. Also, (Shafieezadeh et al. 2020d, 201-216) found that dynamic resource allocation is the best policy to enhance the schedule performance index of the project in the cases of scope changes.

Change orders are one of the scope changes that affect productivity (Al-Kofahi, Mahdavian, and Oloufa 2020, 1-12). Production changes directly fluctuate the project performance regarding time and cost (Alvanchi, Lee, and AbouRizk 2011, 77-91). In these cases, PBO may depend on outsourcing tasks (subcontracting) to finish parts of the work. The quality of the subcontractor is the most influencing factor in the project's performance (Lisse and Student 2012). The outsourced workload directly affects the project performance and rework percentage.

Rework and changes between different phases affect the project's time and cost. For example, (Li and Taylor 2014, 04014044) studied the rework in the design phase and its effect on the downstream of the project execution rework. The delays in the interaction between the two phases make the bullwhip effect transmits and extends to other subsystems.

5.1.3 Chapter goal

This chapter focuses on achieving the third goal of the research by building an SD model using the factors identified in chapter 3. This work builds on the previously mentioned studies to address the workload fluctuation in PBO. It contributes by reflecting the market voice on the decisions taken. Also, addresses the effect of these decisions on the organization's long-term performance. The boundaries for this model are set to consider the interaction of PBO's dynamics with the industry's dynamics. This is achieved by feeding the model with project-portfolio execution parameters, industry competitiveness parameters, and contractor-to-industry relationships. This study considers the competition benchmark by normalizing the performance of competing organizations in the market and can calculate the winning percentage. The proposed model builds on (Sterman 1989, 321-339). Yet the proposed solution assumes that the manager fully understands the underlying structure but the mental model capacity limits the solution's suitability. So, the application of computer simulation using SD will support the manager to find the optimum decision to manage workload fluctuations.

5.2 RESEARCH METHODOLOGY

The building of the proposed system dynamic model goes through multiple steps to ensure its robustness as shown in Figure 5.1. First, the data is collected through an intensive literature review of academic articles, published industry reports, and industry experts. This is to collect as large as possible of trustworthy data either hard (as form databases) or soft data, such as logical policies of decision-making. Second, rearrange these fragmented pieces of information into interacting subsystems (industry demand and capacity planning, work execution and capacity allocation, contractor competitiveness, and organization financial subsystem). Third, validation and assessment of the model are performed through various tests, such as structural tests and structure-oriented behavior.

The proposed model is validated through various tests of checking model equation dimensions to ensure the dimension consistency of the model (Zarghami and Dumrak 2020, 253-262). In addition, the proposed model is gone through a set of experiments to check the configuration, behavior, extreme case tests, and sensitivity test of the model response to uncertainty in parameter values to gain trust in the model (Cosenz 2017, 57-80). The sensitivity analysis of the model is conducted to provide top managers and scholars with a better knowledge of how various parts of the organization impact the overall performance. This helps organizations to enhance their decision-making model by understanding the holistic effect of individual decisions. It is worth mentioning that the nature of these steps is not linear. However, it is a kind of loop that can go back and forth multiple times till reaches a validated output.

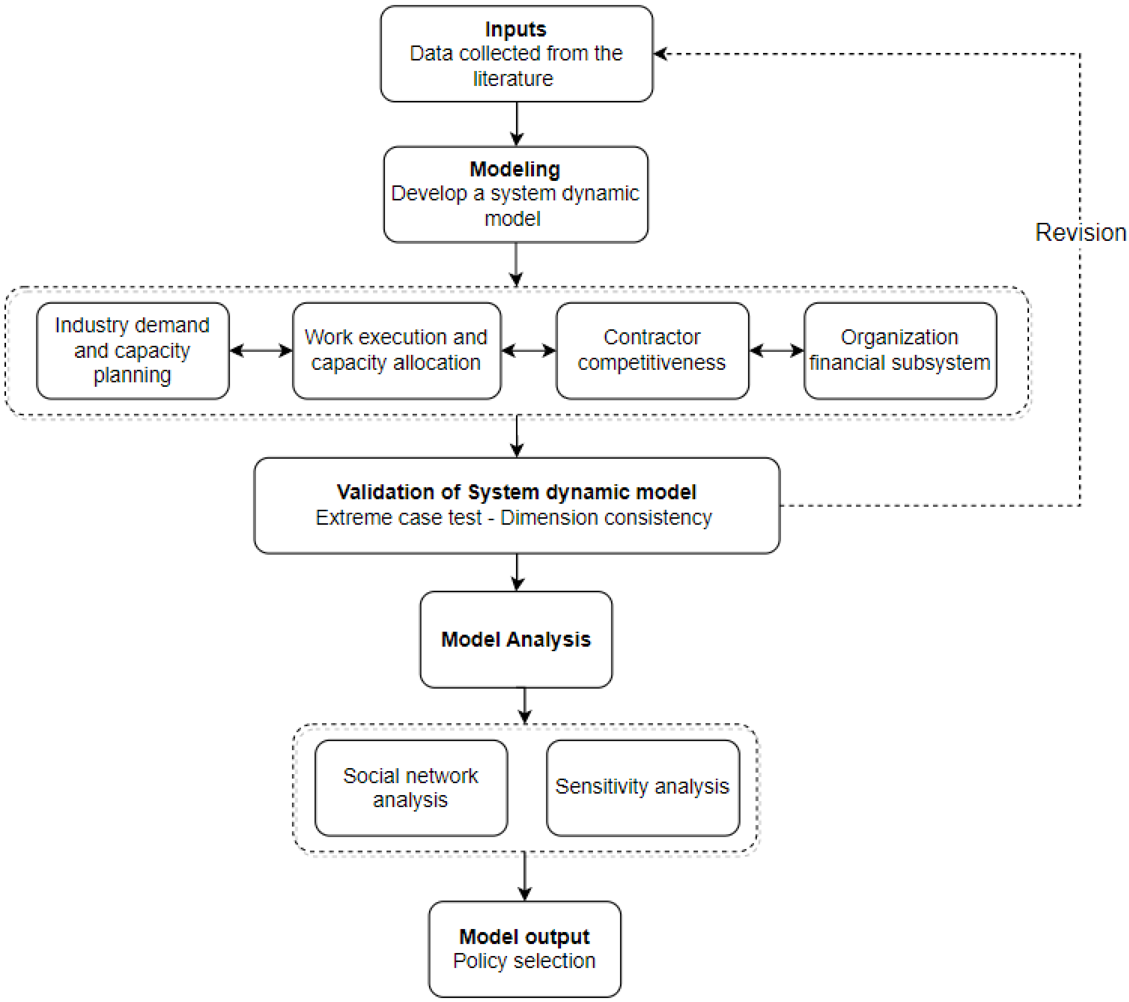


Figure 5.1 Model building methodology

5.3 DYNAMIC HYPOTHESIS

The dynamic hypothesis is a visual representation of the system under investigation. It includes causal relationships based on the data collection process (Tang and Ogunlana 2003b, 127-136). This study's dynamic hypothesis is the interaction of two main loops affecting the organization's workload as shown in Figure 5.2. The first one is the reinforcing (+ve) loop, which consists of the organization's cash that increases the capacity to execute more workload. After a while, accepted executed work increases the organization's cash again. The other loop is a balancing (-ve) loop, which consists of organization cash invested in increasing the capacity to increase the competitiveness of the organization to gain more workload. The higher the backlog the more consumption of the financial resources available reduces the ability of the organization to add more resources for work execution. The interaction between those two major loops shapes workload behavior (Gu and Kunc 2019).

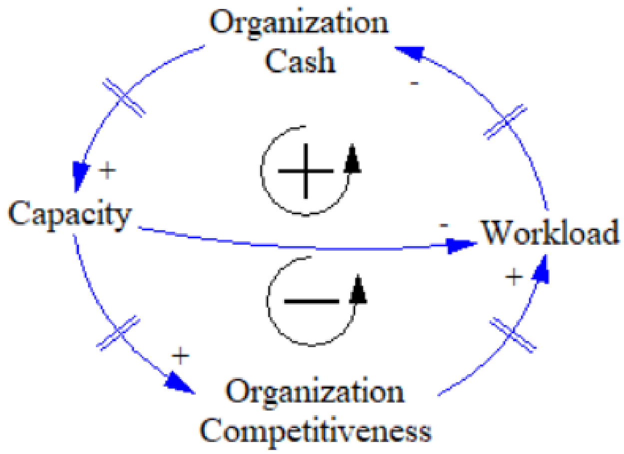


Figure 5.2 Higher-level dynamic hypothesis

The boundaries for this model are set to consider the interaction of PBO's dynamic environment with the industry's dynamics (Arafa 2011). This is achieved by feeding the model with project-portfolio execution parameters, industry competitiveness parameters, and contractor-to-industry relationships (Tang and Ogunlana 2003, 127-136). Multiple feedback loops are utilized to transform these connections into a system dynamic (SD) model. Which can be configured to represent any number of contractors working on numerous simultaneous projects.

On the supply side, each contractor bids for projects, and if awarded, they are added to the contractor's workload. The proposed model considers the contractor's strategic intent for capacity adjustment, and markup adjustment to compete in the market and ensure organizational sustainability (NGHIA 2017).

On the demand side, owners decide the criteria for selecting the awarded contractor, either based on the best qualifications combination or bid-price attractiveness (Badawy 2018). The industry demand is also modeled to provide heads-up of the near future demand size.

PBOs utilize strategic decisions to obtain their goal market share and prevent opponents from dominating the market (Arafa 2011). In such cases, market share, organization cash, profit, capacity utilization, and capacity variability are used as the macro feedback indicators. The organization's goal is to maximize and/or minimize these indices by optimizing its capacity, pricing, delays in responding to such changes, and investing in new technology. This is to achieve maximum matching with the market (Mahdavi et al. 2019, 1200-1217).

Generally, the key to success is a regular best-matching strategy among evolving industry demands and the contractor's dynamic competence. As a result, new projects will be awarded to the contractor who can establish their business model (BM) functions to "fit" with the present criterion at a certain moment and fulfill owner expectations. Contractors with high responsiveness and adaptable dynamic skills may be able to survive in the business during such market dynamics. The priority and weights of these factors may alter from industry to industry, organization to organization, and from time to time. As a result, one of the most important preliminary tasks for any contractor is to identify the landscape variables, their priority, and competition performance (i.e. benchmarking), and then adapt their strategies using their available capabilities to "max match" with the industry fitness function at any point in time to maximize the payoff (i.e. profitability and market share).

5.4 GENERAL FRAMEWORK

The extracted factors from the literature (identified in chapter 3) were arranged into three main groups. The pre-award project, the after-award project, and the organization's financial system. This division facilitates communication with industry experts. Because the industry experts' mental models distinguish between those three subsystems. For instance, the main goal in the pre-award phase is to win the bid (award the project). This is different from the experts' mental goal in the after-award project phase, which successfully delivers the project. The financial subsystem works as the motivator and controller for the organization. The financial system swings between those roles based on the phase. During the pre-award phase, it works as a motivation for the contracting organization to gain more financial resources by bidding for new projects and winning them. While in the after-award phase, it controls the production rate of the organization based on the available liquidity. The description of each phase is illustrated in the following subsections.

5.4.1 Pre-award stage

At this stage, the PBO (contractor) contributes to decision-making intending to be awarded a new project, and multiple key stakeholders are involved at this juncture. The variables appearing in Figure 5.3 illustrate that the contractor, owner, project, and market characteristics at this point are interacting. The financial capacity (running cash) of the organization and its bonding capacity limit the size of projects available for the organization to compete for. If a suitable opportunity becomes available in the market, the organization assesses it and decides based on its strategic planning whether the opportunity is worthwhile to pursue. If it is determined that it is suitable, the organization prepares a plan accordingly and estimates the cost and expected profit based on various interacting variables related to market conditions, need for work, owner strictness, and project. The interactions among these variables govern the likelihood that the contracting organization will be awarded the project. If the project is awarded to the contracting organization, the second phase is initiated.

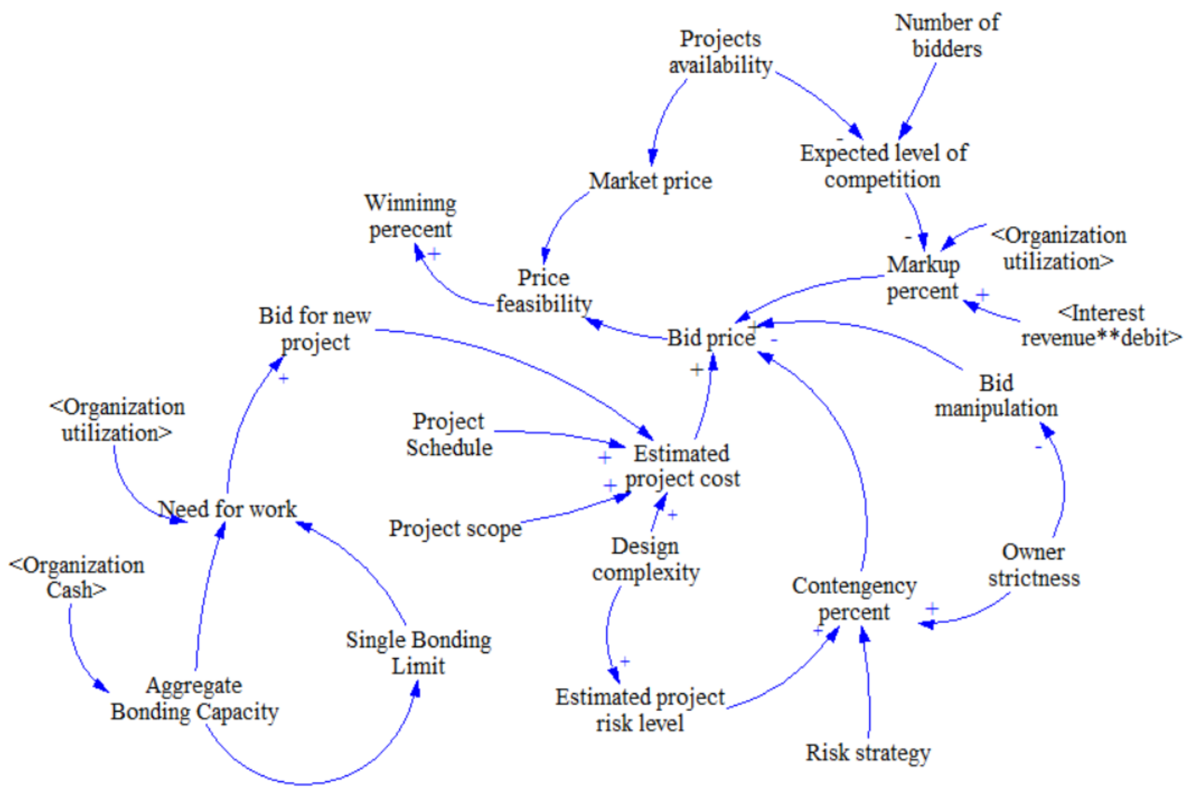


Figure 5.3 Pre-awarding project conceptual framework

5.4.2 Post-award stage

At this stage, the same four previously mentioned key stakeholders continue to interact. As shown in Figure 5.4, the organization adds a new workload to its existing workload. Resources are then reallocated to accommodate the organization's total workload. The execution of the workload is subject to multiple variables that affect the productivity and quality of the executed workload.

After a set time, the executed workload is either approved or rejected by the owner following the terms of the contract. The scope of work that is rejected at this juncture becomes rework, while the approved work will add to the organization's cash flow through payments as shown in Figure 5.5. Other external and/or internal variables also affect this process, and these variables are potential sources of risk. The risk may be in the form of expected delays (due to internal management decisions or allocation of resources, productivity issues) and/or external variables such as variations in material cost or wages. These risks and project operations affect the organization's financial system, as described in the following subsection.

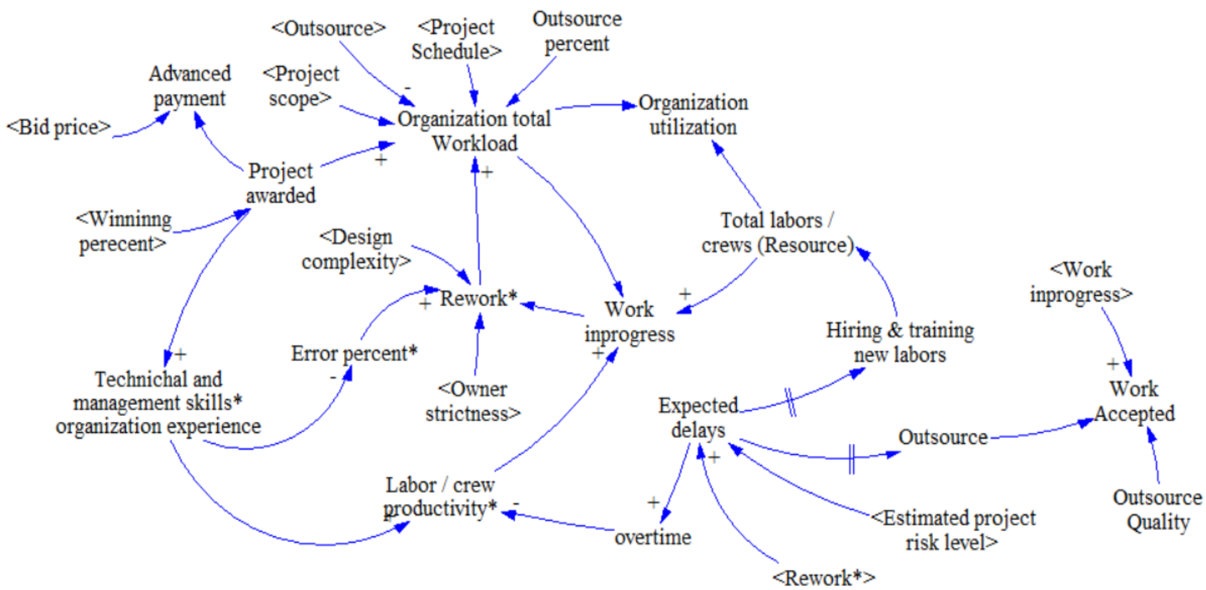


Figure 5.4 After awarding the project conceptual framework

5.4.3 Financial system

Contracting organizations rely on payments from accepted workloads (projects), as shown in Figure 5.5. These payments are subject to delays and retention based on the terms of the contract. Contracting organizations use these payments to cover the cost of subcontractors (outsourcing), organizational overhead, equipment maintenance, labor wages, and debt. The contracting organization must resort to debt in the case of negative cash flow (overdraft), and this exerts financial stress on the organization.

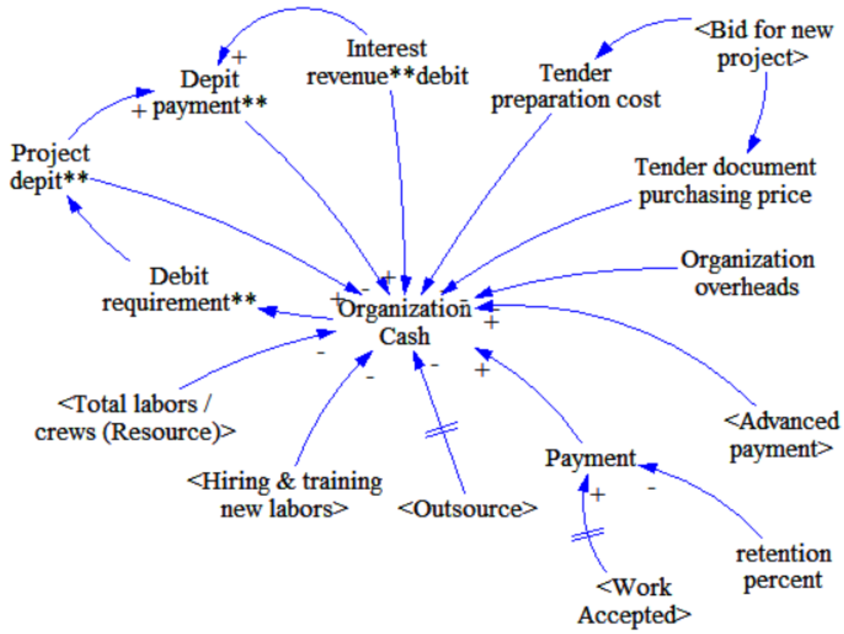


Figure 5.5 Financial subsystem

5.5 MODEL ASSUMPTIONS

The connections between different phases (pre-award and after-award the project) were not considered in the previous studies as highlighted in the literature review. In reality, the connection between these phases, as mentioned above in the general cycle of how the organization gain and execute workload, create complexity. This general representation is refined through collaboration with an industry partner to fully understand the cycle details and how to reduce the real complexity. This complexity is traditionally solved by expert mental models. This work applies some assumptions to reduce the complexity of reality. These assumptions are:

- Although the contracting organization could be involved in any upstream or downstream construction activities, the model assumes that the organization is strictly exclusive to project-based activities.
- Intellectual capital is thought to exist as labor skills and an organization's records. It is uniformly distributed across the organization's workers to form its average specialized knowledge.
- The technical capacity of the staff is assumed to affect the project schedule and cost.
- The project is assumed to be fully represented by its workload, duration, and price.

- PBO is assumed to be fully represented by its capacity, cash, and soft variables.
- Material delays and other supply chain constraints are assumed to be met.
- Cash is assumed to be invested at the start of the simulation without allowing cash borrowing.

5.6 CONCEPTUAL FRAMEWORK

The previous assumptions are incorporated into the general framework and discussed with the industry practitioner. There are some simplifications applied to the general framework based on the best practices applied. However, the organization can work on various types of projects, each project is assigned to a specific department based on the project type. This means the organization departments look like small organizations. Hence, the model is simplified to represent one type of project.

Figure 5.6 represents the causal loop diagram of the organization's workload. It can be divided into two higher-level causal loops. The first loop is the organization's execution of the current workload using its available resources, and the second loop is the effect of the execution phase on the organization's attractiveness in the market to gain more workload. These two loops are highly tight and coupled with multiple feedbacks, which will be illustrated in the next subsections. This represents the complexity of the decision made by the practitioners' mental model. Unfortunately, mental models could be easily directed or biased.

Each time they face changes in the workload level, they make an instant decision to mitigate this variation. However, they are fully aware of the entire factors, and in most cases, the decision is usually biased toward the direct cause and the direct effect. For example, if the workload exhibits some variations in one project, the instant decision is to adjust the capacity to cover the workload changes. This decision instantaneously stresses the financial resources of the organization. In the long-term, this decision stresses the organization to reduce its markup percentage to award a new project to have fully utilized resources. The low markup percentage will continue the stress over the organization's financial resources. This reinforcing loop could lead the organization to file for bankruptcy.

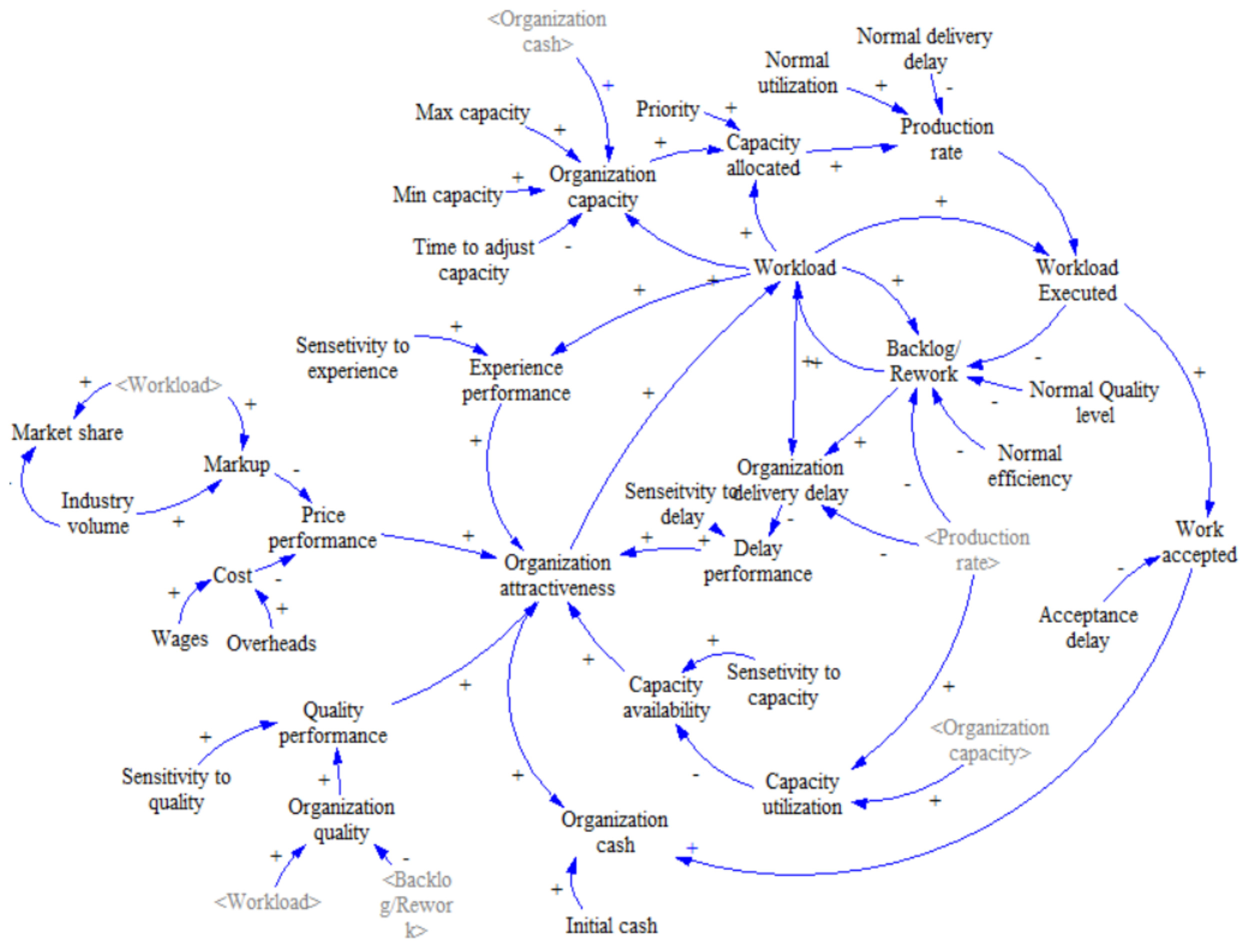


Figure 5.6 Conceptual model diagram

5.6.1 Workload execution subsystem

Figure 5.7 shows the cycle of executing the workload. It starts with an amount of workload that requires the organization's capacity to adjust to it. Organizational capacity has some constraints to adjust for this workload. These constraints are the minimum capacity, maximum capacity, available cash resources, and time consumed to adjust the capacity for the required level. Minimum capacity is the minimum value of required resources to maintain a smooth workflow for the organization and to be competitive in the market. Maximum capacity is the maximum value allowed to hire new resources. This value is usually constrained by the managers based on the available cash and core resources.

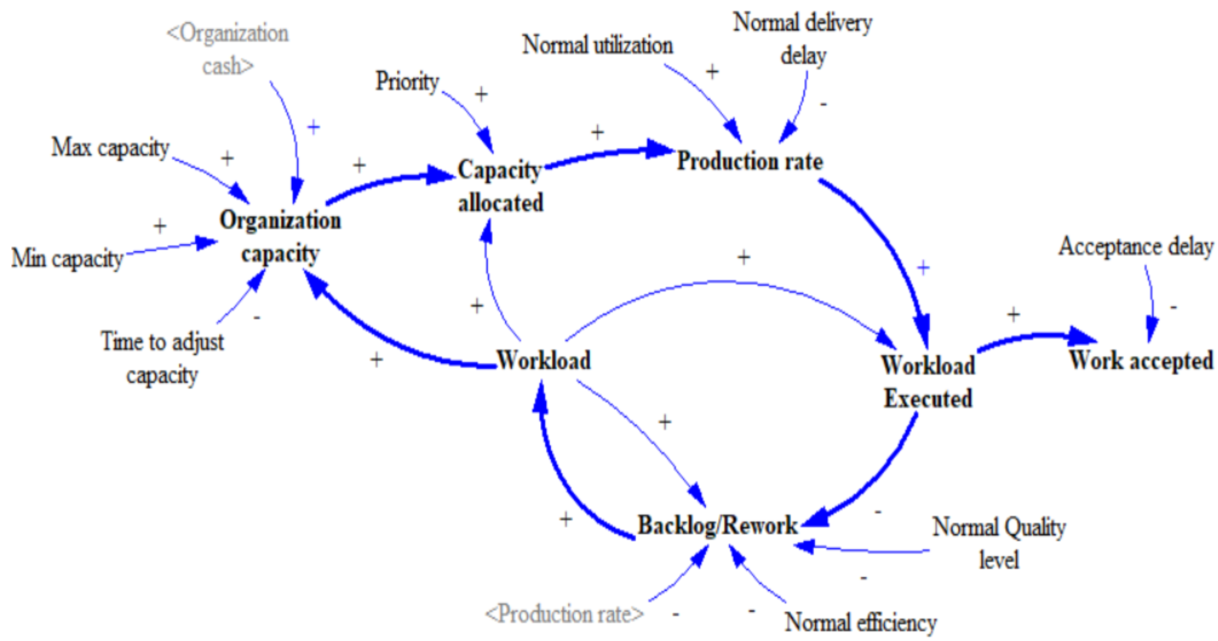


Figure 5.7 Workload execution loop

Part of the organization's capacity is allocated to this workload based on the priority of this work. This allocated capacity affects the production rate, which is affected also by the utilization of the resources and the delay in executing the workload. This step transforms the workload into executed work. Based on the efficiency and the quality level, part of the executed work is accepted after a delay time for checking, and the other part is transformed into the backlog or rework. This backlog will be rescheduled again and the cycle continue. The internal performance of the organization affects its relationship with the industry and other competitiveness as will be illustrated in the next subsection.

5.6.2 Organization-to-industry relationship

Figure 5.8 shows the relationship between the organization and industry is represented in the organization's attractiveness. The attractiveness of the organization is simply its probability to award a new project based on its performance relative to other organizations' performance. There are multiple performance indices to define the attractiveness of the organization, experience, delivery delay, capacity availability, quality, and price performance.

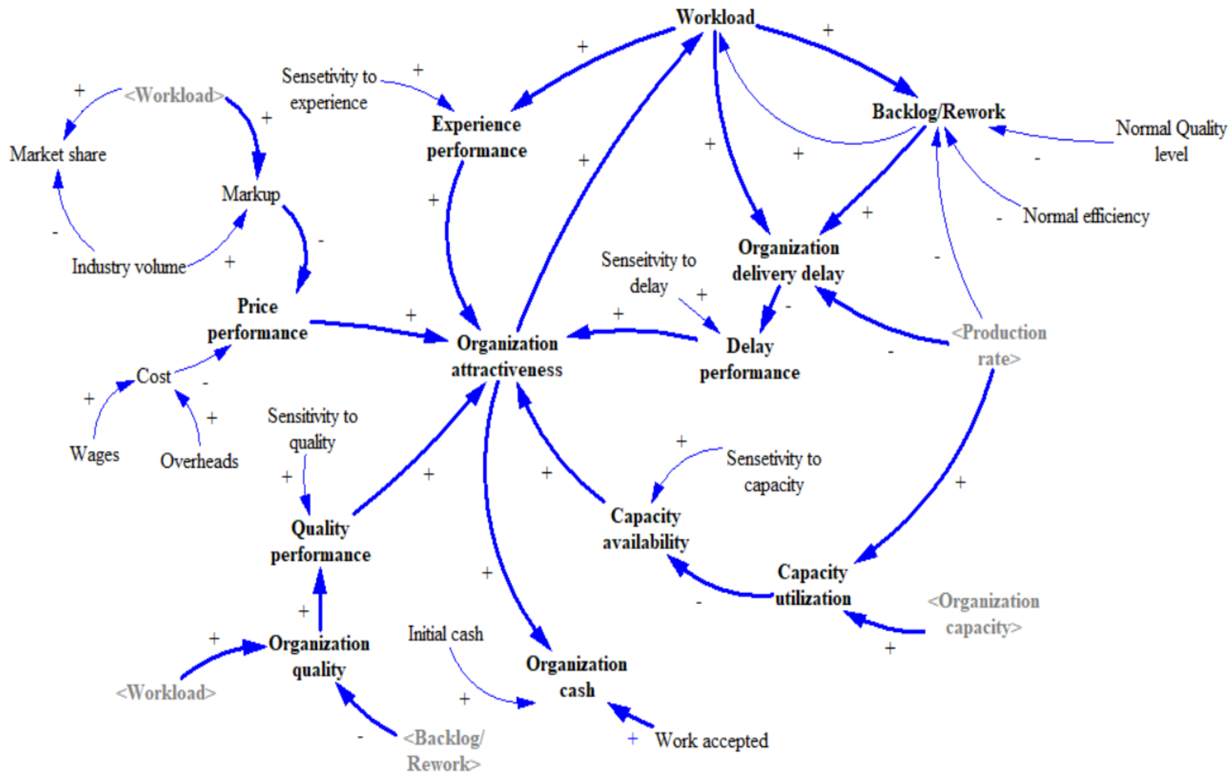


Figure 5.8 Organization to industry loop

Each performance index is measured based on two parts, one related to the organization and the other related to the industry. The first part is the organization's historical values in each part. The second part is the market sensitivity to this index. The benchmark to compare the organizations in the market is updated continuously based on the values from the historical data at each bidding or comparison. For illustration, let's assume there are two organizations in the market. One has experienced 100 hours of work and the other has an experience of 50 hours of work. The benchmark is calculated based on the maximum of these values which is 100 hours. The performance of the first organization will be 1 (i.e. 100 /100) and the other organization's experience performance will be 0.5 (i.e. 50/100). The portion of the experience performance added to the organization's attractiveness is the multiplication between the performance by the sensitivity of the market to the experience in the awarding process.

This causal loop directly links the historical performance of the organization to its future projections. This representation helps to understand how the organization has control over the internal factors that can be managed properly to build a more sustainable and competitive organization.

5.7 SUMMARY

This chapter builds a causal loop diagram for project-based organizations (PBOs). This work links multiple work phases (pre-award and after-award the project) with external and internal organizational dynamics. The main goal of this model is to analyze the workload fluctuations and PBO business model performance. The proposed conceptual model holistically addresses the consequences of short-term decisions taken in response to dynamic changes in the internal and external environments on its long-term performance. The conceptual model is revised by the industry partner to validate it.

This work holistically presents the cycle of managing the construction project within a contracting organization. Condensing and integrating these interactions in the proposed conceptual model opens the gate for other researchers to add to the body of knowledge with mathematical applications using real case studies. It will also encourage other researchers to analyze further the complex topic of predicting workload in PBO. This topic is crucial for the construction industry to face the current challenges of a nowadays volatile and uncertain market.

CHAPTER 6 COMPUTERIZED MODEL

6.1 INTRODUCTION

Workload management can be considered a problem of stock management which has two main parts. First, the workload level (stock) and the flows affecting it. Second, the management decisions to avoid and mitigate the variations (Sterman 1989, 321-339). The mathematical problem of workload fluctuation can be presented by Equation 6.1 (Sterman 1989, 321-339)

$$W = \int_{t_0}^{t} (A - P)dt + W_0 \qquad (6.1)$$

Where:

- W is the current workload level.
- A is inflows for the workload such as the awarding rate of new projects, scope changes, and rework.
- P is outflows for the workload such as the production rate.
- W_0 is the initial value of the workload.
- t is the time interval

In the stock problem, the management needs to set the ordering frequency over time to maintain the inventory levels near the target. While in the case of workload management, both inflow and outflow are beyond the manager's control. Intake is determined, for example, by market, owner, and organization, while outflow is determined, for example, by project, owner, organization's resources, and productivity. The scale and complexity of the feedback between such variables, and their typical behavior patterns feature oscillation and instability, make it hard to determine the best approach.

The general solution for such stock problems includes continuous supply (might be in patches/discrete) to maintain a relatively balanced level for the workload. Such solutions enforce constraints for that supply to be non-negative, and the loss rate is also non-negative (Sterman 1989, 321-339). Moreover, (Sterman 1989, 321-339) proposed a heuristic approach based on estimating a reference quantity and adjusting it due to expected changes. The main difference between (Sterman 1989, 321-339) solution and the proposed solution in this study is that (Sterman 1989, 321-339) solution assumes that the manager does not know the structure of the problem, i.e., the managers are solving the problem by the open system perspective or aware of a local subsystem without fully understanding of the holistic feedback system affecting the problem. Yet the proposed solution assumes that the manager fully understands the underlying structure but the mental capacity limits the solution's suitability, i.e., due to the experience of the manager and digitalization and modularity of the industry, the manager is aware of almost the holistic feedback system affecting the problem but the complexity of the problem is not suitable to be solved just by mental models. So, the application of computer simulation using SD will support the manager to find the optimum decision to manage workload fluctuations.

6.2 DATA COLLECTION

Variables affecting the organization's workload fluctuations were collected from an analysis of the available body of knowledge as mentioned in Chapter 3. Twenty-eight dynamic variables were identified. They are categorized into contractor, project, owner, and market-related factors. This study reallocates them into pre-award, after-award phases, and financial-related causes based on the soft logic of industry experts. The majority of data collected to mimic the project-based organization's (PBO) performance consists of administrative and logical decisions (called soft variables (Sterman and John 2002, 42-42.)). Values of exogenous variables are set to have large limits to make sure that the model does not overlook feedback effects that managers frequently overlook throughout their decision-making process. Finally, the strength or weights of variables are determined by the industry and vary from one to another.

6.3 SIMULATION MODEL

This previously mentioned hypothesis develops the model structure. The development of the proposed model requires a significant amount of effort. Particularly in terms of ensuring that the model is capable of capturing the behavior of various project phases—pre-award and post-award project—with consideration of the organization's underlying financial system and industry competition.

The model is simulated using VENSIM DSS. Screenshots from the model subsystems and their structure are presented in the following sections.

6.3.1 Contractor competitiveness Sub-model

Competitiveness is a wide expression that does not have a unique definition. In this study, contractor competitiveness is their ability (probability) to win a tender. It is derived from their attractiveness function and their fit to the market. For instance, contractors improve their competitiveness through drop bid prices, engage in technology transfer to improve service functionality, minimize rework, shorten delay times, or expand the addressable market of services. Not all of these criteria must be present to be successful. The most considered factors to influence the award of a bid are price performance, experience, financial stability, quality performance, and safety performance (Mahdavi et al. 2019, 1200-1217). Contractors are either awarded based on best value or minimum bid price. This divided the customers into two groups: those who are drawn by price and those who are attracted to the greatest value (best combination) even if they were public or private organizations. In most cases, the drive parameter is the price. A comparison between the contractor's bidding price and the lowest available price at the bidding period determines the contractor's competitiveness via pricing. In this study, to reflect the various industry preference, the model can change the best price to the nearest to the mean of available bidding prices or the second lowest bid price. Generally, the competitiveness of the contractor is calculated based on Equation 6.2.

$$\mathrm{C_C} = \sum (x_c(i) * \frac{P_c(i)}{P(i)}) \qquad (6.2)$$

Where C_C is the Contractor competitiveness, x_c is the weight of the criterion. $P_c(i)$ is the contractor's performance in such criteria, and P(i) is the industry benchmark value for this criterion.

The benchmark value in the model is calculated based on the minimum/maximum of available values for such criterion, and x_c is fed to the model based on user preference. The project's owner compares the competitiveness of contractors, C_C, and awards the bid to the largest available competitive contractor. As a result of the varying owner requirements, the preferences for contractor selection are set up to the lowest bid price and can be altered to a specified metrics based on user preferences. The criterion considered in this model is capacity availability, quality, experience, delay, and price as shown in Figure 6.1. Also, the causal loop is shown in Figure 6.13.

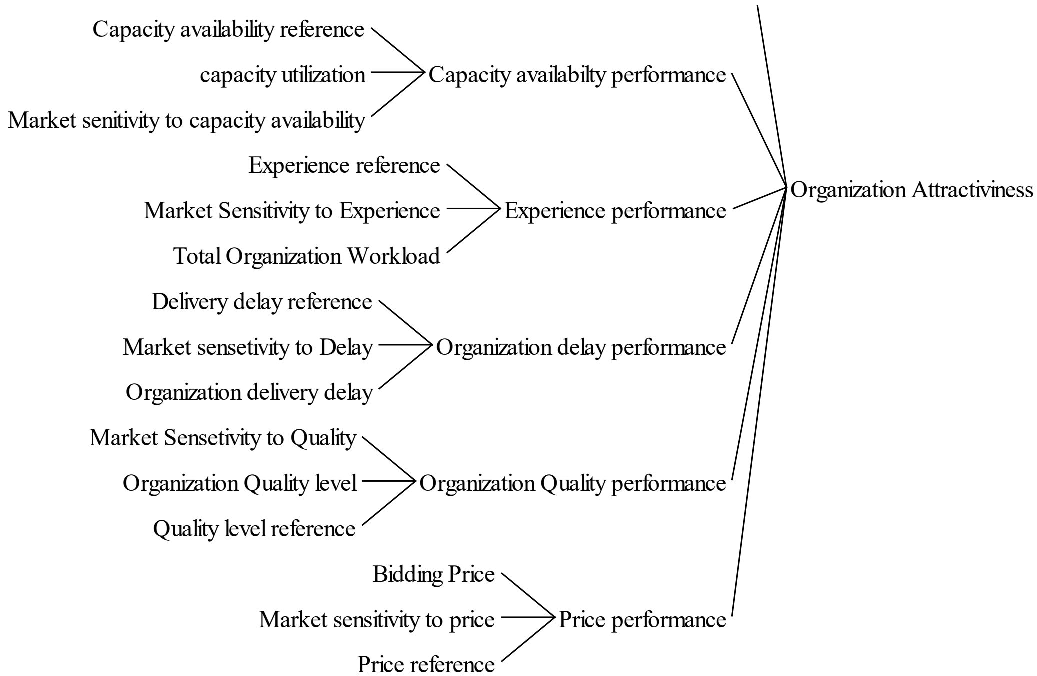


Figure 6.1 Causes tree of Organization Attractiveness

6.3.2 Demand and capacity adjustment

The process of evaluating the market-needed capabilities and respective volume to be achieved is known as capacity planning. Change in demand drives the contractor strategy in the markup percentage and delivery method. For example, if the market is hot, it means the demand is greater than the industry's capacity, and contractors will tend to increase their markup, use cost-plus contracts, or expand the organization. On the other side, if the market is cold (recession), they tend to reduce their markup percentage, accept lumpsum contracts, or shrink the organization's size.

There are two types of capacity, fixed, and variable. The fixed capacity is the core resource of the organization. Variable capacity is the temporary resources to balance the required production rate with the required capacity. PBOs seek to have the minimum ratio between variable to fixed resources. Organizations that can have a stable fixed capacity like factories are more profitable, stable, and competitive.

Organization fixed capacity is adjusted to expansion-shrink decisions. Variable capacity is modified to the current workload. Although the capacity adjustment is represented as an irreversible strategic action, the model allows for both fixed and variable capacity adjustment. The model excludes immediate capacity adjustment. The organization capacity is calculated as shown in Equation 6.3.

$$\text{Org. capacity} = \text{SMOOTH3I}[\text{MAX}(\text{Required capacity}, \text{Min Capacity}), \text{Time to adjust Capacity}, \text{Initial Capacity}] \quad (6.3)$$

$$\text{Required capacity} = \text{MIN}(\text{Work in Hand}, \text{Max Capacity}) \quad (6.4)$$

The model constrains the ratio between the maximum and minimum allowed capacity. This stems from the assumption that variable capacity is managed by fixed capacity. The delay in acquiring the required capacity comes from the time difference between the agreement to adjust capacity and the recruitment procedure. In addition, the time spent acquiring new equipment and training labor causes capacity growth to be delayed. This delay is represented by a third-order delay.

6.3.3 Capacity allocation

The resources of the organization are represented by their production capacity. i.e. the organization has 10 crews, and each crew can produce 8 hrs per day then these resources are represented by 80 human hours (Ma.Hrs). Project-required resources are calculated at the beginning of the project and high swings in allocating these resources are not allowed. The number of resources calculated considers the normal efficiency and normal capacity utilization as in Equation 6.5 and Equation 6.6.

$$\text{Cp} = \text{WH} / \text{PD} \quad (6.5)$$

$$\text{Call} = \text{Min}(\text{Cp}, \text{Ca}) \quad (6.6)$$

Where Cp is the project-required production rate, WH is the project workload in man hours, and PD is the project duration. The allocated capacity (Call) to a project is the minimum of available capacity (Ca) or the required capacity. Organization capacity is allocated to running projects according to two parameters, the project required crews and the priority of this project. In this model, it is assumed that projects have priority (trapezoidal shape) based on the percent completed as shown in Figure 6.2. It is assumed in this model that maximum priority is when the project is between 25% to 75% completed and it reduces linearly at the start and end of project execution.

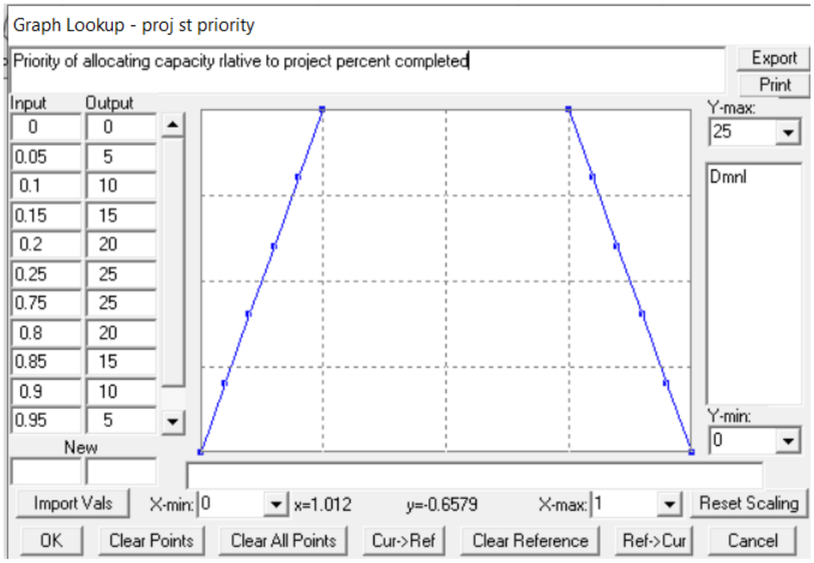


Figure 6.2 Project priority in allocating capacity

6.3.4 Financial sub-model

Contractors rely on running cash for almost all activities. There is one source for gaining cash considered in the model, which is cash received from the accepted work. This cash is spent on hiring resources, labor wages, material costs, and other activities. Organization cash is represented by a stock and its value is calculated based on Equation 6.7.

$$Organization\ Cash = \int (Cash\ in - Cash\ out)dt + Initial\ Cash \qquad (6.7)$$

The cash-out rate is from spending cash instantaneously on direct or indirect work. The cash-in rate from the accepted work is affected by a delay, which is around 30 to 60 days. Not all of the due amount is received by the contractor because of the retention percent, which is the percent stated in the contract and retained from the receipts till the 50% of the project progress is completed and paid to the contractor plus the final payment at the end of the project.

6.4 MODEL VALIDATION

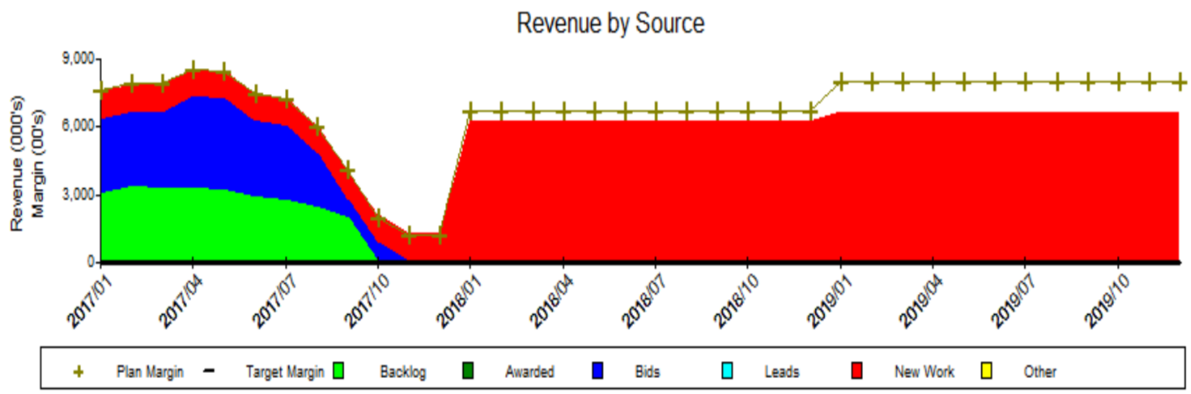
The validation of a system dynamics model is far more difficult than that of a black-box model since determining the validity of a model's underlying structure is extremely difficult, both philosophically and technically. It is conceptually challenging because the difficulty is intimately tied to the unresolved philosophical question of proving the validity of a (scientific) assertion. The problem is technically tough since there are no recognized formal criteria (such as statistical hypothesis tests) that can be used to determine if the structure of a particular model is near enough to the "actual" structure. Furthermore, due to autocorrelation and multicollinearity issues, typical statistical tests cannot be utilized to validate the behavior of a system dynamics model (Barlas 1996, 183-210). Finally, the actual testing is expensive (Cosenz and Noto 2018, 127-140), (Mahdavi et al. 2019, 1200-1217) because:

- The nature of market competition and the highly responsive nature of bidding data in this environment.
- It is impossible to enforce scenarios on a contractor in a stable environment to track the result over time to test the hypothesis.
- The data's longitudinal aspect adds to the difficulty of data synthesis.

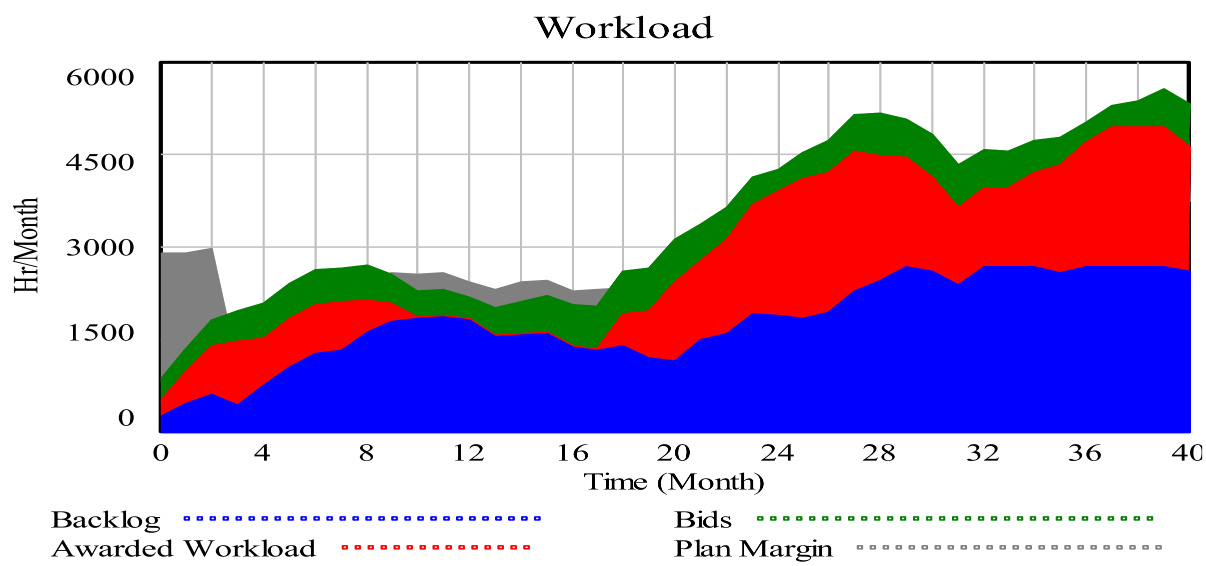
This study builds confidence in the model in a gradual process. It starts with model conceptualization by identifying its purpose and boundaries. This is achieved by: 1) a systematical analysis of the literature (in Chapter 2 and Chapter 3) to prove the need for such a model and type of analysis, 2) discussing the problem of workload fluctuation, its boundaries, and need for a decision support system with volunteer practitioners.

The second part is model generalization by defining the key variables, which makes the model customizable for various project-based organizations and ensures the depth of defining the problem. This is achieved in Chapter 3 by extracting these factors from the literature and verifying them with industry experts. Chapter 2 is meant to reject the null hypothesis of workload fluctuations as a problem that has been solved and there is no room to add to it and accept the hypothesis of there is a lack of a dynamic representation and analysis of this problem.

Third is internal model structure inspection by industry and academic volunteer experts. The detailed step-by-step model performance is investigated by the volunteer experts to get the model closest to the PBO's business model. This step includes variables behavior with the reality-perceived behavior. For example, organization workload in dollars (Figure 6.3 – a) is compared to workload behavior generated by the model (Figure 6.3 – b) and they performed various experiments by the model to ensure the behavior of the variables is logically matched with reality. It is worth mentioning that this step did not perform once but in recursive cycles. Finally, the model equations' dimensions are checked and passed the test to ensure the dimension consistency of the model (Zarghami and Dumrak 2020, 253-262).



(a) Organization Revenue behavior (Workload multiplied by the revenue/expected revenue)



(b) Workload behavior from the SD model

Figure 6.3 Organization planning from two perspectives

Figure 6.3–a presents the organization's planning in dollars. The left part of the figure is actual data and near-future expectation, that ends by the year 2017. The right part of the figure is the plan for the next two years. The plan is very simple to just mention available resources plus a small margin. Also, the drop that appears by the end of 2017 and the start of 2018 is because of the data available to the end of 2017, and the rest of Figure 6.3–a is the expectations for the future based on the organization's available resources. This simple plan is acceptable as long as there is no available tool to integrate the organization-to-industry dynamics. In the case of integrating these

dynamics into this plan, the straight line of the planned margin or new work should be a curve like the left part of Figure 6.3–a. This result is achieved in Figure 6.3–b after integrating these dynamics into the organization's plan. The behavior of the plan represented in the organization's workload is investigated by the volunteer industry experts and the model is edited till the behavior matches the real behavior. The initial values for the test case are presented in Table 6.1. The discussion and editing of the model are presented in the next subsection.

Table 6.1 Variables' initial values for the test case

Variable	Initial value	Unit	Variable	Initial value	Unit
Average Duration	12	Month	New Project Duration Medium	12	Month
Average Load	3000	Man.Hour	New Project Duration Small	10	Month
Bid Project duration 1	12	Month	New Project Load Large	10000	Man.Hour
Bid Project load 1	3000	Man.Hour	New Project Load Medium	5000	Man.Hour
Bid Project price 1	275000	CAD	New Project Load Small	2000	Man.Hour
Bidding Time	6	Month	normal delivery delay	1	Month
cash time buffer	3	Month	normal delivery delay COMP	1	Month
current market share	0.1	Dml	normal efficiency	0.9	Dml
Current Status COMP	1	Dml	normal efficiency COMP	0.9	Dml
Demand level	5	Project	normal quality level	0.95	Dml
discount rate	0.003	Dml	normal quality level COMP	0.95	Dml
FINAL TIME	100	Month	normal time to perceive competitor capacity	2	Month
frequency of updating	12	Month	normal utilization	0.9	Dml
frequency of updating COMP	12	Month	normal utilization COMP	0.9	Dml
Initial Capacity	2500	Man.Hour	Number of Competitors	2	Competitor
Initial Capacity COMP	2500	Man.Hour	Number of Competitors COMP	2	Competitor
Initial Cash	100000	CAD	Overheads	1000	CAD
Initial Number of Running Projects COMP	1	Project	Percent completed 1	0.5	Dml
INITIAL TIME	0	Month	percent of minimum liquid cash	0.1	Dml
initial trend	0	Dml	Project Basket switch	0	Dml
Market Orientation	1	Dml	Project duration 1	12	Month
Market sensitivity to capacity availability	0.25	Dml	Project load 1	3000	Man.Hour
Market sensitivity to Delay	0.25	Dml	Project price 1	275000	CAD
Market Sensitivity to Quality	0.25	Dml	Start Delay	3	Month
Market Sensitivity to Experience	0.25	Dml	Strategy switch	1	Dml

Variable	Initial value	Unit	Variable	Initial value	Unit
Market sensitivity to price	0.25	Dml	TIME STEP	1	Month
Max Capacity	3000	Man.Hour	Time to adjust Capacity	3	Month
Min Capacity	500	Man.Hour	Time to adjust Capacity COMP	3	Month
Min Capacity COMP	500	Man.Hour	Time to start project 1	3	Month
New Project Duration Large	18	Month	Wages	5	CAD

6.4.1 Model test case behaviour and modifications

The model variables are initialized by soft values mentioned in Table 6.1 to ensure that the model is calibrated to a specific market. Then the analysis of its behavior is conducted by discussing the following questions:

- How does the contractor define the need to bid for a new project?
- How did the contractor get awarded a project?
- How does the organization define its minimum profit margin and how to set it during the Bid?
- How does the organization define that there is a need to adjust the capacity?
- Does the organization's capacity adjust relative to the expected workload or current workload?
- How long does the organization need to adjust its capacity?
- How does the organization allocate its capacity between different projects?

The workload behavior presented in Figure 6.4 is investigated by asking “Why is there an exponential growth in the workload after 20 Months?”. To answer this question lets start by answering the 6 questions mentioned above:

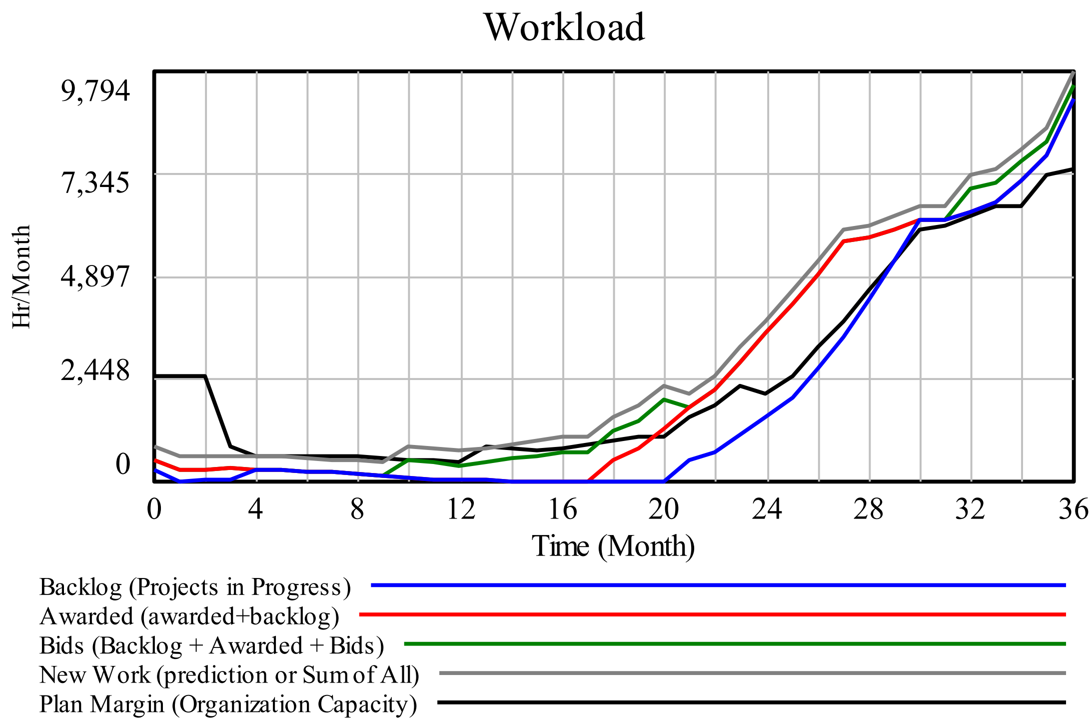


Figure 6.4 Organization workload

1. How does the contractor define there is a need to bid for a new project?

The contractor defines his need to bid for a new project based on:

a) The cash flow of running projects is positive
b) The capacity utilization of resources is below the max allowed (we defined It as 0.9 percent)
c) There is available cash in the organization that covers the minimum percentage of the project price (we defined it in this case as 10 percent). This means if the organization is running 5 projects, each has a price of 100k CAD$, then the organization's cash available should be 50k CAD$ to be able to bid for a new project.

These conditions should be met to allow the contractor to bid for a new project. These rules are defined to make sure the cash flow does not go negative. Based on these rules the organization wasn’t intended to bid for any project in the first 12 months of simulation.

There were multiple discussions about considering the borrowing option to the dynamics but it was excluded from this model because of the high variation in different borrowing methods and the scope of the model. Also, analysis of various financial strategies reveals that the more conservative strategy is the best for the organization's long-term performance. so, the borrowing option was excluded from the model dynamics.

2. How did the contractor get awarded a project?

Based on the market orientation the contractor is awarded a project or not. In this case, we defined market orientation by these rules:

a) The Experience of the contractor is defined by the number of working hours that are accepted (project hours performed).
b) The Delay to perform the workload.
c) The rework percent of the contractor.
d) The available capacity is based on capacity utilization.
e) Bidding price

The model ranks the Contractors based on scaling the values of these parameters and then defining a winning percentage for each contractor.

3. How did the organization define its minimum profit margin and how to set it during the Bid?

The minimum profit is set to be 10 to 15 percent and can be adjusted based on the number of bidders and the need for work (capacity utilization).

4. How did the organization define that there is a need to adjust the capacity?

The capacity is adjusted based on the expected workload. This means if the contractor expects to get more work in the upcoming periods then they tend to increase the organization's capacity and vice versa. This process has no limitations. i.e. the capacity can go higher like 1m hr/month or lower like 0hr/month. Based on this if the contractor expects more workload then will increase the capacity and if awarded the workload and expects more than this could result in overshooting as shown in Figure 6.4 till one of the conditions in question 1 does not meet or the rank in question 2 is low to stop this reinforcement loop. To limit this loop, a range for the maximum and minimum capacity is enforced.

5. Did the organization's capacity have been adjusted relative to the expected workload or current workload?

The capacity is adjusted based on the expected workload, not the actual workload. This explains why there are valleys in the capacity utilization graph.

To enhance the capacity behavior, the capacity is adjusted based on the workload in hand, i.e., the current workload added to the awarded project's new load.

6. How long did the organization need to adjust its capacity?

The organization is assumed to take 3 months to adjust its capacity. This explains why the planned margin is delayed from the expected workload in Figure 6.4.

7. How did the organization allocate its capacity between different projects?

In this model, there is a priority assigned to projects based on the percentage of completion.

There is a limitation on capacity variation assigned to a project based on the initial production rate calculations. Also, high swings are not allowed.

6.4.2 Extreme case analysis

The model is tested to extreme values of variables to assure its logic. The contracting organization variables such as quality, efficiency, cash, and capacity are set to zero, one at a time.

The effect of quality and efficiency is set to zero drives the organization to lose its cash resources as shown in Figure 6.5 and kicked out of the market as shown in Figure 6.6. The oscillation in market share in the first few months is due to the initial condition of the variables and it is stabilized after a few months.

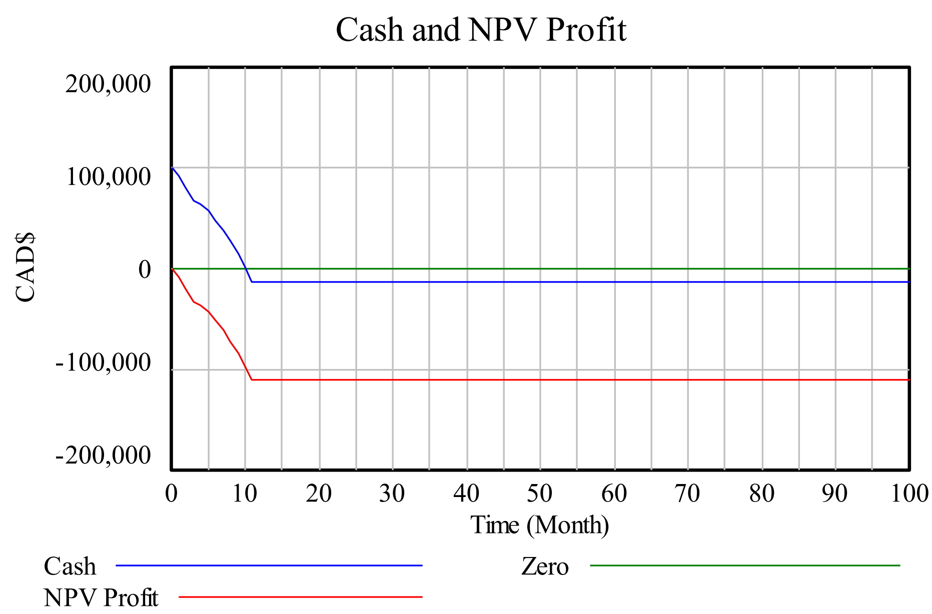


Figure 6.5 Organization cash and the profit

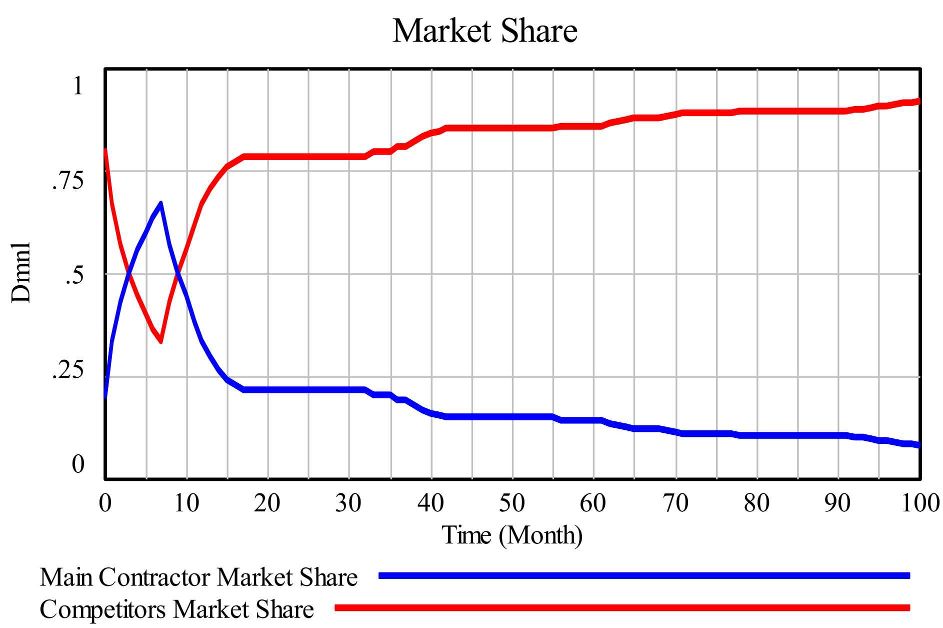


Figure 6.6 Organization market share

Setting the organization's initial cash to zero makes the organization out of the market instantaneously. While setting the organization capacity to zero pops up floating errors and the model stop running.

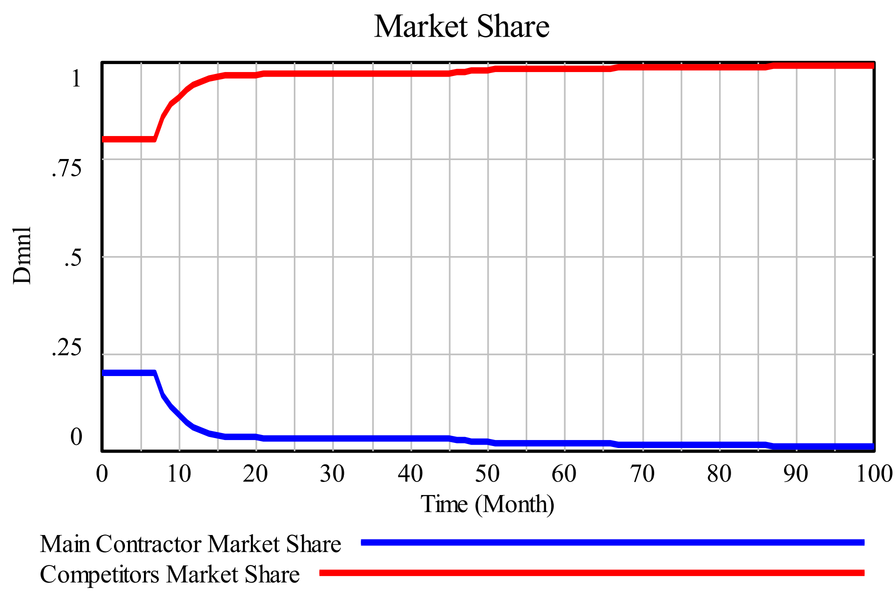


Figure 6.7 Organization market share due to zero cash

Moreover, the model can generate the cumulative s-curve of the project's workload behavior as shown in Figure 6.8, which is similar to the curves presented in (Love, Edwards, and Irani 2008, 234-247), (Okasha, Arafa, and Amer 2019, 42-51), and (Amer, Okasha, and Arafa 2019)

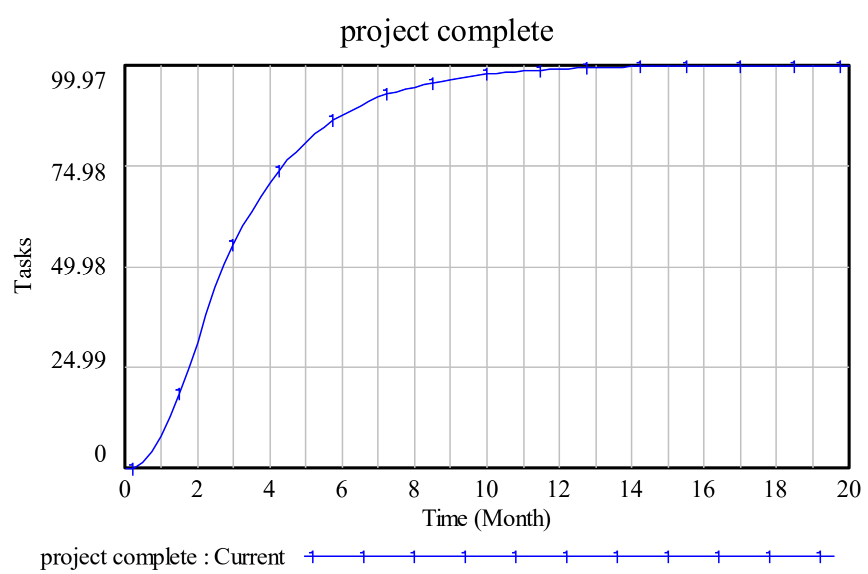


Figure 6.8 Project's workload accumulation progress

6.5 MODEL VIEWS FROM VEMSIM LAYERS

The model is applied on the VENSIM DSS platform. The model starts with a screen that provides the higher-level concept of the model and subsystems to go through the models' parameters as shown in Figure 6.9. Each hexagon directs the user to a specific subsystem to check the internal model structure and parameters equations. The initial values of the variables are set based on the data collected. It can be easily changed to reflect user preferences.

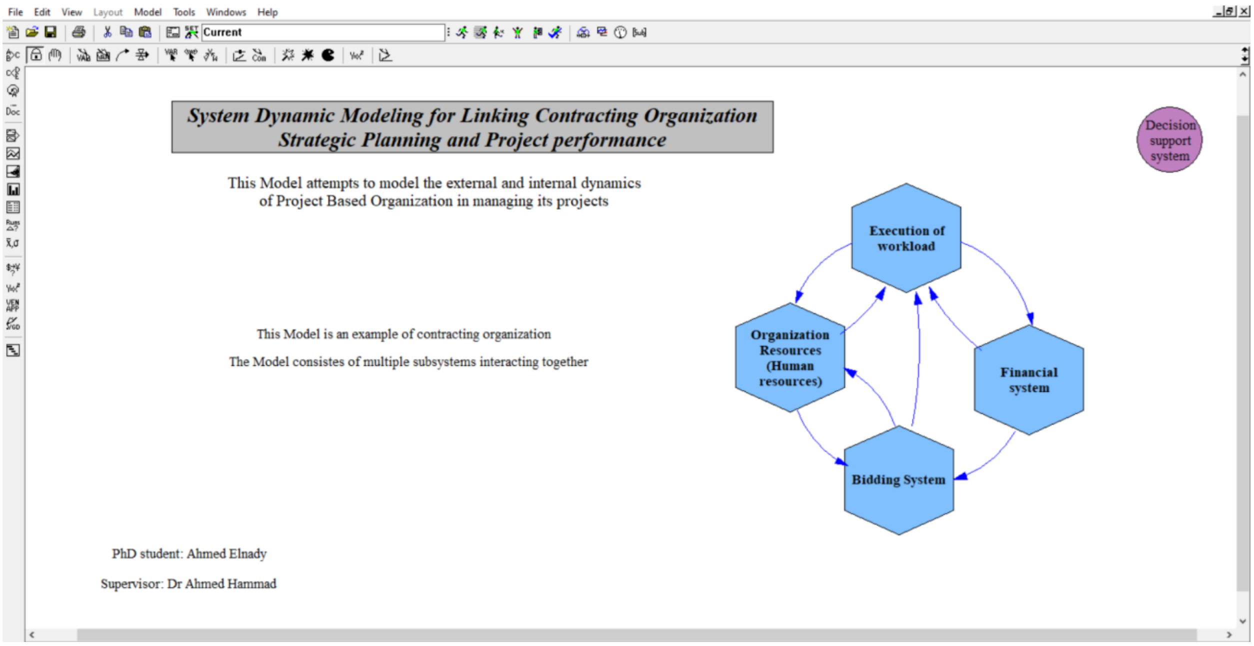


Figure 6.9 Model's welcome screen

6.5.1 Decision support system

The decision support system button directs the user to the decision support screen as shown in Figure 6.10. In this view, the main variables of each category appear beside some figures of the main indices. The output of these figures is updated instantaneously as the user changes the values of the parameters. The main purpose of this view is to support decision-makers in their decisions regarding parameter uncertainty and what-if scenarios.

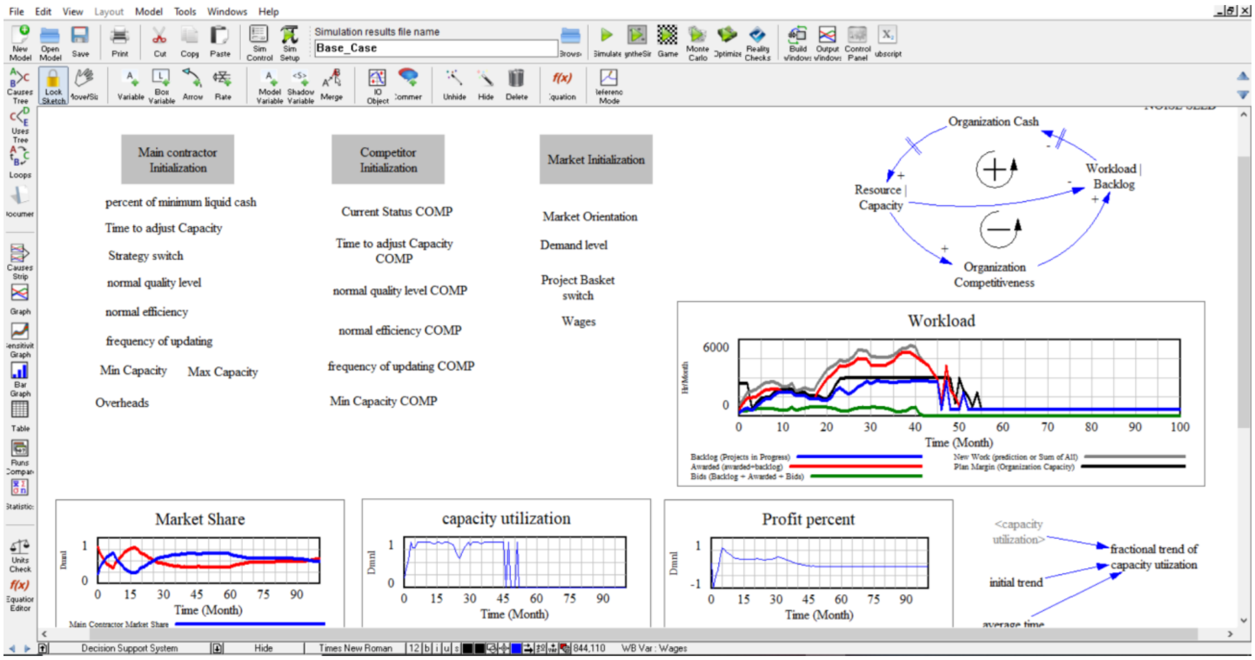


Figure 6.10 Decision support system view

6.5.2 Work execution

The execution of the workload hexagon directs the user to the internal structure of the project-portfolio execution subsystem as shown in Figure 6.11. The causal structure starts with the rate of adding a new workload to the system. This rate is controlled by different subsystems, the organization's competitiveness, which will be discussed later in this section. The work added is accumulated in the workload stock. Each project's workload can be tracked. The workload is executed by the production rate. This rate is controlled by the organization's capacity subsystem. The allocation of capacity is based on project progress as shown in Equation 6.5 and Equation 6.6. Because of the resources' efficiency, some of the work might be backlogged. The executed workload is exposed to checking. If the quality level or for any other sources of errors, some of the executed work might require rework that is accumulated at the backlog level. The backlog is replanned again and redone. The organization is compensated for the accepted work after a delay and retention deduction as presented in the financial subsystem.

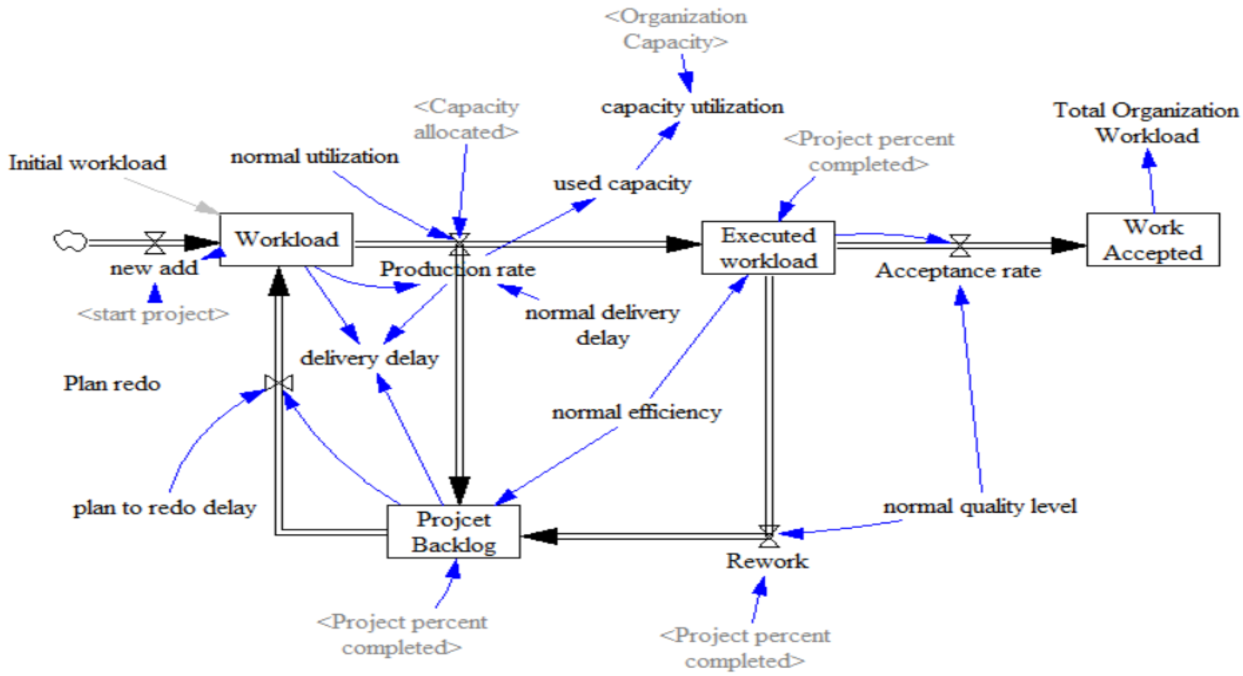


Figure 6.11 Workload execution view

6.5.3 Capacity planning

The organization resources hexagon directs the user to the capacity planning and resources allocation subsystem as shown in Figure 6.12. The capacity of the organization is directly affected by the workload organization. This flexibility of altering capacity comes from the industry practice of outsourcing (subcontracting). The organization's capacity is allocated to the running projects based on each project's required capacity and the priority of the work. The priority of work is defined based on the percentage of completion of the project related to this work as mentioned previously.

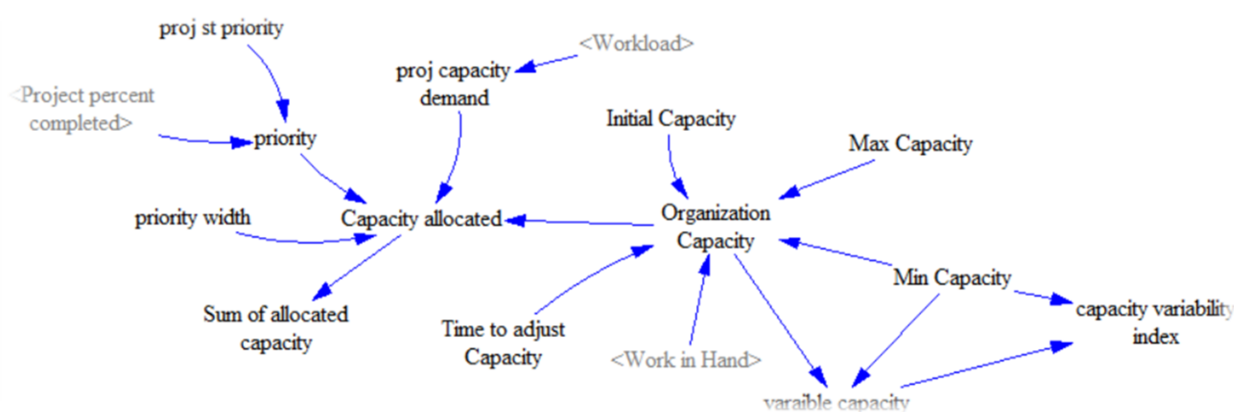


Figure 6.12 Capacity planning view

6.5.4 Organization competitiveness

The bidding hexagon directs the user to the organization attractiveness view as shown in Figure 6.13. organization attractiveness is calculated based on the performance of the organization in quality, experience, delay, capacity availability, and bidding price. The most competitive (max attractive) organization in the bidding process is awarded the project. These awarded projects add to the organization's workload through the newly added rate, previously shown in Figure 6.11.

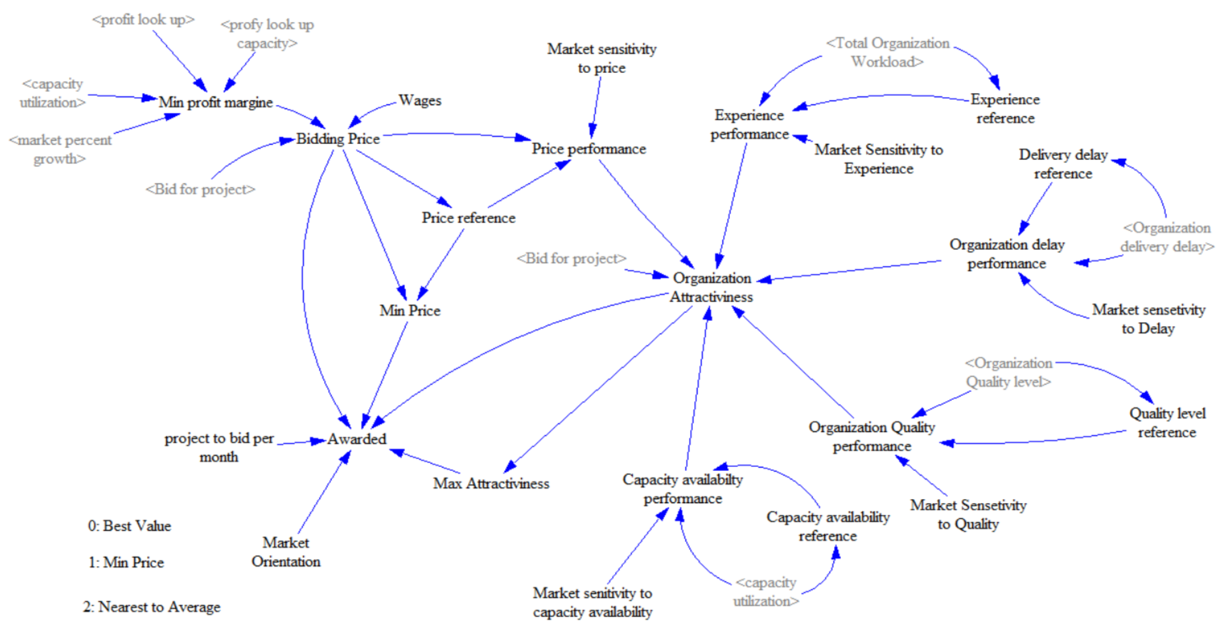


Figure 6.13 Organization attractiveness view

6.5.5 Financial system5

The financial system hexagon directs the organization to the financial subsystem shown in Figure 6.14. The expected cash of the organization is increased by the awarded projects from the bidding process. The organization's cash is increased by the reimbursement of the accepted work. The organization uses this cash to hire new resources and pay for direct and indirect costs.

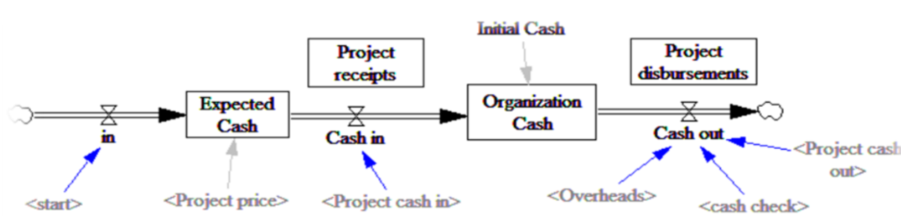


Figure 6.14 Financial system view

6.6 SUMMARY

This chapter builds a computerized system dynamic model for project-based organizations (PBOs). The model is built using VENSIM DSS software. This model utilized the stock and flow tools of system dynamics and other tools to simulate the conceptual model built in the previous chapter. Various views are developed to assess decision-makers and strategic planners in their policy-making. Also, a decision support user interface is developed to instantaneously simulate the effect of the user changes to the controller variables. The model is validated through various tests to build confidence in the model by validating its goal, dimension consistency, and reality check. The analysis of this model is presented in the following chapter.

CHAPTER 7 ANALYSIS OF PBO WORKLOAD USING SYSTEM DYNAMIC

7.1 INTRODUCTION

This chapter presents the analysis of the system dynamic model. The causal loop diagram is analyzed using social network analysis. This allows the extraction of the characteristics of the variables based on the network structure as a static system structure. The mathematical (simulation) model is analyzed using sensitivity analysis to measure the dynamic effect of the variables from the dynamic structure and delays. This is done to find the most significant uncertain variables.

7.2 SOCIAL NETWORK ANALYSIS

7.2.1 Network construction

The model causal feedback loop is analyzed using social network analysis. This analysis is to extract the characteristics of the underlying structure of the model, i.e., the nature of the problem and the significance of variables. The analysis starts by converting the pictorial representation of the model structure into an adjacent matrix as shown in

Table 7.1. This matrix is built based on the relations between the variables from the causal loop diagram. The matrix rows and columns are the model variables. If the variable in a row has a causal effect on the variable in the column, the intersection cell between these two variables is assigned a value of 1. If the row variable is affected by the column variable, then the intersection cell is assigned a value of -1. If there is no relation between them, then the intersection cell is assigned a value of 0. This matrix is fed to Gephi software to extract the characteristics of this structure.

Table 7.1 Adjacent matrix of the causal loop diagram

Names	variable	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19
Normal utilization	V1				1															

Names	variable	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19
Normal delivery delay	V2				-1															
Capacity Allocated	V3				1															
Production rate	V4					1				-1										
Work executed	V5								1	-1										
Workload	V6			1		1			-1	1						1		1		
Acceptance delay	V7																			
Work accepted	V8																			
Backlog/Rework	V9						1													
Normal Efficiency	V10									-1										
Normal Quality level	V11									-1										
Time to adjust capacity	V12															-1				
Min Capacity	V13															1				
Max Capacity	V14															1				
Organization Capacity	V15			1																
Priority	V16			1																

Names	variable	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19
Markup	V17																		-1	
Price Performance	V18																			
Cost	V19																		-1	
Wage	V20																			1
Overheads	V21																			1
Organization Attractiveness	V22						1													
Experience performance	V23																			
Sensitivity to Experience	V24																			
Delay performance	V25																			
Sensitivity to Delay	V26																			
Organization delivery delay	V27																			
Capacity Availability	V28																			
Sensitivity to Capacity availability	V29																			
Capacity utilization	V30																			

Names	variable	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19
Quality performance	V31																			
Organization quality	V32																			
Rework	V33																			
Sensitivity to quality	V34																			
Market share	V35																			
Industry volume	V36																	1		
Initial cash	V37																			
Organization Cash	V38															1				

Table continue Adjacent matrix of the causal loop diagram

Names	V20	V21	V22	V23	V24	V25	V26	V27	V28	V29	V30	V31	V32	V33	V34	V35	V36	V37	V38
Normal utilization																			
Normal delivery delay																			
Capacity Allocated																			
Production rate								-1			1								
Work executed																			
Workload				1				1					1			1			
Acceptance delay																			
Work accepted																			
Backlog/Rework								1											

Names	V20	V21	V22	V23	V24	V25	V26	V27	V28	V29	V30	V31	V32	V33	V34	V35	V36	V37	V38
Normal Efficiency																			
Normal Quality level																			
Time to adjust capacity																			
Min Capacity																			
Max Capacity																			
Organization Capacity											1								
Priority																			
Markup																			
Price Performance			1																
Cost																			
Wage																			
Overheads																			
Organization Attractivenes																			1
Experience performance			1																
Sensitivity to Experience				1															
Delay performance			1																
Sensitivity to Delay						1													
Organization delivery delay						-1													
Capacity Availability			1																

Names	V20	V21	V22	V23	V24	V25	V26	V27	V28	V29	V30	V31	V32	V33	V34	V35	V36	V37	V38
Sensitivity to Capacity availability									1										
Capacity utilization									-1										
Quality performance			1																
Organization quality												1							
Rework													-1						
Sensitivity to quality												1							
Market share																			
Industry volume																-1			
Initial cash																			1
Organization Cash																			

7.2.2 Network measures

Multiple measures are available to provide insights into the network. Centrality degree, specially out-degree, measures the most influential variables in the network based on the number of links out of this variable. The in-degree measures the most affected variable based on the number of inflows to this variable.

The betweenness centrality measures the frequency of the appearance of this parameter on the shortest pass between two variables. The variables with high betweenness mean a high effect on other variables and their uncertainty propagates faster within the network. These variables can affect the stability of the network structure.

The closeness centrality measures the shortest pass between one variable and other variables in the network. This measure differs from degree centrality because it considers the indirect links between variables as well. The closeness means that a variable is highly affected by other variables not only by a direct effect but by the indirect effect of the network structure. This means these variables are vulnerable and exposed to fluctuations or disruptions because of the indirect effect. Also, closeness highlights the variables with the highest indirect influence in the network. These variables should be monitored closely because of their highest indirect effect on the structure. Controlling these variables is highly recommended as these variables have the most indirect effect.

7.3 SOCIAL NETWORK ANALYSIS RESULTS

Results from the social network analysis are represented in Table 7.2. The most influential variable based on the network structure is workload (V06). It has the highest out-degree centrality. The second influential variable is the production rate (V04). These two variables are directly affecting other organization performance variables. On the other hand, the most affected variables are the backlog (V09), organization capacity (V15), and organization attractiveness (V22). This indicates that an organization's strategic decisions to control these variables should be the influential variables, not a unidirectional decision to enforce a specific result on them.

Table 7.2 Social network analysis results

Variable names	ID	In-Degree	Out-Degree	Degree	Closeness Centrality	Betweenness Centrality
Normal utilization	V01	0	1	1	0.296	0
Normal delivery delay	V02	0	1	1	0.296	0
Capacity Allocated	V03	3	1	4	0.3	0.078
Production rate	V04	3	4	7	0.4	0.096
Work executed	V05	2	2	4	0.315	0.008
Workload	V06	2	10	12	0.642	0.301
Work accepted	V08	2	0	2	0	0
Backlog/Rework	V09	5	2	7	0.418	0.092
Normal Efficiency	V10	0	1	1	0.306	0
Normal Quality level	V11	0	1	1	0.306	0
Time to adjust capacity	V12	0	1	1	0.223	0

Variable names	ID	In-Degree	Out-Degree	Degree	Closeness Centrality	Betweenness Centrality
Min Capacity	V13	0	1	1	0.223	0
Max Capacity	V14	0	1	1	0.223	0
Organization Capacity	V15	5	2	7	0.272	0.104
Priority	V16	0	1	1	0.240	0
Markup	V17	2	1	3	0.253	0.036
Price Performance	V18	2	1	3	0.321	0.069
Cost	V19	2	1	3	0.253	0.030
Wage	V20	0	1	1	0.210	0
Overheads	V21	0	1	1	0.210	0
Organization Attractiveness	V22	5	2	7	0.439	0.265
Experience performance	V23	2	1	3	0.315	0.019
Sensitivity to Experience	V24	0	1	1	0.25	0
Delay performance	V25	2	1	3	0.321	0.034
Sensitivity to Delay	V26	0	1	1	0.253	0
Organization delivery delay	V27	3	1	4	0.253	0.032
Capacity Availability	V28	2	1	3	0.327	0.056
Sensitivity to Capacity availability	V29	0	1	1	0.256	0
Capacity utilization	V30	2	1	3	0.260	0.053
Quality performance	V31	2	1	3	0.3214	0.041
Organization quality	V32	2	1	3	0.253	0.038
Rework	V33	0	1	1	0.211	0

Variable names	ID	In-Degree	Out-Degree	Degree	Closeness Centrality	Betweenness Centrality
Sensitivity to quality	V34	0	1	1	0.253	0
Market share	V35	2	0	2	0	0
Industry volume	V36	0	2	2	0.220	0
Initial cash	V37	0	1	1	0.191	0
Organization Cash	V38	2	1	3	0.225	0.035

Moreover, the highest betweenness centrality variable, i.e, the variable usually appears in the path of propagation between cause and effect variables is workload (V06). This means the workload is not only a direct causal variable but its uncertainty affects other variables through paths of propagation. This highlights the importance of analyzing the workload fluctuations in such a dynamic structure. Organization attractiveness (V22) is the second important variable due to its position in the network structure. Because it has an indirect effect on most variables due to its position in the shortest path between causal variables and the affected variables. Organization capacity (V15) is another important middle ring. These variables (V06, V22, and V15) highly affect the propagation of uncertainties in the network.

Closeness centrality measures the distance between the variable and other neighborhood variables. Workload (V06) is the highest closeness. This means it, directly and indirectly, affects most of the variables in the network (60% of the variables). Organizational attractiveness (V22), backlog (V09), and production rate (V04) have a high influence due to their closeness to other variables. They influence 40 % of the variables within the network.

Overall, workload (V06), organization attractiveness (V22), backlog (V09), organization capacity (V15), and production rate (V04) are very important variables to be monitored and require further investigation of their behavior.

The previously mentioned results show that the structure of the PBO's workload flow is a very tight and highly coupled system. Variations in one variable are easily transmitted to other variables. This effect is amplified by the structure and delays effect.

7.4 SENSITIVITY ANALYSIS

Because the system dynamics technique generates models with a huge number of very unknown parameters (Hekimoğlu and Barlas 2010, 2015). One would believe that the parameters with the most uncertainty are the most significant and should receive the most attention. Some readers, on the other hand, might think that the crucial parameters are those in a strategic position in the model, or perhaps the essential parameters in the model are those that govern the gain around a key loop (Tian et al. 2016, 1043-1057).

Sensitivity analysis, which is a component of rigorous model validation, evaluates which model inputs have the greatest influence on the model response (Wang, Yung-Chieh et al. 2012, 2719-2742). Sensitivity analysis output can be utilized to improve a model and comprehend its consequences. It may be used to determine where efforts should be spent to collect more data to develop the model most effectively. Sensitivity analysis may be used to identify leverage points in the system where action can have a significant and robust influence on the results. It also may be used to better understand model resilience and to identify places where a model might be reduced with minimum impact on results (Kasperska, Mateja-Losa, and Marjasz 2013, 29-44).

Monte Carlo simulation is utilized through a set of experiments to assess how sensitive the model outputs to the uncertainty of its parameters' values and to gain trust in it (Cosenz 2017, 57-80). In this work, most of the parameters' values are not based on hard data but on soft data to replicate the behavior of the real parameters. Soft data sources are shown at the right end of the data collection spectrum. Although these sources do not give numerical data, they are frequently the most essential sources of knowledge for model construction and parameter estimation (Sterman, J. D. 2002, 42).

Commonly, system dynamics practitioners prefer to use their gut instinct to calibrate the model rather than eliminate this variable in the case of no data available for this variable (Ford and Flynn 2005, 273-303). This strategy is to continue with educated guesses, certain that the significance of the unknown factors can be evaluated by sensitivity analysis.

Sensitivity analysis starts by selecting the variables that will vary to test the model for their uncertainty. They are selected in this study based on whether the contractor can control them, i.e.

they can take measures that enable them to control these factors or variables that are completely outside their control.

Defining the range and distribution for these parameters is the second step. It is assumed that the values change uniformly across the simulations. Values ranges and distributions are defined in Table 7.3.

Table 7.3 Variables distribution for sensitivity analysis

	Category	Variable	Definition	Range	Distribution
1	Out of control	Wages	The rate of paying resources (CAD$/Hr)	(2,10)	Uniform
2		Demand level	The average number of projects available in the market (project)	(2,10)	Uniform
3		Bidding Time	The time between starting bidding and knowing the bidding results (Month)	(1,12)	Uniform
4		Average Duration	The average project duration (Month)	(6,18)	Uniform
5		Average Load	The average project load (Hr)	(1500,5000)	Uniform
6		Initial Capacity	The organization capacity of production at the start time of simulation (Hr/Month)	(2000,3000)	Uniform
7		Initial Cash	The organization cash at the start time of simulation (CAD$)	(10000,1000000)	Uniform
8		Discount rate	Bank interest rate (Dml)	(0.001,0.1)	Uniform
9	Can take action to control	Normal delivery delay	The average organization delay to finish the required workload at the start of the simulation (Month)	(0.5,6)	Uniform
10		Normal efficiency	The average organization's efficiency to utilize the time in executing the required workload at the start of the simulation (Dml)	(0.8,1)	Uniform
11		Normal quality level	The average organization quality (1 - error percent or rework percent) to finish the required workload at the start of the simulation (Dml)	(0.9,1)	Uniform
12		Normal utilization	The average organization utilization of resources at the start of the simulation (Dml)	(0.8,1)	Uniform

	Category	Variable	Definition	Range	Distribution
13		Frequency of updating	The response time to adjust the organization's capacity (Month)	(1,24)	Uniform
14		Cash time buffer	The cash available should be enough to run the organization for this duration (Month)	(1,12)	Uniform
15		Max Capacity	The maximum capacity that an organization can manage includes fixed and variable resources (Hr/Month)	(500,10000)	Uniform
16		Min Capacity	The minimum capacity of an organization to be competitive in the market (Hr/Month)	(100,6000)	Uniform
17		Time to adjust Capacity	The time required to modify the available capacity to the required capacity (Month)	(1,12)	Uniform
18		Profit Margin Factor	Factor to adjust the markup percent policy (Dml)	(0,2)	Uniform
19		Wage overhead factor	The percent of overheads to wages (Dml)	(0,2)	Uniform

Before running the sensitivity analysis, the monitored parameters (variables under investigation) should be defined. This is not the general case but VENSIM requires defining a set of monitored variables to save their values. This step is meant to shorten the simulation time (model execution time), especially for big models. Analysis of the output sensitivity to input changes (uncertainty) starts after this step. The set of monitored variables is mentioned in Table 7.4

Table 7.4 Monitored variables

	Variable	Definition
1	Market Share	The percent of market share based on the number of projects awarded (Dml)
2	Actual Error percent	The ratio of rework to the total work done (Dml)
3	Capacity variability index	The ratio between variable capacity the fixed capacity (Dml)
4	Organization delivery delay	The organization delayed finishing the required workload (Month)
5	Min profit margin	The markup percent (Dml)

	Variable	Definition
6	Profit percent	The profit after delivering the project and doing all rework (Dml)
7	Capacity utilization	The ratio of idle capacity to the organization capacity (Dml)
8	Organization Capacity	The production capacity of the organization resources (Hr/Month)
9	Organization Cash	The available cash of the organization (CAD$)

7.4.1 Methods of calculating sensitivity

Monte Carlo simulation is utilized to generate hundreds of simulations over a sample range. VENSIM can do multiple simulations in which input values are updated for each run. This may be extremely beneficial in comprehending a model's behavioral bounds and assessing the durability of model-based policies to establish model credibility. An example of the result from the Monte Carlo simulation is shown in Figure 7.1. The output from the Monte Carlo simulation is analyzed using the common methods in the sensitivity analysis.

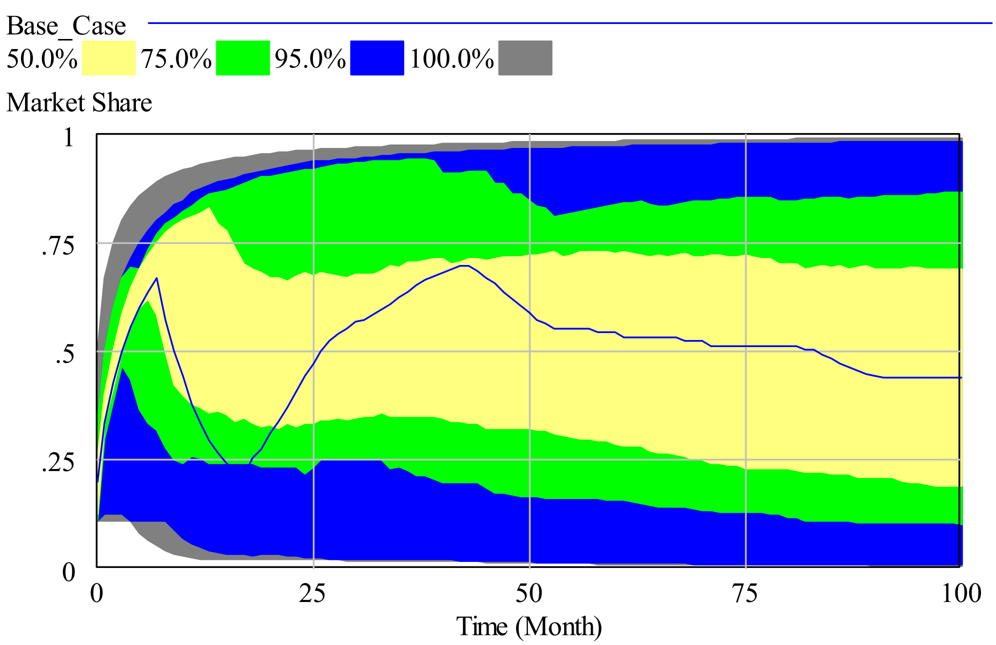


Figure 7.1 Monte Carlo simulation results for organization market share

There are three common methods to calculate sensitivity: screening method, linear regression, and analysis of variance. The screening method uses a correlation coefficient to quantify the sensitivity of an output to an input. A high correlation factor between input and output means high sensitivity of the output to the input. The linear regression method is calculated based on the factor related to the input variable (independent variable) in the regression equation. A high factor value means high sensitivity to this factor. This method assumes independency between input (independent) variables. Analysis of variance (ANOVA) calculates the sensitivity based on the statistical significance. The possibility that a link between two or more variables is not due to random chance is referred to as statistical significance. In essence, ANOVA is a method of demonstrating the dependability of a specific statistic. A data set is regarded as statistically significant if it has acquired a specific degree of confidence in the result via statistical hypothesis testing. Statistical hypothesis testing, states that given the null hypothesis, the hypothesis is improbable to have happened. A null hypothesis states that there is no link between the variables in question.

The following subsections discuss the results of each sensitivity method between monitored variables identified in Table 7.4 and the controller variables identified in Table 7.3. This is to extract the most important decision variables and areas of improvement.

7.5 SENSITIVITY ANALYSIS RESULTS

7.5.1 Screening method

After performing Monte Carlo simulation using VENSIM software, results are migrated to the python module to calculate the correlation coefficient and visualize the results. Table 7.5 presents the sensitivity of the monitored set to the controller set. For instance, profit percent is very sensitive to overheads and wages at the start of a simulation, both are negatively correlated. For the rest of the simulation, overheads and the average project workload have a higher negative influence on it. While on the positive side normal efficiency, at the start of the simulation, has the highest impact and is gradually overpassed by the initial capacity for the rest of the simulation.

An organization's error (rework) percent is highly inversely correlated with the normal quality level of the organization this can be considered as proof that model logic is correct. The error percent is influenced, by the lifetime of the organization with normal delivery delays as well. This is because the delivery delay is an indication of backlog and schedule pressure. So, the longer delivery delay means more rework and cost overruns. Another important factor at the start of the simulation is the frequency of updating and the need for capacity altering. While for the rest of the simulation, initial cash has a higher impact on the rework. Cash is responsible for the capacity, i.e. the amount of available cash defines the room for capacity boost.

Organizational delivery delay, at the start of the simulation, is highly affected by its history, i.e. the initial value of the normal delivery delay, but this is rapidly diminished as the simulation time goes forward. Other variables that directly affect the delivery delay are average load and normal utilization. The minimum capacity level has a higher negative effect on the delivery delay than the maximum capacity. Because minimum capacity is the core resource of the organization that is available without a need for time to adjust while variable capacity is affected by delays. So, the first layer interacting with the delay is the fixed (core or minimum) capacity as defined by the model.

Table 7.5 Screening method results

Variable	Start of simulation				Rest of simulation			
	+ correlation	value	- correlation	value	+ correlation	value	- correlation	value
Profit percent	normal efficiency	0.1	wage overhead factor	-0.65	initial capacity	0.22	wage overhead factor	-0.65
	-----	-----	wages	-0.5	-----	-----	average project load	-0.32
Actual Error percent	frequency of updating	0.14	normal quality level	-1	initial cash	0.15	normal quality level	-1
	profit margin factor	0.1	normal delivery delay	-0.1	profit margin factor	0.1	normal delivery delay	-0.1
	bidding time	0.1	-----	-----	bidding time	0.1		

<table>
<tr><th rowspan="2">Variable</th><th colspan="4">Start of simulation</th><th colspan="4">Rest of simulation</th></tr>
<tr><th>+ correlation</th><th>value</th><th>- correlation</th><th>value</th><th>+ correlation</th><th>value</th><th>- correlation</th><th>value</th></tr>
<tr><td rowspan="2">Organization</td><td>normal delivery delay</td><td>0.9</td><td>normal utilization</td><td>-0.2</td><td>demand level</td><td>0.25</td><td>minimum capacity</td><td>-0.4</td></tr>
<tr><td>average load</td><td>0.5</td><td>-----</td><td>-----</td><td>-----</td><td>-----</td><td>Maximum capacity</td><td>-0.2</td></tr>
<tr><td rowspan="2">Organization Cash</td><td>initial capacity</td><td>1</td><td>wage overhead factor</td><td>-0.1</td><td>time to adjust capacity</td><td>0.25</td><td>wage overhead factor</td><td>-0.48</td></tr>
<tr><td>initial cash</td><td>0.22</td><td>normal delivery delay</td><td>-0.1</td><td>initial capacity</td><td>0.32</td><td>wages</td><td>-0.31</td></tr>
<tr><td rowspan="2">Organization</td><td>initial capacity</td><td>1</td><td>wage overhead factor</td><td>-0.22</td><td>all variables</td><td>0.1</td><td>all variables</td><td>-0.1</td></tr>
<tr><td>initial cash</td><td>0.22</td><td>minimum capacity</td><td>-0.12</td><td>-----</td><td>-----</td><td>-----</td><td>-----</td></tr>
<tr><td rowspan="2">Min profit margin</td><td>profit margin factor</td><td>0.9</td><td>all</td><td>-0.15</td><td>initial cash</td><td>0.2</td><td>normal quality level</td><td>-0.2</td></tr>
<tr><td>all</td><td>0.1</td><td>-----</td><td>-----</td><td>bidding time</td><td>0.18</td><td>minimum capacity</td><td>-0.18</td></tr>
<tr><td rowspan="2">Market Share</td><td>initial cash</td><td>0.32</td><td>all</td><td>-0.1</td><td>all</td><td>0.1</td><td>profit margin factor</td><td>-0.55</td></tr>
<tr><td>all</td><td>0.1</td><td>-----</td><td>-----</td><td>-----</td><td>-----</td><td>wage overhead factor</td><td>-0.3</td></tr>
</table>

Variable	Start of simulation				Rest of simulation			
	+ correlation	value	- correlation	value	+ correlation	value	- correlation	value
Capacity variability	frequency of updating	0.18	minimum capacity	-0.62	all	0.1	all	-0.1
	initial capacity	0.17	project average duration	-0.16	-----	-----	-----	-----
Capacity utilization	time to adjust capacity	0.43	normal delivery delay	-0.71	initial cash	0.4	minimum capacity	-0.38
	initial cash	0.39	initial capacity	-0.5	demand level	0.28	wage overhead factor	-0.37
	-----	-----	-----	-----	-----	-----	wages	-0.2
	-----	-----	-----	-----	-----	-----	Maximum capacity	-0.23

The organization’s cash is highly affected by the amount of initial cash invested at the start of the simulation and the initial capacity (very sensitive to initial conditions). This effect decays over time as other factors related to the processing cycle take over this influence. Time to adjust capacity starts to take over after the first year and its effect is oscillating with a high direct correlation. On the other side, normal delivery delays and wage overhead factors highly inverse influence the cash flow. The negative impact of overheads and wage increases affects the organization's cash as time goes forward.

The organization’s capacity is highly correlated to the initial value of the organization's capacity and is directly affected by the initial cash. It is inversely influenced by the overheads to wages ratio and the normal delivery delay. These variables diminish by only a few months and all the variables take over. The variables all oscillate between positive and negative correlation within a range of ± 10%. This is a significant insight that organization capacity is not affected by only workload. Indeed, it is affected by all the organization variables and the business model structure affects its value. The influence of the variables is almost equal and changes their direction of effect as a result of a balanced loop with delay to maintain the required capacity level.

The minimum profit margin (markup percent) is directly affected by all factors at the start of the simulation with an influence range of ±15%. While during simulation it is mostly affected directly by the initial cash invested and bidding time. It is inversely affected by normal quality levels and minimum capacity.

The organization's market share is directly affected by the initial cash at the beginning of the simulation. As time moves forward the profit margin and wages overhead factor takes over and they negatively impact it.

The capacity variability index is negatively affected by the organization's minimum capacity and project average duration. At the start of the simulation, the frequency of updating, the need for capacity, and the initial capacity directly affect it. During the simulation time, all factors are oscillating in their influence between direct and inverse with a range of ±10%.

Capacity utilization is highly affected by the time to adjust the capacity and initial cash available. The initial capacity and normal delivery delay are inversely affecting it at the beginning of the simulation. As time progress, the minimum capacity, wages, overheads, and maximum capacity has a higher negative impact on it. The demand level, also, has a high direct impact as time progresses.

7.5.1.1 Insights summary compilation of screening method

To sum up the previously mentioned results, Figure 7.2 shows the most influencing variables from the controller set at the start and during the simulation. This is calculated by counting the frequency of showing up for each variable as the most effective variable on a monitored set. It appears that cash availability is the most direct influencing factor at the start and along the simulation. Interestingly, overheads (one of the cash aspects) are the most inverse influencing variable. The organization fixed capacity (minimum capacity) has the same rank as cash and its effect is not just instantaneous (at the start of the simulation) but the effect increases along the simulation time.

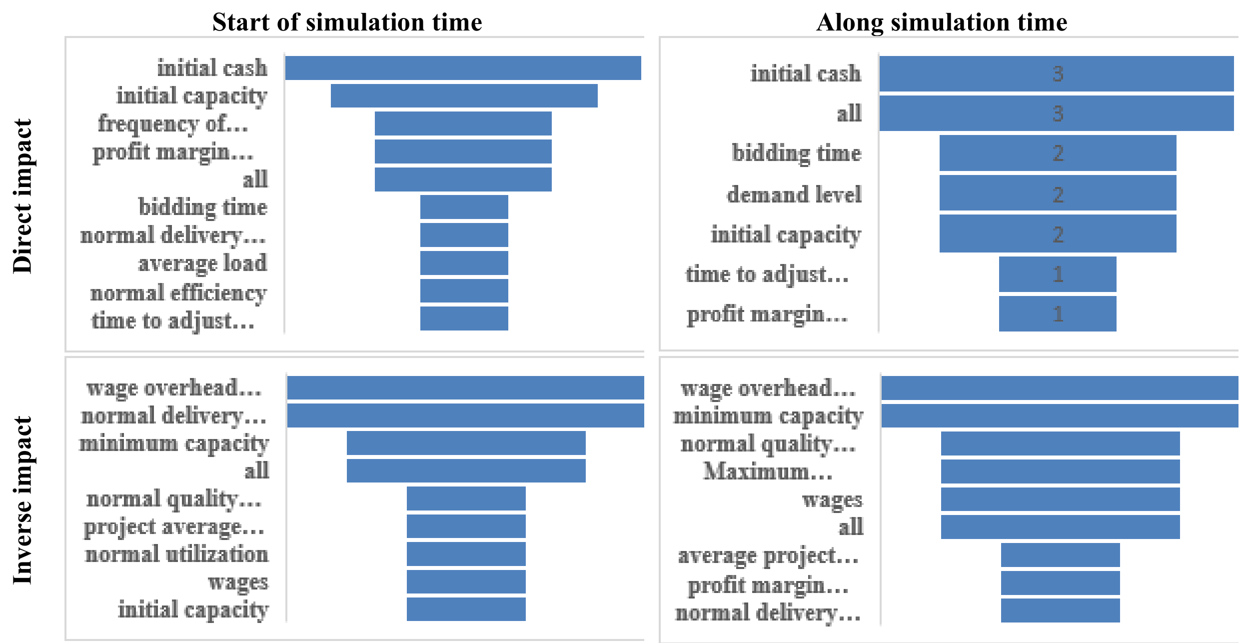


Figure 7.2 Most influencing variables on the monitored set from the screening method

These results show that organization capacity requires more attention, not only because other variables are sensitive to it and its influence increases as time progresses, but also because it has a positive and negative impact on various variables. So, a kind of optimization between pros and cons is highly suggested with a careful definition of the payoff function driving this optimization. This importance increases considering its indirect cause of the delivery delay, which appears as one of the variables that have a significant impact on the organization's performance in the long run.

Profit margin (markup percent) selection requires a wise optimized decision support system. Because it has an instantaneous and increasing long-term effect, positive on some variables and negative on others. This suggests having a multi-objective optimization function that includes capacity and markup percent.

On the other side, bidding duration has a little frequency on its instantaneous impact while a higher frequency on its long-term impact. The explanation from investigating its feedback loop is, that it has an indirect impact on a huge number of factors, like, the cash flow, capacity level and utilization, workload, and other variables by the indirect connection from one variable to another. The network effect amplifies its impact over time. This highlights the need to provide more attention and make a detailed study to report how the organization's performance is indirectly impacted by the bidding duration.

7.5.2 Linear regression method

In the linear regression method, the migrated Monte Carlo simulation results to the python module are used to calculate the linear regression factors and visualize the results. Table 7.6 presents the sensitivity of the monitored set to the controller set based on regression factors. A high factor value means higher sensitivity. For instance, the capacity variability index is directly influenced by capacity and cash. It is inversely affected by the utilization of capacity, quality level, and wages. The sensitivity between capacity variability and these factors is interesting because the intensity of this sensitivity is amplified exponentially over time. This might mean higher variability in the organization's capacity, but it is balanced by equivalence between direct and inverse influencing variables as they look mirroring around zero.

Capacity utilization is affected directly by the time to adjust capacity and inversely by normal delivery delay at the start of the simulation. The project average load and demand level have an impact that increases with time and they directly affect the capacity utilization. On the other hand, the quality level has the highest inverse effect in the long term on the organization's capacity utilization. This reveals that a higher backlog makes resources always fully overutilized. This backlog might come from rework or demand levels as factors revealed. Another major effect comes from wages, overheads, and initial capacity level. These factors are directly related to altering the capacity level to optimize cash flow which inversely affects the utilization level of these resources.

Actual error percent is affected directly, at the start of the simulation, by delivery delay, project average duration, and cash. It is negatively impacted by efficiency. Contrarily, over time, the project's average workload and demand level directly affect the organization's rework (error) percentage and are inversely affected by the utilization of resources. This indicates that rework/errors are highly sensitive to the variables affecting the resources-workload-pressure. Hence, to increase organizational work quality and reduce cost structure the resources-workload-pressure variables should be monitored.

Table 7.6 Sensitivity results from linear regression method

Variable	Start of simulation				Rest of simulation			
	+ factors	value	- factors	value	+ factors	value	- factors	value
Capacity variability index	initial capacity	e	normal utilization	e	initial capacity	e	normal utilization	e
	time to adjust capacity	e	normal quality level	e	time to adjust capacity	e	normal quality level	e
	profit margin factor	e	average duration	e	profit margin factor	e	average duration	e
	minimum capacity	e	normal efficiency	e	minimum capacity	e	normal efficiency	e
	frequency of updating	e	bidding time	e	frequency of updating	e	bidding time	e
	cash time buffer	e	wages	e	cash time buffer	e	wages	e
	normal delivery delay	e	wage overhead factors	e	normal delivery delay	e	wage overhead factors	e
Capacity utilization	normal utilization	0.48	initial capacity	-0.85	initial cash	0.5	normal quality level	-1.1
	time to adjust capacity	0.48	normal delivery delay	-0.4	average load	0.48	wage overhead factor	-0.52
	initial cash	0.3	-----	-----	demand level	0.46	wages	-0.4
	-----	-----	-----	-----	-----	-----	initial capacity	-38
Actual Error percent	normal delivery delay	0.13	normal quality level	-10	Average load	0.08	normal quality level	-9
	average duration	0.04	normal efficiency	-0.17	demand level	0.05	normal utilization	-0.14
	initial cash	0.04	-----	-----	-----	-----	-----	-----
Market Share	initial cash	0.3	demand level	-0.8	normal efficiency	0.4	profit margin factor	-0.6
	normal efficiency	0.28	normal quality level	-0.3	initial cash	0.3	normal quality level	-0.4
Profit percent	normal efficiency	1.5	wage overhead factor	-1.5	normal efficiency	0.45	wage overhead factor	-0.45
	normal quality level	-0.38	wages	-1.48	initial capacity	0.2	wages	-0.43
Organization delivery delay	normal delivery delay	0.5	normal utilization	-0.38	normal efficiency	0.3	minimum capacity	-0.2
	average load	0.4	normal quality level	-0.3	normal quality level	0.1	normal efficiency	-0.1
	demand level	0.3	time to adjust capacity	-0.1	demand level	0.1	time to adjust capacity	-0.05
Organization Cash	initial cash	1	-----	-----	initial capacity	0.5	wage overhead factor	-0.6

Variable	Start of simulation				Rest of simulation			
	+ factors	value	- factors	value	+ factors	value	- factors	value
	-----	-----	-----	-----	time to adjust capacity	0.3	wages	-0.55
	-----	-----	-----	-----	frequency of updating capacity	0.2	normal quality level	-0.4
	-----	-----	-----	-----	cash time buffer	0.2	normal utilization	-0.25
	-----	-----	-----	-----	profit margin	0.2	-----	-----
Organization Capacity	initial capacity	1	-----	-----	initial capacity	2	normal utilization	-3
	-----	-----	-----	-----	minimum capacity	0.6	normal quality level	-2.5
	-----	-----	-----	-----	profit margin factor	0.55	project average duration	-1
	-----	-----	-----	-----	time to adjust capacity	0.5	normal efficiency	-0.55
Min profit margin	profit margin factor	1	initial capacity	-0.5	profit margin factor	0.6	normal quality level	-0.55
	time to adjust capacity	0.15			average load	0.15	initial capacity	-0.2

Note: e means the value increases exponentially over the simulation

Market share is sensitive to the organization's cash, and normal efficiency. This influence increases over time. Negatively it is influenced by the quality level (actual error percent) and markup percent. This indicates the direct relation of market share with competition. A more efficient organization will gain more market share.

The organization's overall profit percent is influenced directly by organization efficiency and quality level i.e. less rework. It is inversely influenced by overheads and wages i.e. the organization's cost structure. So, the organization should invest in technology to make the business model more efficient and apply lean concepts to minimize its cost structure for more profit.

The organizational delivery delay is directly influenced by the project's average load and demand level. Interestingly, these external factors (i.e. not caused by internal business structure) affect strategic decisions. Their impact is diminished over time. The higher effect on the delivery delay is related to organizational efficiency and quality level i.e. internal organization causes. These internal causes have a higher impact even though their influence direction is changed between positive and negative, i.e. they are the influencers in a goal-seeking loop that exhibits a delay.

Other internal variables such as fixed (minimum) capacity and time to adjust capacity inversely influence the delivery delay time. The most significant about the delivery delay sensitivity is that all variables related to the internal business model are contributing almost the same as time moves forward and external variables such as demand level, project duration, and project load influence vanish over time. This highlights the need for more investigation of the business model's soft variables like labor training, communication, lean practices, etc. this will directly add to the organization's competitiveness, profit, and sustainability.

Organization cash is determined at the start of the simulation by its initial value i.e. initial cash available. This effect diminishes rapidly over time. Capacity-related factors such as its initial value, response time to adjust it, capacity utilization, and quality level are factors gaining more influence as time progresses. Cost-related factors such as overheads, wages, markup, and cash time buffer share the same influence as capacity-related factors. This reveals the importance of capacity and cost structure to the availability of an organization's cash flow.

Organization capacity is influenced directly by initial capacity, minimum (fixed) capacity, markup percent, and time to adjust capacity. It is inversely influenced by quality level, capacity utilization, normal efficiency, and project average load. These factors have a direct impact on the capacity except for the markup percentage. It has an indirect impact through the feedback network. It affects directly the organization's fitness function i.e. competitiveness and probability of winning a new project. In short, capacity is influenced by the net workload level (project average load and winning rate) and net production rate (all other factors directly related to the net production rate). It is worth mentioning that these factors' influence is exponentially amplified by the network effect as time progresses.

The minimum profit margin (markup percent) is affected by the capacity and time to adjust this capacity at the beginning of the simulation. The effect of quality level, average load, and capacity increases as simulation time progresses.

7.5.2.1 Insights summary compilation of linear regression method

In summary, initial cash, profit margin, and quality level are the most important factors in the organization's performance as shown in Figure 7.3. Initial cash is a very important factor at the start of the simulation, this influence is reduced by time and other factors control the organization's performance. The profit margin (markup percent) impact is significantly increased over time because its effect is amplified by the network structure and time. This result agrees with the screening method.

The organizational delivery delay is still having a higher influence as concluded from the screening method. This difference between the two methods is they show that delivery delay has a positive impact (from the screening method) and a negative impact (from the linear regression method) on the long-term behavior of the organization.

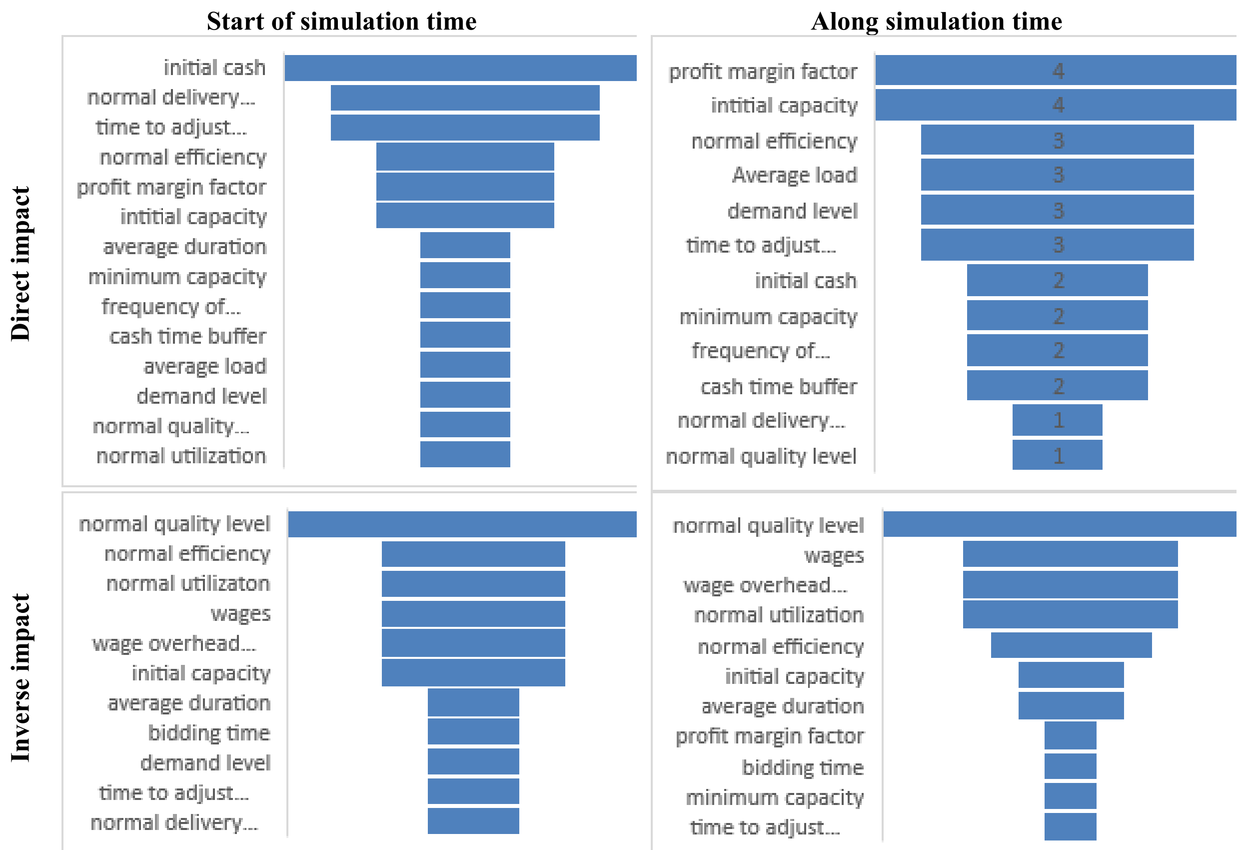


Figure 7.3 Most influencing variables on the monitored set from the linear regression method

Time to adjust the capacity has a higher influence on the positive side either at the start or during the simulation than the negative impact. This indicates that this variable should be monitored carefully by the organization and invested in it as the performance is very sensitive to its variation.

Normal efficiency is one of the variables that maintain a high influence on various variables and a stable increasing effect as time progress. This could be one of the areas in the organization to invest in it.

Organization capacity, either the initial value or the minim value (fixed capacity), sensitivity results agrees with the results from the screening method. Contrary, project load and duration have a higher impact using linear regression than the screening method.

Overheads and wages have a high negative impact on the organization considering short- and long-term effects. This result agrees with the screening method and assures the importance of the organization's cost structure.

7.5.3 **ANOVA method**

The analysis in this method is based on dividing the space set that arises from points into ordered pairs of the dependent and independent variables into equal clusters as shown in Figure 7.4. Then, measure the difference between the clusters' centers and the space set center. In Figure 7.4, the blue dots are the space set arising from wages on the x-axis and profit percent on the y-axis, as an example, from the Monte Carlo simulation results at a time of 41 months. The red dots are the center of clusters, and the green line is the center of the space set. If the difference between the cluster's center and space set center is significant, this means the dependent variable is significantly sensitive to the uncertainty in the independent variable. The significant difference is measured by calculating the p-value based on the ANOVA F test using `scipy.stats.f_oneway` function. Because the variables follow the F-distribution under the normality assumption.

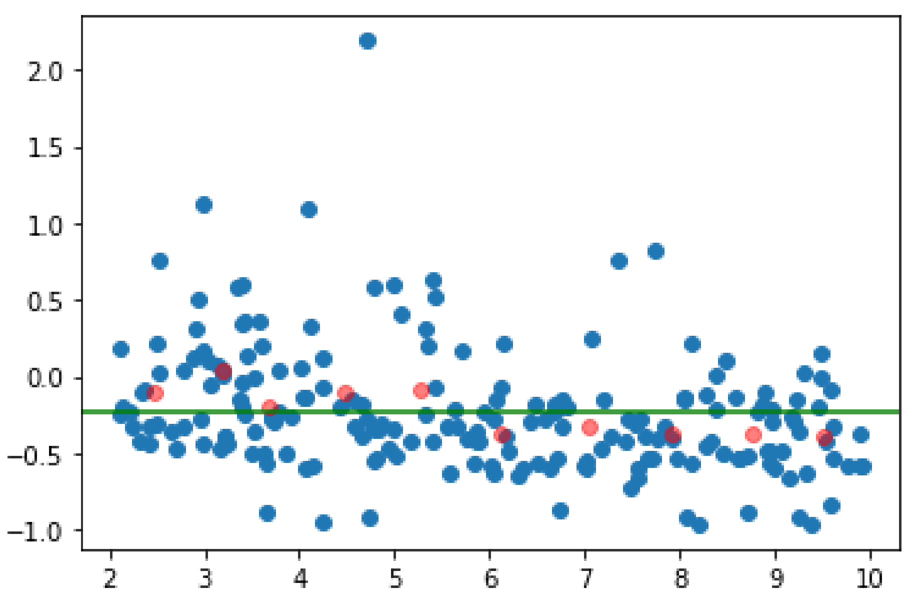


Figure 7.4 Scatter plot between Wages and Profit percent at time 41 month

The results are presented in Table 7.7. For instance, the actual error percent is significantly sensitive to the quality level. This is logical because errors are the other side of quality. Other factors such as overheads and average load can be considered not significantly sensitive. This means the changes in such factors will slightly affect the rework (errors) of the organization.

Capacity utilization, at the beginning of the simulation, is highly sensitive to the normal utilization initial value and quality level. By that time, capacity utilization is highly sensitive to the delivery delay, time to adjust capacity, initial cash, maximum capacity, and overheads. This means it is better for the organization to be more responsive and has a higher level of capacity allowance to maintain a highly utilized capacity. This might not be the best solution for the organization because high levels of under-utilized capacity will add to overheads. So, this is a suggested area for future improvement.

Table 7.7 Sensitivity results from the ANOVA method

Variable	Start of simulation		Rest of simulation	
	Significant	p-value	Significant	p-value
Actual Error percent	normal quality level	0	normal quality level	0
	wage overhead factor	0.1	wage overhead factor	0.1
	Demand level	0.2	Demand level	0.2
	average load	0.2	average load	0.2
Capacity utilization	normal utilization	0.0057	normal delivery delay	0.003
	normal quality level	0.035	time to adjust capacity	0.004
			initial cash	0.005
			maximum capacity	0.008
			wage overhead factors	0.02
Capacity variability index	minimum capacity	0.003	time to adjust capacity	0.044
	time to adjust capacity	0.05	profit margin factor	0.045
			cash time buffer	0.048
			initial capacity	0.05
Market Share	wages	0.01	wages	0.04
	maximum capacity	0.012	initial cash	0
	demand level	0.021	profit margin factor	0.005
			bidding time	0.01
Min profit margin	cash time buffer	0.02	initial capacity	0.1
	time to adjust capacity	0.03	normal delivery delay	0.2
Organization Capacity	initial capacity	0	initial capacity	0.04
	normal delivery	0.007	cash time buffer	0.04

Variable	Start of simulation		Rest of simulation	
	Significant	p-value	Significant	p-value
	wage overhead factors	0.02	profit margin factor	0.049
	normal quality level	0.03	time to adjust capacity	0.052
Organization Cash	initial cash	0.008	initial cash	0.008
	average duration	0.01	average duration	0.005
			time to adjust capacity	0.0004
			profit margin factor	0.03
			wage overhead factors	0.02
			frequency of updating capacity	0.03
Organization delivery delay	normal delivery delay	0.04	minimum capacity	0.0005
	frequency of updating capacity	0.1	maximum capacity	0.0006
			time to adjust capacity	0.005
			demand level	0.03
			average load	0.051
			average duration	0.052
Profit percent	wage overhead factor	0.003	wage overhead factor	0.003
	wages	0.04	initial capacity	0.001
	normal efficiency	0.053	average load	0.00054
			demand level	0.002
			time to adjust capacity	0.008
			initial capacity	0.01

Capacity variability is sensitive to the minimum capacity and time to adjust it. Over time, the adjusting time is more significant, i.e. the sensitivity increases, and factors such as markup, cash time buffer, and initial capacity become more significant in their uncertainty. This indicates the importance of such factors to maintain a stable capacity level.

Market share is sensitive to wages (cost structure), maximum capacity, and demand level at the start of the simulation. This sensitivity is reduced in the first half of the simulation and returns to increase in the second half of the simulation, but sensitivity to demand level reduces with time. The markup percent, initial cash, and bidding time sensitivity increase over time. This shows the importance of cash initial value (initial cash) and the inflow rate (markup percent) for the market share of the organization. Interestingly, market share sensitivity to demand level reduces with time.

The profit margin (markup percent) is highly sensitive to the cash time buffer. i.e. it is sensitive to the availability of cash to run the organization’s awarded projects. It is also sensitive to the time to adjust capacity, i.e. the flexibility of the organization to adapt to the workload. The sensitivity behavior to time to adjust capacity is oscillation. This might mean the level of sensitivity depends on other variables, i.e. this area requires more investigation. In the long term, significant sensitivity is not present, however, it is more sensitive to initial capacity and normal delivery delay.

Organization capacity is sensitive, initially, to the initial capacity, normal delivery delay, overheads, and quality level. Over time, the sensitivity to these factors is diminished except for the initial capacity, and other factors such as cash time buffer, markup percent, and time to adjust capacity. These factors are directly related to the availability of cash and workload, and flexibility to adjust the workforce, i.e. capacity level.

Organization cash is sensitive to its initial value and the project duration. Over time, other factors become more sensitive, such as time to adjust capacity, markup, overhead, and frequency of updating capacity. These variables indicate that flexibility to adjust capacity and cost structure is very important to maintain better cash flow.

The organizational delivery delay is sensitive to capacity, the flexibility of adjusting the capacity, project characteristics (time and load), and demand level. While, profit percent is sensitive to cost structure, workload, and capacity adjustment.

7.5.3.1 Insights summary compilation of the ANOVA method

To sum up, Figure 7.5 shows the factors' importance based on their recurrence frequency. Organizational flexibility to adjust capacity is ranked as the number one important variable for organizational performance. This assures the importance to invest in new technologies and business models to have a more flexible resource base. Markup percent is marked as important for an organization's long-term performance. It affects multiple downstream workflows. The interdependency and feedback structure give it a high rank for the organization's long-term performance.

Interestingly, cost structure (overheads and wages) and strategy to have a suitable liquid amount of cash (cash time buffer) are very important for the organization's current and future performance. The organization's performance is very sensitive at the instantaneous and accumulated level for these factors. Also, project characteristics such as project duration have likely the same short- and long-term performance, but project load has a higher long-term performance than its short-term effect. This indicates the importance of planning regarding activity duration should have more concern when seeking instantaneous and long-term effects on the organization's performance.

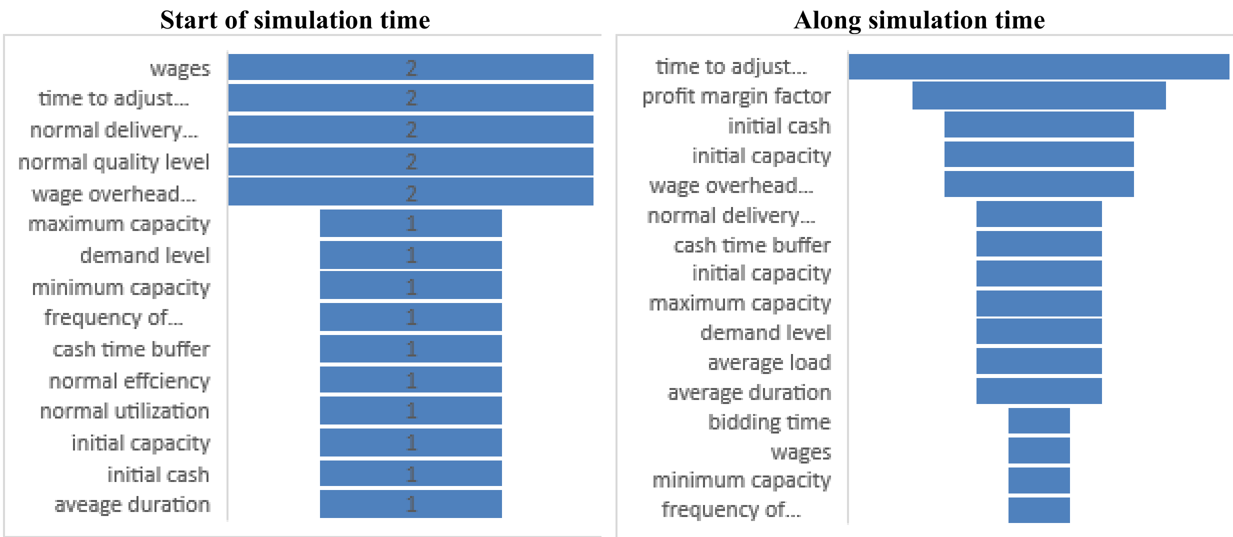


Figure 7.5 Most influencing variables on the monitored set from the ANOVA method

7.6 SENSITIVITY ANALYSIS INSIGHTS FROM THE THREE METHODS

The most obvious finding is that the results from the three analysis methods are slightly different to identify the most important (sensitive) variables affecting the project-based organization (contractor) performance. However, these results can provide the overall importance of each variable from the controller set. Table 7.8 represents the overall frequency of each variable that appears as a significant cause to affect the state of the monitored set variables. Initial organization capacity is ranked as the most important factor to affect the organization's performance. It is ranked the second most important variable for short-term effect and number one for the longest-term effect. Minimum and maximum capacity has a relatively lower impact than the initial capacity, but minimum capacity (fixed capacity) is much more important for organizational stabilization and better performance. The capacity adjustment flexibility is the second important factor in the overall ranking and third on the long-term performance effect. This highlights the importance of maintaining not only a suitable amount of capacity but the organization should, also, have the flexibility to respond to workflow changes. Significantly, maximum capacity has not the much importance as minimum capacity. This is because core resources, i.e. minimum capacity is the controller of how much variable capacity could be.

The other significant result is that quality level is more important than the initial cash. Initial cash invested is very important for short-term performance but the quality has many effects on the organization's performance in the long-term behavior.

Table 7.8 Frequency of variables usage based on their significance

variable	start	end	overall
initial capacity	9	13	22
normal quality level	8	10	18
time to adjust capacity	7	11	18
initial cash	9	8	17
wage overhead factor	7	10	17
profit margin factor	4	11	15
normal delivery delay	10	4	14
normal efficiency	6	6	12
wages	5	7	12
minimum capacity	4	7	11
demand level	3	7	10
normal utilization	5	4	9
all	4	5	9
average duration	4	4	8
average load	2	6	8
frequency of updating	4	3	7
cash time buffer	2	4	6
bidding time	2	4	6
maximum capacity	1	4	5

Overheads and markup percent have a significant impact on long-term behavior. Overheads have a relatively more effect on short-term behavior than the markup percent. This requires the organization have a balance between both variables to maintain a competitive long-term performance in the market.

Interestingly, demand level has a much more significant impact on the long-term effect than the short-term performance. So, it is recommended for the organizations in case of recessions, booming, or force majors to focus on strategies to deal with these events in the long term rather than a short-term mitigation plan.

Finally, project characteristics (load and duration) have a moderate impact on the organization's performance. Relatively, by comparing their impact with internal factors impact, it is obvious that internal organization factors have the highest impact on its performance more than other factors. This highly recommends more insight investigation of project-based organizations' business models for future studies.

7.7 WORKLOAD ANALYSIS

The workload is tested for sensitivity for the same parameters shown in Table 7.3. It is analyzed using the three mentioned methods, screening, regression, and ANOVA. The results from these methods are utilized to build the influence matrix presented in Table 7.9.

ANOVA method shows that normal utilization and initial cash are significantly important at the start of the simulation and the sensitivity of workload to them decayed over time. Hence, it is recommended for start-ups to give attention to the size of the organization in its initial steps.

the normal delivery delay has not the much significant at the start of the simulation but its importance increases with time. This indicates that long-term competition requires more attention to the organization's time to market for sustainability and a more stable workload.

Table 7.9 Workload Influence Matrix

	Start of simulation			Rest of simulation		
	Screening	Linear regression	ANOVA	Screening	Linear regression	ANOVA
time to adjust capacity				x	x	x
demand level	x	x				x
average load	x	x				
cash time buffer	x					
minimum capacity				x		x
average duration	x					x
normal utilization			x		x	
minimum capacity		x				
normal quality level					x	
normal efficiency		x				
initial cash	x		x			
normal delivery delay						x

The most significant variables from start to end of the simulation are minimum capacity, demand level, time to adjust capacity, and project average load. The workload is very sensitive to these variables. Their level of significance is almost stable throughout the simulation. These might be areas for improvement for the organization, because of workload higher sensitivity to them, and their long-term effect.

It is interesting to find that workload is low sensitivity to efficiency, initial capacity, maximum capacity, quality level, wages, discount rate, project average duration, bidding time, and frequency of updating. These variables highlight the importance of meeting the minim requirements for each variable is enough for the organization and spending much effort to improve them will be costly relative to their impact. Also, they highlight that market conditions applied to all contractors such as wages are not that significant to workload fluctuations.

Another interesting variable is the profit margin factor (markup percent), its importance to workload oscillates over the simulation. This indicates that its effect on the workload is not instantaneous, i.e. subjected to a delay in its effect. Also, it indicates that this factor is a balancing factor for workload, i.e. organization could increase and decrease its workload based on the markup percent.

From the screening method, at the start of the simulation, demand level, initial cash, and project average load are directly affecting the workload. Their influence is reduced by time but the project's average load increases relative to its initial value. This, interestingly, shows that market conditions have a high impact on startups this effect is slightly mitigated by time. Inversely, cash time buffer and project average duration have the highest effect on the workload at the start of the simulation, and their effectiveness decreases over time. So, the conservative strategy will reduce the workload initially but will develop a strong organization.

Minimum capacity (positively correlated), and time to adjust capacity (negatively correlated) are the highest impact on the workload during the simulation time. This highlights the significance of such variables in the organization's decisions. i.e. slight changes in the capacity or flexibility of adjustment will affect the workload instantaneously and in the long term. So, local decisions related to such variables should be considered at the organizational level.

From the regression method, demand level, project average load, minimum capacity, and normal efficiency are positively affecting the workload. While, normal quality level, normal utilization, and time to adjust capacity are negatively impacting the workload. The screening method shows that the demand level is highly correlated with the workload at the start of the simulation. This result is different from the regression and ANOVA methods. This indicates a nonlinear positive relation between workload and demand level that requires further investigation.

Normal efficiency has a higher regression factor but a not significant sensitivity to its uncertainty. This confirms the conclusion from the ANOVA method that as long as the minimum requirements are met for such factors then much enhancement is not required and is an expensive alternative. Other factors are in agreement with other methods.

7.8 POLICY ANALYSIS

After the analysis of the organization's performance, the model is utilized to assess the policies used by contracting organizations. Various scenarios are generated as presented in the following sections and analyzed in different cases.

7.8.1 Scenario generation

To generate different scenarios, the variables are categorized into three categories organization’s goals, the organization’s controllers, and the organization’s gauges as presented in Table 7.10. The organization’s goal setting is the variable used to define the goal of the organization based on different dimensions like profit, utilization, and market share. For example, if the organization is oriented toward profit the weight of the profit percentage will be higher than other variables.

The organization’s controllers set are the variables used by the organization to set its strategy and control its performance such as the cash time buffer of the organization and its capacity cap. The organization’s gauges are the variables used by the organization to measure its performance such as its market share and profit.

Table 7.10 Scenario generation parameters

Organization’s Goals	Organization’s Controllers	Organization’s Gauges
Profit percent	Cash time buffer	Market Share
Capacity utilization	Frequency of updating	Error Percent
Capacity variability index	Max Capacity	Capacity variability

Organization's Goals	Organization's Controllers	Organization's Gauges
Market Share	Min Capacity	Organization delivery delay
Organization delivery delay	Time to adjust Capacity	Capacity Utilization
Organization cash	Profit Margin Factor	Profit percent

The organization's goal variables are used to define three policies for the organization, balanced policy, competing for policy, and stable capacity as shown in Table 7.11. The balanced policy provides similar weight to the policy dimensions. This means the organization is interested in increasing profit and market share, decreasing the variability of the capacity and its delivery delay, and has utilized capacity.

The competing policy makes the organization a risk taker. In this policy, the organization provides a higher weight to the market share but keeps the importance of other dimensions. On the other hand, the risk avers policy, i.e., the stable capacity policy oriented the organization toward the full utilization of its resources. In this policy, the organization can have a high variable capacity but this capacity should be fully utilized. Also, the organization is interested in the profit not the amount of available cash. This policy aims to reduce the expenses of the organization to the minimum required for operation.

Table 7.11 Different organization's policies dimensions

Policy dimensions	Balanced policy Scenario 1	Competing policy Scenario 2	Stable capacity Scenario 3
Profit percent	1	1	1
Capacity utilization	1	1	1
Capacity variability index	-1	-1	0
Market Share	1	100	0
Organization delivery delay	-1	-1	-1
Organization Cash	1	1	0

7.8.2 Scenario analysis

The different policies (scenarios) are tested on two different conditions for the market, the market is oriented toward the lowest price and the market is oriented toward the nearest to the average price. The lowest price orientation of the market means that other dimensions are not considered in the attractiveness of the organization and the lowest bid price is awarded the project. The nearest to the average means that the price is still the main criterion and the average price of the bidders is the standard base and the nearest price to this standard is awarded the project.

7.8.2.1 Lowest price market

The results of the three scenarios are presented in Figure 7.6, Figure 7.7, Figure 7.8, and Figure 7.9. The workload of the organization shown in Figure 7.6 for the competing policy is doubled twice more than the other two policies. The market share shown in Figure 7.7 is more stable for policy number two than the other two policies. The organization delivery delay shown in Figure 7.8 is way better for policy number two than the other two policies. The capacity variability index shown in Figure 7.9 is more stable and better in policy number two than the other two policies. From these results, the competing policy is recommended for the PBOs in the lowest price-oriented market. This policy will allow the organization to have better utilization of its resources, more market share, higher workload (more experience), and better response to the market by decreasing its delivery delay

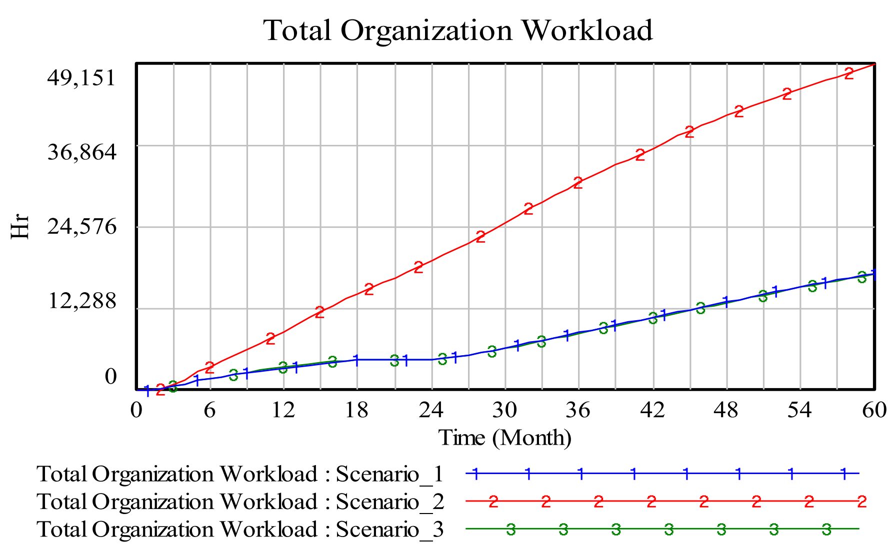


Figure 7.6 Comparing the organization’s workload for the three scenarios (Case1)

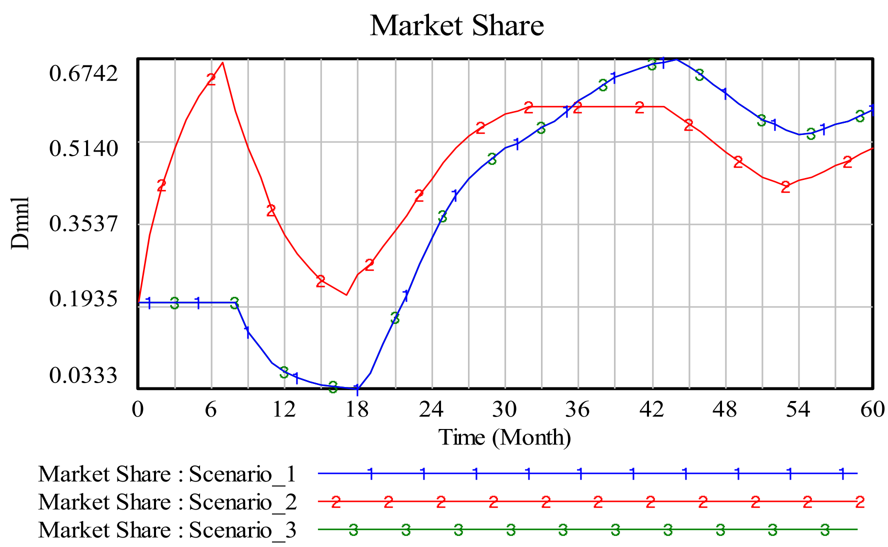


Figure 7.7 Comparing the organization's market share for the three scenarios (Case1)

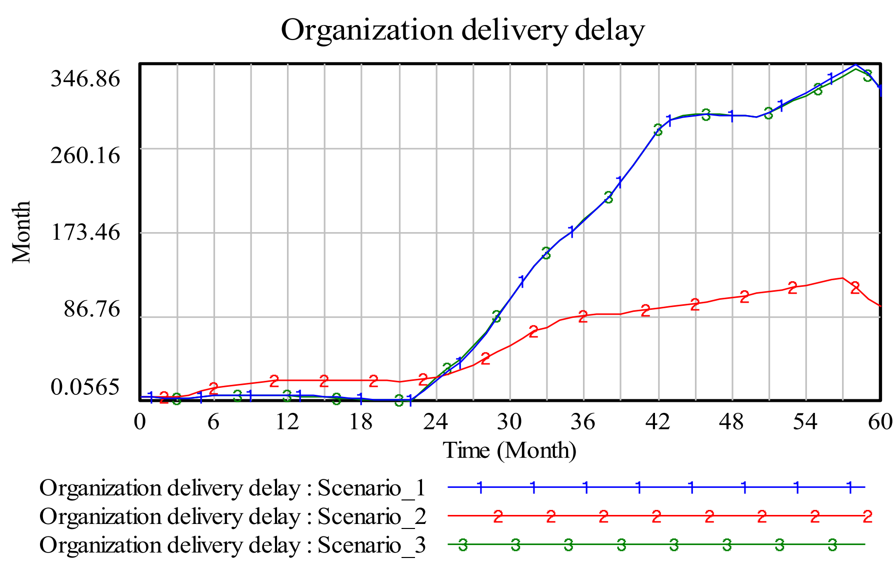


Figure 7.8 Comparing the organization's delivery delay for the three scenarios (Case1)

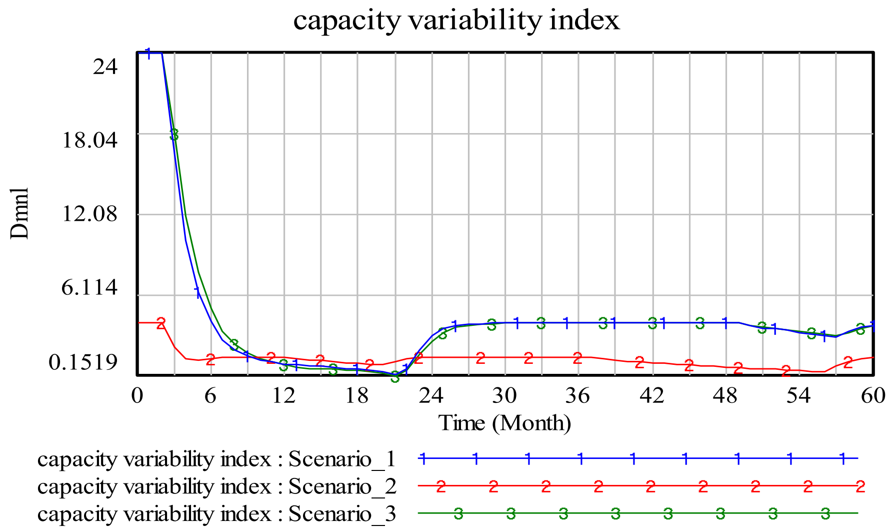


Figure 7.9 Comparing the organization's capacity variability index for the three scenarios (Case1)

7.8.2.2 Nearest to the average price market

The results are presented in Figure 7.10, Figure 7.11, and Figure 7.12. Policy number three provides the organization with a higher workload as shown in Figure 7.10. This policy guarantees a relatively stable market share than other policies as shown in Figure 7.11. Moreover, the delivery delay for policy number three is way less than for other policies as shown in Figure 7.12. From these results, the moderate policy (the more utilized resources policy) is recommended in the nearest to the average market. This policy, i.e., policy number three, will allow the organization to have a more stable market share, lower delivery delay, and a higher workload.

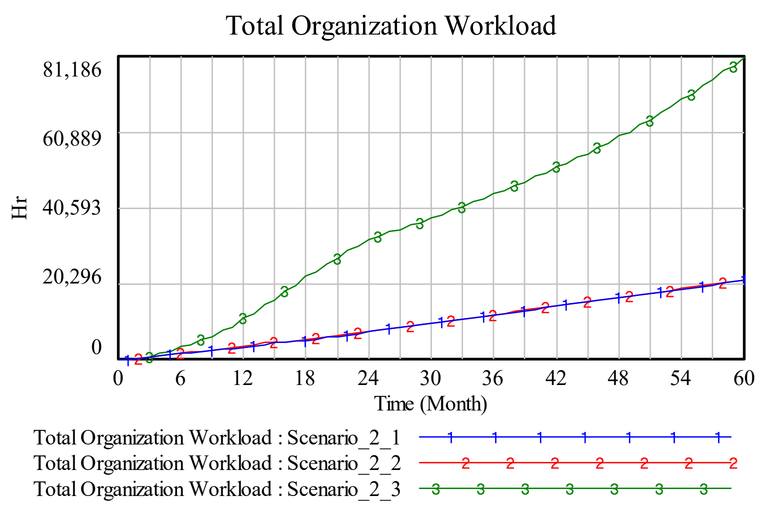


Figure 7.10 Comparing the organization's workload for the three scenarios (Case2)

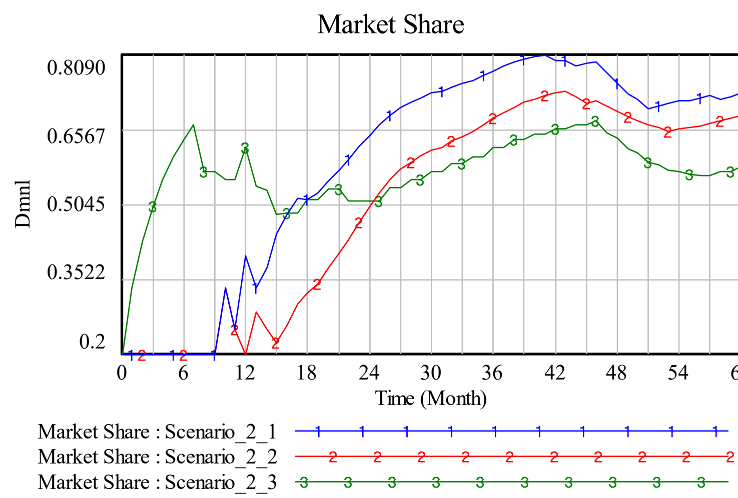


Figure 7.11 Comparing the organization's market share for the three scenarios (Case 2)

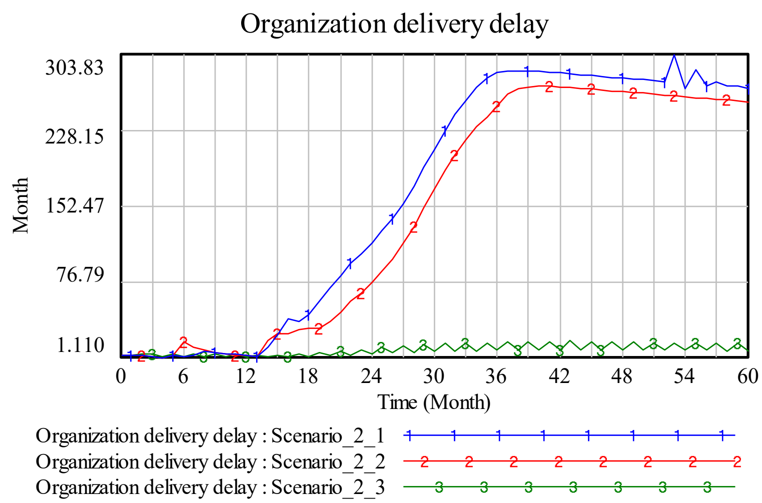


Figure 7.12 Comparing the organization's delivery delay for the three scenarios (Case2)

From the two cases of market orientation and the three policies applied. It is obvious that in a market-oriented toward the lowest price, policy number two which is oriented toward market share and highly competitive is recommended. While in the market-oriented toward reasonable pricing, policy number three which is oriented toward utilization of the organization's resources and moderate competition is recommended.

7.9 SUMMARY

This chapter analyzed the PBO performance parameters using social network analysis (SNA) and sensitivity analysis. The SNA measures the importance of the variables within the network structure due to their position in the network. Sensitivity analysis measures the relative importance between variables due to the effect of dynamics and delays. SNA resulted that variables are very important due to their positions and influence on the information flow in the network.

Sensitivity analysis is performed using three different statistical methods: screening, ANOVA, and linear regression. The results from each method are slightly different from one another. This chapter has identified the importance of internal factors on the organization's long-term performance. For instance, initial organization capacity is ranked as the most important factor to affect the organization's performance. Minimum capacity (fixed capacity) is much more important for organization stabilization and better performance. The capacity adjustment flexibility is the second important factor in the overall ranking and third on the long-term performance effect. This highlights the importance of maintaining not only a suitable amount of capacity but the organization should, also, have the flexibility to respond to workflow changes.

The other significant result regarding short and long-term effects is that quality level is more important than the initial cash in the long term. Overheads and markup percent have a significant impact on long-term behavior. Moreover, overheads have a relatively more effect on short-term behavior than the markup percent.

Interestingly, demand level has a much more significant impact on the long-term effect than the short-term performance. So, it is recommended for the organizations in case of recessions, booming, or force majors to focus on strategies to deal with these events in the long term rather than a short-term mitigation plan. Project characteristics (load and duration) have a moderate impact on the organization's performance. Internal organization factors have the highest impact on its performance more than other factors. This highly recommends more insight investigation of project-based organizations' business models for future studies. The internal causes have a higher impact even though their influence direction is changed between positive and negative, i.e. they are the influencers in a goal-seeking loop that exhibits a delay.

PBO’s workload is analyzed using the prementioned statistical tools. The results are utilized to build an influencing matrix between the controller variables and the workload level. This helps managers to understand the effect of the significant variables on short and long-term behavior. Also, facilitate the workload management policy assessment.

Moreover, the competing policy for the PBO with consideration of other performance dimensions is recommended for better performance and a stable market share.

This work can serve as an initial step for future research by expanding its causal loop diagram to include other factors such as project delivery method, productivity incentives, and bank loans. These variables will add more complexity to the model but will add a new layer of knowledge. Another area for improvement is the direct linkage of the model parameters with organization databases to get synchronized update parameter values. Also, this work highlights the need for more investigation of the business model's soft variables like labor training, communication, lean practices, etc. this will directly add to the organization's competitiveness, profit, and sustainability. Finally, This work is limited to representing the contracting organizations at the execution phase and can be improved by considering the project design phase's impact on the organization's performance.

CHAPTER 8 RESEARCH SUMMARY AND FUTURE RECOMMENDATIONS

This chapter presents a summary of the research, including the objectives achieved. The contributions of this research to academia and industry are also presented. Finally, the limitations of this work and recommendations for further research in this area are presented.

8.1 RESEARCH SUMMARY

In spite of the relative importance of the construction industry, most of the research on construction management has been at the project level. Although previous studies have considered operational-level activities (e.g., planning, control, contract management, risk, etc.), planning at the organization (portfolio) level has received comparably less attention among scholars than project-level planning. Based on the literature review, the gaps identified were (1) the lack of research identifying the variables affecting the PBO workload cycle; (2) the need for a method of predicting demand that considers economic variability, is precise, and that delivers critical information to aid planners in planning and decision making; and (3) the lack of support systems and holistic analysis that could aid managers in enhancing their decision making and in better understanding the holistic effect of their decisions. This research fills these gaps in consecutive steps as described in the following subsections.

8.1.1 First phase

In the first phase of this research, the literature on planning and control in construction is reviewed to obtain a clear image of the current research trends and gaps. A systematic literature review approach is used in this phase as a preliminary step to identify the research articles warranting further investigation. The defined set of articles is identified and reviewed, and the notable insights obtained in this process are compiled. A notable finding is that most of the articles in this area focus on cost and time control at the project level. Accordingly, the tools used in these studies are, primarily, cost- and time-oriented. Moreover, although scope and integration are important aspects of planning and control, the review of the relevant research reveals that these two areas have received relatively little attention. This research thus explores the use of system dynamics (SD) as a means of filling this gap. SD is selected based on its ability to facilitate the investigation of the structures underlying a given problem by integrating multiple areas and subsystems in a common structure and supporting feedback between the subsystems.

To determine the current state of SD applications in construction, a second systematic literature review is conducted, revealing that SD has been used in integration, but that the internal project dynamics still tend to be studied in isolation from the external dynamics. This is due to the orientation of studies toward project dynamics and finding the optimum solution at the project level. In other words, operational research tends to dominate the domain of SD applications in construction. Another notable observation is that SD when it has been used in research related to scope (i.e., workload management), has typically been limited to rework problems and change requests. The previous application deals with the workload as a well-defined entity, where changes to workload during the course of the project are considered side effects that should be mitigated by first quantifying their impact on the project time and cost. Hence, the present research studies workload fluctuations at the organizational level to understand the underlying causes and analyze the structure of these causes. On this basis, an influence matrix for workload fluctuations is developed, and the significance of the controller parameters to the project-based organization (PBO) is evaluated, as will be presented in the following sections.

8.1.2 Second phase

Based on the findings of the first phase, the aim of the second phase of the research is to identify the factors affecting workload fluctuations in PBOs. A systematic literature review approach is again used, this time to identify articles related to workload fluctuation at the organizational level. The identified articles are then clustered into three categories: dynamic modelling, non-dynamic modelling, and surveys. The dynamic modelling category includes studies that use an SD approach to model workload management. The non-dynamic modelling category, meanwhile, includes studies that use tools other than SD for this purpose. Surveys, finally, are studies that use questionnaires or interviews to define the factors affecting the workload management. The articles having been identified and categorized. They are studied in greater detail to extract the factors considered in the various models and surveys.

Analysis of these factors is conducted using social network analysis (SNA) and relative usage index (RUI). SNA is used to quantify the importance of variables based on industry experts' mental models, while RUI is used to quantify the importance of variables based on their frequency of use as reported in the literature. In this way, the results of the dynamic modelling articles and a combination of non-dynamic modelling articles and surveys can be compared. The results reveal a disparity between the expert mental model and the dynamic models applied, thus pointing to the need for integrating more dynamic variables to model workload fluctuation. The most used variables are resources, organization experience, project schedule, and risk. On the other hand, The least used variables are owner strictness, bidding time, outsourcing quality, and organization utilization. These variables are recommended to be considered in the decision support system for workload management.

The identified factors are grouped into those influencing the pre-award phase, those influencing the post-award phase, and those influencing the organization's financial system. It is found that the importance of the factors in each category is higher in the assigned phase but it affects other phases too. For example, the factors in the pre-award phase are defined in the pre-award phase but their influence propagates to the after-award phase. These factors are then structured into a causal loop diagram that links the various subsystems. This diagram is then evaluated by industry experts and they stressed the need for understanding market dynamics. This is because isolating market dynamics from the organizational dynamic leads to unreliable planning and an inadequate understanding of the problem at hand. Hence, the focus of the next two phases of research is on gaining an understanding of market demand and predicting it and analyzing the causal structure of workload fluctuation.

8.1.3 Third phase

The focus of the third phase of the study is on analyzing and predicting industry demand, where industry demand is represented by the number of building permits issued in the market at a given time (as this metric is reflective of the effect of various economic and political conditions). Analysis of this univariant time series is conducted using statistical tests, with the results of the analysis revealing various characteristics of industry demand. For instance, it is observed that construction industry demand in Canada (i.e., the case jurisdiction) has a one-year cycle that corresponds with the calendar year. The peak of this cycle is at the interface of the second and third quarters of the year, while the valley occurs at the interface of the fourth and first quarters. The analysis also reveals that construction demand in Canada is stationary, normally distributed, relatively stable, fluctuates around the average, and has low variability in terms of the number of projects issued.

The prediction of demand volume using statistical and machine-learning methods is also evaluated. The statistical tools, especially exponential smoothing, are found to outperform the machine-learning algorithms in cases in which the volume of data available for training is limited. It is observed that SARIMA is the most suitable tool for correlated and stationary data, but that Holt-Winter (HW) performs better than SARIMA for 85% of the data. Moreover, Gaussian with Kernels is the best-suited tool for normal and low-variability data.

Overall, exponential smoothing is determined to be the best algorithm for predicting demand, as it does not require sophisticated calculations, has a relatively short training time, and has an acceptable error margin. However, there is still uncertainty in the prediction due to errors. In this respect, the present work aids strategic planners in mitigating market uncertainty, quantifying risk, and optimizing markup margins to ensure profitability and competitiveness. Another advantage of this work is that the approach used in this study can be applied to different industries and markets to support contracting organizations in their strategic decision making to expand in existing markets or penetrate new markets. Finally, the tools proposed in this research assume that the previous pattern is replicated in the future so it is recommended to apply a causal-driven approach to understand the market dynamics.

8.1.4 Fourth phase

The fourth phase involves analyzing the causal structure of workload fluctuation at the organizational level. The dynamic hypothesis driving this structure comprises two major “loops”, one of them a positive (reinforcing) loop and the other a negative (balancing) loop. The reinforcing loop consists of the organization's available cash for increasing the capacity to take on more workload, where accepted and executed work in turn increases the organization's available cash. The balancing loop, meanwhile, refers to the cash invested by the organization in increasing its capacity and competitiveness to gain more workload. The higher the backlog workload is, the more the consumption of financially available resources reduces the ability of the organization to add more resources for work execution.

This hypothesis is used to link the various identified variables and arrange them into four subsystems: contractor competitiveness, demand and capacity adjustment, capacity allocation, and financial subsystem. The model is subjected to various tests to validate its goal, dimension consistency.

Meanwhile, the causal loop diagram is analyzed using SNA to gain insights into the relative importance of the various factors based on their positions in the network structure. Three different statistical methods—screening, ANOVA, and linear regression—are used to analyze the sensitivity of the model, where the results are found to vary slightly depending on the method. A notable finding is that internal factors have a higher impact on the organization's short- and long-term performance than do external factors, even though their direction of influence tends to oscillate between positive and negative, i.e., they are the influencing factors in a goal-seeking loop that exhibits a delay.

Capacity is found to be the most important factor affecting the organization's performance from the three methods of analysis applied, while capacity adjustment flexibility is the second-most important factor in the overall ranking and third in terms of the effect on long-term performance. This highlights the importance of maintaining not only a suitable amount of capacity but also the flexibility to respond to workflow changes.

Demand, meanwhile, is found to have a much more significant impact on long-term performance than on short-term performance. As such, it is recommended that organizations focus on long-term strategies to deal with recessions, booms, and forces majeures rather than on short-term mitigation plans.

Finally, the results of the PBO workload analysis are used to build an influence matrix characterizing the relationship between controller variable and workload level. Such a tool can aid decision-makers in understanding the effect of significant variables on short- and long-term behaviour, as well as facilitate the assessment of workload management policy.

8.2 RESEARCH CONTRIBUTIONS

8.2.1 Academic contributions

1) Identification of the factors affecting workload fluctuations in PBOs:

The fragmented intellectual knowledge and niche research topics such as project management, contractor selection, and portfolio optimization are transformed into a comprehensive list that collects and maps coherent information about workload fluctuations. This provides structured, comprehensive, and holistic information to scholars concerning the variables affecting workload fluctuations. Another contribution in this regard is that the lack of dynamic models for evaluating workload fluctuations is identified.

2) Increased understanding of market variations and prediction of future demand:
Previous studies have represented demand in terms of the orders received by a given organization. However, this indicator is not representative of actual demand in the market. The present study thus represents unconstrained demand by using building permits as the metric. Not only is this representation more accurate in capturing actual market conditions, but it is straightforward and efficient because the effect of economic and political variations on demand is inherently reflected in the number of building permits. In this manner, it provides a statistical tool for demand prediction with a reasonable error using very limited data. Moreover, this representation aids understanding of the demand cycle, its peak, valley, average, range, and other significant aspects, and it can be extended to applications analyzing and predicting demand in other industry sectors. Contrary, it is limited to the analysis of one factor and assumes the future demand is derived from only the previous demand.

3) Development of a decision support system for strategy selection:
The developed model provides decision-makers with an integrated tool that considers the internal and external dynamics of the PBO. Previous studies have tended to focus on project dynamics in terms of project time and cost. The model developed in the present research considers the interacting dynamics of the project, organization, and market. Also, it considers the nondeterministic nature of the variables influencing the problem at hand. Another innovative feature is that it applies various indices to measure the organization's performance, such as market share, capacity variability index, and capacity utilization. These indices have been largely overlooked in previous studies, which have been oriented toward finding local optimum solutions for specific projects. The present study fills this gap and links the organization's business model to various

projects operated by the same contractor in order to find a global optimum solution at the organizational level. Moreover, a workload influence matrix is developed, and the significant factors affecting a PBO's performance are identified.

8.2.2 Contributions to industry practice

1) Assessment of the factors affecting a PBO's workload fluctuation:

   An assessment is developed to aid contractors and practitioners in understanding the relative importance of factors affecting workload fluctuations at the organizational level. It provides insights into how the overall fluctuation behaviour emerges from project-oriented decisions, and maps the complicated linkages among industry experts' mental models in dealing with known local behaviours to support practitioners in understanding, holistically, the emergent behaviour of decisions.

2) Increased understanding of demand fluctuations and prediction of future demand.

   Predicting the unconstrained demand provides practitioners and contractors with a significant piece of information to facilitate downstream decision making, such as capacity planning and defining the competition landscape. The characteristics of demand provided to practitioners support them in better understanding the demand cycle. This helps the practitioner to form a reliable mental model in assessing fluctuating market demand.

3) Development of a decision support system:

   The developed decision support system aids practitioners in making decisions in a time-efficient manner. In this way, contractors can achieve a stable resource level based on a fuller understanding of the fluctuating nature of the workload and the variables influencing it. Moreover, by better understanding which variables have the most influence on the organization's performance, contractors can make sound decisions regarding areas of future investment.

8.3 RESEARCH LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORK

8.3.1 Identification of the factors affecting the PBO's workload fluctuation

The identification of PBO's workload fluctuation factors focused on the previous research published related to this area. Two decades was the limited time to investigate these factors. This could be eliminated in future research by increasing the time spectrum and categorizing these factors into decades. These clusters of factors can be utilized in the assessment of the expert mental model evolution in the consideration of this problem.

Moreover, the focus on the previous studies to extract the factors limits the variables collected to historical data (previous studies). Communication with industry experts to validate these variables was limited because of COVID-19 restrictions. This can be eliminated in future research by surveying multiple contracting organizations and various practitioners.

8.3.2 Prediction of future industry demand

The analysis and prediction of the industry demand represented in a univariant time series (TS) assume that historical behavior is replicated in the future. This makes TS analysis falls short to explain why behaviors occur. It doesn't explain why the demand has a seasonal cycle and exponential or damped trend. This can be covered in future research by utilizing a causal-driven approach to analyze the construction industry demand.

Moreover, this work considers unconstrained demand prediction. In future work, this can be integrated with other models to reflect the organization's constraints in order to predict their market share, i.e., their constrained demand.

8.3.3 Analysis of PBO's workload fluctuation

The project in this study is assumed to be identified using its average time and workload. This assumption limits the analysis from considering other factors that identify the project such as the project owner's characteristics. This factor can be studied in future research to provide a more enhanced assessment of the organization's performance.

In future work, the developed model could be integrated with an optimization model to automate the decision-making process.

This research used soft data due to the unavailability of hard data. This can be addressed in future research by applying a direct link between the model parameters and an organization's databases (if available) to obtain synchronized and updated parameters.

Finally, this work is limited to representing the contracting organizations at the execution phase and can be built upon by incorporating interactions with design–build organizations during the design phase.

BIBLIOGRAPHY

Abbaspour, Soroush and Shahin Dabirian. 2019. "Evaluation of Labor Hiring Policies in Construction Projects Performance using System Dynamics." *International Journal of Productivity and Performance Management*.

Abd Elrehim, Mostafa Z., Mohamed A. Eid, and Mostafa G. Sayed. 2019. "Structural Optimization of Concrete Arch Bridges using Genetic Algorithms." *Ain Shams Engineering Journal* 10 (3): 507-516. doi:10.1016/j.asej.2019.01.005. http://dx.doi.org/10.1016/j.asej.2019.01.005.

Abolghasemi, Mahdi, Eric Beh, Garth Tarr, and Richard Gerlach. 2020. "Demand Forecasting in Supply Chain: The Impact of Demand Volatility in the Presence of Promotion." *Computers & Industrial Engineering* 142: 106380.

Abotaleb, Ibrahim S. and Islam H. El-adaway. 2018a. "First Attempt Toward a Holistic Understanding of the Interdependent Rippled Impacts Associated with Out-of-Sequence Work in Construction Projects: System Dynamics Modeling Approach." *Journal of Construction Engineering and Management* 144 (9): 04018084.

———. 2018b. "Managing Construction Projects through Dynamic Modeling: Reviewing the Existing Body of Knowledge and Deriving Future Research Directions." *Journal of Management in Engineering* 34 (6): 04018033.

Adafin, Johnson, James O. B. Rotimi, and Suzanne Wilkinson. 2016. *Determining Significant Risks in the Variability between Design-Stage Elemental Cost Plan and Final Tender Sum*. Vol. 32 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)me.1943-5479.0000448.

Adhikari, Ratnadip and Ramesh K. Agrawal. 2013. "An Introductory Study on Time Series Modeling and Forecasting." *arXiv Preprint arXiv:1302.6613*.

Aiyetan, Olatunji A. and Dillip Das. 2015. "Using System Dynamics Modelling Principles to Resolve Problems of Rework in Construction Projects in Nigeria." *Journal of Construction Project Management and Innovation* 5 (2): 1266-1295.

Aje, Isaac Olaniyi, Timo Olugbenga Oladinrin, and Angeline Ngozika Chibuike Nwaole. 2016a. "Factors Influencing Success Rate of Contractors in Competitive Bidding for Construction Works in South-East, Nigeria." *Journal of Construction in Developing Countries* 21 (1): 19.

———. 2016b. "Factors Influencing Success Rate of Contractors in Competitive Bidding for Construction Works in South-East, Nigeria." *Journal of Construction in Developing Countries* 21 (1): 19.

Akbari, Saeed, Farzad Pour Rahimian, Moslem Sheikhkhoshkar, Saeed Banihashemi, and Mostafa Khanzadi. 2020. "Dynamic Sustainable Success Prediction Model for Infrastructure Projects: A Rough Set Based Fuzzy Inference System." *Construction Innovation* 20 (4): 545-567. doi:10.1108/CI-04-2019-0034. https://www.emerald.com/insight/content/doi/10.1108/CI-04-2019-0034/full/html.

Al-Humaidi, H. M. 2016. "Construction Projects Bid Or Not Bid Approach using the Fuzzy Technique for Order Preference by Similarity FTOPSIS Method." *Journal of Construction Engineering and Management* 142 (12): 04016068.

Ali, Gasser Galal. 2017. "Cash Flow Optimization for Construction Engineering Portfolios." .

Al-Kofahi, Zain Ghazi, Amirsaman Mahdavian, and Amr Oloufa. 2020a. "System Dynamics Modeling Approach to Quantify Change Orders Impact on Labor Productivity 1: Principles and Model Development Comparative Study." *International Journal of Construction Management*: 1-12. doi:10.1080/15623599.2020.1711494.

———. 2020b. "System Dynamics Modeling Approach to Quantify Change Orders Impact on Labor Productivity 1: Principles and Model Development Comparative Study." *International Journal of Construction Management*: 1-12.

Alleman, Doug and Dan Tran. 2020. *Challenges of Implementing Progressive Design-Build in Highway Construction Projects*. Vol. 12 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)la.1943-4170.0000327.

Alvanchi, Amin, SangHyun Lee, and Simaan AbouRizk. 2012. "Dynamics of Working Hours in Construction." *Journal of Construction Engineering and Management* 138 (1): 66-77.

———. 2011. "Modeling Framework and Architecture of Hybrid System Dynamics and Discrete Event Simulation for Construction." *Computer-Aided Civil and Infrastructure Engineering* 26 (2): 77-91.

Alzraiee, Hani, Osama Moselhi, and Tarek Zayed. 2012. "A Hybrid Framework for Modeling Construction Operations using Discrete Event Simulation and System Dynamics.".

Amarkhil, Qais, Student, Emad Elwakil, Bryan Hubbard, and Emad Elwakil. 2020. *S Rank and Relative Importance Index Integrated Approach*.

Amer, N., A. Okasha, and A. Arafa. 2019. "Enhancing Planning, Monitoring and Controlling of Road Construction Projects in Egypt." .

Anđelić, Ognjen and Zoran Rakićević. 2020. "Time-Series Analysis Application in Demand Forecasting: A Case Study of Fmcg.".

Arafa, Amir Taher Abd-Allah. 2011. "Dynamic Analysis for Enterprise Strategic Flexibility using System Engineering Methodology." .

Araújo, Lissa Gomes and Gunnar Lucko. 2016. *Slip Chart–Inspired Project Schedule Diagramming: Links, Extension to Network Schedules, and Unification*. Vol. 142 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)co.1943-7862.0001120.

Art Chaovalitwongse, W., Wanbin Wang, Trefor P. Williams, and Paveena Chaovalitwongse. 2012. "Data Mining Framework to Optimize the Bid Selection Policy for Competitively Bid Highway Construction Projects." *Journal of Construction Engineering and Management* 138 (2): 277-286.

Asamoah, Richard Oduro, Bernard Kofi Baiden, Gabriel Nani, and Ernest Kissi. 2019. "Review of Exogenous Economic Indicators Influencing Construction Industry." *Advances in Civil Engineering* 2019.

Ayhan, Bilal Umut and Onur Behzat Tokdemir. 2020. *Accident Analysis for Construction Safety using Latent Class Clustering and Artificial Neural Networks*. Vol. 146 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)co.1943-7862.0001762.

Azhari, Fardin, Farshid Abdi, and Amir abbas Shojaie. 2014. "Using System Dynamics Method to Manage Construction and Demolition Waste." *International Journal of System Dynamics Applications (IJSDA)* 3.4: 65-86.

Aznar, Beltran, Eugenio Pellicer, Steven Davis, and Pablo Ballesteros-Perez. 2017. "Factors Affecting Contractor's Bidding Success for International Infrastructure Projects in Australia." *Journal of Civil Engineering and Management* 23 (7): 880-889.

Badawy, Ahmed. 2018. "No Title." *An Evaluation Model for Competitiveness Index of Construction Companies*.

Bageis, Abdulrahman Salem and Chris Fortune. 2009. "Factors Affecting the Bid/no Bid Decision in the Saudi Arabian Construction Contractors." *Construction Management and Economics* 27 (1): 53-71.

Bajracharya, Arun, Stephen Olu Ogunlana, and Nguyen Luong Bach. 2000. "Effective Organizational Infrastructure for Training Activities: A Case Study of the Nepalese Construction Sector." *System Dynamics Review: The Journal of the System Dynamics Society* 16 (2): 91-112.

Barlas, Yaman. 1996. "Formal Aspects of Model Validity and Validation in System Dynamics." *System Dynamics Review: The Journal of the System Dynamics Society* 12 (3): 183-210.

Barlas, Yaman and Stanley Carpenter. 1990. "Philosophical Roots of Model Validation: Two Paradigms." *System Dynamics Review* 6 (2): 148-166.

Beker, Pablo F. and Angel Hernando-Veciana. 2015. "The Dynamics of Bidding Markets with Financial Constraints." *Journal of Economic Theory* 155: 234-261.

Bengio, Yoshua, Patrice Simard, and Paolo Frasconi. 1994. "Learning Long-Term Dependencies with Gradient Descent is Difficult." *IEEE Transactions on Neural Networks* 5 (2): 157-166.

Bortolini, Rafaela, Forcada Núria, and Matheu. 2018. *Enhancing Building Performance: A Bayesian Network Model to Support Facility Management Doctoral Thesis By*.

Checkland, Peter. 1999. "Systems Thinking." *Rethinking Management Information Systems*: 45-56.

Chen, Kuan-Yu and Cheng-Hua Wang. 2007. "A Hybrid SARIMA and Support Vector Machines in Forecasting the Production Values of the Machinery Industry in Taiwan." *Expert Systems with Applications* 32 (1): 254-264.

Cheng, T., M. Venugopal, J. Teizer, and P. A. Vela. 2011a. "Performance Evaluation of Ultra Wideband Technology for Construction Resource Location Tracking in Harsh Environments." *Automation in Construction* 20 (8): 1173-1184.

Cheng, T., M. Venugopal, J. Teizer, and P. A. Vela. 2011b. "Performance Evaluation of Ultra Wideband Technology for Construction Resource Location Tracking in Harsh Environments." *Automation in Construction* 20 (8): 1173-1184. doi:10.1016/j.autcon.2011.05.001. http://dx.doi.org/10.1016/j.autcon.2011.05.001.

Cheung, Yin-Wong and Kon S. Lai. 1995. "Lag Order and Critical Values of the Augmented Dickey–Fuller Test." *Journal of Business & Economic Statistics* 13 (3): 277-280.

Chisala, Maxwell L. 2017. "Quantitative Bid Or no-Bid Decision-Support Model for Contractors." *Journal of Construction Engineering and Management* 143 (12): 04017088.

Christensen, David S. 1998. "The Costs and Benefits of the Earned Value Management Process." *Journal of Parametrics* 18 (2): 1-16.

Christopher, Martin and Matthias Holweg. 2017. "Supply Chain 2.0 Revisited: A Framework for Managing Volatility-Induced Risk in the Supply Chain." *International Journal of Physical Distribution & Logistics Management*.

Chritamara, S., S. O. Ogunlana, and N. L. Bach. 2002. "System Dynamics Modeling of Design and Build Construction Projects." *Construction Innovation* 2 (4): 269-295. doi:10.1108/14714170210814801. https://www.emerald.com/insight/content/doi/10.1108/14714170210814801/full/html.

Clegg, Stewart, Catherine P. Killen, Christopher Biesenthal, and Shankar Sankaran. 2018. "Practices, Projects and Portfolios: Current Research Trends and New Directions." *International Journal of Project Management* 36 (5): 762-772.

Cosenz, Federico. 2017. "Supporting Start-Up Business Model Design through System Dynamics Modelling." *Management Decision* 55 (1): 57-80. https://doi.org/10.1108/MD-06-2016-0395.

Cosenz, Federico and Carmine Bianchi. 2014. "A System Dynamics Approach to Evaluate Incentive-Based Policies, Human Resource Motivation and Performance of Public Sector Organizations." .

Cosenz, Federico and Guido Noto. 2018. "A Dynamic Business Modelling Approach to Design and Experiment New Business Venture Strategies." *Long Range Planning* 51 (1): 127-140.

Cui, Qingbin, Makarand Hastak, and Daniel Halpin. 2010. "Systems Analysis of Project Cash Flow Management Strategies." *Construction Management and Economics* 28 (4): 361-376.

Dangerfield, Brian, Stuart Green, and Simon Austin. 2010. "Understanding Construction Competitiveness: The Contribution of System Dynamics." *Construction Innovation* 10 (4): 408-420. https://doi.org/10.1108/14714171011083579.

Darko, Amos, Albert P. C. Chan, Michael A. Adabre, David J. Edwards, M. Reza Hosseini, and Ernest E. Ameyaw. 2020. "Artificial Intelligence in the AEC Industry: Scientometric Analysis and Visualization of Research Activities." *Automation in Construction* 112: 103081. doi:10.1016/j.autcon.2020.103081. http://dx.doi.org/10.1016/j.autcon.2020.103081.

Das, Dilip Kumar and Fidelis Emuze. 2017. "A Dynamic Model of Contractor-Induced Delays in India." *Journal of Construction in Developing Countries* 22 (1): 21-39. doi:10.21315/jcdc2017.22.1.2. https://search.proquest.com/docview/1968929957.

Das, Dillip Kumar and Fidelis Emuze. 2017. "A Dynamic Model of Contractor-Induced Delays in India." *Journal of Construction in Developing Countries* 22 (1): 21-39.

Deng, Hui, Hao Hong, Dehuan Luo, Yichuan Deng, and Cheng Su. 2020. *Automatic Indoor Construction Process Monitoring for Tiles Based on BIM and Computer Vision*. Vol. 146 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)co.1943-7862.0001744.

Dorée, André, Elsebeth Holmen, and Jasper Caerteling. 2003. "Co-Operation and Competition in the Construction Industry of the Netherlands." *Greenwwod and D.(Eds)," ARCOM*: 817-826.

East, E. William and Liang Y. Liu. 2006. "Multiproject Planning and Resource Controls for Facility Management." *Journal of Construction Engineering and Management* 132 (12): 1294-1305.

Egemen, Mehmedali and Abdulrezak Mohamed. 2008. "SCBMD: A Knowledge-Based System Software for Strategically Correct Bid/no Bid and Mark-Up Size Decisions." *Automation in Construction* 17 (7): 864-872.

El-Adaway, Islam H., Ibrahim Abotaleb, and Eric Vechan. 2018. "Identifying the most Critical Transportation Intersections using Social Network Analysis." *Transportation Planning and Technology* 41 (4): 353-374.

El-Mashaleh, Mohammad S. 2013. "Empirical Framework for Making the Bid/no-Bid Decision." *Journal of Management in Engineering* 29 (3): 200-205.

Elsayegh, Amr, Cihan H. Dagli, and Islam H. El-Adaway. 2020. "An Agent-Based Model to Study Competitive Construction Bidding and the Winner’s Curse." *Procedia Computer Science* 168: 147-153.

Enshassi, Adnan and Sherif Mohamed. 2010. "Factors Affecting the Bid/no Bid Decision in the Palestinian Construction Industry." *Journal of Financial Management of Property and Construction* 15 (2): 118-142. https://doi.org/10.1108/13664381011063421.

Ford, Andrew and Hilary Flynn. 2005. "Statistical Screening of System Dynamics Models." *System Dynamics Review: The Journal of the System Dynamics Society* 21 (4): 273-303.

Forrester, Jay W. 1993. "System Dynamics and the Lessons of 35 Years." In *A Systems-Based Approach to Policymaking*, 199-240: Springer.

———. 1985. "The" Model Versus a Modeling "process." *System Dynamics Review* 1 (1): 133-134.

Gębczyńska, Magdalena. 2019. "The Influence of Selected Factors on Project Performance in Project-Based Organizations: A Qualitative Comparative Analysis." *Organizacja i Zarządzanie: Kwartalnik Naukowy*.

Gelman, Andrew, John B. Carlin, Hal S. Stern, and Donald B. Rubin. 1995. *Bayesian Data Analysis* Chapman and Hall/CRC.

Gilliland, Michael. 2010. *The Business Forecasting Deal: Exposing Myths, Eliminating Bad Practices, Providing Practical Solutions* John Wiley & Sons.

Gonzalez, Leonardo José, Dusko Kalenatic, and Karol Vivivana Moreno. 2012. "Integral and Dynamic Methodology Applied to Scheduling and Control Project." *Revista Facultad De Ingeniería Universidad De Antioquia* (62): 21-32.

González, Vicente, ;. Luis, F. Alarcón, Sergio Maturana, ;. Fernando Mundaca, ;. , and José Bustamante. *Improving Planning Reliability and Project Performance using the Reliable Commitment Model*. doi:10.1061/ASCÊCO.1943-7862.0000215.

Gransberg, Douglas D. and Keith Molenaar. 2004. *Analysis of Owner's Design and Construction Quality Management Approaches in Design/Build Projects*. Vol. 20 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)0742-597x(2004)20:4(162).

Gu, Yunfei and Martin Kunc. 2019. "Using Hybrid Modelling to Simulate and Analyse Strategies." *Journal of Modelling in Management*.

Habibi, Mohammadreza, Sharareh Kermanshachi, and Behzad Rouhanizadeh. 2019. "Identifying and Measuring Engineering, Procurement, and Construction (EPC) Key Performance Indicators and Management Strategies." *Infrastructures* 4 (2): 14.

Hanneman, Robert A. and Mark Riddle. 2005. *Introduction to Social Network Methods*. http://faculty.ucr.edu/*hanneman/: University of California Riverside.

Hassani, Hossein, Mohammad Reza Yeganegi, Atikur Khan, and Emmanuel Sirimal Silva. 2020. "The Effect of Data Transformation on Singular Spectrum Analysis for Forecasting." *Signals* 1 (1): 4-25.

Hekimoğlu, Mustafa and Yaman Barlas. 2010. "Sensitivity Analysis of System Dynamics Models by Behavior Pattern Measures." *Retrieved on March* 18: 2015.

Hochreiter, Sepp and Jürgen Schmidhuber. 1997. "Long Short-Term Memory." *Neural Computation* 9 (8): 1735-1780.

Hope, Jeremy and Robin Fraser. 2003. *Beyond Budgeting: How Managers can Break Free from the Annual Performance Trap* Harvard Business Press.

Hua, Goh Bee. 1996. "Residential Construction Demand Forecasting using Economic Indicators: A Comparative Study of Artificial Neural Networks and Multiple Regression." *Construction Management and Economics* 14 (1): 25-34.

Huang, M-G, P-L Chang, and Y-C Chou. 2008. "Demand Forecasting and Smoothing Capacity Planning for Products with High Random Demand Volatility." *International Journal of Production Research* 46 (12): 3223-3239.

Ibrahim, Maan Nihad, David Thorpe, and Muhammad Nateque Mahmood. 2019. "Risk Factors Affecting the Ability for Earned Value Management to Accurately Assess the Performance of Infrastructure Projects in Australia." *Construction Innovation*.

Jain, Garima and Bhawna Mallick. 2017. "A Study of Time Series Models ARIMA and ETS." *Available at SSRN 2898968*.

Jarkas, Abdulaziz M. 2013. "Primary Factors Influencing Bid Mark-up Size Decisions of General Contractors in Kuwait." *Journal of Financial Management of Property and Construction* 18 (1): 53-75. https://doi.org/10.1108/13664381311305078.

Jarkas, Abdulaziz M., Saleh A. Mubarak, and Charles Y. Kadri. 2014. "Critical Factors Determining Bid/no Bid Decisions of Contractors in Qatar." *Journal of Management in Engineering* 30 (4): 05014007.

Jaskowski, Piotr, Slawomir Biruk, and Robert Bucon. 2010. "Assessing Contractor Selection Criteria Weights with Fuzzy AHP Method Application in Group Decision Environment." *Automation in Construction* 19 (2): 120-126.

Jerbrant, Anna. 2014. "A Maturation Model for Project-Based Organisations-with Uncertainty Management as an Ever-Present Multi-Project Management Focus." *South African Journal of Economic and Management Sciences* 17 (1): 33-51.

Jiang, Heng and Chunlu Liu. 2011. "Forecasting Construction Demand: A Vector Error Correction Model with Dummy Variables." *Construction Management and Economics* 29 (9): 969-979.

Jing, Wang, Hafeth Ibrahem Naji, Raquim Nihad Zehawi, Zainab Hasan Ali, Nadhir Al-Ansari, and Zaher Mundher Yaseen. 2019. "System Dynamics Modeling Strategy for Civil Construction Projects: The Concept of Successive Legislation Periods." *Symmetry* 11 (5): 677.

Johnston, Robert B. and Marrie Brennan. 1996. "Planning Or Organizing: The Implications of Theories of Activity for Management of Operations." *Omega* 24 (4): 367-384.

Joshi, Hemlata and Deepa Tyagi. 2021. "Forecasting and Modeling Monthly Rainfall in Bengaluru, India: An Application of Time Series Models." *Int.J.Sci.Res.in Mathematical and Statistical Sciences Vol* 8 (1).

Kalekar, Prajakta S. 2004. "Time Series Forecasting using Holt-Winters Exponential Smoothing." *Kanwal Rekhi School of Information Technology* 4329008 (13): 1-13.

Kasperska, Elżbieta, Elwira Mateja-Losa, and Rafał Marjasz. 2013. "Sensitivity Analysis and Optimization for Selected Supply Chain Management Issues in the Company–using System Dynamics and Vensim." *Journal of Entrepreneurship Management and Innovation (JEMI)* 9 (2): 29-44.

Kenefic, Christopher R. 2020. "Systems Dynamics in Project Management: Shifting the Mental Model and Improving Outcomes."Naval Postgraduate School Monterey United States.

Khanzadi, Mostafa, Ehsan Eshtehardian, and Alireza Chalekaee. 2016. "A Game Theory Approach for Optimum Strategy of the Owner and Contractor in Delayed Projects." *Journal of Civil Engineering and Management* 22 (8): 1066-1077. doi:10.3846/13923730.2016.1210222. http://www.tandfonline.com/doi/abs/10.3846/13923730.2016.1210222.

Killen, Catherine P., Kam Jugdev, Nathalie Drouin, and Yvan Petit. 2012. "Advancing Project and Portfolio Management Research: Applying Strategic Management Theories." *International Journal of Project Management* 30 (5): 525-538.

Kim, Byung-Cheol. 2015. "Dynamic Control Thresholds for Consistent Earned Value Analysis and Reliable Early Warning." *Journal of Management in Engineering* 31 (5): 04014077.

Kim, Byung-Cheol and Kenneth F. Reinschmidt. 2011. *Combination of Project Cost Forecasts in Earned Value Management*. Vol. 137 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)co.1943-7862.0000352.

Kim, Sungjin, Soowon Chang, and Daniel Castro-Lacouture. 2020a. *Dynamic Modeling for Analyzing Impacts of Skilled Labor Shortage on Construction Project Management*. Vol. 36 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)me.1943-5479.0000720.

———. 2020b. *Dynamic Modeling for Analyzing Impacts of Skilled Labor Shortage on Construction Project Management*. Vol. 36 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)me.1943-5479.0000720.

———. 2020c. "Dynamic Modeling for Analyzing Impacts of Skilled Labor Shortage on Construction Project Management." *Journal of Management in Engineering* 36 (1): 04019035.

Koskela, Lauri J. and Gregory Howell. 2002. "The Underlying Theory of Project Management is Obsolete."PMI, .

Lazzeri, Francesca. 2020. *Machine Learning for Time Series Forecasting with Python* John Wiley & Sons.

Lee, Jae-Seob. 2015. "Calculating Cumulative Inefficiency using Earned Value Management in Construction Projects." *Canadian Journal of Civil Engineering* 42 (4): 222-232.

Leśniak, Agnieszka and Edyta Plebankiewicz. 2015. "Modeling the Decision-Making Process Concerning Participation in Construction Bidding." *Journal of Management in Engineering* 31 (2): 04014032.

Leu, Sou-Sen, Pham Vu Hong Son, and Pham Thi Hong Nhung. 2015. "Optimize Negotiation Price in Construction Procurement using Bayesian Fuzzy Game Model." *KSCE Journal of Civil Engineering* 19 (6): 1566-1572.

Li, Duanshun and Ming Lu. 2017. *Automated Generation of Work Breakdown Structure and Project Network Model for Earthworks Project Planning: A Flow Network-Based Optimization Approach*. Vol. 143 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)co.1943-7862.0001214.

Li, Guanghua, Guomin Zhang, Chuan Chen, and Igor Martek. 2020. "Empirical Bid Or no Bid Decision Process in International Construction Projects: Structural Equation Modeling Framework." *Journal of Construction Engineering and Management* 146 (6): 04020050.

Li, Yan-Wen and Ke Cao. 2020. "Establishment and Application of Intelligent City Building Information Model Based on BP Neural Network Model." *Computer Communications* 153: 382-389. doi:10.1016/j.comcom.2020.02.013. http://dx.doi.org/10.1016/j.comcom.2020.02.013.

Li, Ying, Li Jiang, Timothy RB Taylor, and David N. Ford. 2018. "Impact of Labour Controls on Tipping Point Dynamics in Large Complex Projects." *Systems Research and Behavioral Science* 35 (6): 605-618.

Li, Ying and Timothy RB Taylor. 2014. "Modeling the Impact of Design Rework on Transportation Infrastructure Construction Project Performance." *Journal of Construction Engineering and Management* 140 (9): 04014044.

Lin, Evelyn Teo Ai, George Ofori, Imelda Tjandra, and Hanjoon Kim. 2017. "Framework for Productivity and Safety Enhancement System using BIM in Singapore." *Engineering, Construction and Architectural Management*.

Lisse, Stephen D. and P. P. Student. 2012. "System Dynamics Applied to Outsourcing Engineering Services in Design-Build Projects." *Construction Management Association of America CM-eJournal*.

Liu, Huan, Chenxi Li, Yingqi Shao, Xin Zhang, Zhao Zhai, Xing Wang, Xinye Qi, Jiahui Wang, Yanhua Hao, and Qunhong Wu. 2020. "Forecast of the Trend in Incidence of Acute Hemorrhagic Conjunctivitis in China from 2011–2019 using the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Exponential Smoothing (ETS) Models." *Journal of Infection and Public Health* 13 (2): 287-294.

Liu, Mingqiang, Yun Le, Yi Hu, Bo Xia, Martin Skitmore, and Xianyi Gao. 2019. "System Dynamics Modeling for Construction Management Research: Critical Review and Future Trends." *Journal of Civil Engineering and Management* 25 (8): 730-741.

Liu, Xiaolei, Zi Lin, and Ziming Feng. 2021. "Short-Term Offshore Wind Speed Forecast by Seasonal ARIMA-A Comparison Against GRU and LSTM." *Energy* 227: 120492.

Lo, W., C. L. Lin, and M. R. Yan. 2007. "Contractor's Opportunistic Bidding Behavior and Equilibrium Price Level in the Construction Market." *Journal of Construction Engineering and Management* 133 (6): 409-416.

Love, Peter ED, David J. Edwards, and Zahir Irani. 2008. "Forensic Project Management: An Exploratory Examination of the Causal Behavior of Design-Induced Rework." *IEEE Transactions on Engineering Management* 55 (2): 234-247.

Love, Peter ED, Gary David Holt, L. Yl Shen, Heng Li, and Zahir Irani. 2002. "Using Systems Dynamics to Better Understand Change and Rework in Construction Project Management Systems." *International Journal of Project Management* 20 (6): 425-436.

Lowe, David J. and Jamshid Parvar. 2004. "A Logistic Regression Approach to Modelling the Contractor's Decision to Bid." *Construction Management and Economics* 22 (6): 643-653.

Lütkepohl, Helmut and Fang Xu. 2012. "The Role of the Log Transformation in Forecasting Economic Variables." *Empirical Economics* 42 (3): 619-638.

Mahalingam, Ashwin, Rahul Kashyap, and Charudatta Mahajan. 2010. "An Evaluation of the Applicability of 4D CAD on Construction Projects." *Automation in Construction* 19 (2): 148-159.

Mahdavi, Arash, Nader Naderpajouh, Juyeong Choi, Amir Bahador Ketabi, Makarand Hastak, and Qingbin Cui. 2019. "Dynamics of Project Selection and Growth in Project-Based Organizations." *International Journal of Construction Management* 21 (12): 1200-1217. https://doi.org/10.1080/15623599.2019.1604307.

Mamula, Maja. 2015. "Modelling and Forecasting International Tourism Demand-Evaluation of Forecasting Performance." *International Journal of Business Administration* 6 (3): 102.

Mansour, Husam, Eeydzah Aminudin, Balqis Omar, and Ali Al-Sarayreh. 2020. "Development of an Impact-on-Performance Index (IPI) for Construction Projects in Malaysia: A Delphi Study." *International Journal of Construction Management*: 1-10.

Marin, Alexandra and Barry Wellman. 2011. "Social Network Analysis: An Introduction." *The SAGE Handbook of Social Network Analysis* 11: 25.

Martín-Martín, Alberto, Mike Thelwall, Enrique Orduna-Malea, and Emilio Delgado López-Cózar. 2021. "Google Scholar, Microsoft Academic, Scopus, Dimensions, Web of Science, and OpenCitations' COCI: A Multidisciplinary Comparison of Coverage Via Citations." *Scientometrics* 126 (1): 871-906.

Martinsuo, Miia. 2013. "Project Portfolio Management in Practice and in Context." *International Journal of Project Management* 31 (6): 794-803.

Martinsuo, Miia and Joana Geraldi. 2020. "Management of Project Portfolios: Relationships of Project Portfolios with their Contexts." *International Journal of Project Management* 38 (7): 441-453.

Marzouk, Mohamed and Emad Mohamed. 2018. "Modeling Bid/no Bid Decisions using Fuzzy Fault Tree." *Construction Innovation* 18 (1): 90-108. https://doi.org/10.1108/CI-11-2016-0060.

Mccabe, Luai Y. and Brenda . 2017. *Control in International Mega-Projects: A Case Study*. Vol. 2017.

Metters, Richard. 1997. "Quantifying the Bullwhip Effect in Supply Chains." *Journal of Operations Management* 15 (2): 89-100.

Mhatre, Tanmay Nitin, J. J. Thakkar, and J. Maiti. 2017. "Modelling Critical Risk Factors for Indian Construction Project using Interpretive Ranking Process (IRP) and System Dynamics (SD)." *International Journal of Quality & Reliability Management*.

Miterev, Maxim, J. Rodney Turner, and Mauro Mancini. 2017. "The Organization Design Perspective on the Project-Based Organization: A Structured Review." *International Journal of Managing Projects in Business* 10 (3): 527-549. https://doi.org/10.1108/IJMPB-06-2016-0048.

Montgomery, Douglas C., Cheryl L. Jennings, and Murat Kulahci. 2015. *Introduction to Time Series Analysis and Forecasting* John Wiley & Sons.

Moshood, Taofeeq D., A. Q. Adeleke, Gusman Nawanir, and Fatimah Mahmud. 2020. "Ranking of Human Factors Affecting Contractors' Risk Attitudes in the Malaysian Construction Industry." *Social Sciences & Humanities Open* 2 (1): 100064.

Nadafi, Samira, Seyed Hamed Moosavirad, and Shahram Ariafar. 2019. "Predicting the Project Time and Costs using EVM Based on Gray Numbers." *Engineering, Construction and Architectural Management*.

Nasir, Muhammad Kamran and Bonaventura HW Hadikusumo. 2019. "System Dynamics Model of Contractual Relationships between Owner and Contractor in Construction Projects." *Journal of Management in Engineering* 35 (1): 04018052.

Nasirzadeh, Farnad, Mostafa Khanzadi, and Mostafa Mir. 2018. "A Hybrid Simulation Framework for Modelling Construction Projects using Agent-Based Modelling and System Dynamics: An Application to Model Construction Workers' Safety Behavior." *International Journal of Construction Management* 18 (2): 132-143.

Nasirzadeh, Farnad and Pouya Nojedehi. 2013. "Dynamic Modeling of Labor Productivity in Construction Projects." *International Journal of Project Management* 31 (6): 903-911.

Nazaripouya, Hamidreza, B. Wang, Y. Wang, P. Chu, H. R. Pota, and R. Gadh. 2016. "Univariate Time Series Prediction of Solar Power using a Hybrid Wavelet-ARMA-NARX Prediction Method."IEEE, .

NGHIA, NGUYEN HOAI. 2017. "No Title." *System Dynamics Modeling of Profit Enhancement in Real Estate Projects in Ho Chi Minh City, Vietnam*.

Nguyen, Long D., Long Le-Hoai, Dai Q. Tran, Chau N. Dang, and Chau V. Nguyen. 2019. "Effect of Project Complexity on Cost and Schedule Performance in Transportation Projects." *Construction Management and Economics* 37 (7): 384-399. doi:10.1080/01446193.2018.1532592. http://www.tandfonline.com/doi/abs/10.1080/01446193.2018.1532592.

Okasha, Ahmed Abd El-Rady, Amir Arafa, and Nabil Amer. 2019. "SI Model of Measuring the Success of Strategies and Decisions in Construction Projects using System Dynamics." *Journal of Engineering Science and Military Technologies* 3 (1): 42-51.

Oke, Ayodeji, Alexander Omoraka, and Abiodun Olatunbode. 2020. "Appraisal of Factors Affecting Bidding Decisions in Nigeria." *International Journal of Construction Management* 20 (2): 169-175.

Olatunji, Oluwole Alfred, Olaniyi Isaac Aje, and Sina Makanjuola. 2017. "Bid Or no-Bid Decision Factors of Indigenous Contractors in Nigeria." *Engineering, Construction and Architectural Management* 24 (3): 378-392. https://doi.org/10.1108/ECAM-01-2016-0029.

Pagoni, Eirini Grammatiki and Patroklos Georgiadis. 2020. "System Dynamics Approaches to Public–private Partnerships: A Literature Review." *Systems Research and Behavioral Science* 37 (2): 277-291. doi:10.1002/sres.2626. https://onlinelibrary.wiley.com/doi/abs/10.1002/sres.2626.

Paparoditis, Efstathios and Dimitris N. Politis. 2018. "The Asymptotic Size and Power of the Augmented Dickey–Fuller Test for a Unit Root." *Econometric Reviews* 37 (9): 955-973.

PMI. 2017. *A Guide to the Project Management Body of Knowledge (PMBOK Guide) / Project Management Institute.* PMBOK Guide. Sixth edition. ed. Library of Congress Cataloging-in-Publication Data: Project Management Institute, Inc.

Polat, Gul, Befrin Neval Bingol, and Enis Uysalol. 2014. "Modeling Bid/no Bid Decision using Adaptive Neuro Fuzzy Inference System (ANFIS): A Case Study.".

Rad, Farzad Haghighi and Seyed Mojtaba Rowzan. 2018. "Designing a Hybrid System Dynamic Model for Analyzing the Impact of Strategic Alignment on Project Portfolio Selection." *Simulation Modelling Practice and Theory* 89: 175-194.

Ramage, Magnus and Karen Shipp. 2009. "Jay Forrester." In *Systems Thinkers*, 99-108: Springer.

Rastogi, Nitank and M. K. Trivedi. 2016. *Pestle Technique -a Tool to Identify External Risks in Construction Projects* IRJET.

Ribeirinho, M. J., J. Mischke, G. Strube, E. Sjödin, J. L. Blanco, R. Palter, J. Biörck, D. Rockhill, and T. Andersson. 2020. "The Next Normal in Construction." *How Disruption is Reshaping the World's Largest Ecosystem.McKinsey & Company*.

Richard, Cédric, José Carlos M. Bermudez, and Paul Honeine. 2008. "Online Prediction of Time Series Data with Kernels." *IEEE Transactions on Signal Processing* 57 (3): 1058-1067.

Richmond, Barry. 1993. "Systems Thinking: Critical Thinking Skills for the 1990s and Beyond." *System Dynamics Review* 9 (2): 113-133.

Roberts, Stephen, Michael Osborne, Mark Ebden, Steven Reece, Neale Gibson, and Suzanne Aigrain. 2013. "Gaussian Processes for Time-Series Modelling." *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 371 (1984): 20110550.

Sacco, Tommaso, Michele Compare, Enrico Zio, and Giovanni Sansavini. 2019. "Portfolio Decision Analysis for Risk-Based Maintenance of Gas Networks." *Journal of Loss Prevention in the Process Industries* 60: 269-281. doi:10.1016/j.jlp.2019.04.002. http://dx.doi.org/10.1016/j.jlp.2019.04.002.

Sacks, Rafael, Mark Girolami, and Ioannis Brilakis. 2020. "Building Information Modelling, Artificial Intelligence and Construction Tech." *Developments in the Built Environment* 4: 100011. doi:10.1016/j.dibe.2020.100011. http://dx.doi.org/10.1016/j.dibe.2020.100011.

Sacks, Rafael, Olli Seppänen, Vitaliy Priven, and Jonathan Savosnick. 2017. "Construction Flow Index: A Metric of Production Flow Quality in Construction." *Construction Management and Economics* 35 (1-2): 45-63.

Said, Hisham and Khaled El-Rayes. 2011. "Optimizing Material Procurement and Storage on Construction Sites." *Journal of Construction Engineering and Management* 137 (6): 421-431.

Salehizadeh, Abdol Mehdi and Jaffar Mahmudi. 2019. "A Systems Dynamics Model for Project Management Systems of Project-Based Organization." *Journal of Industrial Strategic Management* 4 (2): 12-22.

Semaan, Nabil and Michael Salem. 2017. "A Deterministic Contractor Selection Decision Support System for Competitive Bidding." *Engineering, Construction and Architectural Management*.

Senge, Peter M. 1990. "The Art and Practice of the Learning Organization." .

Shafieezadeh, Mahdi, Mehdi Kalantar Hormozi, Erfan Hassannayebi, Loza Ahmadi, Marjan Soleymani, and Arezou Gholizad. 2020a. "A System Dynamics Simulation Model to Evaluate Project Planning Policies." *International Journal of Modelling & Simulation* 40 (3): 201-216. doi:10.1080/02286203.2019.1596779. http://www.tandfonline.com/doi/abs/10.1080/02286203.2019.1596779.

———. 2020b. "A System Dynamics Simulation Model to Evaluate Project Planning Policies." *International Journal of Modelling & Simulation* 40 (3): 201-216. doi:10.1080/02286203.2019.1596779. http://www.tandfonline.com/doi/abs/10.1080/02286203.2019.1596779.

———. 2020c. "A System Dynamics Simulation Model to Evaluate Project Planning Policies." *International Journal of Modelling and Simulation* 40 (3): 201-216.

———. 2020d. "A System Dynamics Simulation Model to Evaluate Project Planning Policies." *International Journal of Modelling and Simulation* 40 (3): 201-216.

Shokri-Ghasabeh, Morteza and Nicholas Chileshe. 2016. "Critical Factors Influencing the Bid/no Bid Decision in the Australian Construction Industry." *Construction Innovation* 16 (2): 127-157. https://doi.org/10.1108/CI-04-2015-0021.

Shrestha, K. J., Jeong, H. D. and Gransberg, Douglas D. "Multidimensional Highway Construction Cost Indexes using Dynamic Item Basket." Iowa State University Digital Repository, last modified Aug 01, https://lib.dr.iastate.edu/ccee_pubs/175.

Shrestha, Pramen Prasad, Giovanni Ciro Migliaccio, James T. O'Connor, and G. Edward Gibson. 2007. "Benchmarking of Large Design–Build Highway Projects." *Transportation Research Record* 1994 (1): 17-25. doi:10.3141/1994-03.

Silvestre, Gabriel Dalforno, Moisés Rocha dos Santos, and André CPLF de Carvalho. 2021. "Seasonal-Trend Decomposition Based on Loess Machine Learning: Hybrid Forecasting for Monthly Univariate Time Series."IEEE, .

Singh, D. A. and Robert LK Tiong. 2005. "A Fuzzy Decision Framework for Contractor Selection." *Journal of Construction Engineering and Management* 131 (1): 62-70.

Song, Xiaoling, Jiuping Xu, Charles Shen, and Feniosky Peña-Mora. 2018. "Conflict Resolution-Motivated Strategy Towards Integrated Construction Site Layout and Material Logistics Planning: A Bi-Stakeholder Perspective." *Automation in Construction* 87: 138-157. doi:10.1016/j.autcon.2017.12.018. http://dx.doi.org/10.1016/j.autcon.2017.12.018.

Squires, Alice, Jon Wade, Pete Dominick, and Don Gelosh. 2011. "Building a Competency Taxonomy to Guide Experience Acceleration of Lead Program Systems Engineers."STEVENS INST OF TECH HOBOKEN NJ SCHOOL OF SYSTEMS AND ENTERPRISES, 14-16 April 2011.

Stave, Krystyna and Megan Hopper. 2007. "What Constitutes Systems Thinking? A Proposed Taxonomy."The System Dynamics Society., July.

Sterman, John D. 1994. "Learning in and about Complex Systems." *System Dynamics Review* 10 (2\u20103): 291-330. doi:10.1002/sdr.4260100214. https://onlinelibrary.wiley.com/doi/abs/10.1002/sdr.4260100214.

———. 1989. "Modeling Managerial Behavior: Misperceptions of Feedback in a Dynamic Decision Making Experiment." *Management Science* 35 (3): 321-339.

———. 2001. "System Dynamics Modeling: Tools for Learning in a Complex World." *California Management Review* 43 (4): 8-25.

———. 2002. "Systems Dynamics Modeling: Tools for Learning in a Complex World." *IEEE Engineering Management Review* 30 (1): 42.

Sterman and D. John. 2002. "Systems Dynamics Modeling: Tools for Learning in a Complex World." *IEEE Engineering Management Review* 30.1: 42-42.

Sulasikin, Andi, Yudhistira Nugraha, Juan Intan Kanggrawan, and Alex L. Suherman. 2021. "Monthly Rainfall Prediction using the Facebook Prophet Model for Flood Mitigation in Central Jakarta."IEEE, .

Suprun, Emiliya, Oz Sahin, Rodney Anthony Stewart, and Kriengsak Panuwatwanich. 2019. "Examining Transition Pathways to Construction Innovation in Russia: A System Dynamics Approach." *International Journal of Construction Management*: 1-23. doi:10.1080/15623599.2019.1637628.

Suprun, Emiliya, Oz Sahin, Rodney Anthony Stewart, Kriengsak Panuwatwanich, and Yaroslav Shcherbachenko. 2018. "An Integrated Participatory Systems Modelling Approach: Application to Construction Innovation." *Systems* 6 (3): 33.

Sweeney, Linda Booth and John D. Sterman. 2000. "Bathtub Dynamics: Initial Results of a Systems Thinking Inventory." *System Dynamics Review: The Journal of the System Dynamics Society* 16 (4): 249-286.

Swei, Omar. 2020. *Forecasting Infidelity: Why Current Methods for Predicting Costs Miss the Mark*. Vol. 146 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)co.1943-7862.0001756.

Syntetos, Aris A., Zied Babai, John E. Boylan, Stephan Kolassa, and Konstantinos Nikolopoulos. 2016. "Supply Chain Forecasting: Theory, Practice, their Gap and the Future." *European Journal of Operational Research* 252 (1): 1-26.

Tan, Yongtao, Craig Langston, Min Wu, and J. Jorge Ochoa. 2015. "Grey Forecasting of Construction Demand in Hong Kong Over the Next Ten Years." *International Journal of Construction Management* 15 (3): 219-228.

Tan, Yongtao, Liyin Shen, and Craig Langston. 2012. "Competition Environment, Strategy, and Performance in the Hong Kong Construction Industry." *Journal of Construction Engineering and Management* 138 (3): 352-360.

Tang, Yu Hoe and Stephen O. Ogunlana. 2003a. "Modelling the Dynamic Performance of a Construction Organization." *Construction Management & Economics* 21 (2): 127-136.

———. 2003b. "Modelling the Dynamic Performance of a Construction Organization." *Construction Management & Economics* 21 (2): 127-136.

Tayeh, Bassam A., Khalid Al Hallaq, Hafiz Zahoor, and Abdulla H. Al Faqawi. 2019. "Techniques and Benefits of Implementing the Last Planner System in the Gaza Strip Construction Industry." *Engineering, Construction, and Architectural Management* 26 (7): 1424-1436. doi:10.1108/ECAM-01-2018-0039. https://www.emerald.com/insight/content/doi/10.1108/ECAM-01-2018-0039/full/html.

Taylor, Timothy RB and David N. Ford. 2008. "Managing Tipping Point Dynamics in Complex Construction Projects." *Journal of Construction Engineering and Management* 134 (6): 421-431.

Tennant, Stuart, David Langford, and Michael Murray. 2011. *Construction Site Management Team Working: A Serendipitous Event*. Vol. 27 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)me.1943-5479.0000053.

Thadewald, Thorsten and Herbert Büning. 2007. "Jarque–Bera Test and its Competitors for Testing Normality–a Power Comparison." *Journal of Applied Statistics* 34 (1): 87-105.

Thompson, Benjamin P. and Lawrence C. Bank. 2010. "Use of System Dynamics as a Decision-Making Tool in Building Design and Operation." *Building and Environment* 45 (4): 1006-1015.

Tian, Yuan, Kristen Hassmiller Lich, Nathaniel D. Osgood, Kirsten Eom, and David B. Matchar. 2016. "Linked Sensitivity Analysis, Calibration, and Uncertainty Analysis using a System Dynamics Model for Stroke Comparative Effectiveness Research." *Medical Decision Making* 36 (8): 1043-1057.

Toharudin, Toni, Resa Septiani Pontoh, Rezzy Eko Caraka, Solichatus Zahroh, Youngjo Lee, and Rung Ching Chen. 2020. "Employing Long Short-Term Memory and Facebook Prophet Model in Air Temperature Forecasting." *Communications in Statistics-Simulation and Computation*: 1-24.

Tokdemir, Onur B., Huseyin Erol, and Irem Dikmen. 2019a. "Delay Risk Assessment of Repetitive Construction Projects using Line-of-Balance Scheduling and Monte Carlo Simulation." *Journal of Construction Engineering and Management* 145 (2): 04018132.

———. 2019b. "Delay Risk Assessment of Repetitive Construction Projects using Line-of-Balance Scheduling and Monte Carlo Simulation." *Journal of Construction Engineering and Management* 145 (2): 4018132. doi:10.1061/(ASCE)CO.1943-7862.0001595. http://ascelibrary.org/doi/abs/10.1061/(ASCE)CO.1943-7862.0001595.

Too, Eric G. and Patrick Weaver. 2014. "The Management of Project Management: A Conceptual Framework for Project Governance." *International Journal of Project Management* 32 (8): 1382-1394.

Tseng, Fang-Mei and Gwo-Hshiung Tzeng. 2002. "A Fuzzy Seasonal ARIMA Model for Forecasting." *Fuzzy Sets and Systems* 126 (3): 367-376.

Turner, J. Rodney. 2009. *Handbook of Project-Based Management: Leading Strategic Change in Organizations* McGraw-Hill Education.

Turner, Rodney and Maxim Miterev. 2019. "The Organizational Design of the Project-Based Organization." *Project Management Journal* 50 (4): 487-498.

Umer, Waleed, Heng Li, Wei Lu, Grace Pui Yuk Szeto, and Arnold Y. L. Wong. 2018. "Development of a Tool to Monitor Static Balance of Construction Workers for Proactive Fall Safety Management." *Automation in Construction* 94: 438-448. doi:10.1016/j.autcon.2018.07.024. http://dx.doi.org/10.1016/j.autcon.2018.07.024.

van der Meer, Jeroen, Andreas Hartmann, Aad van der Horst, and Geert Dewulf. 2020. "Multi-Criteria Decision Analysis and Quality of Design Decisions in Infrastructure Tenders: A Contractor's Perspective." *Construction Management and Economics* 38 (2): 172-188.

Vishwas, B. V. and Ashish Patel. 2020. *Hands-on Time Series Analysis with Python* Springer.

Votto, Rodrigo, Linda Lee Ho, and Fernando Berssaneti. 2020. "Applying and Assessing Performance of Earned Duration Management Control Charts for EPC Project Duration Monitoring." *Journal of Construction Engineering and Management* 146 (3): 04020001.

Wang, Jidong, Jiahui Wu, and Yanbo Che. 2019. "Agent and System Dynamics-Based Hybrid Modeling and Simulation for Multilateral Bidding in Electricity Market." *Energy* 180: 444-456.

Wang, Lin, Martin Kunc, and Si-jun Bai. 2017. "Realizing Value from Project Implementation Under Uncertainty: An Exploratory Study using System Dynamics." *International Journal of Project Management* 35 (3): 341-352.

Wang, Xiaozhe, Kate Smith-Miles, and Rob Hyndman. 2009. "Rule Induction for Forecasting Method Selection: Meta-Learning the Characteristics of Univariate Time Series." *Neurocomputing* 72 (10-12): 2581-2594.

Wang, Yuanyuan, Jianzhou Wang, Ge Zhao, and Yao Dong. 2012. "Application of Residual Modification Approach in Seasonal ARIMA for Electricity Demand Forecasting: A Case Study of China." *Energy Policy* 48: 284-294.

Wang, Yung-Chieh, Yu-Pin Lin, Chun-Wei Huang, Li-Chi Chiang, Hone-Jay Chu, and Wen-Sheng Ou. 2012. "A System Dynamic Model and Sensitivity Analysis for Simulating Domestic Pollution Removal in a Free-Water Surface Constructed Wetland." *Water, Air, & Soil Pollution* 223 (5): 2719-2742.

White, A. S. 2011. "A Control System Project Development Model Derived from System Dynamics." *International Journal of Project Management* 29 (6): 696-705. doi:10.1016/j.ijproman.2010.07.009. http://dx.doi.org/10.1016/j.ijproman.2010.07.009.

Wibowo, Mochamad Agung, I. Nyoman Yudha Astana, and H. A. Rusdi. 2017. "Dynamic Modelling of the Relation between Bidding Strategy and Construction Project Performance." *Procedia Engineering* 171: 341-347.

Williams, Christopher K. and Carl Edward Rasmussen. 2006. *Gaussian Processes for Machine Learning*. Vol. 2 MIT press Cambridge, MA.

Wolf, Carola and Steven W. Floyd. 2017. "Strategic Planning Research: Toward a Theory-Driven Agenda." *Journal of Management* 43 (6): 1754-1788.

Wu, Dengsheng, Jianping Li, Tongshui Xia, Chunbing Bao, Yang Zhao, and Qianzhi Dai. 2018. "A Multiobjective Optimization Method Considering Process Risk Correlation for Project Risk Response Planning." *Information Sciences* 467: 282-295. doi:10.1016/j.ins.2018.07.013. http://dx.doi.org/10.1016/j.ins.2018.07.013.

Wu, Xiuyu, Hongping Yuan, Ge Wang, Shuquan Li, and Guangdong Wu. 2019. "Impacts of Lean Construction on Safety Systems: A System Dynamics Approach." *International Journal of Environmental Research and Public Health* 16 (2): 221.

Xiao, Jun, Xiaodong Xiaodong Li, Zhihui Zhang, and Jianhan Zhang. 2018. *Ontology-Based Knowledge Model to Support Construction Noise Control in China*. Vol. 144 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)co.1943-7862.0001425.

Xie, Wenjia, Xiangyang Liu, and Shuai Zhang. 2021. "Research on Systematic Construction of Organizational Project Management (OPM) for Large Business."IOP Publishing, .

Xue, Xiaoxiang. 2020. *Benchmark the Selection Model of the Project Delivery Method (PDM) on K-12 Public School Projects*.

Yan, Min-Ren. 2015. "Project-Based Market Competition and Policy Implications for Sustainable Developments in Building and Construction Sectors." *Sustainability* 7 (11): 15423-15448.

Yaseen, Zaher Mundher, Zainab Hasan Ali, Sinan Q. Salih, and Nadhir Al-Ansari. 2020. "Prediction of Risk Delay in Construction Projects using a Hybrid Artificial Intelligence Model." *Sustainability (Basel, Switzerland)* 12 (4): 1514. doi:10.3390/su12041514. https://explore.openaire.eu/search/publication?articleId=doajarticles::33702b06eef02094caa7abb4c6cac72c.

Ye, Kunhui, Liyin Shen, Bo Xia, and Bingheng Li. 2014. "Key Attributes Underpinning Different Markup Decision between Public and Private Projects: A China Study." *International Journal of Project Management* 32 (3): 461-472.

Yu, Tao, Geoffrey Qiping Shen, and Qian Shi. 2017. *Comparing the Performance Quality of Design-Bid-Build and Design-Build Delivery Methods*. Vol. 143 American Society of Civil Engineers (ASCE). doi:10.1061/(asce)co.1943-7862.0001262.

Yuan, X-X. 2011. "A Correlated Bidding Model for Markup Size Decisions." *Construction Management and Economics* 29 (11): 1101-1119.

Zarghami, S. A. and J. Dumrak. 2020. "Application of System Dynamics in the Assessment of Project Portfolio Performance." *International Journal of Industrial Engineering and Management* 11.4: 253-262.

Zhao, Jianyu, Olli Seppänen, Antti Peltokorpi, Behnam Badihi, and Hylton Olivieri. 2019. "Real-Time Resource Tracking for Analyzing Value-Adding Time in Construction." *Automation in Construction* 104: 52-65. doi:10.1016/j.autcon.2019.04.003. http://dx.doi.org/10.1016/j.autcon.2019.04.003.

Zhou, Jianguo, Henglin Xiao, Weiwei Jiang, Wenfeng Bai, and Guanlan Liu. 2020. "Automatic Subway Tunnel Displacement Monitoring using Robotic Total Station." *Measurement : Journal of the International Measurement Confederation* 151: 107251. doi:10.1016/j.measurement.2019.107251. http://dx.doi.org/10.1016/j.measurement.2019.107251.

Zhu, Jin and Ali Mostafavi. 2014a. "A System-of-Systems Framework for Performance Assessment in Complex Construction Projects." *Organization, Technology & Management in Construction: An International Journal* 6 (3): 0.

———. 2014b. "Towards a New Paradigm for Management of Complex Engineering Projects: A System-of-Systems Framework."IEEE, .

Zou, Patrick X. W., Guomin Zhang, and Jia-Yuan Wang. 2006. *Identifying Key Risks in Construction Projects: Life Cycle and Stakeholder Perspectives*.

Zwikael, Ofer. 2009. "The Relative Importance of the PMBOK® Guide's Nine Knowledge Areas during Project Planning." *Project Management Journal* 40 (4): 94-103.

APPENDIX I

Articles utilized in the literature review analysis related to knowledge areas

	year	Title	Integration	Cost	Human resources	Risk	Communications	Quality	Time	Procurement	Scope
1	2000	URBAN FREEWAY BRIDGE RECONSTRUCTION PLANNING: CASE OF MOCKINGBIRD BRIDGE				1			1		
2	2000	CONSTRUCTION BUSINESS COMPETITIVENESS AND GLOBAL BENCHMARKING									
3	2001	DYNAMIC PLANNING AND CONTROL METHODOLOGY FOR DESIGN/BUILD FAST-TRACK CONSTRUCTION PROJECTS	1						1		
4	2001	MODEL FOR EVALUATING BRIDGE CONSTRUCTION PLANS		1		1			1		
5	2001	MODEL FOR EVALUATING BRIDGE CONSTRUCTION PLANS		1	1	1		1	1		
6	2002	Integrating barcode and GIS for monitoring construction progress							1		
7	2003	Constraint-Based Planning with Integrated Production Scheduler over Internet					1		1	1	
8	2003	Redefining performance measures for construction project managers: an empirical evaluation		1	1		1	1	1		
9	2004	Effective Practice Utilization Using Performance Prediction Software		1					1		
10	2004	Reliability Buffering for Construction Projects						1	1		
11	2004	An algorithm for optimal scheduling and riskassessment of projects		1		1			1		
12	2004	Effective Practice Utilization Using Performance Prediction Software		1					1		
13	2004	Project Performance versus Use of Technologies at Project and Phase Levels		1				1	1		
14	2005	Continuous Value Enhancement Process			1			1	1		
15	2006	Multiproject Planning and Resource Controls for Facility Management		1	1						
16	2006	Interpretation of Automatically Monitored Lifting Equipment Data for Project Control						1			
17	2006	Balancing employee needs, project requirements and organisational priorities in team deployment			1						
18	2006	Conceptual Planning Process for Electrical Construction									
19	2006	Exploring the integration of health and safety with pre-construction planning				1			1		

	year	Title	Integration	Cost	Human resources	Risk	Communications	Quality	Time	Procurement	Scope
20	2006	Relating risk to project performance in Indonesian building contracts				1			1		
21	2007	Controlling construction waste by implementing governmental ordinances in Hong Kong						1			
22	2007	Using genetic algorithms in optimizing construction material delivery schedules		1						1	
23	2008	Analysis of Techniques Leading to Radical Reduction in Project Cycle Time							1		
24	2008	Discriminant Analysis for Predicting Ranges of Cost Variance in International Construction Projects		1							
25	2008	Minimum performance bounds for evaluating contractors performance during construction of highway pavement projects		1				1	1		
26	2008	Project Performance Evaluation Based on Statistical Process Control Techniques						1	1		
27	2009	Characterization and Search of Construction Inspection Plan Spaces Developed Using a Component-Based Planning Approach		1				1	1		
28	2009	Time, Cost, and Quality in a Road Building Project		1				1	1		
29	2009	An evaluation of the applicability of 4D CAD on construction projects					1		1		
30	2009	Combining ad hoc decision-making behaviour with formal planning and scheduling rules: a case study in the synthetic fibre production industry			1				1		
31	2009	Cost and Schedule Monitoring of Industrial Building Projects: Case Study		1					1		
23	2009	Developing a Performance Index for Relationship-Based Construction Projects in Australia: Delphi Study		1		1	1	1	1		
33	2009	Probabilistic Forecasting of Project Duration Using Bayesian Inference and the Beta Distribution				1			1		
34	2009	Selection of performance objectives and key performance indicators in public–private partnership projects to achieve value for money									
35	2009	Implementation of project change management best practice in different project environments				1					1
36	2010	Contemporaneous Time Series and Forecasting Methodologies for Predicting Short-Term Productivity						1	1		
37	2010	Improving Planning Reliability and Project Performance Using the Reliable Commitment Model						1	1		
38	2010	Clearing the Utilities on Time and Under Budget					1		1		
39	2010	Management Thinking in the Earned Value Method System and the Last Planner System									
40	2010	Prediction of schedule performance of Indian construction projects using an artificial neural network			1		1		1		
41	2010	Safety and production: an integrated planning and control model		1		1			1		
42	2010	Six-sigma as a strategy for process improvement on construction projects: a case study		1	1			1	1	1	

	year	Title	Integration	Cost	Human resources	Risk	Communications	Quality	Time	Procurement	Scope
43	2010	Systems analysis of project cash flow management Strategies		1							
44	2010	Visualized EVM system for assessing project performance		1			1		1		
45	2011	Optimizing Material Procurement and Storage on Construction Sites							1	1	
46	2011	Optimizing Cash Flows for Linear Schedules Modeled with Singularity Functions by Simulated Annealing		1					1		
47	2011	Pricing and production decisions in dual-channel supply chains with demand disruptions		1						1	
48	2011	Combination of Project Cost Forecasts in Earned Value Management		1					1		
49	2011	Construction Site Management Team Working: A Serendipitous Event			1						
50	2011	Modelling the network of commitments in the Last Planner System			1				1		
51	2011	Performance evaluation of ultra wideband technology for construction resource location tracking in harsh environments		1	1				1	1	
52	2012	Causes and Penalties of Variation: Case Study of a Precast Concrete Slab Production Facility		1				1	1		
53	2012	Rethinking Lookahead Planning to Optimize Construction Workflow							1		
45	2012	Hybrid principal component analysis and support vector machine model for predicting the cost performance of commercial building projects using pre-project planning variables		1					1		
55	2012	Using the Earned Value Management System to Improve Electrical Project Control		1		1			1		
56	2012	A Model for Quantification of Construction Waste in New Residential Buildings in Pearl River Delta of China						1			
57	2013	Advancing Optimization of Hybrid Housing Development Plans Following Disasters: Achieving Computational Robustness, Effectiveness, and Efficiency		1		1			1		
58	2013	CHAOTIC INITIALIZED MULTIPLE OBJECTIVE DIFFERENTIAL EVOLUTION WITH ADAPTIVE MUTATION STRATEGY (CA-MODE) FOR CONSTRUCTION PROJECT TIME-COST-QUALITY TRADE-OFF		1		1		1	1		
59	2013	SCHEDULE CONTINGENCY ANALYSIS FOR TRANSIT PROJECTS USING A SIMULATION APPROACH							1		
60	2013	Performance Measurement to Aid Decision Making in the Budgeting Process for Apartment-Building Construction: Case Study Using MCDA-C		1							
61	2013	Relationship between Construction Safety and Quality Performance				1		1			
62	2013	EVALUATING CONSTRUCTION PROJECT SUCCESS WITH USE OF THE M-TOPSIS METHOD	1								

	year	Title	Integration	Cost	Human resources	Risk	Communications	Quality	Time	Procurement	Scope
63	2014	Quality Management Evaluation Based on Self-Control and Cosupervision Mechanism in PIP						1			
64	2014	Anticipating Roadway Expansion and Tolling Impacts: Toolkit for Abstracted Networks		1					1		
65	2014	Multi-objective genetic optimization for scheduling a multi-storey building		1					1		
66	2014	Dynamic Control Thresholds for Consistent Earned Value Analysis and Reliable Early Warning		1		1			1		
67	2014	Effects of the location-based management system on production rates and productivity			1				1		
68	2014	Impact of Measuring Operational-Level Planning Reliability on Management-Level Project Performance							1		
69	2014	Impacts of Different Types of Owner-Contractor Conflict on Cost Performance in Construction Projects		1		1					
70	2014	Sensitivity of Earned Value Schedule Forecasting to S-Curve Patterns							1		
71	2015	Optimizing Earthmoving Job Planning Based on Evaluation of Temporary Haul Road Networks Design for Mass Earthworks Projects		1					1		
72	2015	Dynamic Control Thresholds for Consistent Earned Value Analysis and Reliable Early Warning		1					1		
73	2015	Impact of Measuring Operational-Level Planning Reliability on Management-Level Project Performance							1		
74	2015	An ontological approach for technical plan definition and verification in construction							1		
75	2015	Autonomous production tracking for augmenting output in off-site construction		1					1		
76	2015	Calculating cumulative inefficiency using earned value management in construction projects			1				1		
77	2015	A Review of Construction Delivery Systems: Focus on the Construction Management at Risk System in the Korean Public Construction Market				1					
78	2015	Credibility Evaluation of Project Duration Forecast Using Forecast Sensitivity and Forecast-Risk Compatibility				1			1		
79	2015	Method to Assess the Level of Implementation of Productivity Practices on Industrial Projects		1	1			1	1		
80	2015	Project Completion Time and Cost Prediction Using Change Point Analysis		1		1			1		1
81	2016	Lessons Learned from Applying the Individuals Control Charts to Monitoring Autocorrelated Project Performance Data						1	1		
82	2016	Slip Chart–Inspired Project Schedule Diagramming: Links, Extension to Network Schedules, and Unification				1			1		
83	2016	Introduction to Techniques for Resolving Project Performance Contradictions					1		1		
84	2016	Determining Significant Risks in the Variability between Design-Stage Elemental Cost Plan and Final Tender Sum		1		1			1		

	year	Title	Integration	Cost	Human resources	Risk	Communications	Quality	Time	Procurement	Scope
85	2016	A GAME THEORY APPROACH FOR OPTIMUM STRATEGY OF THE OWNER AND CONTRACTOR IN DELAYED PROJECTS		1		1			1		
86	2016	A study of best management practices for enhancing productivity in building projects: construction methods perspectives				1			1		
87	2016	Cost Performance as a Stochastic Process: EAC Projection by Markov Chain Simulation		1							
88	2016	Estimating Cumulative Damages due to Disruptions in Repetitive Construction						1	1		
89	2016	Line-of-balance against linear scheduling: critical comparison							1		
90	2016	Lessons Learned from Applying the Individuals Control Charts to Monitoring Autocorrelated Project Performance Data		1				1	1		
91	2016	Performance Analysis of Construction Manager at Risk on Pipeline Engineering and Construction Projects		1		1	1		1		1
92	2016	Slip Chart–Inspired Project Schedule Diagramming: Links, Extension to Network Schedules, and Unification					1		1		
93	2016	Customer Earned Value: Performance Indicator from Flow and Value Generation View		1				1	1		
94	2016	Statistical Analysis of the Effectiveness of Management Programs in Improving Construction Labor Productivity on Large Industrial Projects			1						
95	2016	A Survey on Production Planning System in Construction Projects Based on Last Planner System	1								
96	2017	Automated Generation of Work Breakdown Structure and Project Network Model for Earthworks Project Planning: A Flow Network-Based Optimization Approach							1		
97	2017	Causes of Construction Delays in Countries with High Geopolitical Risks				1		1	1		
98	2017	Multidimensional Highway Construction Cost Indexes Using Dynamic Item Basket		1		1					
99	2017	Effective material logistics in urban construction sites: a structural equation model		1		1	1		1	1	
100	2017	Framework for productivity and safety enhancement system using BIM in Singapore			1	1			1		
101	2017	Improving transparency in construction management: a visual planning and control model					1	1	1		
102	2017	Construction flow index: a metric of production flow quality in construction						1	1		
103	2017	Coordination Challenges of Production Planning & Control in International Mega-Projects: A Case Study				1			1		
104	2017	Estimated Cost at Completion: Integrating Risk into Earned Value Management		1		1		1	1		
105	2017	Improving transparency in construction management: a visual planning and control model						1	1		
106	2017	Social network analysis for construction crews			1						

	year	Title	Integration	Cost	Human resources	Risk	Communications	Quality	Time	Procurement	Scope
107	2018	Ontology-Based Knowledge Model to Support Construction Noise Control in China						1	1		
108	2018	A multiobjective optimization method considering process risk correlation for project risk response planning		1		1		1	1		
109	2018	Conflict resolution-motivated strategy towards integrated construction site layout and material logistics planning: A bi-stakeholder perspective							1	1	
110	2018	Development of a tool to monitor static balance of construction workers for proactive fall safety management				1					
111	2018	Techniques and benefits of implementing the last planner system in the Gaza Strip construction industry							1	1	
112	2018	Optimization for Roads' Construction: Selection, Prioritization, and Scheduling		1	1				1		
113	2018	Effect of project complexity on cost and schedule performance in transportation projects		1	1				1		
114	2019	Delay Risk Assessment of Repetitive Construction Projects Using Line-of-Balance Scheduling and Monte Carlo Simulation				1			1		
115	2019	Tools for Measuring Construction Materials Management Practices and Predicting Labor Productivity in Multistory Building Projects				1		1	1	1	
116	2019	Assessing the Impacts of an IT LPS Support System on Schedule Accomplishment in Construction Projects						1	1		
117	2019	What CPI = 0.85 Really Means: A Probabilistic Extension of the Estimate at Completion		1		1			1		
118	2019	Production and shipment planning for Project Based Enterprises: Exploiting learning-forgetting phenomena for sustainable assembly of Curtain Walls			1				1	1	
119	2019	BIM-based Last Planner System tool for improving construction project Management			1			1	1		
120	2019	Real-time resource tracking for analyzing value-adding time in construction							1		
121	2019	Portfolio decision analysis for risk-based maintenance of gas networks		1		1		1	1		
122	2019	Risk factors affecting the ability for earned value management to accurately assess the performance of infrastructure projects in Australia		1		1	1		1	1	
123	2019	Predicting the project time and costs using EVM based on gray numbers		1		1			1		
124	2019	SIGNIFICANCE RISKS EVALUATION OF COMMERCIAL CONSTRUCTION PROJECTS		1		1			1	1	
125	2019	Green Performance Evaluation System for Energy-Efficiency-Based Planning for Construction Site Layout		1	1				1	1	
126	2019	Long-Term Railway Network Planning Using a Multiperiod Network Design Model		1					1		
127	2019	The impact of make-ready process on project cost performance in heavy civil construction projects		1	1		1		1		

	year	Title	Integration	Cost	Human resources	Risk	Communications	Quality	Time	Procurement	Scope
128	2019	An Evaluation of a Predictive Conceptual Method for Contract Time Determination on Highway Projects Based on Project Types		1				1	1	1	
129	2020	Automatic Indoor Construction Process Monitoring for Tiles Based on BIM and Computer Vision				1		1	1		
130	2020	Applying and Assessing Performance of Earned Duration Management Control Charts for EPC Project Duration Monitoring						1	1		
131	2020	Predicting Construction Labor Productivity Based on Implementation Levels of Human Resource Management Practices			1				1		
132	2020	Methodological Pluralism: Investigation into Construction Engineering and Management Research Methods									

APPENDIX II

Literature articles on system dynamics

	Title	Author	Year	*Publication*
1	System Dynamics Review and publications 1985–2017: analysis, synthesis and contributions	Juan P. Torres*	2019	*System Dynamics Review*, *35*(2),
2	Applying System Dynamics Modelling to Strategic Management: ALiterature Review	Federico Cosenz and Guido Noto	2016	*Systems Research and Behavioral Science* 33.6
3	A recent overview of the integration of System Dynamics and Agent-based Modelling and Simulation	Graciela d. C. Nava Guerrero*1, Philipp Schwarz*1, Jill H Slinger1,2	2016	*System Dynamics Conference*
4	Are complexity and uncertainty distinct concepts in project management? A taxonomical examination from literature	Milind Padalkar, Saji Gopinath	2016	International Journal of Project Management
5	SYSTEM DYNAMICS MODELING FOR CONSTRUCTION MANAGEMENT RESEARCH: CRITICAL REVIEW AND FUTURE TRENDS	Mingqiang LIU, Yun LE, Yi HU, Bo XIA, Martin SKITMORE, Xianyi GAO	2019	Journal of Civil Engineering and Management
6	A Systematic Literature Review on Integrative Lean and Sustainability Synergies over a Building's Lifecycle	Adrieli Cristina Vieira de Carvalho 1 , Ariovaldo Denis Granja 1,* and Vanessa Gomes da Silva	2017	*Sustainability* 9.7
7	System Dynamics Modeling in the Project Environment	Peter E.D. Love	2013	Mathematical and Computer Modelling
8	Applying System Dynamics Modelling to Strategic Management: A Literature Review	Cosenz, Federico, and Guido Noto	2016	*Systems Research and Behavioral Science* 33.6
9	System dynamics applied to projectmanagement: a survey, assessment,and directions for future research	Ford, David N., and James M. Lyneis	2007	System Dynamics Review
10	Review and structural analysis of system dynamics models in sustainability science	Honti, Gergely, Gyula Dörgő, and János Abonyi.	2019	Journal of Cleaner Production
11	Best practices in system dynamics modeling	Martinez-Moyano, Ignacio J., and George P. Richardson	2013	System Dynamics Review
12	On the validation of system dynamics type simulation models	Qudrat-Ullah, Hassan	2012	*Telecommunication Systems* 51.2
13	System dynamics—the next fifty years	Forrester, Jay W.	2007	*The Journal of the System Dynamics Society* 23.2-3

APPENDIX III

Literature articles used in the system dynamic analysis related to knowledge areas

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
Impacts of Lean Construction on Safety Systems: A System Dynamics Approach	Xiuyu Wu 1 , Hongping Yuan 2, Ge Wang 3,* , Shuquan Li 1 and Guangdong Wu 4	2019					1						
Dynamic modelling of human resource allocation in construction projects	Shahin Dabiriana, Soroush Abbaspourb, Mostafa Khanzadic and Mostafa Ahmadic	2019	International Journal of Construction Management	1	1							1	
A system dynamics simulation model to evaluate project planning policies	Mahdi Shafieezadeha, Mehdi Kalantar Hormozib, Erfan Hassannayebi c, Loza Ahmadid, Marjan Soleymanie and Arezou Gholizadf	2019	International Journal of Modelling and Simulation	1	1	1						1	1
System dynamics modeling of design and build construction projects	S. Chritamara, S. O. Ogunlana , N. L. Bach	2002	Construction Innovation	1	1				1	1		1	1
Dynamic simulation for effective workforce management in new product development	M. Mutingi	2012	Management Science Letters									1	
Forensic Project Management: An Exploratory Examination of the Causal Behavior of Design-Induced Rework		2008		1	1	1							
Integral and dynamic methodology applied to scheduling and control project	Leonardo José Gonzalez*, Dusko Kalenatic, Karol Vivivana Moreno	2012	Magazine Faculty of Engineering University of Antioquia	1									
Evaluating Construction Methods for Low Carbon Emissions Using System Dynamics Modeling	G. Ozcan-Deniz1 and Y. Zhu2	2012	COMPUTING IN CIVIL	1	1								1

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
			ENGINEERING										
Schedule risk analysis of infrastructure projects: A hybrid dynamic approach	XiaoxiaoXuaJiayuanWangbClyde ZhengdaoLibWenke HuangbNiniXiac	2018	Automation in Construction	1			1						
Key challenges of system dynamics implementation in project management	David Rumesera, Margaret Emsleyb	2016	3rd International Conference on New Challenges in Management and Organization: Organization and Leadership								1	1	
A control system project development model derived from System Dynamics	A.S. White	2011	International Journal of Project Management	1								1	
Dynamic planning of construction activities using hybrid simulation	Hani Alzraiee, Tarek Zayed, Osama Moselhi	2015	Automation in Construction	1								1	
System Dynamics Modeling Strategy for Civil Construction Projects: The Concept of Successive Legislation Periods	Wang Jing , Hafeth Ibrahem Naji , Raquim Nihad Zehawi , Zainab Hasan Ali , Nadhir Al-Ansari and Zaher Mundher Yaseen	2019	Symmetry	1	1						1		
UNINTENDED NEGATIVE EFFECTS OF CLIENT PROJECT COST CONTROLS: A SYSTEM DYNAMICS APPROACH	A.M. Chitongo & L. Pretorius	2018	South African Journal of Industrial Engineering	1	1								
A dynamic model for project review in the construction industry		2011	Journal of information technology and	1	1	1							

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
			construction										
System Dynamics Model of Contractual Relationships between Owner and Contractor in Construction Projects	Muhammad Kamran Nasir1 and Bonaventura H. W. Hadikusumo	2019	Journal of Management in Engineering								1		
System Dynamics for Outsourcing Construction Services	Stephen D. Lisse	2013	International Journal of Construction Engineering and Management	1	1							1	
A system dynamics approach to risks description in megaprojects development		2012					1						
A System Dynamics Approach to Evaluate Incentive-based Policies, Human Resource Motivation and Performance of Public Sector Organizations	Federico Cosenz and Carmine Bianchi	2014	RJSH Vol. 1 No. 1									1	
System Dynamics (SD) -based concession pricing model for PPP highway projects	Yelin Xu a, b,⁎, Chengshuang Sun c, d, Miroslaw J. Skibniewski c , Albert P.C. Chan e , John F.Y. Yeung f , Hu Cheng a	2011	International Journal of Project Management		1		1						
Using a hybrid system dynamics and interpretive structural modeling for risk analysis of design phase of the construction projects	Hannaneh Etemadinia & Mehdi Tavakolan	2018	International Journal of Construction Management				1						
Examining transition pathways to construction innovation in Russia: a system dynamics approach	Emiliya Suprun, Oz Sahin, Rodney Anthony Stewart & Kriengsak Panuwatwanich	2019	International Journal of Construction Management		1	1					1	1	
A Dynamic Model of Contractor-Induced Delays in India	Dillip Kumar Das and Fidelis Emuze	2017	Journal of Construction in Developing	1	1	1	1	1	1	1	1	1	1

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
			Countries,										
USING SYSTEM DYNAMICS MODELLING PRINCIPLES TO RESOLVE PROBLEMS OF REWORK IN CONSTRUCTION PROJECTS IN NIGERIA	Olatunji A. AIYETAN 1 and Dillip DAS2	2015	Journal of Construction Project Management and Innovation	1	1	1	1	1	1	1	1	1	1
Modelling Construction Project Management Based on System Dynamics	Yujing, Wanga , Yongkui, Lib , Peidong, Guoc	2015	metaljournal/ Machine building/ Metallurgical and Mining Industry	1		1							
APPLYING SYSTEM DYNAMICS FOR NUCLEAR POWER PLANT DESIGN	Stephen D. Lisse	2014	Proceedings of the ASME 2014 Small Modular Reactors Symposium	1	1							1	
Modelling the dynamics of design error induced rework in construction	Peter E. D. Love , Purnendu Mandal , Jim Smith & Heng Li	2010	Construction Management and Economics	1	1	1	1					1	
Dynamic Modeling for Analyzing Impacts of Skilled Labor Shortage on Construction Project Management	Sungjin Kim, Ph.D.1 ; Soowon Chang2 ; and Daniel Castro-Lacouture, Ph.D., P.E., M.ASCE	2019	e Journal of Management in Engineering,	1	1	1	1					1	
RESOLVING CONTRACTOR COMMITMENT CHALLENGES IN PROJECT DELIVERY BY USING CONCETPUAL SYSTEM DYNAMICS MODELS	Olatunji Ayodeji AIYETAN1 and Das DILLIP	2016	Journal of Construction Project Management and Innovation	1	1	1	1				1	1	

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
Modeling the rework cycle: capturing multiple defects per task	Hazhir Rahmandada * and Kun Hua	2010	System Dynamics Review										
DEVELOPMENT OF MECHANISMS BY USING CONCEPTUAL SYSTEM DYNAMICS MODELS TO RESOLVE DELAY IN CONSTRUCTION PROJECTS	Diilip Kumar Das	2015	5th International/11th Construction Specialty Conference										
System Dynamics Approach to Mitigating Skilled Labour Shortages in the Construction Industry: A South African Context	Olatunji Ayodeji Aiyetan1* and Das Dillip2	2018	Construction Economics and Building	1	1	1	1					1	
Dynamic modelling of building services projects: A simulation model for real-life projects in the Hong Kong construction industry	Sammy K.M. Wana,∗ , Mohan Kumaraswamy b , Davis T.C. Liu	2013+ Accepted 15 June 2011	Mathematical and Computer Modelling										
Some results from a system dynamics model of construction sector competitiveness	Norman Gilkinsona,∗ , Brian Dangerfieldb	2013/ 2011	Mathematical and Computer Modelling	1	1				1				
Modelingthedynamicsofurbandevelopmentproject:Focusingonself-sufficientcitydevelopment	MoonseoParkYoungjooKimHyun-sooLeeSangwonHanSungjooHwangMinJiChoi	2013 / Accepted 31May2011	Mathematical and Computer Modelling										
Circular Economy Model of Indonesian Construction Industry Waste Based on System Dynamics	Trie Sony Kusumowibowo 2nd Tri Joko Wahyu Adi	2019	Third International Conference on Sustainable Innovation 2019 – Technology and Engineering										

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
Modeling the Impact of Design Rework on Transportation Infrastructure Construction Project Performance	Ying Li1 and Timothy R. B. Taylor, M.ASCE	2014	Journal of Construction Engineering and Management	1	1	1	1						
Dynamics of Working Hours in Construction	Amin Alvanchi1 ; SangHyun Lee, A.M.ASCE2 ; and Simaan AbouRizk, M.ASCE	2012	Journal of Construction Engineering and Management	1		1	1					1	
Rework Causation: Emergent Theoretical Insights and Implications for Research	Peter E. D. Love, Ph.D., Sc.D.1 ; David J. Edwards, Ph.D.2 ; and Jim Smith, Ph.D.	2016	Journal of Construction Engineering and Management	1	1	1	1						
Assessment of labor productivity in construction projects using system dynamic approach	M. Khanzadia; , A. Kavehb , M. Alipoura and R. Khan Mohammadia	2016	Sharif University of Technology	1			1					1	
A Framework for Modelling Masonry Construction Using Hybrid Simulation Approaches	Orsolya Bokor, Laura Florez, Allan Osborne, Barry J. Gledson	2018	Creative Construction Conference 2018, CCC 2018, 30 June - 3 July 2018, Ljubljana, Slovenia	1								1	
Dynamic Management of Risk Contingency in Complex Design-Build Projects	Alberto De Marco, Ph.D.1 ; Carlo Rafele2 ; and Muhammad Jamaluddin Thaheem, Ph.D.3	2015	Journal of Construction Engineering and Management		1		1						
Dynamic Modeling of Building Services Projects: A Simulation Model for Real-Life Hospital Project	V. Abhishek1 and P. Jagadeesh2	2013	Journal of Construction	1	1		1	1				1	

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
			Engineering and Project Management										
System Dynamics Approach for Investigating the Risk Effects on Schedule Delay in Infrastructure Projects	Jiayuan Wang1 and Hongping Yuan, Ph.D.	2016	Journal of Management in Engineering	1			1						
Applied Systems Analysis for Analysing Challenges in Construction Projects: A Methodological Approach	Dillip Kumar Das		: CIDB 2019, The Construction Industry in the Fourth Industrial Revolution, pp. 168–178, 2020.	1		1	1						
Dynamic Simulation Model for Project Change-Management Policies: Engineering Project Case	Ramin Ansari	2019.	Journal of Construction Engineering and Management	1			1			1	1	1	
A system dynamics approach to determine construction wastedisposal charge in Hong Kong	Tiffany M.W. MakPi-Cheng ChenLei WangDaniel C.W. TsangS.C. HsuChi Sun Poon	2019	Journal of Cleaner Production		1	1							
Using System Dynamics for Strategic Performance Management in Construction	Acelya Ecem Yildiz, Ph.D.1 ; Irem Dikmen2 ; and M. Talat Birgonul3	2019	Journal of Management in Engineering	1		1	1						
Application of System Dynamics in Environmental Risk Management of Project Management for External Stakeholders	Chao-Chung Yang • Chao-Hsien Yeh	2013	Syst Pract Action Res				1				1	1	
Modeling and analysis of water resources system problems by using the causal feedback loop diagram of system dynamics	CHIU-SUNG LIN1 , CHAO-CHUNG YANG2 , CHAO-HSIEN YEH	2015	WSEAS TRANSACTIONS on				1					1	

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
			ENVIRONMENT and DEVELOPMENT										
A structure-based System Dynamics Approach for Assessing Engineering Design Processes	Daniel Kasperek, Markus Lindinger, Sebastian Maisenbacher, Maik Maurer			1		1	1	1				1	
System Dynamics Approach for Forecasting Performance of Construction Projects	Hany Leon1 ; Hesham Osman2 ; Maged Georgy3 ; and Moheeb Elsaid4	2017	Journal of Management in Engineering	1	1	1	1	1			1	1	
System Dynamics Modeling of Chinese Urban Housing Markets for Pedagogical and Policy Analysis Purposes	Xin Zhang1 & David Geltner 1 & Richard de Neufville	2018	J Real Estate Finan Econ										
Architecting systems-of-systems and their constituents: A case study applying Industry 4.0 in the construction domain	Jakob Axelsson1,2 Joakim Fröberg2 Peter Eriksson	2019	Systems Engineering	1				1			1		
First Attempt Toward a Holistic Understanding of the Interdependent Rippled Impacts Associated with Out-of-Sequence Work in Construction Projects: System Dynamics Modeling Approach	Ibrahim S. Abotaleb, A.M.ASCE1 ; and Islam H. El-adaway, F.ASCE2	2018	Journal of Construction Engineering and Management	1		1						1	
Managing Construction Projects through Dynamic Modeling: Reviewing the Existing Body of Knowledge and Deriving Future Research Directions	Ibrahim S. Abotaleb, A.M.ASCE1 ; and Islam H. El-adaway, F.ASCE	2018	Journal of Management in Engineering	1	1		1	1					
System dynamics modelling of construction safety culture	Sherif Mohamed, Thanwadee Chinda	2010	Engineering, Construction and Architectural Management				1						
A CONCEPTUAL SYSTEM DYNAMIC MODEL TO DESCRIBE THE IMPACTS OF CRITICAL WEATHER CONDITIONS IN MEGAPROJECT CONSTRUCTION	Boateng, P1 , Chen, Z2 , and Ogunlana, S.3	2012	Journal of Construction Project Management and	1	1		1						

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
			Innovation										
Circular Economy Model of Indonesian Construction Industry Waste Based on System Dynamics	Kusumowibowo, Trie Sony, and Tri Joko Wahyu Adi	2019	Third International Conference on Sustainable Innovation			1						1	
System Dynamics versus Agent-Based Modeling: A Review of Complexity Simulation in Construction Waste Management	Ding, Zhikun, et a	2018	sustainability			1						1	
Dynamics of Rework in Complex Offshore Hydrocarbon Projects	Love, Peter ED, et al.	2011	Journal of Construction Engineering and Management										
A System Dynamics Model for Construction Waste Resource Recovery Management in China	Guo, Hui	2016	Revista de la Facultad de Ingeniería U.C.V			1						1	
Dynamic analysis of construction and demolition waste management model based on system dynamics and grey model approach	Jia, Shuwei, Xiaolu Liu, and Guangle Yan	2018	*Clean Technologies and Environmental Policy* 20.9			1						1	
A Dynamic Model for Assessing the Effects of Construction Workers' Waste Behavior to Reduce Material Waste	Suciati, Herlina, Tri Joko Wahyu Adi, and I. Putu Artama Wiguna	2018	international journal on advanced science, engineering, information technology	1		1					1	1	
A system dynamics-based environmental benefit assessment model ofconstruction waste	Ding, Zhikun, et al.	2017	Journal of Cleaner	1	1	1					1	1	

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
reduction management at the design andconstruction stages			Production										
A system dynamics-based environmental performance simulationof construction waste reduction management in China	Ding, Zhikun, et al.	2016	Waste Management	1	1	1					1	1	
A system dynamics model for simulating urban sustainabilityperformance: A China case study	Tan, Yongtao, et al.	2018	Journal of Cleaner Production			1					1	1	
Using system dynamics principles for conceptual modelling to resolve causes of rework in construction projects	Aiyetan, Olatunji Ayodeji, and Dillip Das.	2015	*Journal of construction project management and innovation*	1	1	1		1		1	1	1	
A system dynamics model for assessing the impacts of design errors in construction projects	Han, Sangwon, Peter Love, and Feniosky Peña-Mora	2011	Mathematical and Computer Modelling	1		1							
Effects of Payment Delays at Two Links in Payment Chains on the Progress of Construction Projects: System Dynamic Modeling and Simulation	Xie, Hongtao, et al.	2019	Sustainability	1	1								
Developing safety archetypes of construction industry at project level using system dynamics	Mohammadi, Amir, Mehdi Tavakolan, and Yahya Khosravi.	2018	Journal of Safety Research	1	1		1				1	1	
Applying system dynamics for outsourcing services in design-build projects	Lisse, Stephen	2013	Journal of Project, Program & Portfolio Management	1	1							1	
Using System Dynamics Method to Manage Construction and Demolition Waste	Azhari, Fardin, Farshid Abdi, and Amir abbas Shojaie	2014	International Journal of System Dynamics Applications		1	1						1	

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
Someresultsfromasystemdynamicsmodelofconstructionsectorcompetitiveness	Gilkinson, Norman, and Brian Dangerfield.	2011	Mathematical and Computer Modelling						1				
Modelling critical risk factors for Indian construction project using interpretive ranking process (IRP) and system dynamics (SD)	Mhatre, Tanmay Nitin, J. J. Thakkar, and J. Maiti.	2017	International Journal of Quality & Reliability Management				1						
INTEGRATING BIM WITH SYSTEM DYNAMICS AS A DECISION-MAKING FRAMEWORK FOR SUSTAINABLE BUILDING DESIGN AND OPERATION	Bank, Lawrence C., et al	2010	First International Conference on Sustainable Urbanization	1	1		1	1	1			1	
A system dynamics model for evaluating the alternative of type in construction and demolition waste recycling center – The case of Chongqing, China	Zhao, W., H. Ren, and V. S. Rotter	2011	Resources, Conservation and Recycling		1	1						1	
A system dynamics model for determining the waste disposal charging fee in construction	Yuan, Hongping, and Jiayuan Wang.	2014	European Journal of Operational Research		1	1						1	
A SYSTEM DYNAMICS-BASED ECONOMIC PERFORMANCE SIMULATION OF CONSTRUCTION WASTE REDUCTION MANAGEMENT: EFFECTIVE APPLICATION OF PREFABRICATION	Maqsoom, Ahsen, et al.	2019	Environmental Engineering and Management Journal		1	1					1	1	
System dynamic analysis of construction waste recycling industry chain in China	Liu, Jingkuang, et al.	2019	Environmental Science and Pollution Research		1	1						1	

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
Feasibility Study of Concrete and Brick Waste Recycling Program using System Dynamics Modelling Approach	Doan, Dat Tien, and Thanwadee Chinda.	2015	Australian Journal of Asian Country Studies		1							1	
Modeling the Impact of Design Rework on Transportation Infrastructure Construction Project Performance	Li, Ying, and Timothy RB Taylor.	2014	Journal of Construction Engineering and Management	1	1	1							
System Dynamics Aproach For Quantitative Risk Allocaion	Khanzadi, Mostafa, Farnad Nasirzadeh, and Mahdi Rezaie.	2013	International Journal of Industrial Engineering & Production Research	1	1		1						
Studying Dynamic Decision-Making in Construction Management using Adaptive Interactive Simulations	Tang, Pei, Amlan Mukherjee, and Nilufer Onder.	2010	Construction Research Congress	1	1		1						
Dynamic Modeling of Workforce Planning for Infrastructure Projects	Sing, Michael CP, et al	2016	Journal of Management in Engineering	1								1	
Prediction System for Change Management in Construction Project	Zhao, Zhen Yu, et al.	2010	Journal of Construction Engineering and Management	1	1		1						
System dynamic modeling on construction waste management in Shenzhen, China	Tam, Vivian WY, Jingru Li, and Hong Cai.	2014	Waste Management & Research	1	1	1		1			1	1	
Towards greening the U.S. residential building stock: A systemdynamics approach	Onat, Nuri Cihat, Gokhan Egilmez, and Omer Tatari.	2014	Building and Environment	1	1	1			1		1	1	
A HYBRID FRAMEWORK FOR MODELING CONSTRUCTION OPERATIONS USING	Alzraiee, Hani, Osama Moselhi, and Tarek Zayed.	2012	Construction Research	1	1	1	1		1			1	

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
DISCRETE EVENT SIMULATION AND SYSTEM DYNAMICS			Congres s										
Environmental and economic impact assessment of construction and demolition waste disposal using system dynamics	Marzouk, Mohamed, and Shimaa Azab.	2013	Resourc es, Conserv ation and Recyclin g		1	1	1		1		1	1	
Integrating system dynamics and fuzzy logic modeling to determine concessionperiod in BOT projects	Khanzadi, Mostafa, Farnad Nasirzadeh, and Majid Alipour.	2012	Automat ion in Construc tion	1	1								
Dynamic modeling of labor productivity in construction projects	Nasirzadeh, Farnad, and Pouya Nojedehi	2013	Internati onal Journal of Project Manage ment	1	1	1	1	1	1		1	1	
Dynamic modeling of the quantitative risk allocationin construction projects	Nasirzadeh, Farnad, Mostafa Khanzadi, and Mahdi Rezaie.	2014	Internati onal Journal of Project Manage ment	1	1		1				1	1	
Analyzingsustainabilityinlow-incomehousingprojectsusingsystemdynamics	Marzouk, Mohamed, and Shimaa Azab.	2017	Energya ndBuildi ngs	1	1				1		1	1	
Using a hybrid system dynamics and interpretive structural modeling for risk analysis of design phase of the construction projects	Etemadinia, Hannaneh, and Mehdi Tavakolan.	2018	nternatio nal Journal of Construc tion Manage ment				1						
Evaluating system dynamics models of risky projects using decision trees: alternative energy projects as an illustrative example	Tan, Burcu, et al.	2010	System Dynamic s Review	1	1		1						
A system dynamics model for construction method selection with sustainability considerations	Ozcan-Deniz, Gulbin, and Yimin Zhu.	2016	Journal of Cleaner Producti on	1	1		1						
Evaluation of labor hiring policies in construction projects performance using system dynamics	Abbaspour, Soroush, and Shahin Dabirian.	2019	Internati onal Journal of Producti vity and Perform	1								1	

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
			ance Management										
Using system dynamics to better understand quality management in the construction industry	Olafsdottir, Anna Hulda, et al.	2019	International Journal of Productivity and Quality Management		1	1							
Designing a hybrid system dynamic model for analyzing the impactof strategic alignment on project portfolio selection	Rad, Farzad Haghighi, and Seyed Mojtaba Rowzan.	2018	Simulation Modelling Practice and Theory	1	1	1	1	1	1		1	1	
A dynamic system approach to risk analysis for megaproject delivery	Chen, Zhen, Prince Boateng, and Stephen O. Ogunlana.	2019	*Proceedings of the Institution of Civil Engineers-Management, Procurement and Law* 172.6	1	1	1	1			1	1	1	
SI model of measuring the success of strategies and decisions in construction projects using system dynamics	Okasha, Ahmed Abd El-Rady, Amir Arafa, and Nabil Amer.	2019	Engineering of Science and Military Technologies	1	1	1	1			1	1	1	
Identifying MajorProject Delay Causes in Egypt and Assessing their Impacts Using System Dynamics	Okasha, A. A., A. T. Arafa, and N. H. Amer	2018	12th International Conference on Civil and Architecture Engineering ICCAE-12-2018	1	1	1	1			1	1	1	

Title	Author	year of publication	Journal	Time	Cost	Quality	Risk	Communicati	Procurement	Scope	Stakeholder	Resource	Integration
A prototype system dynamic model for assessing the sustainability ofconstruction projects	Zhang, Xiaoling, et al.	2014	International Journal of Project Management	1	1	1	1		1		1	1	
Use of system dynamics as a decision-making tool in building designand operation	Thompson, Benjamin P., and Lawrence C. Bank	2010	Building and Environment	1	1	1	1				1	1	