

Integrated conceptual design of automated modular manufacturing
systems

By

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Abstract

In Canada, demand for automated construction manufacturing has increased, and, consequently, there has been an increase in the demand for automated manufacturing systems. An opportunity exists in Canada to tap into the growing market for automated manufacturing systems; however, there is limited experience in this area.

Designing a manufacturing system involves multiple technical disciplines consisting primarily of mechanical, electrical, and instrumentation and control engineers. A function modelling methodology during the conceptual design phase ensures that the various disciplines work according to a common design intent. A systematic approach to efficiently capturing the design intent promotes interdisciplinary communication, clarity, and early systematic determination of a functional design that fulfills customer needs.

Modern modular construction demands cost-effective and efficient production of high-quality components. These requirements have led to the emergence of offsite construction manufacturing, which enables the use of automated machines. Compared to traditional onsite methods, offsite modular construction has a positive impact on quality, safety, cost, and productivity. In this regard, a number of methodologies have been introduced with respect to the design of automated modular construction machines. This automation consists of not only the machines, but also the supportive electrical and pneumatic systems, where the design approaches used for the automated machines can also be applied to the design of their associated systems. Accordingly, the following problems addressed in this research are summarized.

Avoiding costly design changes necessitates a systematic, visual, transdisciplinary, and iterative design methodology during the conceptual design phase, which calls for matrix-

based model-based engineering approach. However, existing matrix-based model-based systems engineering approaches, when used independently, do not fully satisfy the aforementioned solution for avoiding costly design changes at the conceptual design phase. Identifying customer requirements is the most important activity in conceptual design. Reducing the design complexity at the customer requirement definition phase translates to further cost savings. Although current techniques are successfully used, they are limited in fulfilling this cost-saving opportunity. Finally, conceptual design methodologies do not exist for essential components, such as electrical control panels and controllers, of automated construction manufacturing machines. Currently, the common practice in machine control system design depends on experience and trial-and-error during the implementation phase. Thus, developing a methodology to incorporate controller design and planning at the conceptual design phase is an opportunity that can be advantageously explored.

A systematic and iterative design methodology during the conceptual design phase would help avoid costly design changes. An integrated function modelling methodology is proposed that combines the advantages of axiomatic design, design structure matrix, and integrated function modelling and applies the methodology to the design of an automated steel wall-framing machine. To reduce the design complexity at the customer requirement definition stage, machine learning techniques applied to a quality function deployment matrix can be investigated to overcome the limitations of existing techniques. Integrating the methodology developed for the integrated conceptual design solution with the dynamic representation of the quality function deployment matrix enables the early planning of controller design at the conceptual design phase. For the control panel, the conceptual

design method introduced facilitates the development of the subsequent computer-aided design at the detailed design stage. Integrated function modelling, combined with axiomatic design and design structure matrix, constitutes the conceptual design approach for the control panel. In this work, a linear time complex algorithm is developed for automating the layout of the electrical devices and wiring connections in order to facilitate computer-aided design implementation in the detailed design phase. Furthermore, the control panel guidelines and standards that constitute the prior knowledge of the design process are embedded in the algorithm.

This research builds on previous studies of the automated steel and wood wall-framing machine in providing a systematic approach to building automated modular manufacturing machines.

Preface

This thesis is the original work of Edgar C. Tamayo. Four journal papers and two conference papers related to this thesis have been submitted or published and are listed below. This thesis is organized in paper format by following the paper-based thesis guidelines.

1. **Tamayo, E. C.**, Khan, Y. I., Qureshi, A. J., and Al-Hussein, M. “Conceptual design of an automated steel wall framing assembly using axiomatic design and integrated function model.” *Construction Robotics*. (under review)
2. **Tamayo, E. C.**, Khan, Y. I., Qureshi, A. J., and Al-Hussein, M. (2018). “Design Automation of control panels for automated modular construction machines.” *Procedia CIRP 70*.
3. **Tamayo, E. C.**, Khan, Y. I., Qureshi, A. J., and Al-Hussein, M. “Integrating machine learning with QFD for selecting functional requirements in construction automation.” *Artificial Intelligence for Engineering Design, Analysis and Manufacturing* (under review)
4. **Tamayo, E. C.**, Qureshi, A. J., Musilek, P., and Al-Hussein, M. “Conceptual design of controllers for automated modular construction machines.” *Proceedings of the 2019 Creative Construction Conference*
5. **Tamayo, E. C.**, Bardwell, M., Qureshi, A. J., and Al-Hussein, M. (2017). “Automation of a steel wall framing assembly,” *Proceedings of the 9th International Structural Engineering and Construction Conference: Resilient Structures and Sustainable Construction*.

6. Mercado, J.G., **Tamayo, E. C.**, Wolfe, T., Fleck, B., and Qureshi, A. J. (2019).
“Design modeling for additive manufacturing in the case study of a systematic methodology applied to plasma transferred arc additive manufacturing.” *Procedia CIRP*.

Dedication

To Jesus, Mary and Joseph.

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List of Abbreviations

AD	Axiomatic Design
ANP	Analytical Network Process
APC	Advanced Process Control
CAD	Computer-aided Design
CR	Customer Requirement
DM	Design Matrix
DP	Design Parameter
DSM	Design Structure Matrix
FEED	Front-end Engineering Design
FA	Factor Analysis
FL	Fussy Logic
FR	Functional Requirement
IFM	Integrated Function Modeling
MBSE	Model-based Systems Engineering
MIMO	Multiple-input-multiple-output
PCA	Process Component Analysis
QFD	Quality Function Deployment
SISO	Single-input and Single-output
SYSMML	Systems Modeling Language
SVD	Singular Value Decomposition
UML	Unified Modeling Language

Chapter 1 Introduction

1.1 Motivation

Modern modular construction demands high quality, cost-effective, and efficient production of components. These requirements have led to the emergence of offsite construction manufacturing, which enables the use of automated machines. Compared to traditional onsite methods, offsite modular construction has a positive impact on quality, safety, cost, and productivity. In this regard, a number of methodologies have been introduced for the design not only of automated machines for modular prefabrication, but also of the supportive electrical and pneumatic systems for these automated machines, where the design approaches used for the automated machines can also be applied to the design of their associated systems. To avoid costly design changes, a systematic and iterative design methodology is greatly needed in the conceptual design phase.

Construction automation is expected to increase in prevalence due to the inherent inefficiencies and limitations of conventional construction practice (Bock 2015). For example, Tamayo et al. describe an automated machine used in modular construction for steel wall framing and the associated control system that uses a supervisory control and data acquisition (SCADA) or device level (Tamayo et al. 2017). Difficulties may arise when developing a complex system such as those employed in construction automation. Abdelrazek et al. (2017) identify these difficulties and advocate the use of a model-based systems engineering (MBSE) methodology. However, to effectively address the issues concerning the design of a complex system, an MBSE methodology must be systematic, iterative, visual, and transdisciplinary and must be initiated at the conceptual design phase.

An integrated function modelling approach, combined with axiomatic design and design structure matrix, satisfies these criteria.

An integrated conceptual design methodology that is adopted in this research proposal is the integrated function modeling (IFM) approach. However, this methodology lacks the mathematical framework that current state of the art methods such as axiomatic design (AD) and design structure matrix (DSM) possess. This research proposal provides the mathematical models for applicability of IFM as a scientific approach. Moreover, mathematical formulations are introduced for the repeated use of quality function deployment (QFD) throughout the stages of conceptual design, namely: (a) customer requirements definition, (b) IFM development, and (c) control strategy development and control panel design. For the control panel, the conceptual design method introduced in this paper facilitates the subsequent computer-aided design to be performed at the detailed design stage. Integrated function modelling combined with axiomatic design and design structure matrix constitutes the conceptual design approach for the control panel. In this work, a linear time complex algorithm is developed for planning the layout of the electrical devices and for optimizing the wiring connections of these devices. Embedded in the algorithm are the control panel guidelines and standards that aid in the design process.

QFD will be shown to have numeric, Boolean, and transfer function representation depending on which stage of the conceptual design is being developed. An important aspect of the conceptual design is the customer requirement definition stage, where an optimal number of functional requirements (FRs) are specified. To facilitate a systematic specification of FRs, state-of-the-art machine learning techniques will be introduced in the feature selection of FRs.

1.2 Statement of Problem

Construction automation is expected to increase in prevalence due to the inherent inefficiencies and limitations of conventional construction practice (Bock 2015). It is expected that the difficulties in defining customer requirements, in generating documentation and in carrying out traceability may arise during the development of a complex system, such as that of construction automation (Abdelrazek et al. 2017). To overcome these difficulties, Abdelrazek et al. (2017) propose the use of model-based systems engineering (MBSE) methodology. IFM is an excellent MBSE methodology but it does not completely meet the criteria of a conceptual design framework since it requires detailed information to build it and that it lacks the mathematical basis needed for a robust and repeatable process.

Once a mathematical framework is established for IFM, the next issue to address is to determine the minimum number of FRs. Moreover, which technique could be used that works around the difficulties inherent in using other techniques, such as analytical network process (ANP) and fuzzy logic (FL)?

Machine control system design is another area requiring a theoretical framework since it is usually approached from experience and trial-and-error procedures (Lee et al. 2001). Similarly, control panel design can benefit from the application of a conceptual design methodology.

In summary, the questions that this research addresses are as follows:

1. How can the existing matrix-based design model-based systems engineering design approaches be used in the conceptual design of automated modular construction machines that is systematic, visual, transdisciplinary, and iterative?

2. How can a mathematical basis be established for a repeatable application of the integrated function modeling framework?
3. How can machine learning techniques be leveraged for reducing design complexity at the customer requirement definition phase of conceptual design?
4. How can design of electrical control panels and controllers be incorporated in conceptual design?
5. Every matrix-based model-based systems engineering approach is basically an application of quality function deployment. Currently, the quality function deployment represents static data. In conjunction with question 4, can quality function deployment represent dynamic data and therefore facilitate dynamic simulation in conceptual design?

1.3 Background and Literature Review

1.3.1 Current state of the art in integrated system design and product modelling

QFD, a concept created in Japan in the 1960s, is a methodology used by the product development team to identify customer needs and to evaluate the influence of a product or service on achieving these needs (Subbaiah et al. 2016). For the purpose of developing conceptual design methodologies in this proposal, QFD will be referred to as a methodology used by the design team to identify CRs and mapping them to FRs.

1.3.2 Identifying CRs and determining the minimum FRs

Information collecting is one of the tasks of the production design team (Pahl & Beitz, 2013). Customer requirements are identified and finalized in this information collecting activity. Using their expertise, engineering knowledge and company database, the product

design team maps functional requirements against the final customer requirements. This important aspect of conceptual design is referred to in this thesis, the customer requirement definition phase.

Rating the importance of FRs is achieved using techniques such as analytical network process (ANP), FA, fuzzy logic (FL), and principal component analysis (PCA). Karsak et al. (2003) use ANP to rank the FRs and zero-one goal programming to determine the FRs to consider in designing the product. Mazurek and Kiszová (2012) provide two disadvantages of ANP: (1) obtaining the correct network structure is difficult, and (2) forming the supermatrix by pair-wise comparison of all criteria is difficult and unnatural. To overcome these difficulties, Kiszová et al. (2012) suggest the use of fuzzy logic. However, requirement prioritization through fuzzy logic is prone to error due to its reliance on experts (Achimugu et al. 2014). FA is described in a paper by Shin & Kim (2007) as being a classical statistical technique that does not have the difficulties encountered in ANP or fuzzy logic, but Venkata Subbaiah et al. (2016) give preference to PCA over FA due to the weakness of the latter in handling strongly correlated requirements. Weber et al. (2013) have explored PCA in features prioritization of an airport, but have not used this state-of-the-art machine learning technique for features selection that establishes the criteria for determining the minimum FRs.

1.3.3 Conceptual design methodology for automated modular construction manufacturing systems

Bock (2015) argues that the motivation for the automation of construction is that conventional construction methodology has reached its limit. He discusses areas in construction where robotics can be deployed. For building prefabrication, he suggests

automation and robotic technologies for customized components such as concrete, wood, steel, and masonry, but he does not specify the methods for panelized wall frames. Efficiently designing automating technologies for panelized wall frames or for construction methods in general requires functional modelling methodologies to avoid costly construction errors. Elaborating on past and present standardization efforts, Other MBSE solutions are unified modelling language (UML) and systems modelling language (SysML). Rachuri et al. (2003) describe the application of a core product model (CPM) to an electro-mechanical assembly using UML. In multi-storey modular building construction, Ramaji et al. (2008) use UML to represent a product-based design methodology called product architecture model (PAM). Valdes et al. (2016) apply SysML, an extension of UML, to building construction with the objective of minimizing costly construction errors due to conflicting design specifications. Due to its inadequacy in visually representing the system architecture, as noted by Torry-Smith et al. (2011), SysML loses its communication effectiveness in the conceptual design phase where models frequently change. To overcome this and other challenges associated with interactions of DPs, this paper proposes a matrix-based integrated solution involving AD, DSM and IFM, which are then described in the following discussion.

Suh (1997) describes traditional systems design as that based on know-how and trial and error, which can lead to costly errors. Suh (1998) presented the systems design theory based on AD. AD documents the system architecture of a design that maps the design objectives into a hierarchy of FRs, DPs, and process variables (PVs). Aside from the documentation aspect, Suh (1995) defines AD as a thinking process that incorporates fundamental

principles during a synthesis or mapping exercise. Gu et al. (2001) have applied AD to the design of a furniture manufacturing system.

DSM is another design methodology that was developed by Steward (1981). It has been applied to the design of products, organizations, and processes (Browning 2016). Its shortcoming stems from the difficulty of developing the DSM at the conceptual design stage for new designs (Tang et al. 2009). To overcome this shortcoming, the DSM has to be derived from the design matrix (DM).

Tang et al. (2008) underscore the shortcomings of AD in limiting itself to system architecture and thus its inadequacy in providing the final design solution since it does not consider the interactions among DPs. The authors indicate that DSM is a structure modelling method that represents the interactions among DPs. Dong and Whitney (2001) present a technique of obtaining DSM from the DM derived from AD.

Motivated by the need for a theoretical basis for design modelling, Eisenbart et al. (2011) compared design modelling methods used by different disciplines such as mechanical engineering, electrical engineering, mechatronics, software design, and building design. Eisenbart et al. (2013), by analyzing the function modelling approaches of different disciplines, identify an IFM framework consisting of states, effects, transformation processes, interaction processes, use case, technical system allocation, and stakeholder allocation. Eisenbart et al. (2014) adopt design structure matrices in presenting the concept of IFM and use the example of a coffee vending machine in order to describe the approach. Their elaborated IFM framework includes use case, transformation processes, interaction processes, effects, states, technical subsystems, stakeholder, and environment. They have

outlined further enhancement of the IFM approach using a software tool that will automate the design modelling.

Eisenbart et al. (2015) list the advantages and disadvantages of IFM and SysML as design modelling methodologies; for example, IFM requires less modelling effort compared to SysML. In addressing the complexity and consistency of function modelling, Eisenbart et al. (2017) devise an IFM framework that incorporates DSM. Since it incorporates DSM, IFM inherits the difficulty of forming the interactions among the DPs for new designs. As previously discussed, the DSM should be developed by first forming DM from AD and translating the DM to DSM following the procedure developed by Dong and Whitney (2001). It should be noted, though, that IFM, as a new method, has not yet been utilized in modular construction design.

An integrated AD, DSM and IFM systems engineering solution provides an effective representation of the system architecture of a manufacturing system, such as the steel wall-framing machine, due to the following advantages: (1) provides a compact visual representation of the system architecture (this feature is important in ensuring that updates to the documentation consistently accommodate constantly changing models at the conceptual design phase); (2) promotes creativity in the application of fundamental principles and mapping of the design objectives into FRs, DPs and PVs; (3) clearly communicates interactions among DPs, transformation processes, use cases, and states; and (4) provides mathematical support to the resulting IFM framework due to the integration of AD and DSM, which have a mathematical basis.

1.3.4 Customer requirements and minimum functional requirements

In the literature, the current techniques for choosing FRs are analytical network process (ANP), factor analysis (FA), fuzzy logic (FL), and principal component analysis (PCA). Mazurek and Kiszová (2012) have listed two disadvantages of ANP: (1) obtaining the correct network structure is difficult, and (2) forming the supermatrix by pair-wise comparison of all criteria is difficult and unnatural. To resolve these shortcomings, they have suggested to use FL. Due to its reliance on experts, however, FL is prone to error (Achimugu et al. 2014). A classical technique that does not have the difficulties associated with ANP or FL, FA has been introduced by Shin and Kim (2007). These authors, however, have not used FA as a means of selecting FRs but as a method of restructuring the QFD. Moreover, FA lacks the ability to handle strongly correlated FRs (Subbaiah et al. 2016).

1.3.5 Conceptual design of control strategies and control panels

To correct the usual practice in machine control system design that depends on experience and trial and error, Lee et al. (2001) have illustrated the applicability of axiomatic design (AD) in developing control solutions. These authors have not gone through the use of QFD and process control decoupling techniques. QFD is a tool to align product design with customer needs (Franceschini 2002). A sequence of QFDs has been applied from customer needs identification, product planning, part planning, process planning, and production control (Quesada & Bahill 2003), which depicts the usefulness of QFD as a design and analysis tool. Although not specifically called QFD, Lahiri (2017) has applied the methodology to develop a step test plan in the form of an expectation matrix for modelling a multivariable process. A formalized conceptual design methodology is still required in designing a control strategy.

An example of a control system for an automated modular construction machine is described in a paper by Tamayo et al. (2017). In this construction automation or in any manufacturing system automation, control panels play the important role of: (i) housing the electrical devices supporting the field devices, and (ii) maintenance and troubleshooting of these field devices. Design and optimization of control panels are usually done at the detailed design phase using computer aided design (CAD) tools. Computer aided engineering (CAE) assists planning and design of a control panel involving engineers, customers, suppliers, and system integrators (Control Design 2015). Kang et al. (2008) describe a computer-aided design method of designing a control panel to meet functional requirements and ergonomic restrictions. Thus, there is a need for a collaborative control panel design at the conceptual design phase prior to any activity, such as computer-aided design, at the detailed design phase.

1.4 Research Gaps

In summary, the above literature review reveals the following research gaps that have been addressed in this thesis.

1. An integrated conceptual design methodology for automated modular construction machines needs to be systematic, iterative, visual, and transdisciplinary. IFM satisfies these desired qualities of an integrated conceptual design methodology; however, since it is DSM-based it inherits the difficulty of developing the DSM during the conceptual design phase.
2. For IFM to be confidently used as a systematic and scientific design methodology, it has to be formalized in a quantitative, traceable, and repeatable framework. Unlike

AD and DSM, IFM in its current state in the literature lacks the mathematics that describes its formulation.

3. A research opportunity arises in identifying a suitable feature selection technique in the CR determination phase of conceptual design that overcomes the shortcomings of current techniques such as ANP, FA and FL.
4. A methodology for incorporating controller considerations at the conceptual design phase is lacking in the literature. Addressing this research gap brings about an opportunity to introduce the dynamic aspect of QFD.
5. A conceptual design methodology for control panel design does not currently exist in the literature. Addressing this research gap advances the design methodology towards automation of the conceptual design of a control panel.

1.5 Research objectives

This research is built on the following hypothesis:

“Incorporating axiomatic design and design structure matrix into an integrated function model reduces the cost of design changes and streamlines communication within the interdisciplinary design environment.”

Precluding experience and trial-and-error in design requires a conceptual design methodology for automated modular construction machines is iterative, visual, and transdisciplinary. IFM possesses these attributes, however, it lacks the theoretical framework for it to be scientific.

IFM relies on appropriately identifying CRs and determining the minimum number of FRs. An alternative approach of systematically determining the minimum FRs that does not have the difficulties of current state-of-the-art methodologies has to be investigated.

Machine control system design and control panel design are usually performed using experience and trial and error. Conceptual design methodologies developed in this research can be extended to the selection of control strategies and the design of a control panel.

To validate this hypothesis, the following four research objectives are pursued:

1. Development of a conceptual design methodology for automated modular construction manufacturing systems.
2. Development of the mathematical framework for IFM.
3. Development of a methodology for determining the minimum FRs.
4. Application of the methodology to the conceptual design of controllers and to the design automation of a control panel.
5. In conjunction with the fourth objective, develop a methodology for incorporating dynamics into quality function deployment.

1.6 Organization of thesis

This thesis comprises six chapters. Following the introduction in Chapter 1, Chapter 2 presents the integrated conceptual design of automated modular construction machines. Chapter 3 describes the integration of machine learning with QFD for selecting functional requirements in construction automation. Chapter 4 incorporates dynamics into QFD in the conceptual design of controllers for automated modular construction machines. Chapter 5 presents the design automation of control panels for automated construction machines. Finally, Chapter 6 provides conclusions and summarizes the research contributions, limitations, and direction of future work.

Chapter 2 Integrated Conceptual Design of Automated Modular Construction¹

Machines

2.1 Introduction

Design iterations become costlier as a project progresses due to the increasing amount of effort and resources committed to obtain greater certainty about the cost of implementing the project (MacLeamy 2004). In construction projects, where significant capital outlay is incurred, changes beyond the conceptual design phase cause an exponential rise in costs and delays in project completion. Typically, these phases are: conceptual design, front-end engineering design (FEED) or basic engineering, detailed engineering, and implementation. Uppal (2001) indicates the cost estimate accuracies in conceptual, FEED, and detailed engineering to be ± 50 , ± 30 , and ± 10 , respectively, where an increase in cost certainty reflects a corresponding increase in the design effort and resources required. To avoid costly changes, construction managers follow a gated approval process to ensure the design requirements are fulfilled before moving to the next phase (Chao & Ishii 2005). Engineering design packages produced during each phase provide estimates of the project cost and facilitate communication in order to fulfill the design intent of the project among the various stakeholders involved (Oberlender 2014).

Similarly, in designing and implementing manufacturing systems, communication of the design intent is vital to avoid costly iterations throughout the various phases of the project (Chiu 2002). Manufacturing system projects have a more rapid turnaround and are less costly than traditional construction projects, so the FEED phase is omitted from the process

¹ The manuscript appearing as Chapter 2 of this thesis was submitted to the Construction Robotics Journal, at the time of publication of this thesis.

(Adams 2015, Zein 2011). Figure 2.1 illustrates how additional costs arise in a construction manufacturing project during design and as a result of design changes (MacLeamy 2004). Figure 2.1 also serves to reinforce the motivation, described in a paper by Dong & Whitney (2001), which underlies the development of a methodology for obtaining information early in the design process, at which time the cost of changes is low and the positive impact on the project is high. Thus, the proposed methodology described in the figure is best utilized at the conceptual design phase of the manufacturing system. The proposed design methodology combines the advantages of axiomatic design (AD), design structure matrix (DSM), and integrated function modelling (IFM). Functional requirements (FRs) and design parameters (DPs) form the design matrix (DM) that constitutes the AD. DM is then used to form the DSM, which is basically the interaction matrix of IFM. Thus, AD and IFM complement one another and can be combined as a design methodology in the conceptual design phase.

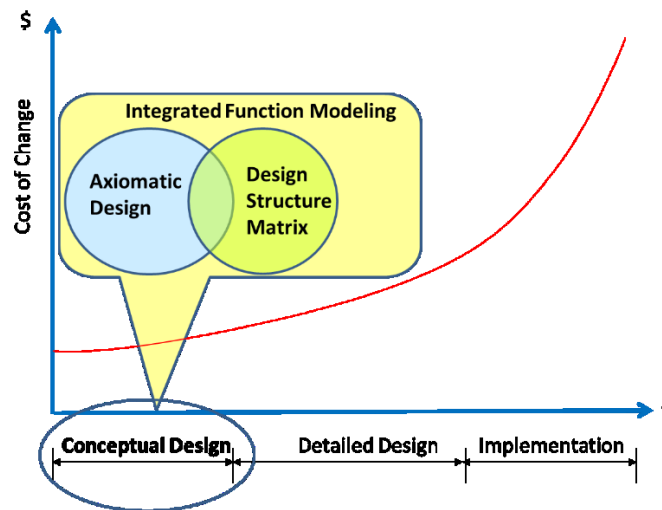


Figure 2.1. Cost over time due to changes throughout the process of realizing a manufacturing system and the focus of the proposed integrated system design

The tasks in the conceptual design phase shown in Figure 2.1 include: (i) identifying customer needs, (ii) establishing target specifications, (iii) generating product concepts, (iv) selecting product concepts, (v) testing product concepts, (vi) setting final specifications, and (vii) planning downstream development (Ulrich & Eppinger 2012). Although prototyping is a method for selecting product concepts (Ulrich & Eppinger 2012), it does not mean that this method replaces the proposed design methodology. In a study by Betasolo et al. (2016), the AD process is used in developing a prototype.

Explicitly conveying the design intent to all disciplines necessitates the use of the model-based system engineering (MBSE) approach (Eisenbart et al. 2013). The proposed methodology takes advantage of the identified strengths of AD, DSM, and IFM. Table 2.1 summarizes the comparison of these three design methodologies. Details of this comparison are given in the ensuing sections. This paper describes a three-stage MBSE design for a manufacturing system and its application to the conceptual design of an automated steel wall-framing machine. To fully describe the three-stage approach, this chapter is structured as follows. Section 2.2 provides a literature review of the current state of the art in the conceptual design of modular construction machines and the current use of AD, DSM, and IFM in the design of manufacturing systems. Sections 2.3 and 2.4 respectively, illustrate the mathematical formulation and application of the three-stage system approach. A discussion of the practical application of the proposed methodology to the conceptual design of the automated steel wall-framing machine is provided in Section 2.5, followed by the discussion and conclusion in Sections 2.6 and 2.7, respectively.

Table 2.1. Comparison of Axiomatic Design, Design Structure Matrix and Integrated Function Modeling

Features	Axiomatic Design	Design Structure Matrix	Integrated Function Modeling
Useful in conceptual design phase (Dong & Whitney 2001)	✓		
Useful in detailed design phase (Dong & Whitney 2001)	✓	✓	✓
Iterative (Suh 1998, Browning 2016)	✓	✓	✓
Explicitly incorporates customer requirements	✓		
Compact visual representation of system architecture (Suh 1997, Browning 2016, Eisenbart et al. 2013)	✓	✓	✓
Accommodates mathematical formulation and techniques available in the literature (Suh 1997, Browning 2016)	✓	✓	
Considers interaction of Design Parameters (Browning 2016 (Eisenbart et al. 2017))		✓	✓
Features integrated multidisciplinary design framework (Eisenbart & Gericke 2017)			✓

2.2 Literature review

A summary of the current state of the art in the design of modular construction manufacturing systems is provided in this section, including: *(i)* description of the current state of the art in systems design in modular construction, and *(ii)* the proposed integrated AD and IFM MBSE solution in conceptual design.

2.2.1 Current state of the art in systems design in modular construction

The prevalent acceptance of automation in construction is due to the limitations of conventional construction methodology (Bock 2015). Robotics are employed to produce high quality, cost effective and efficient prefabrication of building components such as concrete, wood, steel, and masonry.

Unified Modeling Language (UML) and Systems Modeling Language (SysML) are graphical based MBSE solutions. Sudarsan et al. (2003) describe the application of a Core Product Model to an electro-mechanical assembly using UML as a precursor to standard for the exchange of product in the lifecycle of the product. In multi-storey modular building construction, Ramaji et al. (Ramaji et al. 2008)(2008) use UML to represent a product-

based design methodology called product architecture model. Valdes et al. (2016) apply SysML, an extension of UML, to building construction with the objective of minimizing costly construction errors due to conflicting design specifications. Due to its inadequacy in visually representing the system architecture, as noted by Torry-Smith et al. (2011), though, SysML loses its communication effectiveness in the conceptual design phase where models frequently change. To overcome this and other challenges associated with interactions of DPs, this research proposes an integrated matrix-based MBSE solution involving AD, DSM, and IFM.

2.2.2 Axiomatic design

Suh (1997) describes traditional systems design as a paradigm based on know-how and trial and error, which can lead to costly errors. Suh (1998) presents the systems design theory based on AD. AD documents the system architecture of a design that maps the design objectives into a hierarchy of FRs, DPs and process variables (PVs). Aside from the documentation aspect, Suh (1995) defines AD as a thinking process that incorporates fundamental principles during a synthesis or mapping exercise. Gu et al. (2001), meanwhile, apply AD to the design of a furniture manufacturing system.

2.2.3 Design structure matrix

DSM is a design methodology developed by Steward (1981) that has been applied to the design of products, organizations and processes (Browning 2016). Its shortcoming stems from the difficulty of developing the DSM at the conceptual design stage for new designs (Tang et al. 2009). To overcome this shortcoming, the DSM has to be derived from the DM.

Tang et al. (2009) underscore the shortcomings of AD in limiting itself to system architecture and thus its inadequacy in providing the final design solution since it does not consider the interactions among DPs. They indicate that DSM is a structure modelling method that represents the interactions among DPs. Dong and Whitney (2001) present a technique of obtaining DSM from the DM derived from AD.

2.2.4 Integrated function modelling

Motivated by the need for a theoretical basis for design modelling, Eisenbart et al. (2011), compare the design modelling methods used by different disciplines such as mechanical engineering, electrical engineering, mechatronics, software design, and building design. Eisenbart et al. (2013), by analyzing the function modelling approaches of different disciplines, identify an IFM framework consisting of states, effects, transformation processes, interaction processes, use case, technical system allocation and stakeholder allocation. Eisenbart et al. (2014) adopt design structure matrices in presenting the concept of IFM and use the example of a coffee vending machine in order to describe the approach. Their elaborated IFM framework includes use case, transformation processes, interaction processes, effects, states, technical subsystems, stakeholder and environment. They have outlined further enhancement of the IFM approach using a software tool that will automate the design modelling.

Eisenbart et al. (2015) list the advantages and disadvantages of IFM and SysML as design modelling methodologies; for example, IFM requires less modelling effort compared to SysML. In addressing the complexity and consistency of function modelling, Eisenbart et al. (2017) devise an IFM framework that incorporates DSM. Since it incorporates DSM in their framework, IFM inherits the difficulty of forming the interactions among the DPs for

new designs. As previously discussed, the DSM should be developed by first forming DM from AD and translating the DM to DSM following the procedure by Dong and Whitney (2001). It should be noted, though, that IFM, as a new method, has not yet been utilized in the design of automated machines for modular manufacturing.

An integrated AD, DSM, and IFM systems engineering solution provides an effective representation of the system architecture of a manufacturing system, such as the steel wall-framing machine, due to the following advantages: (1) it provides a compact visual representation of the system architecture (this feature is important in ensuring that updates to the documentation consistently accommodate constantly changing models at the conceptual design phase) (Abramovici 2013, Eisenbart et al. 2016, Hong and Park 2009); (2) it promotes creativity in the application of fundamental principles and mapping of the design objectives into FRs, DPs, and PVs (Suh 1995); (3) it clearly communicates interactions among DPs, transformation processes, use cases, and states (Eisenbart et al. 2016); and (4) it provides mathematical support to the resulting IFM framework due to the integration of AD and DSM, which have a mathematical basis (Browning 2016, N. P. Suh 1995).

2.3 Three-stage design methodology

As illustrated in Figure 2.1, the proposed systems engineering design of manufacturing systems is best applied in the conceptual design phase, i.e., the phase where models are most likely to change and where changes are least costly to make. In the detailed design phase, the functional models are implemented using CAD tools such as CATIA or SOLIDWORKS (from Dassault Systemès) for the mechanical systems and software and simulation tools for supervisory control and data acquisition (SCADA) systems. This

research focuses on the application of the integrated AD and IFM systems design approach to the conceptual design of manufacturing systems, particularly the case of an automated steel wall framing machine.

The ultimate goal of the three-stage design methodology is to build the integrated function modelling framework. As Table 2.1 indicates, the DSM and IFM cannot be built directly due to the unavailability of detailed information at the start of conceptual design, such as the customer requirement definition phase. AD, however, can be applied to form its design matrix. Any high-level information obtained at this initial phase is used to create the IFM. The final DPs obtained from the AD form the DSM, which eventually become a subset of the interaction view of the IFM.

2.3.1 Stage 1: Axiomatic design

IFM does not explicitly accommodate customer requirements, whereas axiomatic design (AD) does. AD, therefore, complements IFM since it translates the customer requirements in terms of FRs and considers how to achieve them within the given physical design parameters (DPs). In IFM, the first step is to determine the use cases and their associated high-level processes. This step is adopted in the AD stage since defining the main processes is the natural outcome of mapping the customer needs to the high-level FRs. At this stage, the process flow, use case, and actor views are then defined and constructed for the IFM. Subsequently, each process is broken down into the corresponding FRs and DPs. Following the work of Suh (1998) for the mapping of the functional domain onto the physical domain, the DM establishes the relationship between the FRs and DPs in binary notation expressed as:

$$\{FR\} = [DM]\{DP\} \quad (2.1)$$

$$DM_{ij} = \begin{cases} X, & \text{if an element or effect exists } i, j = 1..n \\ 0, & \text{otherwise} \end{cases} \quad (2.2)$$

To examine the impact of adjusting a DP to an FR, considering all other DPs as constant,

DM is expressed in terms of sensitivities $\frac{\partial FR}{\partial DP}$ and incremental FRs and DPs:

$$\{\Delta FR\} = [DM]\{\Delta DP\} \quad (2.3)$$

$$DM_{ij} = \begin{cases} X, & \text{if } \partial FR_i / \partial DP_j \neq 0, \\ 0, & \text{otherwise} \end{cases} \quad (2.4)$$

In advanced process control (APC) design, FRs and DPs are analogous to controlled variables and manipulated variables, respectively. Given this association, it is of interest to note that the design of multivariable controllers in APC projects is axiomatic, since this methodology also uses a DM in binary form during the brainstorming sessions of the conceptual design phase. At the detailed design phase, the DM consists of transfer functions relating the manipulated variables with controlled variables. This DM, expressed in Laplace transforms, clearly communicates the behaviour of the process to be controlled to the multidisciplinary team comprising the different stakeholders of the control design project. Once the dynamic DM is established, the multivariable controller is also established, because the controller is essentially the inverse of the open-loop DM. A system with a diagonal DM is easiest to control compared to those with coupled or decoupled DMs since the multivariable controller mainly consists of independent single-input-single-output (SISO) controllers. A SISO system provides an ideal situation that allows the simplest implementation of a multi-loop controller. Similarly, a SISO system in AD (Farid & Suh 2016) is an uncoupled design with a diagonal DM, which is concisely expressed as:

$$DM_{ij} = \begin{cases} X, & \text{if } i = j \\ 0, & \text{otherwise} \end{cases} \quad (2.5)$$

An uncoupled design satisfies the independence axiom (Suh 1998). A lower triangular DM is a decoupled design that also satisfies the independence axiom as expressed below.

$$DM_{ij} = \begin{cases} 0, & \text{if } i < j \\ X, & \text{otherwise} \end{cases} \quad (2.6)$$

$$\begin{aligned} \Delta FR_1 &= f\left(\frac{\partial FR_1}{\partial DP_1} \Delta DP_1\right) \\ \Delta FR_2 &= f\left(\frac{\partial FR_1}{\partial DP_1} \Delta DP_1, \frac{\partial FR_2}{\partial DP_2} \Delta DP_2\right) \\ &\vdots \\ \Delta FR_i &= f\left(\frac{\partial FR_1}{\partial DP_1} \Delta DP_1, \dots, \frac{\partial FR_i}{\partial DP_i} \Delta DP_i\right) \end{aligned} \quad (2.7)$$

ΔFR_i in Equation (2.7) is satisfied since it uses previously determined DPs, $DP_1 \dots DP_{i-1}$, and its corresponding DP, DP_i .

A coupled design, on the other hand, does not satisfy the independence axiom. Below is an example of a coupled design with full matrix DM.

$$DM_{ij} = X, \text{ for all values of } i \text{ and } j \quad (2.8)$$

thus,

$$\begin{bmatrix} \Delta FR_1 \\ \vdots \\ \Delta FR_n \end{bmatrix} = \begin{bmatrix} \frac{\partial FR_1}{\partial DP_1} & \dots & \frac{\partial FR_n}{\partial DP_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial FR_n}{\partial DP_1} & \dots & \frac{\partial FR_n}{\partial DP_n} \end{bmatrix} \begin{bmatrix} \Delta DP_1 \\ \vdots \\ \Delta DP_n \end{bmatrix} \quad (2.9)$$

$$\begin{aligned} \Delta FR_1 &= f\left(\frac{\partial FR_1}{\partial DP_1} \Delta DP_1, \dots, \frac{\partial FR_1}{\partial DP_n} \Delta DP_n\right) \\ &\vdots \\ \Delta FR_i &= f\left(\frac{\partial FR_i}{\partial DP_1} \Delta DP_1, \dots, \frac{\partial FR_i}{\partial DP_n} \Delta DP_n\right) \end{aligned} \quad (2.10)$$

Equation (2.10) reveals that an FR of a coupled design is difficult to control since more than one DP has influence over it. In this case, a direction must be provided to resolve the coupling issues (Do & Park 2001). Other forms of coupled design are those involving a

non-square DM, fat matrix, or tall matrix. Such cases necessitate a deeper analysis of the DPs in creating new DPs or choosing the best DPs (Farid & Suh 2016).

If there are multiple designs and the Independence Axiom is satisfied for each design, such as in the choice of DC motor, an engine, or a combination of DC motor and engine (hybrid) for prime movers, the best design is considered to be the one with the least information content (Do & Park 2001), or

$$I_{min} = \min \left\{ \sum_{i=1}^n I_i \right\} \quad (2.11)$$

where

$$\begin{aligned} I_i &= \log_2 \frac{1}{p} \\ &= \log_2 \left(\frac{\text{System range}}{\text{Common range}} \right) \end{aligned} \quad (2.12)$$

In Equation (2.12), p is the probability of satisfying the functional requirement FR_i . Equation (2.12) reflects the following three points: (1) simplicity in design is associated with the least information satisfying the FRs; (2) a simple design ensures a high probability of success in achieving the FRs, since, if p is at maximum, or equal to 1, then the information content I is 0; and (3) a simple design is fulfilled if FRs are consistently satisfied without bias.

A summary of the steps in the AD stage, also depicted in Figure 2.2, is provided below:

1. Identify the customer needs
2. Map the customer attributes onto the functional domain
3. Map the functional domain onto the physical domain

4. Check if the independence axiom is satisfied
5. Revise the design
6. Choose the best design, or least information content, if there are multiple designs

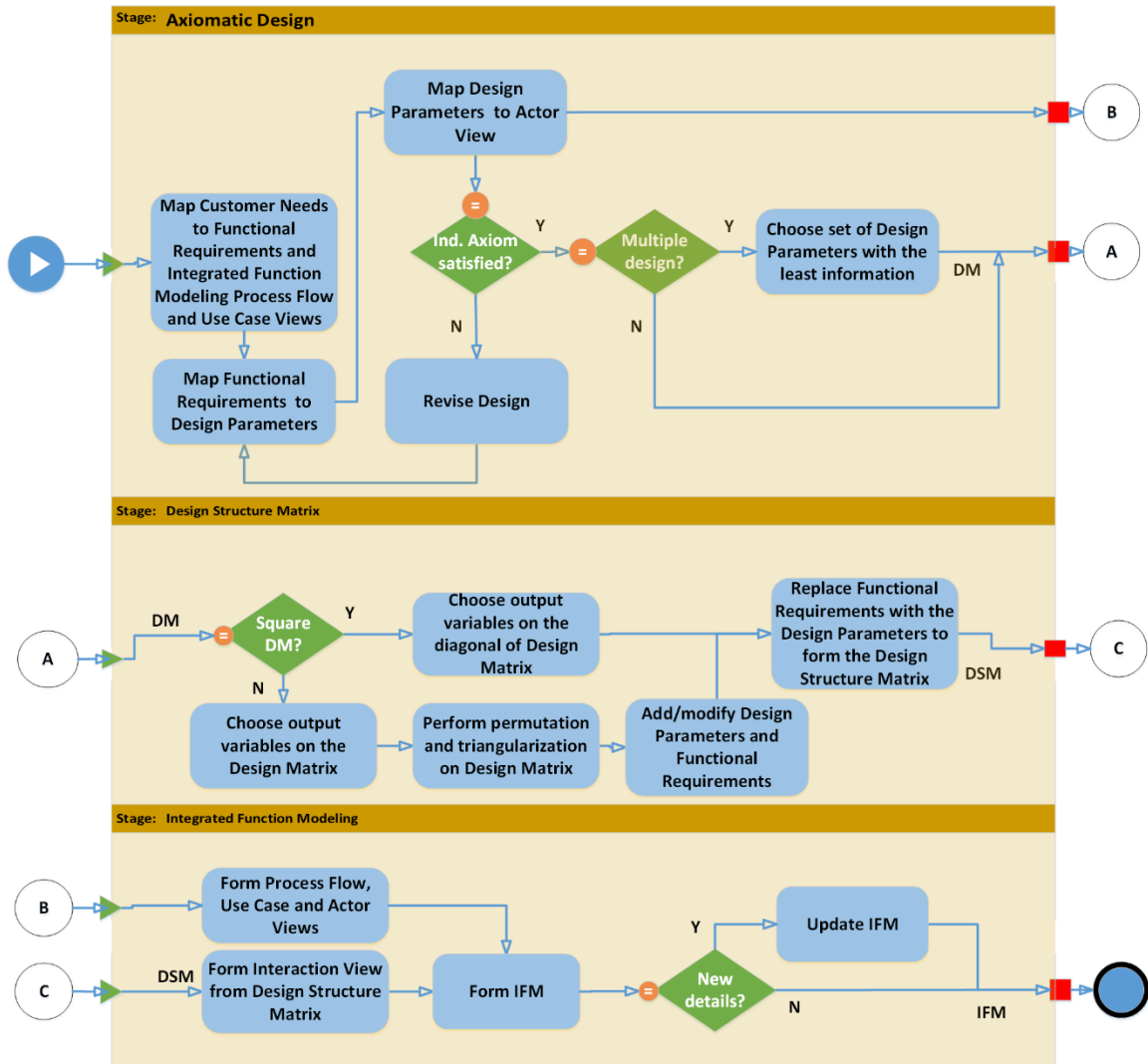


Figure 2.2. The three-stage approach

Figure 2.2 illustrates the significance of the AD stage due to its iterative procedure. It has been noted that the best phase during which to detect design errors and make changes is the conceptual design phase, where the cost impact of changes is still low. In the AD stage,

the design goals are fully communicated and design loopholes are identified and corrected through the iterative process. However, a process for considering the interaction among the DPs in order to finalize the design still does not exist in AD. This design process is discussed in the next section.

2.3.2 Stage 2: Design structure matrix

At the AD stage, the process flow, use case, and actor views of IFM are constructed. In the DSM stage, a method for building the interaction view in IFM by deriving the DSM from the DM obtained in AD is described. As previously discussed, the interaction view only includes the DSM.

Since DSM considers the interactions among DPs on an existing design, it is best utilized in the detailed design phase (Dong & Whitney 2001). After the design has been determined through AD, DSM can then be used to finalize the design, hence, the DSM method complements AD in the conceptual design phase.

Information about the interactions among the DPs is visualized by a matrix of DPs. Decomposition of DPs in the interaction matrix is referred to as the DSM method. Sequential, parallel, and coupled interactions are the different types of interactions in DSM, as described in Figure 2.3. Among these types of interactions, the reverse sequential and coupled interactions are undesirable due to the assumptions made by the preceding DPs to carry out their tasks. Decomposition of interaction matrices into lower triangular matrices in DSM, therefore, is the goal that can be achieved by minimizing the coupling of DPs through clustering, tearing, or triangularization (Guenov & Barker 2005).

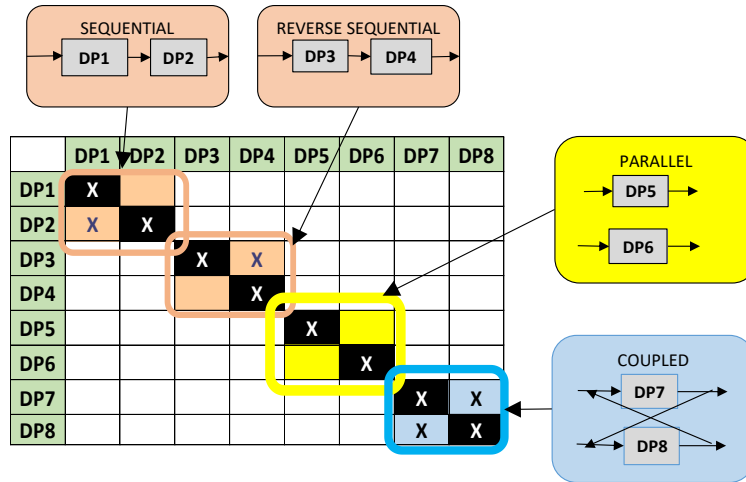


Figure 2.3. Types of interactions in design structure matrix

Coupled interactions such as those presented in Figure 2.3 may be unavoidable. For example, consider a position control mechanism in a closed-loop system consisting of a DC motor equipped with an encoder. The target position is provided as a setpoint, and the controller drives the motor to this setpoint based on the feedback information provided by the encoder. Relating this example to Figure 2.3, $G(s)$ and $H(s)$ are the motor assembly and control system transfer functions, respectively. Coupling between $G(s)$ and $H(s)$ signifies a feedback control signal, $Y(s)$, through the encoder that corrects the position of $G(s)$ until the setpoint, $R(s)$, is achieved. This closed-loop system is depicted in Figure 2.4. Evidently, a lesson can be drawn from this automatic feedback system: for complex systems, couplings are clustered into smaller independent modules to enable faster corrections to the assumptions made at the outset. A performance indication of the speed at which the feedback signal approaches the target is described by the closed-loop transfer function in Equation (2.13). If $K(s)$ is the controller transfer function for this control system, $H(s)$, then the closed-loop transfer function of this feedback system is:

$$\frac{Y(s)}{R(s)} = \frac{K(s)G(s)}{1 + K(s)G(s)} \quad (2.13)$$

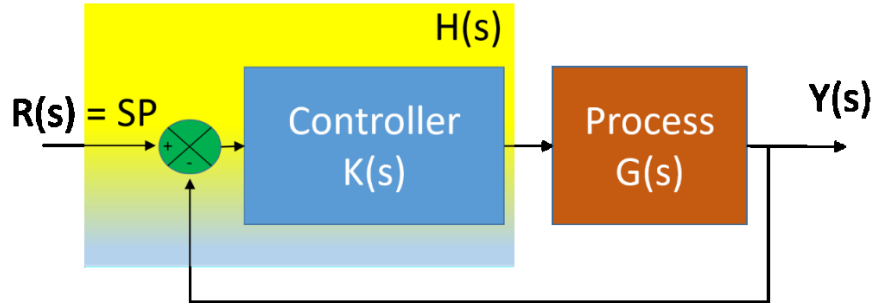


Figure 2.4. Coupled interaction for H and G in a feedback control loop

The AD phase having been completed, the DM is then finalized in the DSM stage. The dominant DP for each FR is chosen as the output variable of each row of the DM. For square DM, the output variables are simply the diagonal DPs; refer to the proof of this assertion in Dong and Whitney (2001). If DM is not square, however, the rows are permuted and DPs and FRs are added or modified while placing the output variables on the diagonal. This permutation is combined with triangularization and the FRs are replaced with the DPs of the columns to obtain the DSM (Guenov & Barker 2005). As in AD, DSM involves any of the forms discussed for DM, such as the following equations for a lower triangular matrix:

$$\{DP\} = [DSM]\{DP\} \quad (2.14)$$

where

$$DSM_{ij} = \begin{cases} 0, & \text{if } i < j \\ X, & \text{otherwise} \end{cases} \quad (2.15)$$

For an $n \times n$ DSM,

$$\begin{Bmatrix} DP_1 \\ \vdots \\ DP_n \end{Bmatrix} = \begin{bmatrix} X & & \\ \vdots & \ddots & \\ X & X & X \end{bmatrix} \begin{Bmatrix} \Delta DP_1 \\ \vdots \\ \Delta DP_n \end{Bmatrix} \quad (2.16)$$

2.3.3 Stage 3: Integrated function modelling

DSM of Equation (15), otherwise referred to as the interaction matrix, provides what is needed to build the interaction view of IFM. As in AD and DSM, IFM compactly displays its information in matrices.

Thus, IFM represents a complete picture of the system design for a cross-disciplinary group of technical and nontechnical stakeholders. Based on a survey with designers from various companies, Eisenbart et al. (2015) deem IFM to be useful. It is apparent from the components laid out in Figure 2.5 that IFM is a working framework that captures the interdisciplinary perspectives and facilitates communication of the design goals.

IFM portrays a comprehensive yet compact picture of the design since it encompasses the results obtained from AD and DSM, as well as any other information involved in the design. The procedure for forming the IFM is presented in Figure 2.2 and summarized in Table 2.2.

Table 2.2. Steps as outlined in Figure 2.6 for constructing the integrated function modelling, (Eisenbart et al. 2015)

Steps	Integrated Functional Modeling Display View	Description
①	Use case view	Lists the applications of the design and is built at the axiomatic design stage.
②	Process flow view	Describes the main processes for a specific use case and is built at the axiomatic design stage. Mathematically, the process flow view can be expressed in first order logic.
③	Actor view	Shows the assignment of design parameters that are used to satisfy the processes. This view is built at the axiomatic design stage using the first-level design parameters formed when mapping the functional requirements to the design parameters.
④	Interaction view	This is the design structure matrix derived from the design matrix and is built at the design structure matrix stage.
⑤	State view	Depicts the change in state or transformation caused by actors (design parameters) and operands (inputs) as the system goes through a series of processes to realize a finished product. This view completes the construction of the integrated function modelling.

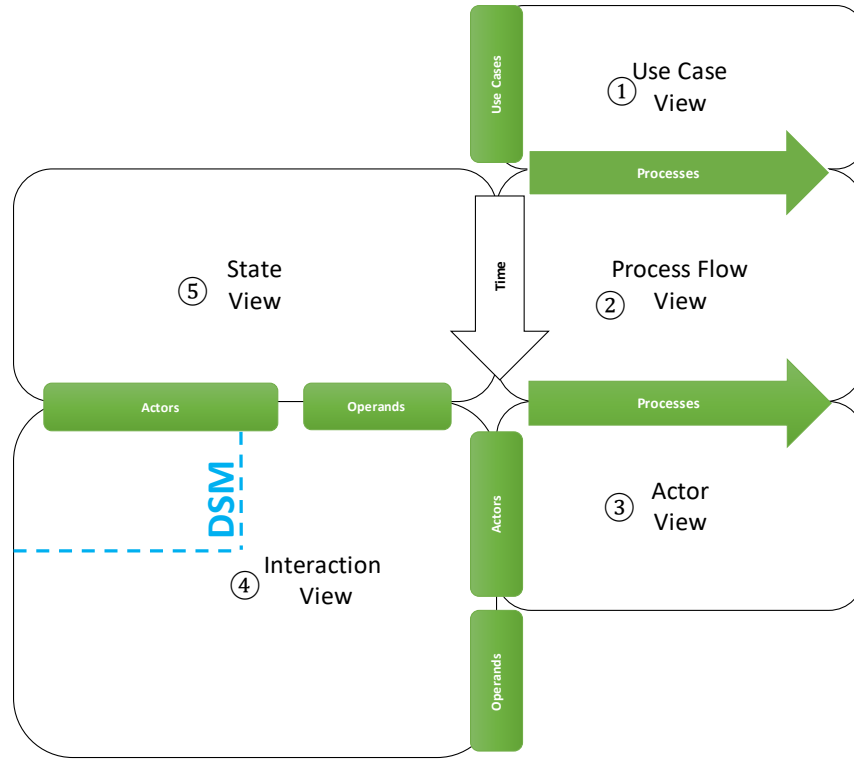


Figure 2.5. Complete integrated function modelling architecture

Mathematically, the formation of IFM using Table 2.2 and Fig. 2.5 can be expressed as follows:

$$\text{Use Cases, } U \leftarrow \{U_i \mid i \in [1, l]\} \quad (2.17)$$

$$\text{Processes, } P \leftarrow \{P_j \mid j \in [1, m]\} \quad (2.18)$$

$$\text{Actors, } A \leftarrow \{A_k \mid k \in [1, q]\} \quad (2.19)$$

$$\text{Operands, } O \leftarrow \{O_\lambda \mid \lambda \in [1, v]\} \quad (2.20)$$

$$\text{States, } S \leftarrow \{S_\theta \mid \theta \in [1, q + v]\} \quad (2.21)$$

$$DP \leftarrow \{DP_\mu \mid \mu \in [1, n]\}, \text{ set of DPs in DSM matrix} \quad (2.22)$$

$$DP \subset A \quad (2.23)$$

$$\forall U \exists r \in \{r_\pi \mid \pi \in [1,5]\}, \text{ where} \quad (2.24)$$

$$r_1: A \times P, \text{ relationship in Actor View} \quad (2.25)$$

$$r_2: U_i \times P, \text{ relationship in Process Flow View} \quad (2.26)$$

$$r_3: P \times P, \quad (2.27)$$

relationship of the adjacency matrix in Process Flow View

$$r_4: (A \cup O) \times (A \cup O), \text{ relationship in Interaction View} \quad (2.28)$$

$$r_5: S \times (A \cup O), \text{ relationship in State View} \quad (2.29)$$

From the above equations, l, m, q, v , and n are the number of use cases, processes, actors, operands, and DPs, respectively. Equation (2.20) indicates that the number of states corresponds to the total number of actors and operands. Equation (2.23) states that the DSM is a subset of the set of actors, which forms the interaction view. Equations (2.24) and (2.26) signify that each use case has its own process flow view. Finally, Equation (2.27) expresses the graphical representation of the process flow view, P , in terms of the relationship of its adjacency matrix, which is formed using the edges of P .

2.4 A Simple illustration

Describing the initial design of the automated steel wall framing machine provides a simple illustration of the basic steps of the integrated design approach depicted in Figure 2.2. For illustrative purposes, this example only considers the high-level FRs of the steel wall-framing machine depicted in Figure 2.6. A detailed illustration of the integrated design approach of the same steel wall frame machine, which includes addressing a potential coupling concern, will be provided in the next section.

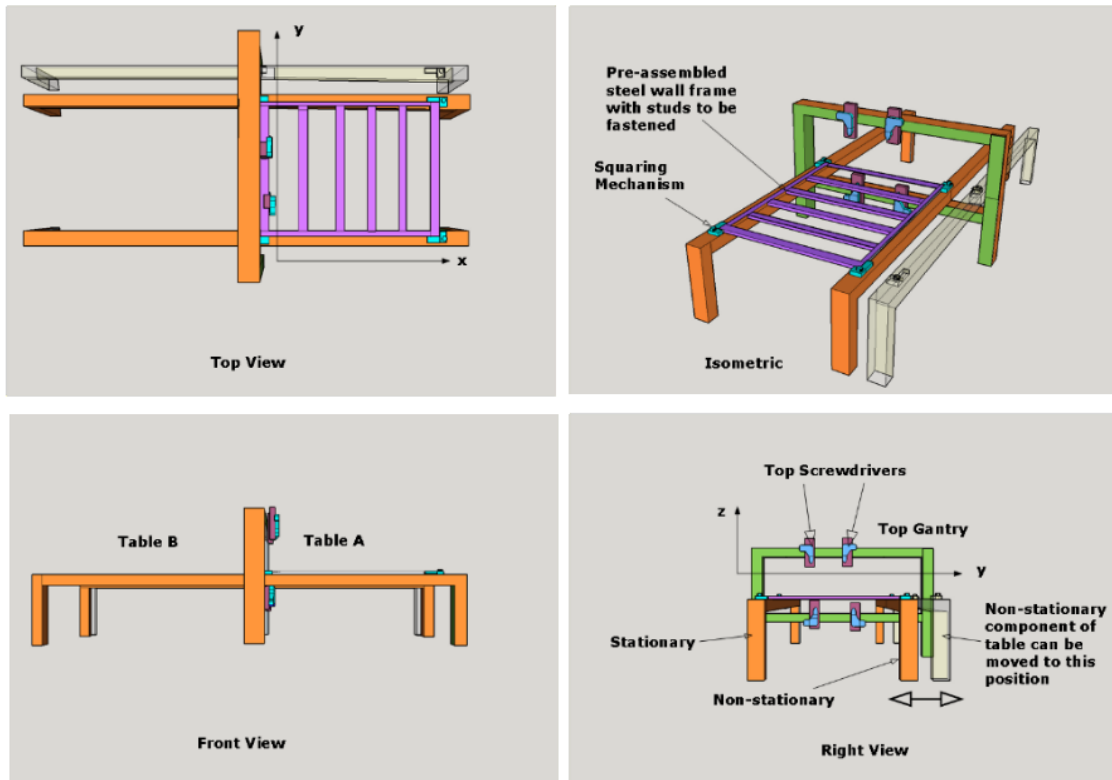


Figure 2.6. Plan, elevation, and isometric views of steel wall framing assembly

Table 2.3 lists the high-level FRs that result from the product design team's effort in determining the customer requirements. At the AD stage in Figure 2.2, the design team forms the DM by mapping the FRs to the following DPs: automated wall-framing machine (DP0), machine for three steel frame types (DP1), right table movement (DP2), manual assembly (DP3), squaring system (DP4), and dragging system (DP5).

Table 2.3. Mapping of high-level functional requirements, processes and use cases

Customer Needs	Mapping		Use Case	
	Axiomatic Design	Integrated Functional Modeling	No.	Label
Automated machine that makes steel wall frame	FR0: Build an automated steel-wall framing machine			
Machine that produces different wall frames	FR1: Include flexibility for machine to make three steel frame types	P1: Get frame information	1	Make frame with studs only
			2	Make frame with studs and window
			3	Make frame with studs and door
Machine for different widths	FR2: Incorporate at least 2DOF in the machine	P2: Table frame positioning		
Manual pre-assembly	FR3: Ensure means for manual access and assembly	P3: Pre-assembly		
Tight wall frame angular tolerance	FR4: Integrate a squaring system	P4: Squaring		
Wall frame securely joined with self-drilling screws	FR5: Adopt a self-drilling screw fastening system	P5: Screw fastening		

As previously mentioned, the process, use case, and actor views are simultaneously constructed for the IFM with the DM. Referring to Table 2.3, mapping of the customer needs for the steel wall-framing machine to the high-level FRs immediately results in the process and use case views of the IFM.

A high-level DM for the simple design example of the automated steel wall frame machine depicted in Figure 2.6 is formed using Equations (2.1) and (2.2) as follows:

$$\begin{Bmatrix} \text{FR0} \\ \text{FR1} \\ \text{FR2} \\ \text{FR3} \\ \text{FR4} \\ \text{FR5} \end{Bmatrix} = \begin{bmatrix} \text{X} & 0 & 0 & 0 & 0 & 0 \\ 0 & \text{X} & 0 & 0 & 0 & 0 \\ 0 & 0 & \text{X} & 0 & 0 & 0 \\ 0 & 0 & 0 & \text{X} & 0 & 0 \\ 0 & 0 & 0 & 0 & \text{X} & 0 \\ 0 & 0 & 0 & 0 & 0 & \text{X} \end{bmatrix} \begin{Bmatrix} \text{DP0} \\ \text{DP1} \\ \text{DP2} \\ \text{DP3} \\ \text{DP4} \\ \text{DP5} \end{Bmatrix} \quad (2.30)$$

Equation (2.30) implies that the independence axiom of Figure 2.2 is satisfied and that the design team can then proceed in forming the high-level DSM by replacing the FRs with their corresponding DPs. In addition to the operator, these DPs become the actors of the interaction view of the IFM in Figure 2.7. Representing another aspect of the interaction

view, the operands that interact with the actors of the steel wall framing machine are the electricity, control system commands, steel channel, 80/20 profile, and screws. How the actors influence or are influenced by the processes are marked as ‘X’ or ‘O’, respectively, in the actor view. The state view shows the change of states of the actors and operands when an actor or a group of actors executes a process.

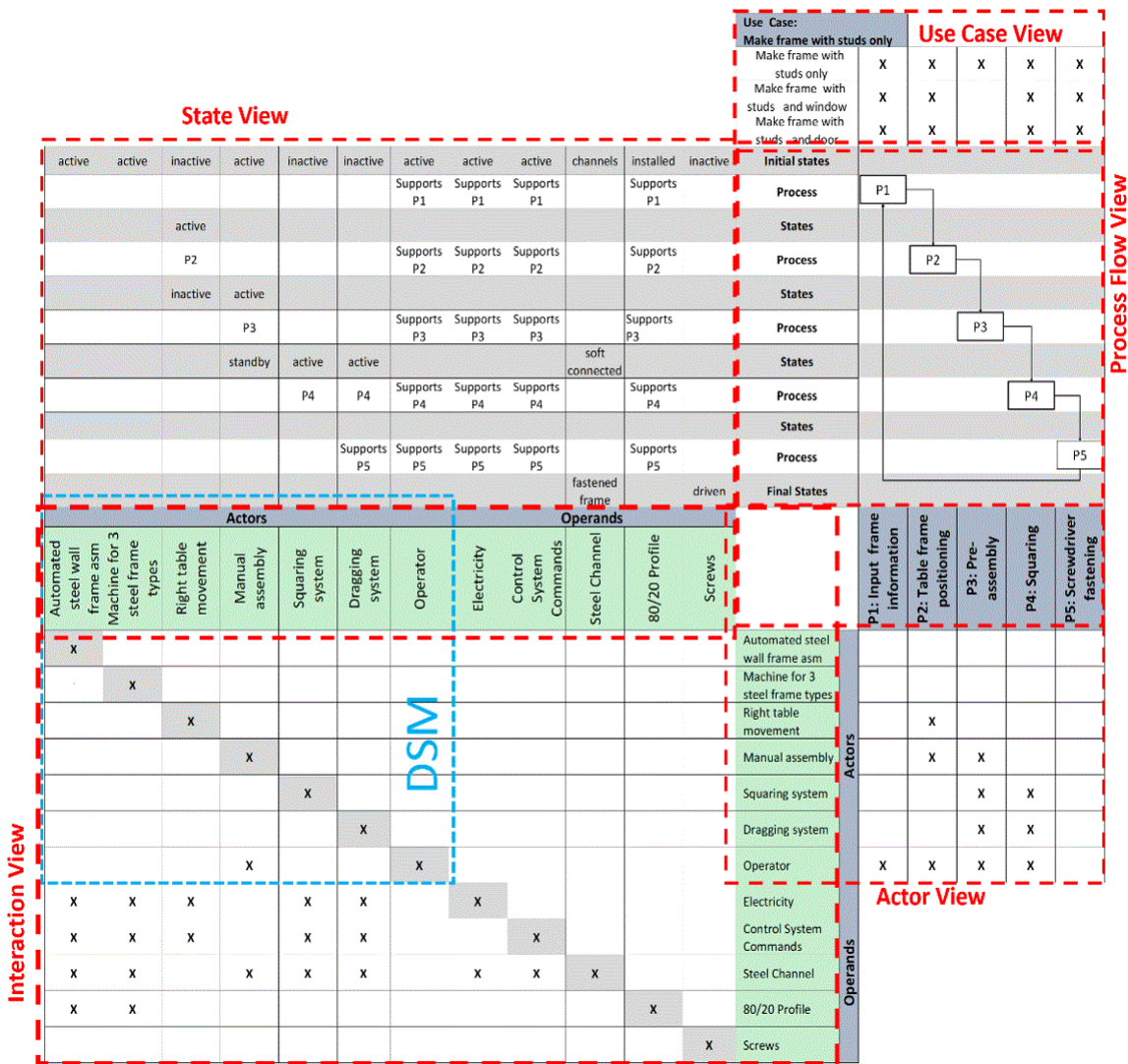


Figure 2.7. Integrated function model incorporating the design structure matrix of the high-level design example of the automated steel wall framing machine. Processes are: input frame information (P1), table frame positioning (P2), pre-assembly (P3), squaring (P4), and screwdriver fastening (P5)

2.5 Application to automated steel wall framing machine

Application of the three-stage approach to the conceptual design of a steel wall framing machine begins with compiling a list of customer needs:

1. Make automated steel wall frame machine
2. Manually pre-assemble wall frame prior to the start of the automated process
3. Fasten pre-assembled wall frame using self-drilling screws
4. Provide a machine that can accommodate at least three wall frame types: studs only, stud with window, and studs with door
5. Provide a wall frame that is properly squared

The following sections provide an overview of how the IFM is built with the aid of the three-stage design methodology.

2.5.1 Formulating the design matrix

The functional design of the steel wall framing machine presented in Figure 2.6 includes the following components: *(i)* two tables (A and B) with one side moveable to accommodate various wall frame widths; *(ii)* top and bottom gantries to hold the power screwdrivers; and *(iii)* squaring mechanisms.

Two sets of power screwdrivers drive screws into the top and the bottom of the pre-assembled wall frame. Positions of these screwdrivers on the *y*-axis are based on the input recipe of wall frame type, width, and use case. These two sets of screwdrivers move along the *z*-axis to drive self-drilling screws into the panel. Positions vary depending on the type of panel to be fabricated.

The feedback control system is a coupled system that is a necessary and acceptable interaction. However, another type of coupling is identified in the self-drilling screw fastening process that violates the desired property of a lower triangular DM. This coupling can be initially shown considering the gantry setup for one screw fastening operation represented by arm consisting of two prismatic joints 1 and 2, and one revolute joint 3, referred to as a PPR arm, as shown in Figure 2.8. Prismatic joint 1 represents the positioning of the screwdriver along the y -axis while prismatic joint 2 represents the positioning of the screw driver along the z -axis. Screw fastening consists of two simultaneous movements of joints 2 and 3. Joint 3 describes the revolute action of the end effector, which is the tip of the screwdriver that drives the screw into the frame. Simultaneous action of two joints signify a coupled relationship that is analyzed using the simple engineering principles outlined in Table 2.4. Re-ordering and triangularization techniques are used to make the DM lower triangular as much as possible.

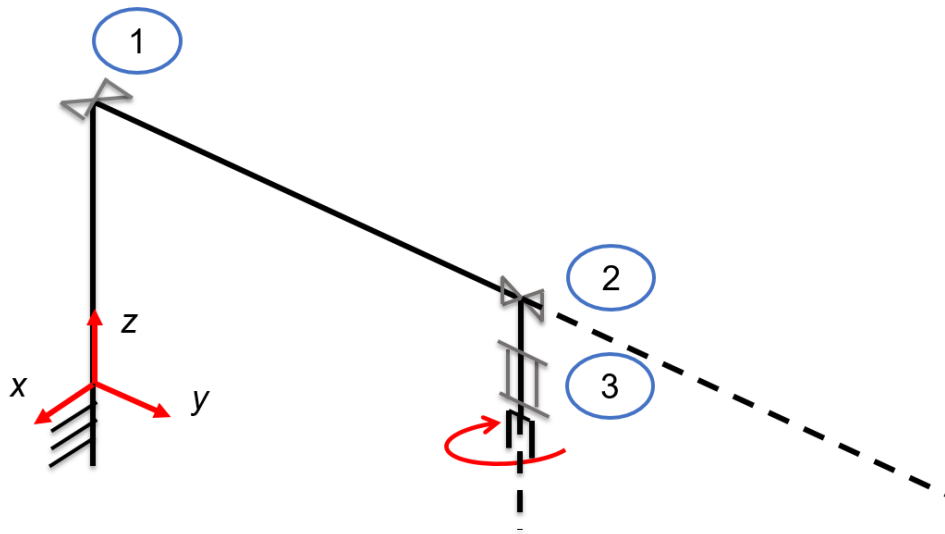


Figure 2.8. PPR Arm representation of a gantry setup for a single screw driver with prismatic joints ① and ② and revolute joint ③

Table 2.4 indicates the coupling derived from the equations governing the torque required to drive the self-drilling screw into the frame and its corresponding thrust, as well as the torque required to drive the screwdriver along the z -axis. In Equations (2.32) and (2.33), K_d , F_f , F_T , F_M , W , and D are the work material factor, feed factor, thrust factor, torque factor, tool wear factor, and drill diameter, respectively. W , A , and B are chisel edge factors. Torque, T , appears in both FRs in Equations (2.31) and (2.32), which indicates that these two FRs are coupled and that the independence axiom is not satisfied. This coupling is resolved by a triangularization process associated with adding new FR and DP.

Table 2.4. Coupling of the functional requirements and design parameters of the fastening system

Functional Requirement	Design Parameter	Equation	Comments
Provide z -axis screwdriver positioning system	z -axis screwdriver positioning system	$M_z = f(T, p)$ (2.31)	Torque, M_z , of the positioning system is a function of the screw fastening thrust, T , and the geometrical parameters, p , of the drive mechanism.
Provide fastening system	Fastening system	$T = 2K_d F_f F_T B W + K_d D^2 J W$ (2.32) $M = 2K_d F_f F_M A W$ (2.33)	T = screw fastening thrust and M = screwdriver torque. equations are taken from Oberg et al. (2016).

A new set of FRs and DPs are created and the process of re-ordering, re-numbering, and triangularization produces a lower triangular DM. Although related to the z -positioning system, the added FRs and DPs signify a software solution that produces the necessary torque to provide the required screwdriver thrust. Figure 2.9 presents the DM resulting from the aforementioned steps. Figure 2.9 also illustrates the result of triangularization accomplished by adding FR10 and DP10 to resolve the coupling between the top and bottom screw drivers during the screw fastening process. This coupling is due to the absence of clamping mechanisms that firmly secure the wall frame during the screw

fastening phase. With the addition of the FR-DP pair, this coupling is shifted to the lower triangular region depicted in Figure 2.9. It must be noted, however, that the introduction of an FR-DP pair is an interim remedy and that the installation of clamping mechanisms is the preferred setup.

2.5.2 Completing the integrated function modelling

Use case, process, and actor views are developed in formulating the DM, which is in turn used to build the DSM. Following the DSM stage procedure provided in Figure 2.2, the output variables are simply the diagonal elements, since the DM is square. Thus, the DSM is the DM represented in Figure 2.9 with the FRs replaced by the DPs. Once the DSM is built, the interaction view is built, leaving the state view as the only display remaining to be constructed. To complete the IFM, the process flow, use case, and actor views obtained from the AD stage are updated using the output of the DSM stage as illustrated in Figure 2.2.

		Automated steel wall frame assembly	Machine for three steel types	User interface	Control Interface	Recipe Data	Right table movement	Right table mechanism	Right table mechanism control	Manual assembly	Squaring system	Holding mechanism	Holding control	Right angle positioning system	Right angle positioning control	Dragging system	Dragging system control	Y-axis screw driver positioning system	Y-axis screw driver positioning control	Z-axis screw driver positioning system	Z-axis screw driver positioning control	Fastening system	Fastening system control	Z-axis top thrust position	Z-axis top thrust position control	Delay Z-axis bottom thrust position	Z-axis bottom thrust position	Z-axis bottom thrust position control
		DP0	DP1	DP1.1	DP1.2	DP1.3	DP2	DP2.1	DP2.1.1	DP3	DP4	DP4.1	DP4.1.1	DP4.2	DP4.2.1	DP5	DP5.1	DP6	DP6.1	DP7	DP7.1	DP8	DP8.1	DP9	DP9.1	DP10	DP11	DP11.1
FR0	Build an automated steel wall frame	x																										
FR1	Include flexibility for machine to make three		x																									
FR1.1	Provide recipe interface			x																								
FR1.2	Provide recipe access			x	x																							
FR1.3	Provide recipe			x	x	x																						
FR2	Incorporate at least 2DOF in the machine						x																					
FR2.1	Provide right table mechanism							x	x																			
FR2.1.1	Provide right table mechanism control							x	x																			
FR3	Ensure means for manual access and									x																		
FR4	Integrate a squaring system										x																	
FR4.1	Provide holding mechanism											x	x	x														
FR4.1.1	Provide holding control											x	x	x														
FR4.2	Provide right angle positioning system													x	x													
FR4.2.1	Provide right angle positioning control													x	x													
FR5	Provide dragging system															x	x											
FR5.1	Provide dragging system control															x	x											
FR6	Provide y-axis screw driver positioning																	x	x									
FR6.1	Provide y-axis screw driver positioning																	x	x									
FR7	Provide z-axis screw driver positioning																			x	x							
FR7.1	Provide z-axis screw driver positioning																			x	x							
FR8	Provide fastening system																					x	x					
FR8.1	Provide fastening system control																					x	x					
FR9	Provide z-axis top thrust position																						x	x				
FR9.1	Provide z-axis top thrust position control																						x	x				
FR10	Provide delay of z-axis bottom thrust position																								x			
FR11	Provide z-axis bottom thrust position																									x	x	
FR11.1	Provide z-axis bottom thrust position control																									x	x	

Figure 2.9. Final design matrix of the automated steel wall-framing machine

Initial and final states of the state view are the basis of the transformation logic of each of the steel wall framing machine’s processes. At a high level, the state view communicates insight on how to control the processes to satisfy the design goals. This view provides a programming framework for the software or control aspect of the design.

High-level results of the completed three-stage design method for the automated steel wall-framing machine can be observed in the IFM framework presented in Figure 2.7. For readability, sections of the detailed IFM are presented, at the end of this chapter, in (i)

Figure 2.10 Use case and process flow views, (ii) Figure 2.11 Actor view, (iii) Figure 2.12 Interaction view, and (iv) Figure 2.13 State view.

As indicated in Table 2.5, the process flow view can be mathematically expressed in first order logic (Russell & Norvig 2016). This formulation will be useful in implementing the processes on any programmable controller platform. For the first order logic, the variables are defined as follows:

$F \leftarrow \{f_i \mid i \in [1, n]\}$; a set of n frames to be produced.

$X \leftarrow \{x_j \mid j \in [1, m]\}$; a set of m x coordinates, defining the position where the screw will be applied to the frame along the x -axis.

$Y \leftarrow \{y_k \mid k \in [1, m]\}$; a set of m y -coordinates, defining the position where the screw will be applied to the frame along the y -axis.

Ls = length of screw; this is the vertical distance the screw will be traversing through the steel channel.

Wd = width of frame to be produced. This is contained in the use case (frame information).

Zsd = Travel of screwdriver in the z direction. This is contained in the use case.

Functions describing the processes are listed in Table 2.5. The first order logic shown in the last row of this table describes the processes involved in producing a certain frame type for a given use case. These processes are: (i) entering the x and y coordinates, (ii) positioning the table width, (iii) manually assembling the frame, (iv) positioning the frame in the x direction, (v) positioning the screwdriver in the y and z direction, and (vi) screw fastening.

Table 2.5. Functions describing the automated steel wall framing machine

Functions	Description
$GetControllerUseCase(F \times Wd \times Zsd \times X \times Y)$	Controller stores the use case information for use in the subsequent processes of producing a wall frame.
$PositionControllerTable(F \times Wd)$	Controller positions the table to the width Wd .
$AssembleOperator(F)$	Operator manually assembles the frame.
$DragController(F \times X)$	Controller drags frame to an x -coordinate.
$PositionControllerScrewDriverY(F \times Y)$	Controller positions the screw driver in y -coordinate.
$PositionControllerScrewDriverZ(F \times Zsd)$	Controller positions the screw driver to vertical distance Zsd .
$DriveControllerScrew(F \times Ls)$	Controller drives screw through its length Ls .
$\mathcal{D} = \mathcal{D} \cup \{F, X, Y\}$ $\forall f \in F: (\forall x \in X; \forall y \in Y. GetControllerUseCase(f, Zsd, Wd, x, y) \wedge$ $PositionControllerTable(f, Wd) \wedge AssembleOperator(f) \wedge DragController(f, x) \wedge$ $PositionControllerScrewDriverY(f, y) \wedge PositionControllerScrewDriverZ(f, Zsd) \wedge$ $DriveControllerScrew(f, Ls))$	

In forming the actor view of Figure 2.11, inputs or operands are added such as those required for realizing the automated steel wall-framing machine. These operands, which complement the previously identified DPs, consist of an operator who oversees the manufacturing process, electricity to power the system, a control system that constitutes the SCADA/sensor level, a steel channel for making the wall frames, the 80/20 profile (from 80/20 Inc.) from which the assembly is built, and the self-drilling screws for fastening the wall frames. An effect is marked by an 'X' if an actor or an operand directly affects a process, and by an 'O' if a process affects an actor or operand. Figure 2.12 presents the DSM with additional information on how the operands affect the system.

2.6 Discussion

Adopting an integrated design methodology that facilitates a collaborative thinking process across a multidisciplinary team is the motivation behind the use of the IFM framework in

conceptual design (Eisenbart et al. 2011). A simple illustration of the initial design of an automated steel wall-framing machine describes how the IFM evolves from mapping the customer needs at the AD stage. Defining customer needs and determining FRs constitutes the first and crucial step in conceptual design (Suh et al. 1998). At this initial phase, the product design team works on a solution that is easily transcribed into matrices such as the DM in AD and the process and use case views in IFM. As the design team presents more details, the DM matures into a visual representation of a desired or undesired function as illustrated in Figure 2.9. In this figure, an undesired coupling has been identified and analyzed, through the use of basic engineering principles listed in Table 2.4 to arrive at additional FRs and DPs in resolving the conflict. This solution demonstrates the visual and iterative advantages of the matrix-based integrated design methodology proposed in this paper. Moreover, the thinking process encourages creativity within the team in arriving at a solution. The thinking process is carried out through brainstorming sessions that generate many ideas (Foley & Harardóttir 2016). As noted in (Eisenbart 2016), the application of the matrix-based integrated design methodology to the automated steel wall-framing machine requires less modelling effort compared to a diagram-based framework such as SYSML. Social interaction is crucial throughout the entire conceptual design stage, but it is especially critical at the initial phase when the product design team is defining the customer requirements with internal and external stakeholders. Mapping of CRs to FRs shown in Table 2.3 and the determination of the optimal number of FRs can be time consuming if it is not done systematically. An automated implementation of the proposed methodology to the conceptual design of the steel wall-framing machine could have facilitated the thinking process more efficiently.

2.7 Conclusion and Future Work

An integrated design approach has been proposed to the conceptual design of an automated modular construction manufacturing system and applies it to a prototype of an automated steel wall-framing machine under development at the University of Alberta, Canada. This systematic approach, consisting of AD and DSM, provides a mathematical basis and iterative design methodology for the IFM framework originally introduced by Eisenbart et al. (2012). Although the ultimate design decision is the responsibility of the design team, the methodology described in this paper facilitates decision making based on customer requirements. Since the three-stage approach is iterative, it is a favorable method in the conceptual design phase where the design iterations have minimal cost impact. It has been demonstrated that early detection of (and solutions to reduce) design complexity arise from the application of basic engineering principles, even if the design parameters and functional requirements are expressed at a high level in the axiomatic design stage of the method. Due to its simplicity, the proposed matrix-based integrated design approach, which is essentially an IFM framework, is faster to develop and requires less training and modelling efforts compared to the diagram-based UML or SYSML (Eisenbart et al. 2015). Microsoft Excel has been used to implement the integrated design of the automated steel wall-framing machine. However, future projects can benefit from the application of the proposed design methodology with the aid of other software tools. Moreover, the mapping of CRs to FRs and the determination of the optimal number of FRs can be efficiently automated in the future using state-of-the-art techniques to achieve quality function deployment (QFD) during brainstorming sessions.

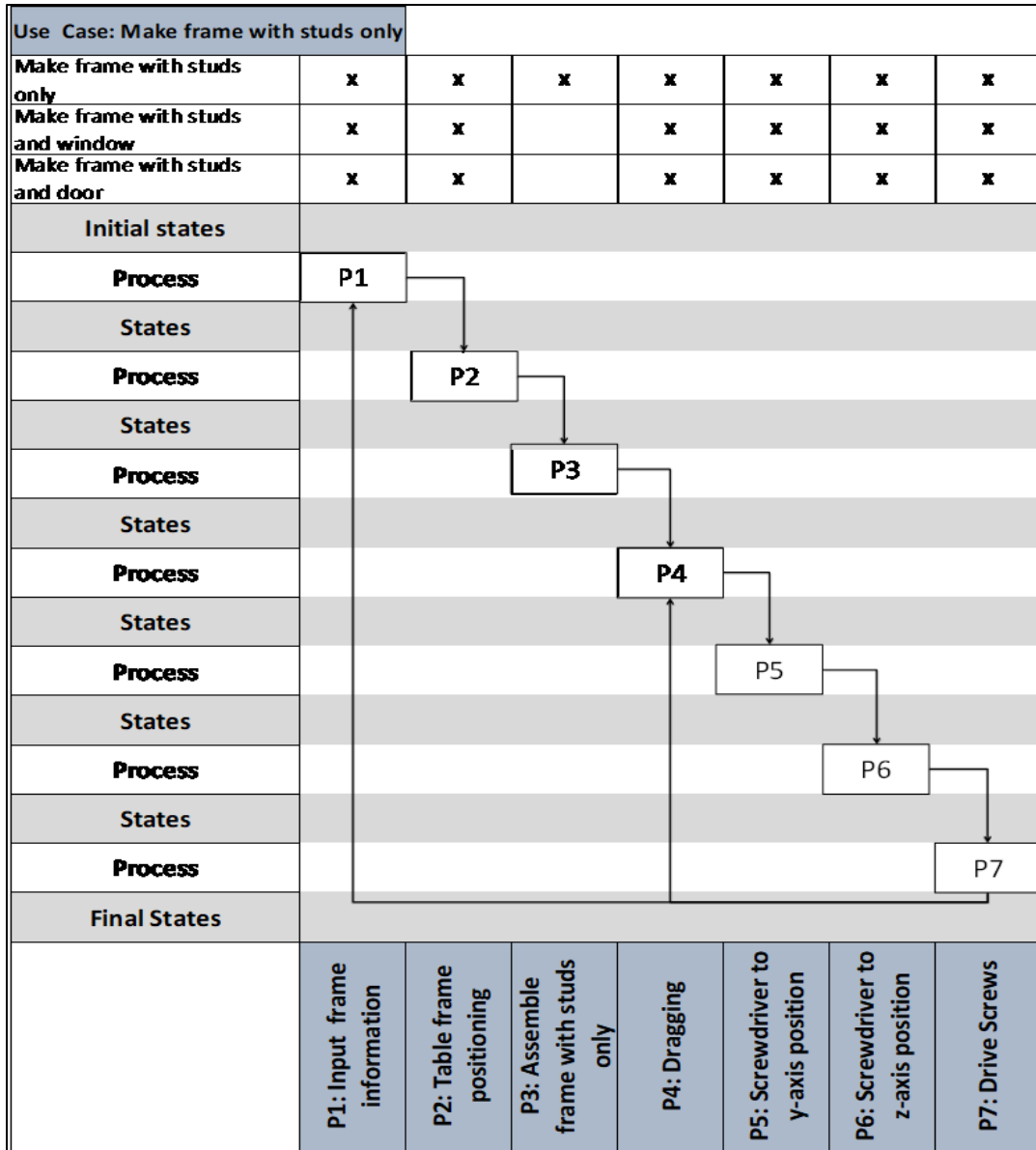


Figure 2.10. Use case and process views of the automated steel wall-framing machine IFM framework

	P1: Input frame information	P2: Table frame positioning	P3: Assemble frame with studs only	P4: Dragging	P5: Screwdriver to y-axis position	P6: Screwdriver to z-axis position	P7: Drive Screws
Automated steel wall frame assembly							
Machine for 3 steel frame types							
User Interface	X						
Control Interface	X	X					
Recipe Data	X	X					
Right table movement		X					
Right table mechanism		X					
Right table mechanism control		X					
Manual assembly		X	X				
Squaring system			X	X			X
Holding mechanism			X	X			X
Holding control			X	X			X
Right angle positioning system			X	X			X
Right angle positioning control			X	X			X
Dragging system			X	X			X
Dragging system control			X	X			X
Y-axis screw driver positioning system					X		
Y-axis screw driver positioning control					X		
Z-axis screw driver positioning system						X	
Z-axis screw driver positioning control						X	
Fastening system						X	X
Fastening system control						X	X
Z-axis thrust position						X	X
Z-axis thrust position control						X	X
Operator	X	X	X	X		X	X
Electricity	X	X	X	X		X	X
Control System Commands	X	X	X	X		X	X
Steel Channel		O	O	O			O
80/20 Profile							
Screws							O

Figure 2.11. Actor view of the automated steel wall-framing machine IFM framework

active	active	active	active	upload	inactive	inactive	inactive	active	inactive	inactive	inactive	inactive	inactive	inactive	inactive	inactive	inactive	inactive	inactive	inactive	active	active	active	active	channels	installed	inactive	Initial states	
		P1	P1	P1																		Supports P1	Supports P1	Supports P1		Supports P1		Process	
				accessed	active	active	active																					States	
		Supports P2	Supports P2	Supports P2	P2	P2	P2															Supports P2	Supports P2	Supports P2		Supports P2		Process	
					inactive	inactive	inactive	active																				States	
		Supports P3	Supports P3	Supports P3				P3														Supports P3	Supports P3	Supports P3		Supports P3		Process	
								standby	active	active	active	active	active	active											soft connected			States	
		Supports P4	Supports P4	Supports P4					P4	P4	P4	P4	P4	P4								Supports P4	Supports P4	Supports P4		Supports P4		Process	
														active	active													States	
		Supports P5	Supports P5	Supports P5									Supports P5	Supports P5	P5	P5						Supports P5	Supports P5	Supports P5		Supports P5		Process	
														inactive	inactive	active	active											States	
		Supports P6	Supports P6	Supports P6									Supports P6	Supports P6			P6	P6				Supports P6	Supports P6	Supports P6		Supports P6		Process	
																			active	active	active	active					drive screw	States	
		Supports P7	Supports P7	Supports P7									Supports P7	Supports P7			Supports P7	Supports P7		P7	P7	P7	Supports P7	Supports P7	Supports P7		Supports P7	P7	Process
																									fastened frame	driven		Final States	
Actors																							Operands						
Automated steel wall frame asm	Machine for 3 steel frame types	User Interface	Control Interface	Recipe Data	Right table movement	Right table mechanism	Right table mech control	Manual assembly	Squaring system	Holding mechanism	Holding control	Right angle positioning sys	Right angle positioning ctl	Dragging system	Dragging system control	Y-axis scdr positioning sys	Y-axis scdr positioning ctl	Z-axis scdr positioning sys	Z-axis scdr positioning ctl	Fastening system	Fastening system control	Z-axis thrust position	Z-axis thrust position control	Operator	Electricity	Control System Commands	Steel Channel	80/20 Profile	Screws

Figure 2.12. Interaction view of the automated steel wall-framing machine IFM framework

active	active	active	active	upload	inactive	inactive	inactive	active	inactive	inactive	inactive	inactive	inactive	inactive	inactive	inactive	inactive	inactive	inactive	inactive	inactive	active	active	active	active	channels	installed	inactive	Initial states	
		P1	P1	P1																			Supports P1	Supports P1	Supports P1		Supports P1		Process	
				accessed	active	active	active																						States	
		Supports P2	Supports P2	Supports P2	P2	P2	P2																	Supports P2	Supports P2	Supports P2		Supports P2		Process
					inactive	inactive	inactive	active																					States	
		Supports P3	Supports P3	Supports P3				P3																Supports P3	Supports P3	Supports P3		Supports P3		Process
								standby	active	active	active	active	active	active	active											soft connected			States	
		Supports P4	Supports P4	Supports P4					P4	P4	P4	P4	P4	P4										Supports P4	Supports P4	Supports P4		Supports P4		Process
															active	active													States	
		Supports P5	Supports P5	Supports P5									Supports P5	Supports P5	P5	P5								Supports P5	Supports P5	Supports P5		Supports P5		Process
															inactive	inactive	active	active											States	
		Supports P6	Supports P6	Supports P6									Supports P6	Supports P6			P6	P6						Supports P6	Supports P6	Supports P6		Supports P6		Process
																			active	active	active	active						drive screw		States
		Supports P7	Supports P7	Supports P7									Supports P7	Supports P7			Supports P7	Supports P7			P7	P7	P7	Supports P7	Supports P7	Supports P7		Supports P7	P7	Process
																										fastened frame		driven	Final States	
Actors																							Operands							
Automated steel wall frame asm	Machine for 3 steel frame types	User Interface	Control Interface	Recipe Data	Right table movement	Right table mechanism	Right table mech control	Manual assembly	Squaring system	Holding mechanism	Holding control	Right angle positioning sys	Right angle positioning ctl	Dragging system	Dragging system control	Y-axis scdr positioning sys	Y-axis scdr positioning ctl	Z-axis scdr positioning sys	Z-axis scdr positioning ctl	Fastening system	Fastening system control	Z-axis thrust position	Z-axis thrust position control	Operator	Electricity	Control System Commands	Steel Channel	80/20 Profile	Screws	

Figure 2.13. State view of the automated steel wall-framing machine IFM framework

Chapter 3 Integrating machine learning with QFD for selecting functional requirements in construction automation²

3.1 Introduction

Defining customer needs and determining the minimum functional requirements (FRs) constitute the first and crucial step in conceptual design (Nam P. Suh 1998). Quality function deployment (QFD), a methodology that originated in Japan, is used by the product development team in this initial phase of conceptual design to identify customer needs and to evaluate the influence of a product or service in achieving these needs (Subbaiah et al. 2016). Shin and Kim (2007) have applied factor analysis (FA), an unsupervised classical statistical method, with QFD to reduce the dimension of the FRs mapped from the CRs in QFD. Dimension reduction pertains to reducing the order of a model by grouping features or attributes, whereas feature selection refers to excluding the least important features from the model. As further discussed in the next section, integrating feature selection with QFD is proposed in this paper to reduce the design complexity that is associated with satisfying a large set of FRs (Suh 1999). To address the limitation of FA in feature selection, this paper will leverage unsupervised machine learning techniques in systematically determining the minimum FRs from the mapping of CRs in QFD.

The current state-of-the-art rating of the importance of FRs is achieved using techniques such as analytical network process (ANP), FA, fuzzy logic (FL), and principal component analysis (PCA). Karsak et al. (2003) have used ANP to rank the FRs and zero-one goal

² The manuscript appearing as Chapter 3 of this thesis was submitted to the Artificial Intelligence for Engineering Design, Analysis and Manufacturing Journal, at the time of publication of this thesis.

programming to determine the FRs to consider in designing the product. Mazurek and Kiszová (2012) highlight two disadvantages of ANP: (1) obtaining the correct network structure is difficult, and (2) forming the supermatrix by pair-wise comparison of all criteria is difficult and unnatural. To overcome these difficulties, Mazurek and Kiszová (2012) suggest the use of FL. However, requirement prioritization through FL is prone to error due to its reliance on experts (Achimugu et al. 2014). Shin and Kim (2007) have introduced FA to restructure QFD. This classical statistical technique does not have the difficulties encountered in ANP or fuzzy logic, but Subbaiah et al. (2016) give preference to PCA over FA due to the weakness of the latter in handling strongly correlated requirements. Weber et al. (2013) have explored PCA in features prioritization of an airport, but, for features selection, they have not used this state-of-the-art machine learning technique to establish the criteria for determining the optimum number of FRs.

Based on the notion that a product design team must not be constrained to using only one technique at the customer requirement definition phase of conceptual design, a comprehensive set of unsupervised machine learning methods will be described in detail. Respecting this notion, the paper will be structured as follows: section 3.1 identifies the limitations of current state-of-the-art techniques and introduces unsupervised machine learning methods to address these limitations; section 3.2 discusses the motivation, and detailed description of the proposed machine techniques, and algorithms; section 3.3 describes the application of the algorithms to the QFD of an automated wood wall framing machine; a discussion of the results is provided in section 3.4, followed by the conclusion in section 3.5.

3.2 Feature Selection Using Machine Learning Techniques

3.2.1 Motivation

Conceptual design is initiated by identifying CRs, a necessary step prior to any design methodology such as that of the integrated conceptual design described in a study by Tamayo et al. (2018). This is the most critical stage of conceptual design since correctly identifying the CRs defines the FRs that make up the design intent of the project. QFD is the methodology used by the design team to evaluate the significance of FRs that achieve these CRs. Degrees of significance are assigned values such as 1 (weak significance), 3 (medium significance), and 9 (strong significance) (Shin & Kim 2007). An example of a QFD matrix is illustrated in Table 3.1, where m and n indicate the total number of CRs and FRs, respectively. This $m \times n$ QFD matrix will be denoted as the dataset matrix X consisting of n columns of features or FRs.

The complexity of the system increases with the increase in the number of FRs as expressed in terms of the probability of achieving the highest FRs, which diminish with larger n (Suh 1999):

$$P = \frac{1}{n!} \tag{3.1}$$

Equation (3.1) suggests the use of minimum number of FRs to increase the probability of finding the right DPs to satisfy n FRs at the axiomatic design (AD) stage and thus reduce the complexity of the design. Selecting an optimum number of FRs is accomplished at the CR definition stage using the feature selection techniques discussed below.

Table 3.1. Typical QFD

	FR_1	FR_2	FR_3	FR_4	FR_5	...	FR_n
CR_1	9		1		9		
CR_2		3					
CR_3	1		9	3	3		
CR_4			3	3	1		
CR_5			3	3	1		
CR_6	9		1		9		
CR_7					9		
CR_8	3						9
\vdots
CR_m			1	9	3		

3.2.2 Principal Component Analysis

Selecting the minimum number of FRs is accomplished by retaining the p number of FRs that adequately satisfy the CRs in the QFD matrix and exclude the least significant FRs. Approaches to determining p include (Kung 2014): (i) filter, and (ii) wrapper models. A simple method of determining p is by setting a threshold in the cumulative of the percent explained variances versus the retained number of FRs. Figure 3.1 describes the general block diagram for system identification, which can be adopted for feature selection by modelling the QFD matrix that serves as the dataset $X \in \mathbb{R}^{m \times n}$. This dataset is the input to the unknown system to be modelled and to the model itself. The goal of the model estimation process is to adjust the parameters of the model until the error, E , between the

actual target value or label, Y , and the predicted target value, \hat{Y} , is minimized. Where a label is involved in the prediction, the modelling approach is called supervised machine learning. A special case of the supervised machine learning is the unsupervised prediction shown in Figure 3.2. For the dataset X shown in Table 3.1, any unsupervised machine learning technique can be used for feature selection. PCA, a popular unsupervised machine dimensionality reduction technique, is illustrated for feature selection.

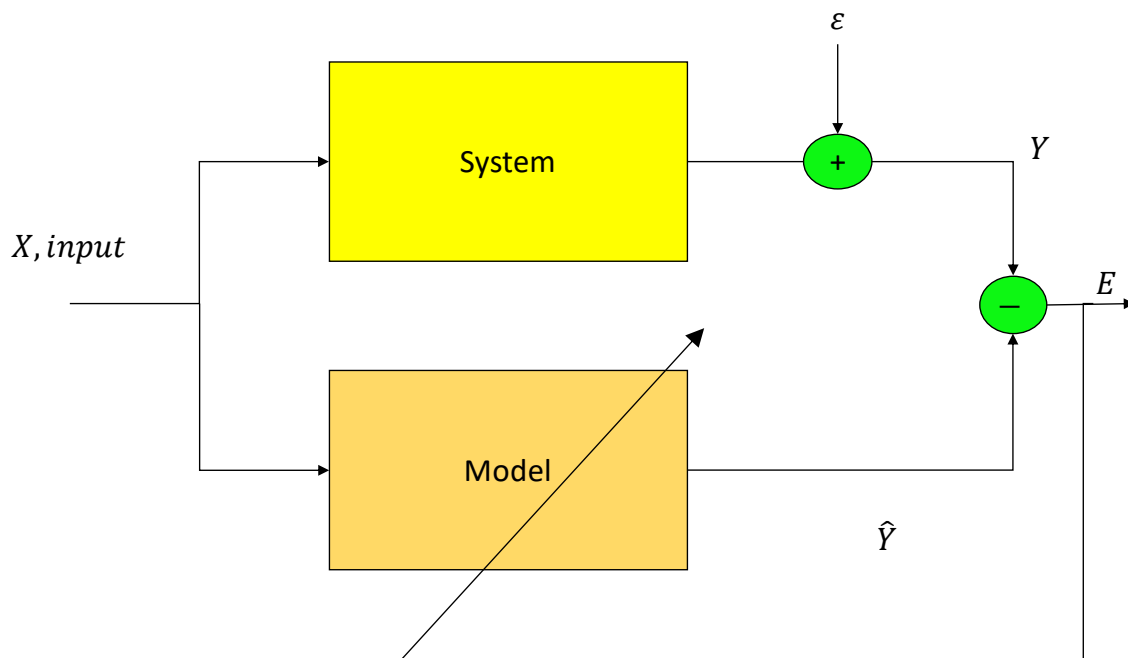


Figure 3.1. General block diagram of a supervised machine learning process

Figure 3.1 is redrawn in Figure 3.2 to represent the unsupervised feature selection that makes use of PCA. Notations commonly used in chemometrics will be adopted in the following derivations (Cordella 2012). PCA is a model of the form:

$$\begin{aligned}
 X &= \hat{X} + E \\
 &= TP^T + E
 \end{aligned}
 \tag{3.2}$$

where \hat{X} is the $m \times n$ reconstructed dataset that approximates X and that is expressed as the product of the scores matrix, $T \in \mathbb{R}^{m \times q}$. and the loadings matrix, $P \in \mathbb{R}^{q \times n}$. Scores matrix T projections of the original features onto the principal components. E is the reconstruction error introduced in approximating the dataset. PCA accomplishes dimensionality reduction by determining $q < \min(m, n)$ principal components (PCs) in the loadings $X \in \mathbb{R}^{m \times n}$. $P \in \mathbb{R}^{q \times n}$ is the scores matrix $T \in \mathbb{R}^{m \times q}$, which follows the orthogonality condition $p_i^T p_j = 0$ and $t_i^T t_j = 0$ for $i \neq j$ (Cordella 2012, Bro & Smilde 2014).

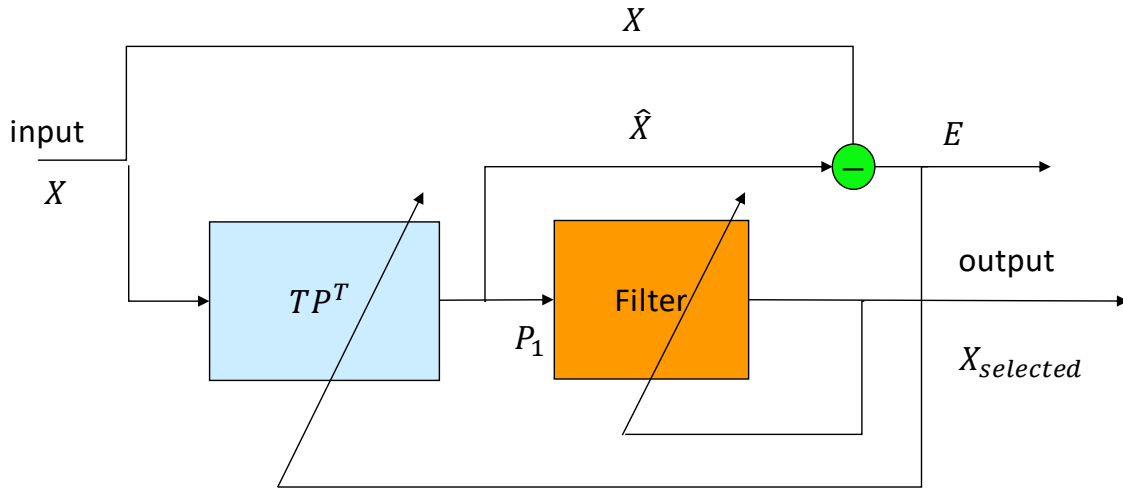


Figure 3.2. Feature selection by Principal Component Analysis

A graphical representation of the PCA involved in projecting the data points for a two-dimensional scatter plot is illustrated in Figure 3.3. Minimizing the error is the criterion for constructing the PCA model of the dataset in the least-mean-squares sense. In multi-dimensional data, the solution to minimizing the reconstruction error is obtained from Equation (3.4) (Ghodsi 2006).

$$T = \arg \min_{T \in \mathbb{R}^n} \|X - TP^T\|^2$$

$$= XP \tag{3.3}$$

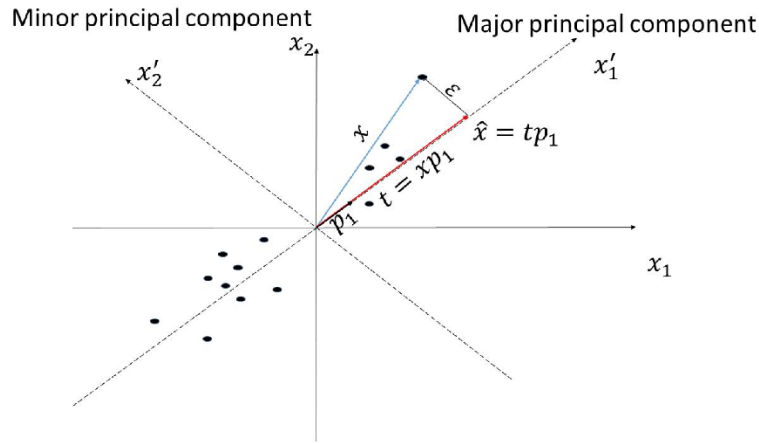


Figure 3.3. Projection of a vector x of a sample point in a two-dimensional data to the major principal component p_1

Forming the singular decomposition of X with respect to a diagonal matrix Σ , and orthogonal matrices U and V such that $UU^T = I$ and $VV^T = I$:

$$X = U\Sigma V^T \tag{3.4}$$

Loadings matrix P is determined by minimizing the reconstruction error as in the study by Hastie et al. (2009):

$$P = \underset{P \in \mathbb{R}^n}{\text{arg min}} \|X - XPP^T\|^2 \tag{3.5}$$

Equation (3.5) indicates that $P = V$ since PP^T is the orthogonal projection of X onto the subspace spanned by the columns of V . Thus, the loadings, scores, and reconstructed dataset are derived through the singular value decomposition of X as follows:

$$P = V$$

$$T = U\Sigma \tag{3.6}$$

$$\hat{X} = XVV^T$$

The expected value of the reconstruction error or mean squares error (MSE) is calculated as the sum of the minor eigenvalues:

$$MSE(q) = \sum_{i=q+1}^n \lambda_i \quad (3.7)$$

The MSE for different values of q principal components and setting a threshold MSE is what determines the optimum number of principal components q^* . $P_{q^*} \in \mathbb{R}^{q^* \times n}$ in Figure 3.4 is the optimal loadings matrix whose columns are the eigenvectors p_i that correspond to n features.

PCA is normally used for feature extraction. However, Song et al. (2010) have shown that PCA can also serve the purpose of feature selection. Since PCs are automatically ranked when singular value decomposition (SVD) is used, for feature selection, the q^* -dimensional P and T matrices are derived by determining the eigenvectors and eigenvalues from the covariance matrix:

$$C_X = \frac{1}{m-1} XX^T \quad (3.8)$$

$$C_X p_i = \lambda_i p_i \quad (3.9)$$

where p_i is the i^{th} column eigenvector of the loadings matrix P and λ_i is the associated eigenvalue. Importance of each feature is obtained by the magnitude of each column eigenvector where the eigenvalue is maximum, i.e., each element of the first principal component, through Equation (3.10) (Malhi & Gao 2004). Xu et al. (2008) have observed

that Equation (3.10) is valid when the maximum eigenvalue, λ_1 , is significantly larger than the rest of the eigenvalues.

$$c_i = |p_i| \text{ for } i = 1:n \quad (3.10)$$

A summary of the steps required to develop Algorithm 1 (Song et al. 2010) for feature selection using principal component analysis is presented below.

Algorithm 1 Feature Selection using Principal Component Analysis

- 1: Dataset: $X \leftarrow \{x_i \mid x_i \in \mathbb{R}^m \wedge i \in [1, n]\}$;
 - 2: Mean-center and scale dataset: $X \leftarrow \text{normalized}(X)$;
 - 3: Perform SVD: $X \leftarrow U\Sigma V^T$, Eq. 4;
 - 4: Evaluate loadings matrix: $P \leftarrow V$, Eq. 6;
 - 5: Rank first column of P : $c_i \leftarrow |p_{1i}|$. Eq. 10;
 \triangleright Ranking of c_i corresponds to the ranking of the features
-

3.2.3 Forward Orthogonal Search

Because of its simplicity and its suitability to highly correlated QFD dataset, PCA is the first feature selection method to use. Two other techniques will be introduced that conform to a specific structure of the QFD matrix. Forward orthogonal search (FOS) (Wei & Billings 2007), depicted in Figure 3.4, is similar to PCA but it does not have the maximum eigenvalue restriction since its feature selection criterion is based on maximum squared-correlation coefficient and average sum of error reduction ratio. Equation (3.11) describes the model that approximates the original QFD matrix.

$$\begin{aligned} X &= \hat{X}\theta + E \\ &= QR\theta + E \end{aligned} \quad (3.11)$$

where the selected number of features is $q < n$; $\hat{X} \in \mathbb{R}^{m \times q}$ is orthogonally decomposed into orthogonal matrix $Q \in \mathbb{R}^{m \times q}$; upper triangular matrix $R \in \mathbb{R}^{q \times q}$; and parameter matrix $\tau \in \mathbb{R}^{m \times n}$. $\theta \in \mathbb{R}^q$ is the parameter vector.

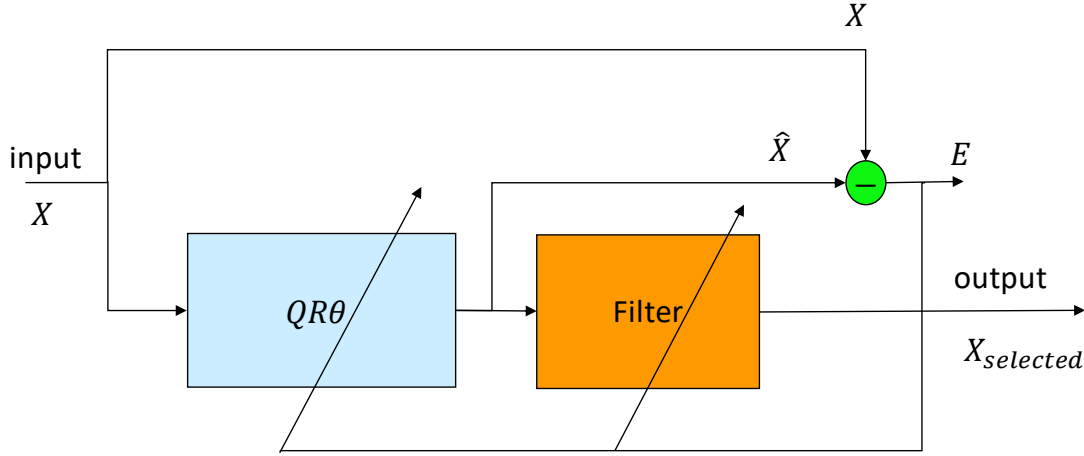


Figure 3.4. Forward orthogonal search unsupervised feature selection method

Algorithm 2 reflects the equations developed by Wei and Billings (2007). Thus the function, $sc(a_i, b_j)$, that calculates the index of the maximum squared-correlation coefficients, $\gamma \in \mathbb{R}^n$, of two vectors a_i and b_j is determined as follows:

$$\gamma_j = \frac{1}{n} \sum_{i=1}^n \frac{(a_i^T b_j)^2}{(a_i^T a_i)(b_j^T b_j)} \quad (3.12)$$

$$l = \underset{j \in [1, n]}{\text{arg max}} \{ \gamma_j \} \quad (3.13)$$

Taking the column vectors of the normalized dataset, X , for both a_i and b_j in the sc function provides the first selected feature vector, x_{l_1} , in \hat{X} . \tilde{X} represents the dataset that results from the removal of the feature vector, x_{l_1} , from X . In the subsequent steps, however, \hat{X} and \tilde{X} are updated through $sc(x_i, q_j)$, where q_j is obtained by applying the Gram-Schmidt orthogonalization function $ortho(\tilde{x}_j, q_k)$, or

$$q_j = \tilde{x}_j - \sum_{k=1}^{r-1} \frac{(\tilde{x}_j^T q_k)}{q_k^T q_k} q_k \quad (3.14)$$

The significance or importance of the selected feature is evaluated through the function $perf(x_j, q_k)$, such that

$$SE = \frac{1}{n} \sum_{j=1}^n \sum_{k=1}^r \frac{(x_j^T q_k)^2}{(x_i^T x_j)(q_k^T q_k)} \times 100 \quad (3.15)$$

A summary of the steps required to develop Algorithm 2 for feature selection using forward orthogonal search is presented below.

Algorithm 2 Feature Selection using Forward Orthogonalized Search

- 1: Dataset: $X \leftarrow \{x_1, \dots, x_i, \dots, x_n\} \in \mathbb{R}^{m \times n}$;
 - 2: Mean-center and scale dataset: $X \leftarrow \text{normalized}(X)$;
 - 3: Initialization at $i = 1$:
 - 4: $\gamma \leftarrow sc(x_i, x_j)$ ▷ Calculate average squared coefficients
 - 5: $l_1 \leftarrow arg\ max(\gamma)$ ▷ Determine 1st index of maximum coefficient
 - 6: $\hat{X} \leftarrow x_{l_1}$ ▷ Approximate model dataset
 - 7: $\tilde{X} \leftarrow X^{-l_1}$ ▷ Dataset \tilde{X} with l_1^{th} column of X removed
 - 8: $Q \leftarrow x_{l_1} \in \mathbb{R}^{m \times 1}$ ▷ Or $q_1 \leftarrow x_{l_1}$ for the 1st step
 - 9: $SE_1 \leftarrow 100 \times perf(x_j, q_1)$ ▷ Evaluate performance
 - 10: $Importance_1 \leftarrow (100 - SE_1)$
 - 11: **for** ($i \in [2, n]$) **do**
 - 12: $q \leftarrow ortho(\tilde{x}, q)$ ▷ Gram-Shmidt Orthogonalization of
▷ \tilde{x} to the previous $q \in \mathbb{R}^{r-1}$
 - 13: $\gamma \leftarrow sc(x, q)$
 - 14: $l \leftarrow arg\ max(\gamma)$
 - 15: $\hat{X} \leftarrow \tilde{x}_l$ ▷ Append l^{th} column of previous \tilde{X} into \hat{X}
 - 16: $\tilde{X} \leftarrow \tilde{X}^{-l}$ ▷ Remove l^{th} column from previous \tilde{X}
 - 17: $Q \leftarrow q_j$ ▷ Append q_j . $Q \in \mathbb{R}^{m \times r}$
 - 18: $SE_i \leftarrow \min(100 \times perf(x, q), 100)$
 - 19: $Importance_i \leftarrow (100 - SE_i)$
 - 20: **end for**
 - 21: Rank selected features in \hat{X} according to Importance
-

3.2.4 Self-organizing map neural network

PCA and FOS are appropriate for linear feature selection; however, Kohonen self-organizing map (SOM) can be utilized for a QFD matrix exhibiting nonlinear relationships (Yin 2008). SOM has been used for clustering, data visualization, dimensionality reduction, and nonlinear data mapping, and its variants are too many to list (Yin 2008). SOM in its original form will be considered in this paper for feature selection and visualization. Figure 3.5 illustrates the Kohonen two-dimensional SOM neural network that is used to model the QFD matrix at the CR definition stage. As in k-means clustering, SOM requires the number of classes be known a-priori. Thus, a strategy developed by Faro et al. (2005) is adopted in this paper to automate the process of determining the number of classes with the use of a single layer SOM.

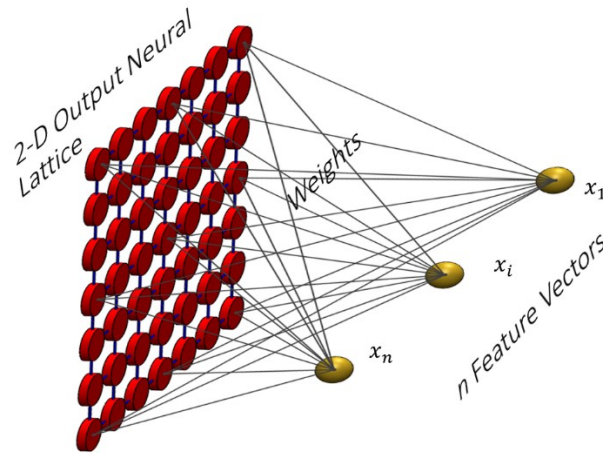


Figure 3.5. Kohonen Self-Organizing Map Neural Network

SOM feature selection starts with transforming the data to similarity matrix in Algorithm 3. Similarity matrix, $S \in \mathbb{R}^{m \times m}$, is used to avoid the difficulties associated with raw data in clustering (Ng et al. 2002). In a study by Faro et al. (2005), similarity matrix is calculated in Equation (3.16) then normalized before using it for classification. This equation

describes the function $sim(X)$ in the algorithm while Equation (3.17) describes the random weights initialization that is uniformly distributed between 0 and 1 in the function $initw$.

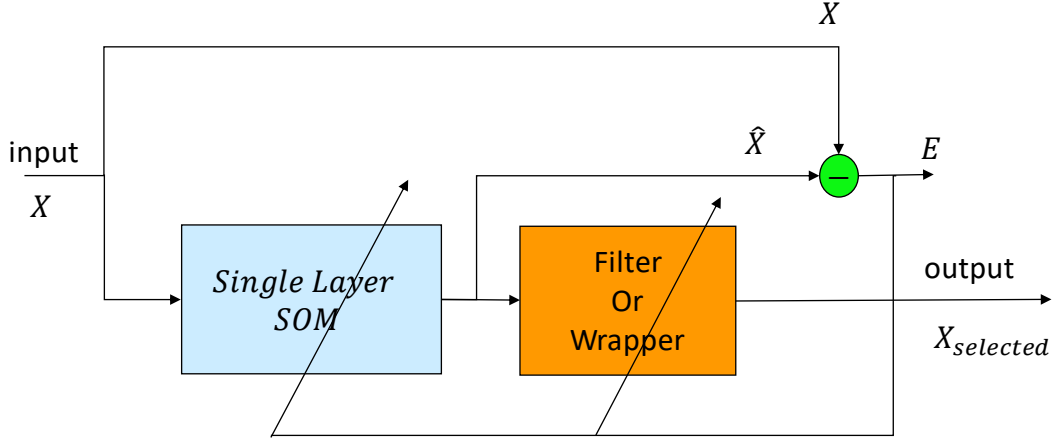


Figure 3.6. Single layer SOM unsupervised feature selection method

$$s_{ij} = \frac{1}{n} \sum_{k=1}^n \min(x_{ik}, x_{jk}) \quad (3.16)$$

$$\omega_{j\kappa} = U(0,1), \kappa \in [1, nu] \quad (3.17)$$

$$d_{\kappa} = \|S_i - \omega_{\kappa}\| \quad (3.18)$$

$$lu = \arg \min_{\kappa \in [1, nu]} \{d_{\kappa}\} \quad (3.19)$$

The function $edist$ does the following: (i) calculates and orders the Euclidean distance vector, $d \in \mathbb{R}^{nu}$, between neurons and row vector of the similarity matrix where the maximum number of neurons, nu , is 3; (ii) calculates the index of neuron with minimum distance; (iii) updates the weights, $\omega(t)$, at a user-configurable learning rate α ; and (iv) evaluates the indices, ind , of the order of d , and the neighborhood function h in the following equations (Faro et al. 2005). It should be noted that $edist$ takes S_i as the row

vector of the normalized similarity matrix of Equation (3.16) as its argument and that s_{ij} is an element of the row vector S_i .

$$ind = order(d) \quad (3.20)$$

$$h(t) = \frac{1}{ind_j^2} \quad (3.21)$$

$$\omega_{j\kappa}(t+1) = \omega_{j\kappa}(t) + \alpha h(t)(s_{ij} - \omega_{j\kappa}(t)) \quad (3.22)$$

Adopting the definitions around the concept of linking energy, E , from a study by Faro et al. (2005) for evaluating whether two classes are similar or not, the function *lenergy* is derived to facilitate the automatic determination of the number of classes, C . Linking energy, E , is the inverse of the average mean distance of all the classes. Aside from E , classification is evaluated by the mean distance D between the centroids, *COGS*, of two classes. Thus,

$$E = \frac{1}{L} \quad (3.23)$$

$$\lambda_j = \frac{1}{C} \sum_{i \in [1, n]} \sum_{r \in [j, C], j \neq r} \sqrt{\omega_{ir}^2 + (1 - \omega_{ij})^2} \quad (3.24)$$

$$le = arg \max_{j \in [1, C]} \{\lambda_j\} \quad (3.25)$$

$$L = \sum_{j \in [1, C]} \lambda_j \quad (3.26)$$

$$CoG_j = \frac{1}{n} \sum_{i \in [1, m], j \leq C-1} \omega_{ij} \quad (3.27)$$

$$D = \sqrt{\sum_{j \in [1, C-1]} (CoG_j - CoG_{j+1})^2} \quad (3.28)$$

Classification starts with evaluating the weights and the linking energy parameters for $nu = 2$. A neuron is then added by replicating the weight vector at the le^{th} column of the weight matrix ω , E and D are updated and compared to their previous values to determine whether to keep or remove the newly added weight vector. Equation (3.2) suggests that the time-dependent weight matrix is updated online, which implies that it is calculated at each row of the dataset input S_i or X_i . At the end of the iteration, the number of columns in the weight matrix corresponds to the optimum number of classes, C .

Having obtained the optimum number of classes, C , SOM feature selection can then be evaluated using the heuristic filter model or the optimal wrapper model. Both filter and wrapper models will be discussed with the purpose of providing designers of modular construction machines feature selection tools at the customer requirement definition phase of conceptual design. Algorithm 4 describes the backward elimination filter approach for SOM feature selection according to Benabdeslem and Lebbah (2007). Either one of these approaches requires the function $somlearn(X, w, C, \alpha)$ that updates the following: (i) the SOM weight matrix, ω , according to Equation (3.22); (ii) the index, lu , of the minimum element in the distance vector d , as called for by Equations (3.18) and (3.19); (iii) the cardinality of class c , that counts the number of hits of a neuron due to the occurrence of lu ; (iv) the quantization error, qe_p with $p \in [1, n]$ and that $qe_1 = 0$; (v) rate of error

reduction ∇e_p . Thus, the equation can be written with ω_{ij} taken to be the weights of the winner unit as:

$$qe_p = \sum_{i \in [1, m]} \sum_{j \in [1, C]} \sqrt{(X_{pi} - \omega_{ij})^2} \quad (3.29)$$

$$\nabla e_p = \frac{qe_p - qe_{p+1}}{qe_p} \quad (3.30)$$

A summary of the steps required to develop Algorithm 3 (Faro et al. 2005) for the optimum number of classes in SOM using forward orthogonal search is presented below. In a study by Faro et al. (2005), this adaptive classification technique has been shown to be simple and effective.

Algorithm 3 SOM optimum number of classes

```
1: Dataset:  $X \leftarrow \{x_i \mid x_i \in \mathbb{R}^m \wedge i \in [1, n]\}$ ;
2: Normalize dataset:  $X \leftarrow \text{normalized}(X)$ ;
3: Input:  $L_{th}, D_{th}$   $\triangleright$  linking energy and class distance thresholds
4: Initialization,  $i = 1$ :
5:    $S \leftarrow \text{sim}(X) \in \mathbb{R}^{m \times m}$   $\triangleright$  Calculate raw similarity matrix
6:    $S \leftarrow \text{snor}(S)$   $\triangleright$  Normalize raw similarity matrix
7:    $w \leftarrow \text{initw}(s, nu)$   $\triangleright$  Randomly initialize weights with
8:    $\triangleright$  number of neurons,  $nu \leftarrow 2$ 
9:    $w \leftarrow \text{edist}(S_i, w, nu, \alpha)$   $\triangleright$  Update weights, index of neuron
    $\triangleright$  with minimum euclidean distance
    $\triangleright S_i$  is  $i^{th}$  row vector of  $S$ 
10:   $[le, E, L, D] \leftarrow \text{lenergy}(S_i, w, nu, \alpha)$   $\triangleright$  Evaluate index of maximum L,
11:   $\triangleright$  link energy, mean class distance,
12:   $\triangleright$  sum of distances between classes
13:   $i \leftarrow i + 1$ 
14: while ( $i \leq m$ ) do
15:   $nu \leftarrow nu + 1$   $\triangleright$  maximum no. of neurons,  $nu$ , is 3
16:   $w \leftarrow w_{le}$   $\triangleright w_{le}$  is replicated at the  $le^{th}$  column of  $w$ 
17:   $w \leftarrow \text{edist}(S_i, w, nu, \alpha)$ 
18:   $[le, E, L, D] \leftarrow \text{lenergy}(w)$ 
19:  Remove neuron if  $(L_1 - L_{i-1}) < L_{th} \vee (D_1 - D_{i-1}) < D_{th}$ 
20:   $i \leftarrow i + 1$ 
21: end while
22:  $C \leftarrow$  number of columns in  $w$   $\triangleright$  Optimal number of classes
```

Backward elimination implies that the algorithm starts with all the features included in the selected feature matrix $\hat{X} \in \mathbb{R}^{m \times n}$. A feature is eliminated from \hat{X} , resulting in $\hat{X} \in \mathbb{R}^{m \times r}$, and the ranking of its selected features are evaluated by: (i) determining the number of times a neuron is activated, ϱ ; (ii) using ϱ to measure the importance of the features associated with each neuron; (iii) ranking the selected features according to importance vector, I , and then (iv) finding the index, lh , of the features to be eliminated that corresponds to the least important element in I . Thus, the equations can be expressed as:

$$\rho = \frac{\text{card}_c}{n} \quad (3.31)$$

$$h_{jc} = \frac{\rho \omega_{jc}}{\sum_{c \in [1, C]} \omega_c} \quad (3.32)$$

$$I_j = \sum_{c \in [1, C]} h_{jc}, \text{ where } j \in [1, r] \quad (3.33)$$

$$lh = \text{arg min}(I) \quad (3.34)$$

As shown in Algorithm 4, $I \in \mathbb{R}^r$ is stacked in a list H , where the set of features that correspond to the maximum rate of error reduction ∇e is retrieved.

Algorithm 5 describes the SOM feature selection that uses the wrapper approach. Genetic algorithm is the optimization routine chosen for this approach, which provides a framework for expressing binary chromosomes to represent the inclusion and non-inclusion of selected features as 1s and 0s, respectively. Table 3.2 illustrates such representation of each row, $b \in P_k$ in a population of N chromosomes, $P \in \mathbb{R}^{N \times n}$.

A summary of the steps required to develop Algorithm 4 (Benabdeslem and Lebbah 2007) for feature selection using backward elimination filter is presented below.

Algorithm 4 Feature selection using backward elimination filter

```

1: Initialization,  $qe_1 = 0$ ,
2:  $\hat{X} \leftarrow X \in \mathbb{R}^{m \times n}$   $\triangleright$  Initialize selected features with full features
3: for ( $p \in [1, n - 1]$ ) do
4:    $w \leftarrow \text{init}w(\hat{X}, nu)$   $\triangleright$  Initialize SOM weights of normalized dataset
5:    $[w, lu, card, qe_{p+1}, te_p] \leftarrow \text{somlearn}(X, w, C, \alpha)$ 
    $\triangleright$  Update  $w$ ,  $lu$ , cardinality of class  $c$  of neuron,
    $\triangleright$  quantization error, and topological error
6:    $\nabla e_p \leftarrow \frac{qe_p - qe_{p+1}}{qe_p}$   $\triangleright$  rate of error reduction
7:   for ( $j \in [1, r]$ ) do  $\triangleright \hat{X} \in \mathbb{R}^{m \times r}$ 
8:     for ( $c \in [1, C]$ ) do
9:        $\rho \leftarrow card_c/n$ 
10:       $h_{jc} \leftarrow \frac{\rho * w_{jc}}{\bigcup_{c \in [1, C]} w_c}$ 
11:    end for
12:     $I_j \leftarrow \bigcup_{c \in [1, n]} h_{jc}$   $\triangleright$  Feature importance
13:  end for
14:   $lh \leftarrow \text{argmin}(I)$   $\triangleright$  Index of the least important
    $\triangleright$  feature to be removed
15:   $\hat{X} \leftarrow \hat{X}^{-lh}$   $\triangleright$  Remove  $lh^{th}$  column from previous  $\hat{X}$ 
16:   $w \leftarrow w^{-lh}$   $\triangleright$  Remove  $lh^{th}$  column from previous  $w$ 
17:   $H_p \leftarrow \text{list}(I)$   $\triangleright$  Update Importance list
18: end for
19:  $\omega \leftarrow \text{reorder}(\nabla e)$   $\triangleright$  indices of the descending values in  $\nabla e$ 
20:  $f_{sel} \leftarrow H_{\omega_1}$   $\triangleright$  The 1st element of  $\omega$  points to the maximum  $\nabla e$  and to
    $\triangleright$  the row of list  $H$  where the desired features can be retrieved

```

Table 3.2. A chromosome of functional requirements, $FR_{j \in [1, n]}$

	FR_j												
P_k	1	1	0	1	0	1	0	0	0	0	1	0	1

Randomly initialized chromosomes form the first set of N parents in the population. At $t = 1$, the 0s in the chromosomes determine which features are excluded to form the selected feature matrix, \hat{X} , for training the SOM neural network. As in the previous algorithm, the

quantization error is evaluated using the functions *initw* and *somlearn*. In randomly selecting the parents for mating, the following fitness function and selection probability are used (Kuo et al. 2006):

$$fitness_{k \in [1,N]} = \frac{1}{qe_k} \quad (3.35)$$

$$P_k = \frac{fitness_k}{\sum_{k \in [1,N]} fitness_k} \quad (3.36)$$

Through crossover, mutation, and elitism, the next generation of parents are produced and the cycle is repeated *NG* times. At the end of *NG* iterations, fitness is ranked in descending order such that first rank points at the most fit row in *P* as the set of desired features to be selected.

All of the unsupervised feature selection algorithms in this chapter can then be implemented on any high-level programming language, such as Python, R, or MATLAB. An application of these algorithms to the conceptual design of an automated wood wall-framing machine is described in the next section. Graphs describing the results of the application have been generated in R (RStudio Team 2015).

A summary of the steps required to develop Algorithm 5 is presented below. This algorithm is a modification of the clustering technique by Kuo et al. (2006) for SOM wrapper feature selection using genetic algorithm.

Algorithm 5 Wrapper feature selection using genetic algorithm

```
1: Initialization,  $P_k \leftarrow \{b_{ki} \mid b_{ki} \in \{1, 0\} \wedge i \in [1, n] \wedge k \in [1, N]\}$ ;
    $\triangleright$  Population corresponds to N Chromosomes
2: Normalize dataset:  $X \leftarrow \text{normalized}(X)$ ;
3: while  $t \leq NG$  do  $\triangleright$  NG is the number of generations
4:    $\tilde{P} \leftarrow P$ 
5:   for  $(k \in [1, N])$  do
6:      $\hat{X}_k \leftarrow X_k^{-lz}$   $\triangleright$  features corresponding to columns
    $\triangleright$  with non-zero elements in  $P_k$ 
7:      $w \leftarrow \text{initw}(\hat{X}_k, nu)$   $\triangleright$  Initialize weights of normalized dataset
8:      $qe_k \leftarrow \text{somlearn}(\hat{X}_k, w, C, \alpha)$   $\triangleright$  Evaluate quantization error
9:      $fitness_k \leftarrow \frac{1}{qe_k}$   $\triangleright fitness_k \propto selection$ 
10:   end for
11:    $P \leftarrow \text{crossover}(P)$   $\triangleright$  Next generation after crossover
12:    $P \leftarrow \text{mutate}(P)$   $\triangleright$  Mutate if required
13:    $P \leftarrow \text{elitism}(\tilde{P})$   $\triangleright$  Retain 1 or 2 most fit chromosomes from  $\tilde{P}$ 
14: end while
15:  $\omega \leftarrow \text{revorder}(fitness)$   $\triangleright$  indices of the descending values in  $fitness$ 
16:  $f_{sel} \leftarrow P_{\omega_1}$   $\triangleright$  The 1st element of  $\omega$  points to the maximum
    $\triangleright fitness$  and to the row of  $P$  where the desired
    $\triangleright$  features can be retrieved
```

3.3 Application to automated wood wall framing machine

A conceptual sketch of an automated wood wall framing machine is depicted in Figure 3.7. This conceptual design of the machine consists of nailing, drilling, and sawing stations, dragging mechanisms and a table that has a non-stationary side to accommodate different widths of wood wall panels. Aside from handling different widths, this machine will be capable of making 4×4 and 4×6 wood panels with studs only, with studs and window, and with studs and door at the construction site. Thus, it is important that this machine be modular.

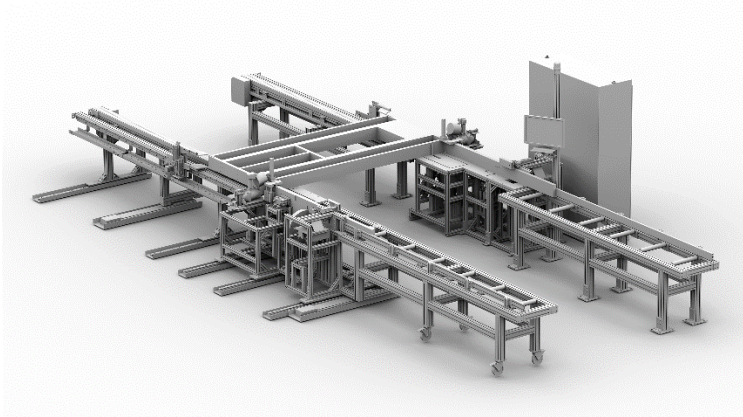


Figure 3.7. Conceptual automated wood wall framing machine

The QFD developed by the product design team at the customer requirement definition phase for the conceptual design of the machine is shown in Table 3.3. This QFD matrix defines the input dataset, $X \in \mathbb{R}^{10 \times 13}$, for all of the feature selection methods previously discussed. It should be noted that the CRs are the m observations of X , where $m = 10$. The list of customer requirements associated with this QFD includes: (CR_2) quality, (CR_2) small, (CR_3) fast, (CR_4) cheap to operate, (CR_5) cheap to purchase, (CR_6) less maintenance, (CR_7) adaptability, (CR_8) safe, (CR_9) user friendly, and (CR_{10}) energy efficient.

Table 3.3. Quality Function Deployment of the automated wall framing machine

	FR_1 : Operational tolerance	FR_2 : Footprint of machine	FR_3 : Wall frame production time	FR_4 : Power usage	FR_5 : Level of automation	FR_6 : Supply chain cost	FR_7 : Cost of installation and training	FR_8 : Component lifetime	FR_9 : Moving parts	FR_{10} : Human intervention	FR_{11} : Modularity	FR_{12} : Dust	FR_{13} : Ease of training
CR_1	9		1		9	3							
CR_2		3											
CR_3	1		9	3	3	3			1	9			
CR_4			3	3	1				3	9			
CR_5	9		1		9	9	9	3	3		1		
CR_6					9	3		9	3			3	
CR_7	3				9	1	3		1		9		
CR_8		1			3	3	1		3	9			
CR_9			1		3					3			9
CR_{10}			1	9	3				3				

Applying the PCA and FOS techniques to the QFD data ranking of the features is shown in Figure 3.8. Since the loadings corresponding to the last few features obtained through PCA are small, FR_{13} , FR_9 , and FR_{10} can be ignored. Likewise, the insignificant features FR_5 , FR_9 , FR_1 , and FR_{13} can be ignored from the set of features selected using FOS. Determining which method is optimal cannot be determined at this point since the

comparison has to be evaluated by the fitness criterion, which is invoked by the application of the SOM wrapper approach.

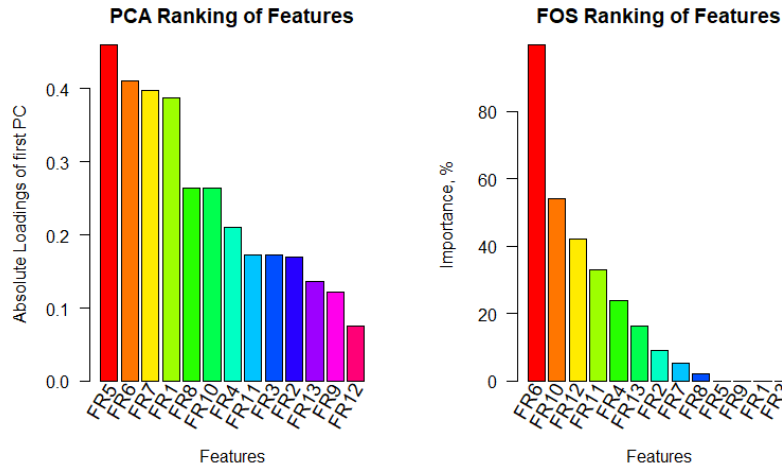


Figure 3.8. PCA and FOS ranking of features

Before applying the SOM filter and wrapper models, the optimum number of classes, C , has to be determined. Figure 3.9 reveals an optimum value of $C = 2$ after the application of automatic SOM classification described in Algorithm 4. This step efficiently facilitates the process of employing SOM filter and wrapper models that provides the selected features in terms of chromosomes shown in Table 3.4.

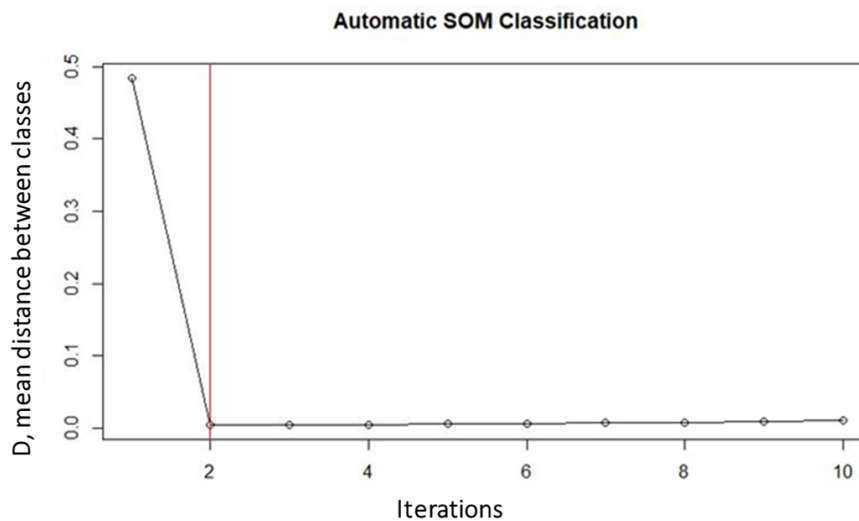


Figure 3.9. Optimum number of classes, $C = 2$, detected in the 2nd iteration

Table 3.4. Chromosomes of selected features from the four methods

Name	FR ₁ : Operational tolerance	FR ₂ : Footprint of machine	FR ₃ : Wall frame production time	FR ₄ : Power usage	FR ₅ : Level of automation	FR ₆ : Supply chain cost	FR ₇ : Cost of installation and training	FR ₈ : Component lifetime	FR ₉ : Moving parts	FR ₁₀ : Human intervention	FR ₁₁ : Modularity	FR ₁₂ : Dust	FR ₁₃ : Ease of training
Wrapper	1	1	0	1	0	1	0	0	0	0	1	0	1
Filter	1	0	0	0	1	1	0	1	1	0	0	0	0
FOS	0	1	1	0	1	1	1	0	1	0	0	1	1
PCA	1	1	0	1	1	1	1	1	0	1	0	0	1

Figure 3.10 shows the ranking according to fitness values of the selected FRs after applying the *somlearn* function of the SOM wrapper algorithm. Ignoring the insignificant features selected, as previously noted, the corresponding set of features selected for the PCA and FOS methods are also represented as chromosomes in the table.

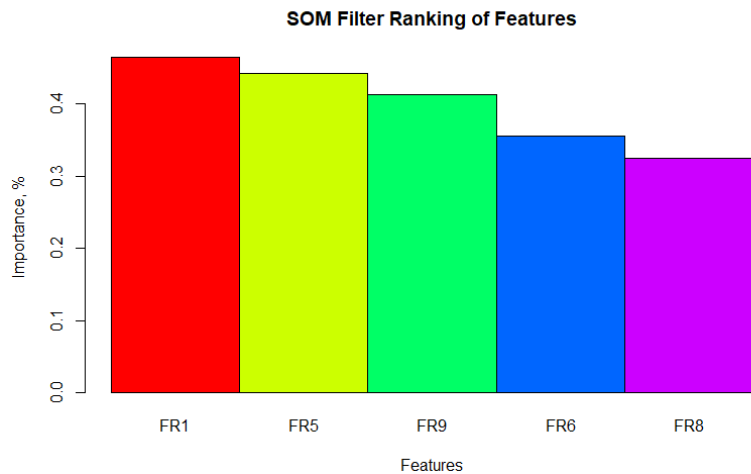


Figure 3.10. Ranking of the selected FRs using SOM filter

3.4 Results and discussion

Table 3.4 presents the set of FRs selected for each of the four feature selection methods. Setting up the results in terms of chromosomes facilitates the ranking of these methods and the evaluation of their performance using the functions provided in Algorithm 5. Executing the *somlearn* and fitness functions for each of the chromosomes provides the comparison of the four techniques in Figure 3.11. Table 3.4 replaces the selection, crossover and mutation when Algorithm 5 is used as a mechanism for the ranking shown in Figure 3.11. This ranking provides a fair comparison of the application of the techniques since Table 3.4 is a mask applied to the same dataset, the same SOM network, and the same fitness criterion. An interesting observation can be derived from this figure. As to be expected, the SOM wrapper model gives an optimum solution due to its use of genetic algorithm, a numerical optimization routine. Not only does SOM wrapper provide the least number of FRs, but it is the only method that identifies modularity as an FR, which delivers the intent of designing an automated wood wall framing machine that can be used at the construction site.

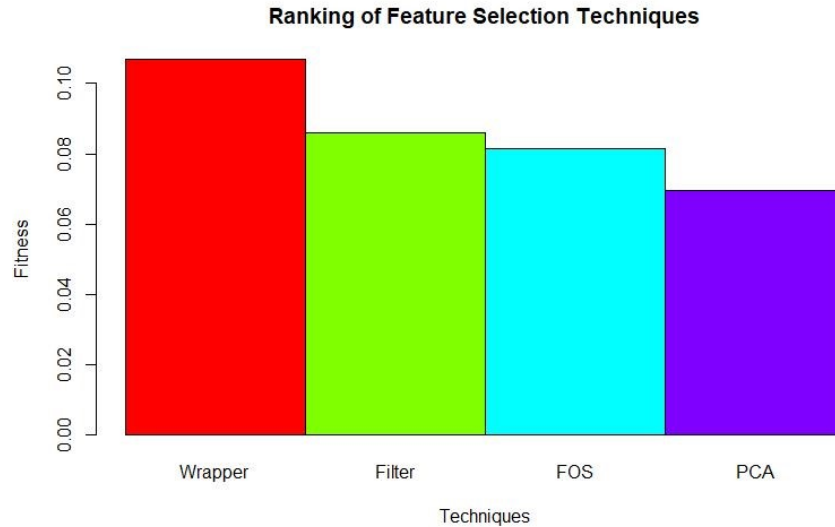


Figure 3.11. Ranking by fitness of the different feature selection techniques

Since the PCA model fails to satisfy the requirement of a significantly large eigenvalue as Xu et al. (2008) have indicated, it has the lowest performance. PCA, however, ought to be used as an alternative tool whenever possible due to its simplicity and efficiency in handling huge QFD matrices. It can also be used for weight initialization to speed up SOM learning (Kinouchi et al. 2002).

Among the medium performers are the SOM filter and FOS models. SOM filter is slightly better than FOS, which signifies a moderate nonlinearity in the QFD dataset. These tools can also serve as alternative tools for obtaining fast preliminary results in applications where the use of wrapper model can be computationally expensive and slow (Mahrooghy et al. 2012).

3.5 Conclusion

A comprehensive set of unsupervised machine learning tools has been introduced to address the limitations, indicated in the literature, of the existing methods in systematically selecting FRs from a QFD matrix (Mazurek and Kiszová 2012, Achimugu et al. 2014). In

place of these difficulties, however, users of the proposed tools have to contend with specifying the learning rate α and the thresholds L_{th} and D_{th} to preclude a priori knowledge of the number of classes, thus automating the classification process in SOM learning.

Quantization error is used to measure the fitness in the SOM wrapper algorithm. Other measures such as entropy (Harp & Samad 1991), Davies-Bouldin Index, and Gini Index (Demiriz et al. 2002)] can be explored into the development of a suite of feature selection tools for future research. It should be noted that the topological error has been intentionally excluded as a fitness measure since it is not appropriate to a simple single layer SOM structure that takes a maximum of only three neurons.

Another consideration for future research should include extending the application of the proposed methods to online CR or FR identification, design alternatives selection, project management, contract management, and marketing. Along with this consideration, a software interface should also be developed.

Chapter 4 Conceptual design of controllers for automated modular construction machines³

4.1 Introduction

Construction automation is expected to increase in prevalence due to the inherent inefficiencies and limitations of conventional construction practice (Bock 2015). Systems that realize the automation are, however, complex. An automated steel wall framing machine (E. Tamayo et al. 2017), for example, consists of mechanical, electrical, and control systems. Difficulties associated with designing an automated system can be overcome by the use of model-based system engineering (MBSE) methodology (Abdelrazek et al. 2017). MBSE methodologies can be categorized as graphical or matrix-based. When adopted during the conceptual design phase, the matrix-based methodology provides a visual, compact, systematic, and transdisciplinary integrated MBSE approach (E. Tamayo et al. 2017).

To correct the usual practices in machine control system design that depend on experience and trial and error, Lee et al. (2001) have illustrated the applicability of axiomatic design (AD) in developing control solutions. These authors have not employed quality function deployment (QFD) and process control decoupling techniques. QFD is a tool to align product design with customer needs (Franceschini 2002). A sequence of QFDs has been applied from customer needs identification, product planning, part planning, process planning, and production control (Quesada & Bahill 2003), which depicts the usefulness of QFD as a design and an analysis tool. Although not specifically called QFD, Lahiri

³ The manuscript appearing as Chapter 4 of this thesis has been accepted for publication in Creative Construction Conference 2019, at the time of publication of this thesis.

(2017) has applied the methodology only to develop a step test plan in the form of an expectation matrix for modelling a multivariable process. A formalized conceptual design methodology is still required in designing a controller.

This paper focuses on the use of the QFD matrix at the AD and design structure matrix (DSM) stages of an MBSE approach to integrated conceptual design, and is structured as follows: section 4.2 describes the QFD matrix for controller design; section 4.3 illustrates the applications of the controller design methodology; section 4.4 contains a discussion of results; and the conclusion follows in section 4.5.

4.2 Conceptual design of controllers

An integrated MBSE methodology involves the repeated use of a quality function deployment (QFD) model throughout the stages of conceptual design, namely: (a) customer requirements definition, and (b) integrated function modelling (IFM) development with the use of axiomatic design (AD) and design structure matrix (DSM). Figure 4.1 depicts the multiple applications of QFD, which establishes a model-based conceptual design approach. In this figure, the controller design extracted from AD and DSM is represented as a QFD matrix, in P-canonical or V-canonical form, that dynamically relates the manipulated variables (MV) and control variables (CV) through continuous or discrete transfer functions. Two QFD matrices are required to fully represent a V-canonical structure and to properly apply a corresponding decoupling strategy. In following the traditional representation, it could have been more appropriate to show only one QFD with its roof comprising the CV correlation matrix. However, two matrices are used to emphasize the AD and DSM steps in the conceptual design of a controller as well. This QFD representation in the design of multivariable predictive controllers is called

expectation matrix (Lahiri 2017). Inside the IFM is a collection of QFD matrices that constitutes the state, process/use case, actors, and interaction views. For the electrical control panel, the conceptual design method introduced in a study by Tamayo et al. (2018) facilitates the subsequent computer-aided design to be performed at the detailed design stage. Controller QFD will be shown to have numeric, Boolean, and transfer function representations depending on the type of systems being developed.

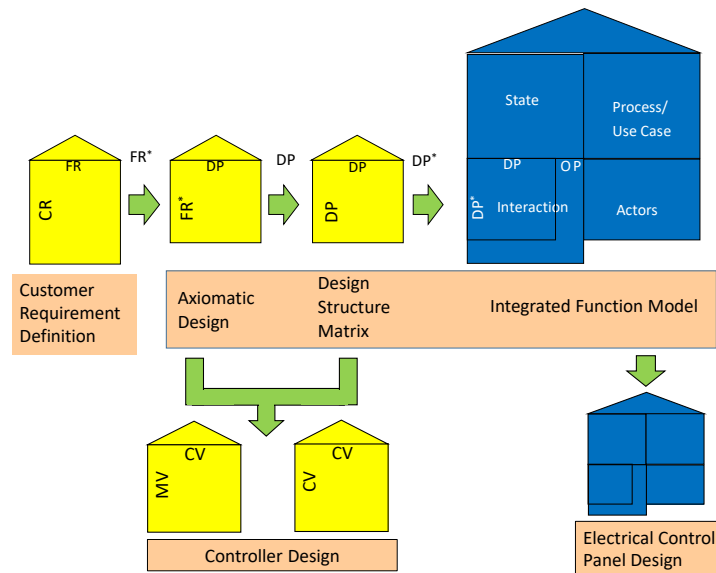


Figure 4.1. Integrated conceptual design overview

4.2.1 QFD structures for controller design

As depicted in Figure 4.1, a QFD matrix for controller design is extracted from the overall design matrix (DM) and DSM for the following reasons: (i) to express interactions in Laplace transfer functions; (ii) to identify coupled interactions; (iii) to design decouplers in enabling the designers to treat the control problem as loops consisting of independent systems; and (iv) to facilitate simulation at the conceptual design phase. Although controllers are not implemented in Laplace transfer functions, this QFD representation effectively communicates the behaviour of the multivariable process.

Figure 4.2 illustrates a 2×2 multivariable process with its corresponding QFD matrix in P-canonical and V-canonical forms (Tham 1999). As in AD, coupling is shown as the off-diagonal elements of the matrix in terms of Laplace transfer functions. A completely decoupled system is desired since it allows designers to implement multiple single-input-single-output (SISO) controllers. A decoupling strategy that is appropriate for each canonical structure is discussed further in the next section.

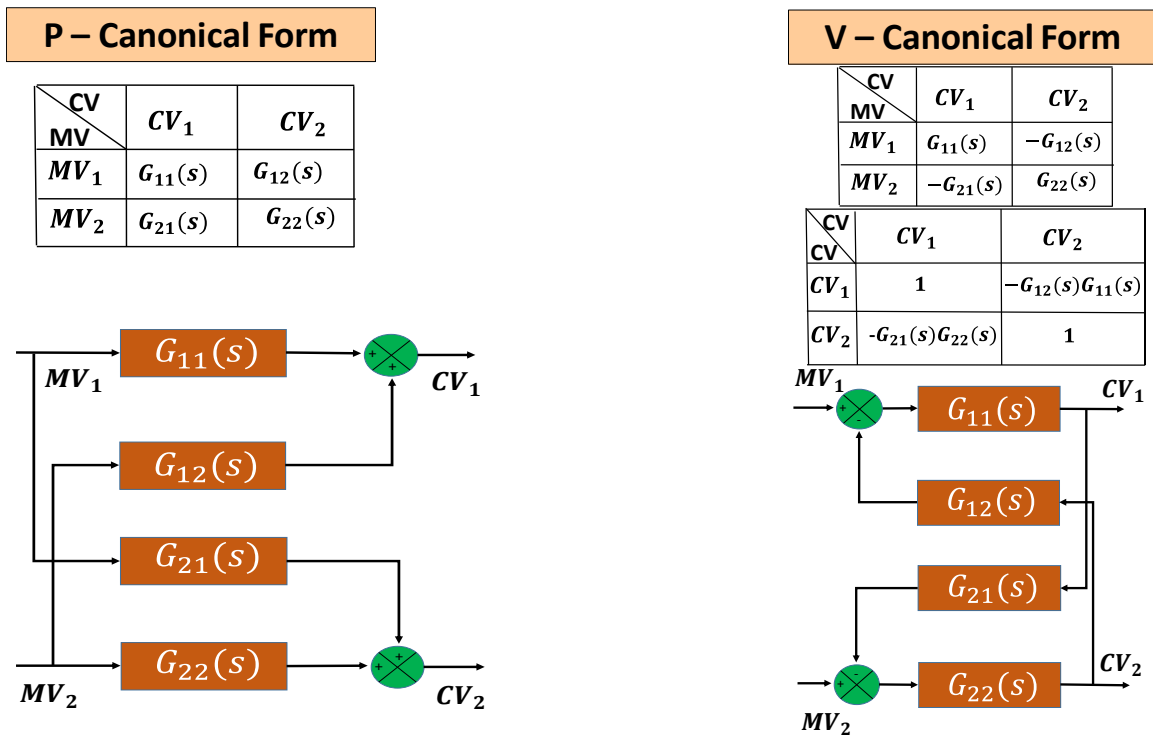


Figure 4.2. QFD representations of a coupled 2×2 multivariable system

4.2.2 Decoupling strategy for P-canonical form

In this section, the decoupling techniques derived for 2×2 multivariable systems are easily extended to $n \times n$ multiple-input-multiple-output (MIMO) systems. It must be noted that a V-canonical form has an equivalent higher order P-canonical structure (Tham 1999). For simplicity, a V-canonical form is considered separately to avoid dealing with higher

order transfer functions. A MIMO system of the P-canonical structure is expressed in the following equations:

$$CV_1(s) = G_{11}(s)MV_1(s) + G_{12}(s)MV_2(s) \quad (4.1)$$

$$CV_2(s) = G_{22}(s)MV_2(s) + G_{21}(s)MV_1(s) \quad (4.2)$$

Figure 4.3 depicts a decoupling technique, with multi-loop PID feedback controllers, for the P-canonical structure that implements a diagonalization process in the following equation:

$$Q(s)G(s) = W(s) \quad (4.3)$$

where the decoupling transfer matrix, $Q(s)$, is chosen such that $W(s)$ is diagonal. Equation (4.1) has multiple solutions but the simplest solution takes $Q_{11}(s) = Q_{22}(s) = 1$. In this case, $Q_{12}(s)$ and $Q_{21}(s)$ are then determined as follows (Marlin 2015):

$$Q_{12}(s) = -\frac{G_{12}(s)}{G_{11}(s)} \quad (4.4)$$

$$Q_{21}(s) = -\frac{G_{21}(s)}{G_{22}(s)} \quad (4.5)$$

Thus, for the general MIMO case, the decoupling transfer matrix can be expressed as follows:

$$Q_{ij}(s) = -\frac{G_{ij}(s)}{G_{ii}(s)}, \quad i, j = 1 \dots n \quad (4.6)$$

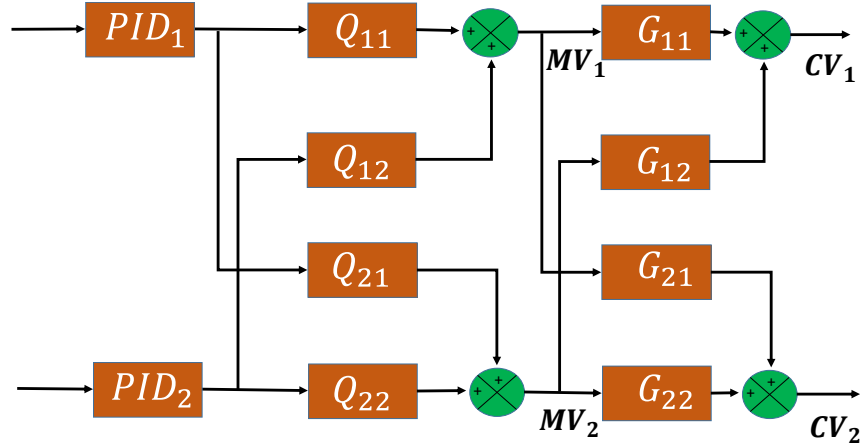


Figure 4.3. Decoupling technique for a P-canonical MIMO system with PID controllers

4.2.3 Decoupling strategy for V-canonical form

A V-canonical structure is encountered in MIMO processes involving the following model, where the transfer function matrix, $G(s) \in \mathbb{C}^{n \times n}$:

$$CV(s) = G(s)MV(s) \quad (4.7)$$

A model reference approach to decoupling requires that the output follow the reference command signal, which implies obtaining a feedforward controller, $Q(s) = G(s)^{-1}$, since

$$\begin{aligned} CV(s) &= Q(s)G(s) CV_{ref}(s) \\ &= CV_{ref}(s) \end{aligned} \quad (4.8)$$

Equation (4.9) defines a feedforward controller that is the inverse of the process. This observation suggests using the linear or non-linear dynamic model of the process for decoupling by simply feeding the appropriate reference signals to the feedforward controller and augmenting its output to that of the feedback controller.

Thus, for the 2×2 MIMO system in Figure 4.4, the feedforward controllers are:

$$Q_1(s) = CV_{1ref}(s)G_{11}(s)^{-1} + G_{12}(s)CV_{2ref}(s) \quad (4.9)$$

$$Q_2(s) = CV_{1ref}(s)G_{22}(s)^{-1} + G_{21}(s)CV_{2ref}(s) \quad (4.10)$$

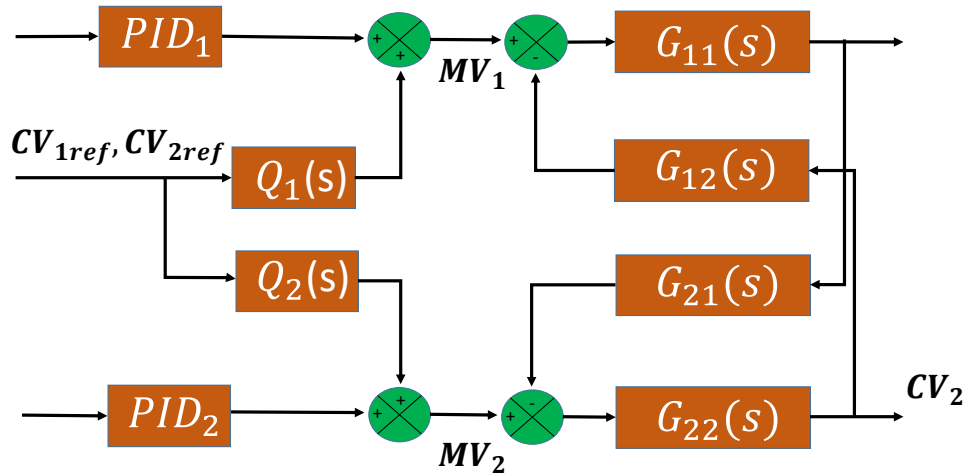


Figure 4.4. Decoupling technique for a V-canonical MIMO system with PID controllers

4.3 Illustrative examples

4.3.1 Steel wall framing machine

An automated steel wall framing machine is illustrated in Figure 4.5. This machine is capable of making three types of wall panels, namely: (i) with studs only; (ii) with studs and window; and (iii) with studs and door. Screw fastening is accomplished by first manually preparing the frames for automatic fastening, then entering the appropriate database for the frame being manufactured, and finally initiating the automatic screw fastening process.



Figure 4.5. Automated steel wall framing machine

Features of the machine includes two power screwdrivers on the top gantry and two on the bottom gantry. To accommodate different widths of wall panels, one side of the table is positioned accordingly. Each dragging device is positioned at a right angle to ensure that the panel is square. Thus, the QFD matrix for control design depicted in Table 4.1 is developed using the functional requirements (FRs) extracted at the AD phase of the integrated conceptual design, and then observing that none of the motors are linked. Since movements are accomplished using stepper motors, the MVs and CVs in the QFD table are torques and distances, respectively.

Table 4.1. QFD matrix for the steel wall framing machine controllers

		CV ₁	CV ₂	CV ₃	CV ₄	CV ₅	CV ₆
Table	MV₁	X					
Clamp	MV₂		X				
Dragging	MV₃			X			
y-axis position	MV₄				X		
z-axis position	MV₅					X	
Fastening	MV₆						X

It is clear from the QFD matrix that the positioning control systems are uncoupled, indicating that each motor can be controlled individually and that closed-loop stepper

motors can be considered to simplify controller implementation. This interesting result when applied to the correct specification of closed loop stepper motors validates the usefulness of the methodology.

4.3.2 Two link planar robotic arm

Robotic manipulators are coupled since the angular position of a motor in a joint affects those in the other joints. To illustrate the use of the QFD controller design described in the previous sections, a two degree-of-freedom (2-DOF) PUMA 560 robotic arm (Seraji 1987) is then discussed.

Torque, $\tau \in R^2$, is dynamically related to the joint angle, $q \in R^2$, for the 2-DOF robotic arm shown in Figure 4.6 as follows (Craig 2005):

$$\tau = M(q)\ddot{q} + V(q, \dot{q}) + G(q) \quad (4.11)$$

where, for the masses and lengths of the first and second link, as, respectively, m_1 , m_2 , l_1 , and l_2 , the following mass matrix, $M(q)$, centrifugal and Coriolis matrix, $V(q, \dot{q})$, and gravity matrix, $G(q)$, are obtained.

$$M(q) = \begin{bmatrix} l_2^2 m_2^2 + 2l_1 l_2 m_2 \cos q_2 + l_1^2 (m_1 + m_2) & l_2^2 m_2^2 + l_1 l_2 m_2 \cos q_2 \\ l_2^2 m_2^2 + l_1 l_2 m_2 \cos q_2 & l_2^2 m_2^2 \end{bmatrix} \quad (4.12)$$

$$V(q, \dot{q}) = \begin{bmatrix} -m_2 l_1 l_2 \sin q_2 \dot{q}_2^2 - 2l_1 l_2 m_2 \sin q_2 \dot{q}_1 \dot{q}_2 \\ l_1 l_2 m_2 \sin q_2 \dot{q}_1^2 \end{bmatrix} \quad (4.13)$$

$$G(q) = \begin{bmatrix} m_2 l_2 g \cos(q_1 + q_2) + (m_1 + m_2) l_1 g \cos q_1 \\ m_2 l_2 g \cos(q_1 + q_2) \end{bmatrix} \quad (4.14)$$

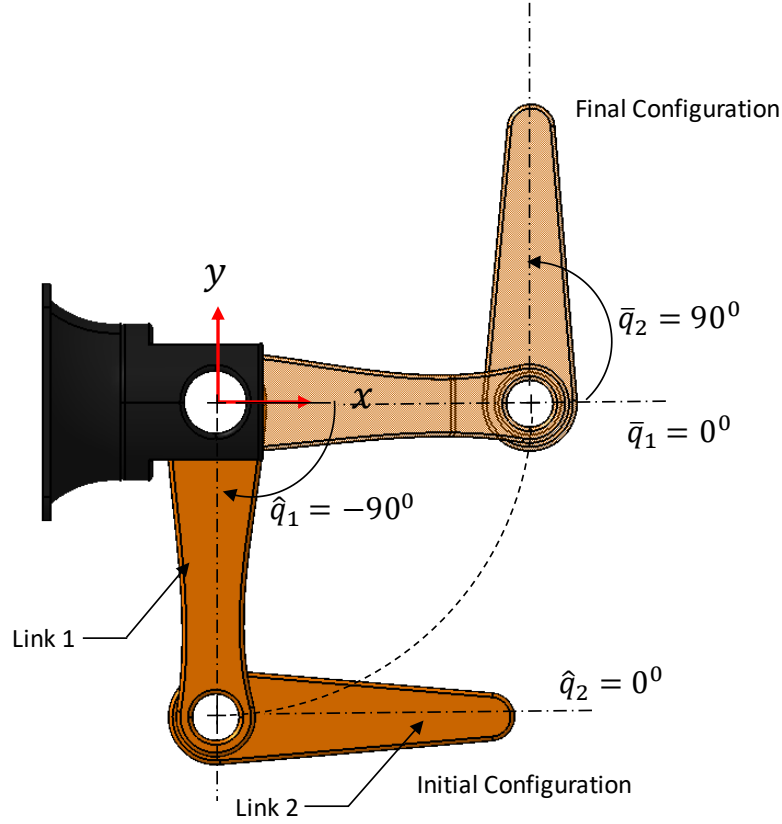


Figure 4.6. 2-DOF robotic arm

Using the example found in a study by Seraji (1987), Equation (4.7) is linearized at the operating point $[\bar{q}_1, \bar{q}_1; \bar{q}_2, \bar{q}_2] = [-\frac{\pi}{2}, 0; 0, 0]$ to obtain the following equation.

$$\tau = A\ddot{q} + B\dot{q} + Cq \quad (4.15)$$

For the PUMA example with model parameters $a_1 = 3.82, a_2 = 2.12, a_3 = 0.71, a_4 = 81.82,$ and $a_5 = 24.06,$

$$A = \begin{bmatrix} a_1 + a_2 \cos \bar{q}_2 + l_1^2 (m_1 + m_2); & a_3 + 0.5 a_2 \cos \bar{q}_2 \\ a_3 + 0.5 l_2 \cos \bar{q}_2 & a_3 \end{bmatrix} \quad (4.16)$$

$$B = \begin{bmatrix} -a_2 \bar{q}_2 \sin \bar{q}_2; & -a_2 (\bar{q}_1 + \bar{q}_2) \sin \bar{q}_2 \\ a_2 \bar{q}_2 \sin \bar{q}_2 & 0 \end{bmatrix} \quad (4.17)$$

$$C = \begin{bmatrix} -a_4 \sin \bar{q}_1 - a_5 \sin(\bar{q}_1 + \bar{q}_2); & -a_5 \sin(\bar{q}_1 + \bar{q}_2) - a_2(\bar{q}_1 \bar{q}_2 + 0.5\bar{q}_2^2) \cos \bar{q}_2 \\ -a_5 \sin(\bar{q}_1 + \bar{q}_2) & -a_5 \sin(\bar{q}_1 + \bar{q}_2) + 0.5a_2 \cos \bar{q}_2 \end{bmatrix} \quad (4.18)$$

Taking the Laplace transform of Equation (4.15) for the 2×2 robotic arm and noting that $\tau = MV$ and $q = CV$, the result is the following equation:

$$MV = (As^2 + Bs + C)CV \quad (4.19)$$

or

$$\begin{bmatrix} MV_1 \\ MV_2 \end{bmatrix} = \left\{ \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} s^2 + \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} s + \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} \right\} \begin{bmatrix} CV_1 \\ CV_2 \end{bmatrix} \quad (4.20)$$

Equation (4.19) reduces to Equation (4.7) if $G(s)$ is taken to be equal to $(As^2 + Bs + C)^{-1}$, therefore $Q(s) = (As^2 + Bs + C)$. Applying the derivations for the feedforward controller of the 2×2 MIMO system leads to the following QFD matrix that utilizes the AD and DSM sections to fully describe the V-canonical structure in Figure 4.7.

CV MV	CV₁	CV₂
MV₁	$G_{11} = \frac{1}{A_{11}s^2 + B_{11}s + C_{11}}$	$-G_{12} = A_{12}s^2 + B_{12}s + C_{12}$
MV₂	$-G_{21} = A_{21}s^2 + B_{21}s + C_{21}$	$G_{22} = \frac{1}{A_{22}s^2 + B_{22}s + C_{22}}$
CV CV	CV₁	CV₂
CV₁	1	$-\frac{A_{12}s^2 + B_{12}s + C_{12}}{A_{11}s^2 + B_{11}s + C_{11}}$
CV₂	$-\frac{A_{21}s^2 + B_{21}s + C_{21}}{A_{22}s^2 + B_{22}s + C_{22}}$	1

Figure 4.7. QFD matrix of the 2-DOF PUMA 560 robot

Using the information provided in the QFD table, the feedforward controller for each loop is obtained as follows:

$$Q_1(s) = (A_{11}s^2 + B_{11}s + C_{11})CV_{1ref} + (A_{12}s^2 + B_{12}s + C_{12})CV_{2ref} \quad (4.21)$$

$$Q_2(s) = (A_{22}s^2 + B_{22}s + C_{22})CV_{1ref} + (A_{21}s^2 + B_{21}s + C_{21})CV_{2ref} \quad (4.22)$$

Figure 4.8 shows the Simulink model that implements the feedforward controller, G_{FF} , defined in Equations (4.13) and (4.14) and the PID controllers shown in Figure 4.4 in controlling a nonlinear 2-DOF robotic arm. Figure 4.9 shows the joint angular responses of the robotic arm to the trajectory configuration described in Figure 4.6.

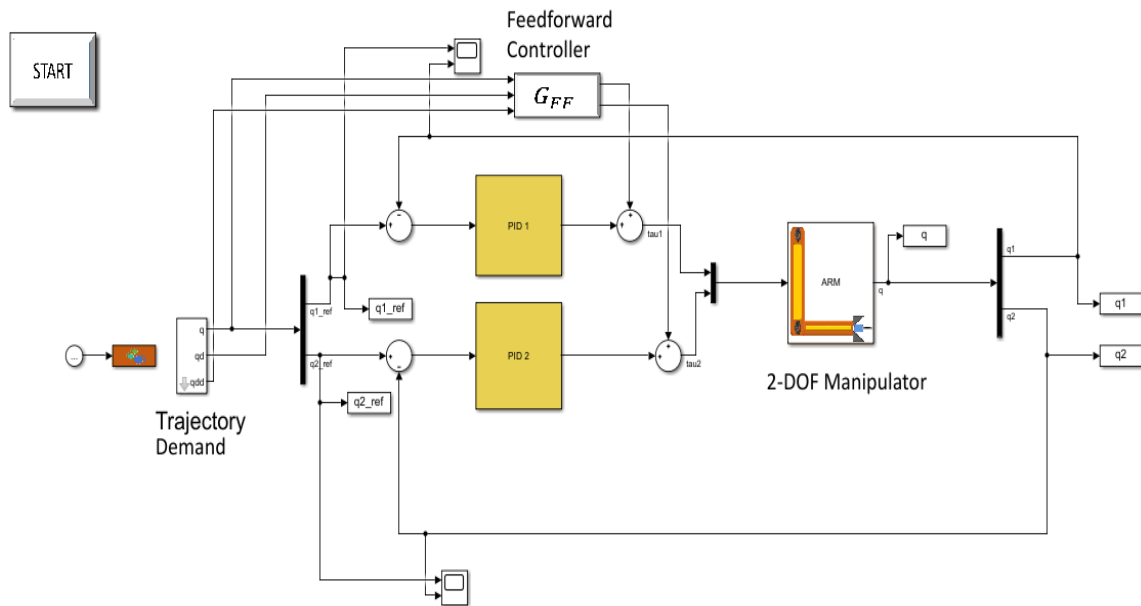


Figure 4.8. Simulink control implementation of the 2-DOF robotic arm for an initial and final trajectory configuration of $[\bar{q}_1, \bar{q}_1; \bar{q}_2, \bar{q}_2]_i = [-\frac{\pi}{2}, 0; 0, 0]$ and $[\bar{q}_1, \bar{q}_1; \bar{q}_2, \bar{q}_2]_f = [0, 0; \frac{\pi}{2}, 0]$

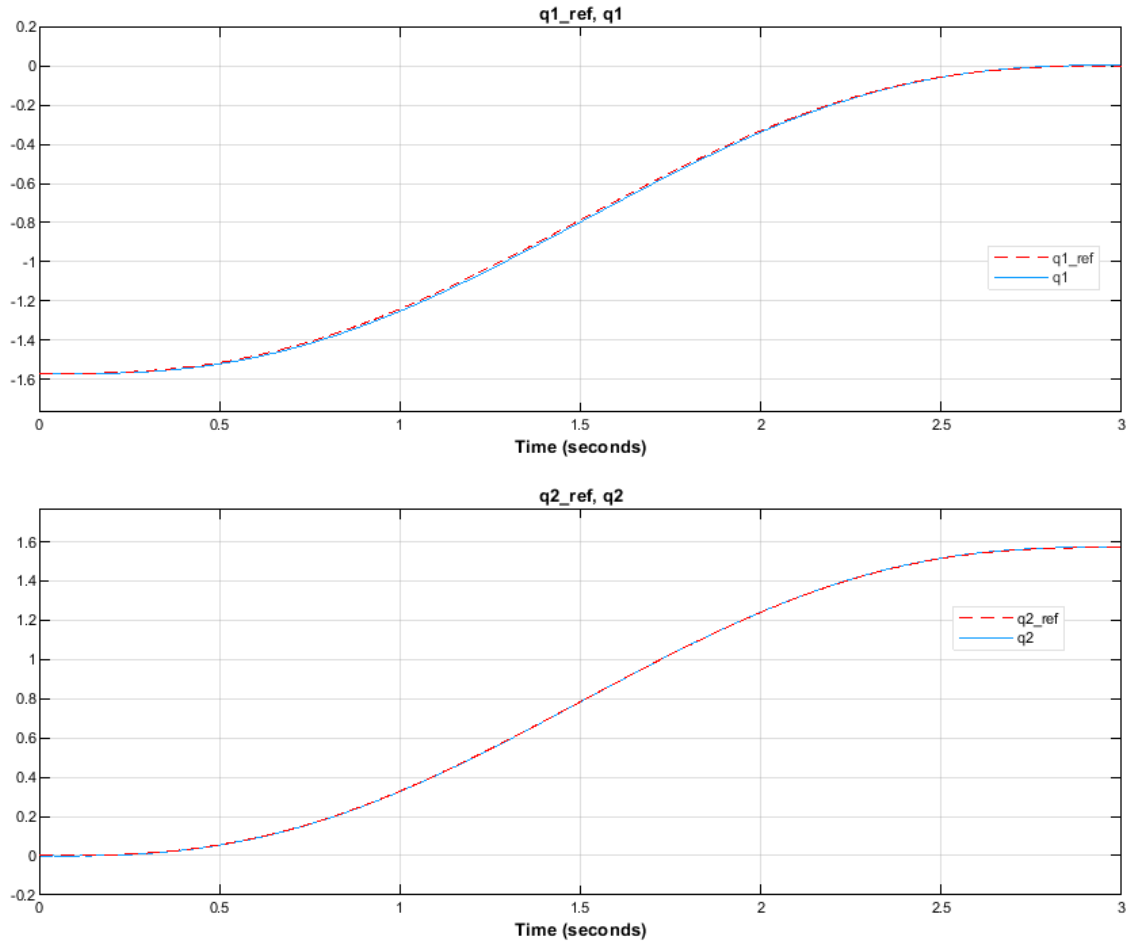


Figure 4.9. Joint angle responses to the trajectory demand configuration of Figure 4.6

4.4 Remarks and discussion

As it has proven useful in conceptual MBSE, QFD has been shown to perform preliminary evaluation of control strategies at the early stage of conceptual design. Although detailed specifications of actuators are not yet known at the conceptual design phase, high level information such as that shown in Table 4.1 is enough to roughly derive dynamic models in applying the techniques developed in this chapter for control strategy identification and simulation. Thus, the effectiveness of the methodology is validated through simulation. A visual and compact methodology, QFD for controller design promotes transdisciplinary communication of the behaviour of a multivariable process. It is shown from the examples

that the structure of the QFD matrix determines the control strategy to adopt. Since the control QFD of the automated steel wall framing machine shows an uncoupled interaction among MVs and CVs, every loop can be safely controlled by a SISO controller. A SISO controller cannot be directly applied to the PUMA 560 example, however, without further analysis. In this case, the control QFD may initially serve as a checklist for the product design team to capture interactions of the interconnected links. The first principles model of the 2-DOF robotic arm provides more details to the checklist to communicate coupled control QFD matrices that are of the V-canonical structure. It can be inferred from this observation that a V-canonical structure comprises two QFD matrices, which are analogous to those of the AD and DSM processes of conceptual design. The decoupling technique previously developed for a V-canonical model has been readily applied and simulated to verify the feasibility of the control strategy. Figure 4.9 shows a well-designed robotic arm control system since the response of its linear feedforward and feedback controllers tracks the joint trajectory demand very closely. As an enhancement in maintaining a satisfactory performance, the feedforward controller gains can be updated at the new operating points.

4.5 Conclusion

A methodology for designing controllers at the conceptual design phase has been developed using QFD matrices. These control QFDs are extracted from the AD and DSM phases of integrated conceptual design. QFD, as a model-based approach to controller design, is a thought process that encourages creativity, collaboration, and communication as illustrated in the systematic representation and analysis of the dynamic structure of MIMO processes and their associated decoupling solutions in this chapter.

When adopted in conceptual design, the matrix-based methodology provides a visual, compact, systematic, and transdisciplinary integrated MBSE approach (E. Tamayo et al. 2017). It has been demonstrated that the structure of the control QFD matrix or matrices corresponds to a particular control strategy to adopt, signifying that the proposed methodology is indeed systematic. Although the emphasis on decoupling a QFD matrix limits the strategy to linear decoupling, the framework developed in this paper can be extended to incorporate nonlinear feedforward and adaptive linear feedforward strategies for future work.

Chapter 5 Design automation of control panels for automated modular construction machines⁴

5.1 Introduction

Construction automation is expected to increase in prevalence due to the inherent inefficiencies and limitations of conventional construction practice (Bock 2015). For example, in modular construction, Tamayo et al. (2017) describe an automated machine for steel wall framing and its associated control system in the supervisory control and data acquisition (SCADA)/Device level. As noted in chapter 1, the difficulties encountered in defining customer requirements, in generating documentation and in carrying out traceability that arise during the development of a complex system, such as that of construction automation can be overcome through the use of MBSE (Abdelrazek et al. 2017) However, to effectively address the issues concerning a complex system, an MBSE methodology must be systematic, iterative, visual, and transdisciplinary and must be initiated at the conceptual design phase. An integrated function modelling approach, combined with axiomatic design and design structure matrix, satisfies these criteria.

Control panels house the electrical components serving the field devices of an automated manufacturing system. Control panel design should be initiated at the conceptual design phase to: (i) consider optimal device layout and wiring connections, (ii) meet safety and maintainability guidelines and standards, and (iii) facilitate computer aided design in the

⁴A version of this chapter has been published in *Procedia CIRP*, 70, pp. 404-409.

detailed design phase. Thus, conceptual design of control panels can be incorporated into the integrated function modelling of automated construction machines.

This paper extracts the control panel design aspect of the integrated function modelling of an automated modular construction system. It attempts to overcome the issues of systematic framework, iterative design, and the best practices in cybermanufacturing described by Shapiro et al. (2017). To illustrate the methodology used in the conceptual design of a control panel, this paper is organized as follows: section 5.2 presents the integrated design methodology; section 5.3 provides the application of the integrated design methodology to a control panel; section 5.4 describes the algorithm for planning the control panel layout and wiring; section 5.5 provides a summary of the integrated function modelling approach; and the conclusion follows in section 5.6.

5.2 Integrated design methodology

Integrated design methodology is essentially an integrated function modelling (IFM) (Eisenbart et al. 2012) approach that is built from axiomatic design (AD) (Nam P Suh 1998) and design structure matrix (DSM) (Browning 2016). This methodology is useful in the conceptual design phase, which offers: *(i)* an effective visual means of communicating the design intent and customer requirements in terms of functional requirements (FRs) and associated design parameters (DPs), *(ii)* a compact representation of the interaction among actors, and *(iii)* a design approach that is systematic and scientific due to the incorporation of the mathematically based AD and DSM techniques. In this section, the main components that form the integrated design methodology, namely AD, DSM and IFM, are discussed.

5.2.1 Axiomatic design

AD effectively addresses the issue of unfulfilled customer requirements, which was named by Abdelrazek et al. as one of the difficulties and common failures inherent in the design of complex systems (2017). Foley et al. (2016) discuss how FRs and DPs are generated by filtering ideas through brainstorming sessions. Customer requirements, however, take the highest level in the hierarchy of FRs and DPs.

Design matrix (DM), in binary format, describes the relationship between FRs and DPs. Mathematically, this is expressed in Equations (5.1) and (5.2) as follows (Suh 1998, Park 2007):

$$\{FR\} = [DM]\{DP\} \quad (5.1)$$

$$DM_{ij} = \begin{cases} X, & \text{if an element or effect exists } i, j = 1..n \\ 0, & \text{otherwise} \end{cases} \quad (5.2)$$

An acceptable design can be visualized through the DM. A lower triangular DM, which includes a diagonal DM, represents an acceptable design. Identity and lower triangular DMs, which fall into the acceptable design region, are referred to as uncoupled and decoupled design, respectively. A lower triangular DM satisfies the first axiom, the axiom of independence, of AD. However, a DM with FR-DP relationship outside of this triangular region indicates an unacceptable design. Since a DM can be initiated even with less information about the system, AD is useful in the conceptual design phase.

Another axiom that must be satisfied in AD is that of simplicity of design. Applying this axiom for a system with multiple designs implies that the design with the least information is picked as the best design. This criterion is expressed mathematically using Equations (5.3) and (5.4) as follows (Do and Park 2001, Babic 1999, N. Suh and Sekimoto 1990):

$$I_{min} = \min \left\{ \sum_{i=1}^n I_i \right\} \quad (5.3)$$

where

$$I_i = \log_2 \frac{1}{p} = \log_2 \left(\frac{\text{System range}}{\text{Common range}} \right) \quad (5.4)$$

In the above equations, I_i and p are the information content and probability of satisfying the i^{th} functional requirement, respectively.

The advantages of AD include its: (i) usefulness in conceptual design, (ii) early consideration of customer requirements, (iii) regard for simplicity in design, (iv) use of a matrix for visual communication, and (v) iterative aspect. However, it fails to consider interactions among DPs and it lacks the functionality of a transdisciplinary modelling framework.

5.2.2 Design structure matrix

Browning (2016, 2002) describes DSM and its application as a modelling framework. DSM requires a significant amount of detail for a product being designed. Its weakness lies in its limited use at the conceptual design phase since it cannot be used to design an entirely new product (Tang et al. 2009). Using the DPs obtained from AD, however, facilitates the development of DSM at the conceptual design stage. This method of forming DSM from AD is described by Dong and Whitney (2001). However, DSM and AD can be enhanced with additional features in order to provide a truly transdisciplinary integrated design framework. By invoking the permutation and triangularization techniques described by Guenov and Barker (2005), DSM becomes an iterative design methodology. Browning (2001) presents several triangularization methods of row and column reordering by using optimization techniques.

DSM provides a visual representation of the interactions among DPs. As in AD, the interactions are expressed in binary notation as

$$\{DP\} = [DSM]\{DP\} \quad (5.5)$$

$$DSM_{ij} = \begin{cases} 0, & \text{if } I < j \\ X, & \text{otherwise} \end{cases} \quad (5.6)$$

Similarities of the above equations with those of AD suggest that rules governing AD in terms of uncoupled, decoupled and coupled interactions apply to DSM as well. In Equation (5.6), the strength of interaction is expressed as 1 if an interaction exists, otherwise it is 0. However, the degree of interaction can also be expressed by other values (Algeddawy 2014).

5.2.3 Integrated function modelling

IFM has been developed to facilitate collaboration of all disciplines involved in the conceptual design of complex systems (Eisenbart et al. 2012). It is structured to visually communicate the design intent among experts across all disciplines through its use of matrices to describe the different views, which include use case, process flow, actor, interaction and state. Eisenbart et al. (2017) provide a more detailed description of the IFM framework. Incorporating the interaction view to visually represent system architecture makes IFM a DSM-based modelling framework (Eisenbart et al. 2017). Interaction view does not only consider the interaction among DPs (actors), but among operands as well. Since IFM is a DSM-based framework, it inherits the limitation discussed in the previous section. However, IFM combined with AD and DSM provides a powerful conceptual design approach that is systematic, iterative, visual, and transdisciplinary. The combined design methodology is discussed in the next section.

5.2.4 The integrated design methodology

A truly transdisciplinary design approach is essentially an IFM that is systematically developed using AD and DSM. Due to the mathematical basis supporting AD and DSM, the resulting IFM establishes a scientific design approach. Figure 5.1 illustrates a simplified flowchart of the development of an integrated design methodology that is basically an IFM formed using AD and DSM. Mapping the customer requirements to high-level FRs and DPs initializes the DM and IFM. At the AD stage, low-level FRs and DPs are provided by the experts across the disciplines to support the customer requirements. From the customer requirements, the process flow, use case, and actor views of the IFM are formed. AD undergoes design iterations until the axioms of independence and information are satisfied. Once the DM is finalized, it is then passed on to the DSM stage. If the DM is not square, DSM undergoes design iterations through modifications, permutations, and triangularization as discussed by Guenov and Barker (2005), otherwise the DSM is formed by defining output variables and permuting columns and replacing the FRs with their corresponding DPs (Dong & Whitney 2001).

At the final stage, the DSM and the operands are taken to form the interaction and state views. If any new details exist, the IFM is updated, otherwise the final IFM is presented.

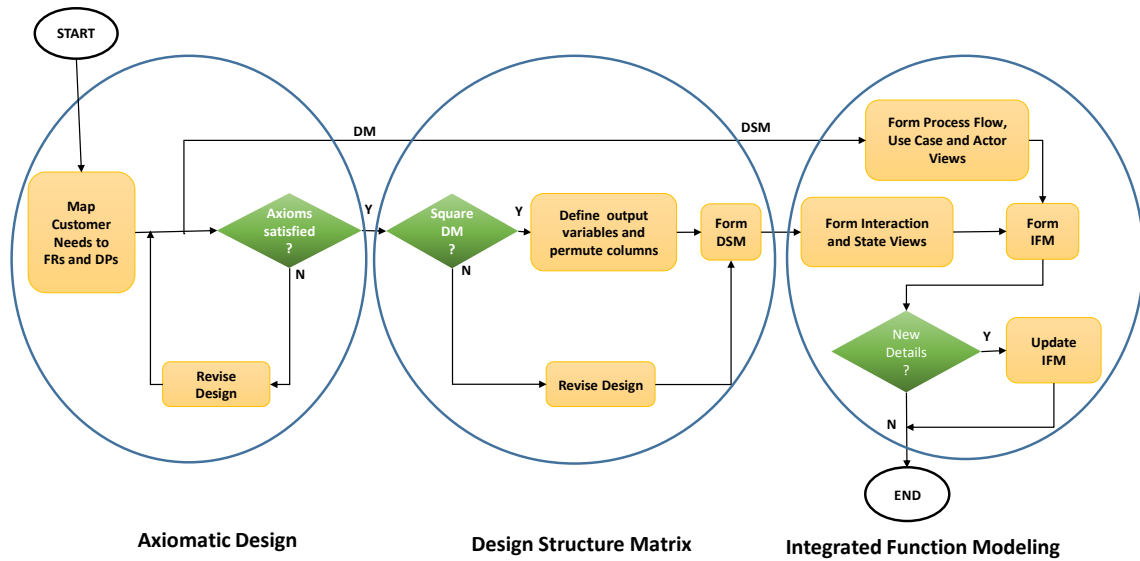


Figure 5.1. Integrated design methodology

5.3 A simple illustration

A simple example that describes the initial design of a control panel is discussed here to apply the basic steps of the integrated design approach depicted in Figure 5.1. For illustrative purposes, this example only considers the high-level FRs of the control panel. In the next section, the integrated design approach will be applied to include the low-level FRs of the control panel as well.

Table 5.1 provides the parallel steps of forming the high-level FRs and the process flow and use case views shown in Figure 5.1. From this table, the DM can then be formed using the FRs and the following DPs: 120-volt AC control panel (DP0), backplate (DP1), electrical devices (DP2), and enclosure for the area classification (DP3).

Table 5.1. Mapping of high-level functional requirements, processes, and use case

Customer Needs	Mapping		Use Case	
	Axiomatic Design	Integrated Functional Modeling	No.	Label
An electrical enclosure built to proper standards	FR0: Build an electrical enclosure conforming to standards/best practices		1	Build control panel
A system of properly laying out devices	FR1: Provide means of mounting devices	P1: Provide energy to the system		
A system of properly laying out other associated components	FR2: Provide the components of the system to be enclosed	P2: Process input and output signals		
Robust enclosure	FR3: Build an enclosure appropriate to the environment	P3: Transmit signals to and from the field		

Equation (5.1) specifies the DM for the simple control panel design example as follows:

$$\begin{pmatrix} FR0 \\ FR1 \\ FR2 \\ FR3 \end{pmatrix} = \begin{bmatrix} X & & & \\ & X & & \\ & & X & \\ & & & X \end{bmatrix} \begin{pmatrix} DP0 \\ DP1 \\ DP2 \\ DP3 \end{pmatrix} \quad (5.7)$$

Since the DM is uncoupled, both the independent and simplicity axioms are satisfied and a revised design is not required. Thus, the DSM can straightaway be formed by replacing the FRs with their corresponding DPs. These DPs become the actors that form part of the interaction view of the IFM in Figure 5.2. Wires that transmit electrical signals through the various devices in the control panel are included as actors. Operands affecting the actors of the control panel are the users, electricity, and environment, which complete the interaction view. In the actor view, how the actors affect or are affected by the processes, are marked 'X' or 'O', respectively. Change of states of actors and operands due to an execution of a process by an actor is shown in the state view. Interaction of the actors and operands is addressed by considering safety to users and signal interference affecting signal

transmission through the wires in the design of the control panel through the application of industry standards and best practices. A more detailed perspective about the application of control panel design standards and best practices and how they are incorporated into the control panel design algorithm are discussed in the subsequent sections.

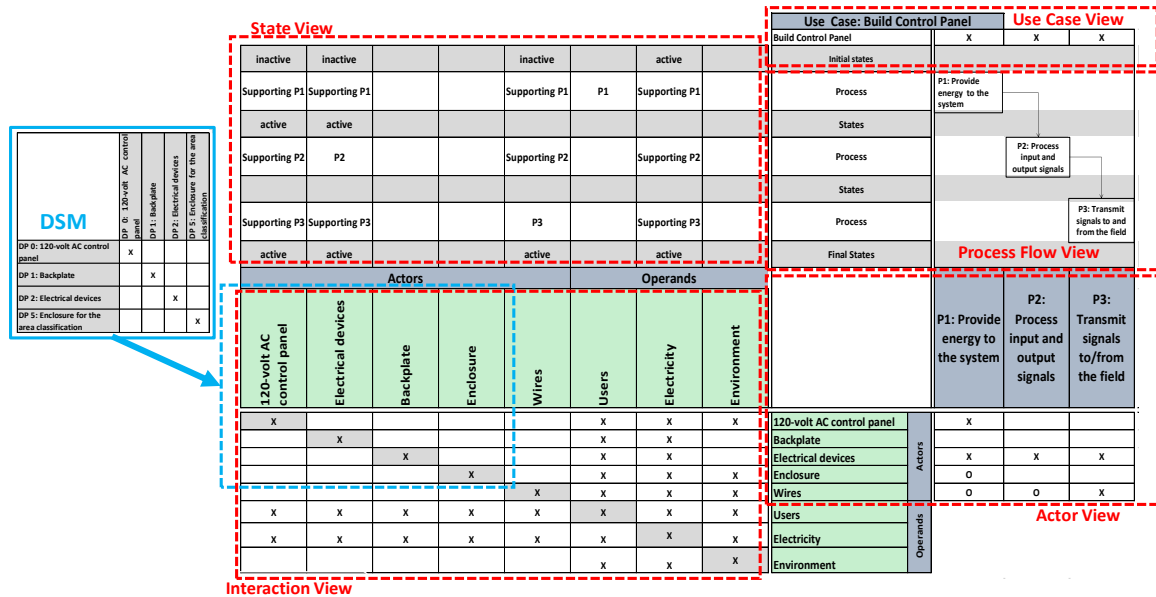


Figure 5.2. Integrated function model incorporating the design structure matrix of the design example

5.4 Integrated design methodology for a control panel

An example of a control system for an automated modular construction machine is described in a paper by Tamayo et al. (2017). In this construction automation, or in any manufacturing system automation, control panels play the important roles of: (i) housing the electrical devices supporting the field devices, and (ii) maintenance and troubleshooting of these field devices. Control panel design and optimization is usually carried out at the detailed design phase using computer-aided design (CAD) tools. Computer-aided engineering (CAE) assists in the planning and design of a control panel and involves

engineers, customers, suppliers, and system integrators (Control Design 2015). Kang et al. (2008) describe a computer-aided design method of designing a control panel to meet functional requirements and ergonomic restrictions. The present research approaches a collaborative control panel design at the conceptual design phase prior to any activity, such as computer-aided design, at the detailed design phase.

5.4.1 Formulating the design matrix

Developing the DM requires identification of customer requirements. For the above-cited control panel of the automated modular construction machine, the customer requirements include: *(i)* must be a 120 V AC control panel, *(ii)* must conform to standards, and *(iii)* must conform to best practices. All other requirements, such as maintainability, safety, and prevailing guidelines, which are included in these customer requirements, constitute the high-level functional requirements. These requirements can be combined into one main requirement, which is to build a 120 V AC control panel. Thus, building a control panel will also be understood to be fulfilling its safety, functionality, and maintainability requirements. Through the application of engineering knowledge, low-level FRs are generated to support the main requirement. Figure 5.3 presents the DM formed from the mechanical, electrical and safety FRs and DPs that conform to control panel design standards. Engineering standards required for the design of a control panel include: *(i)* CSA 22.2 No. 14-13, *(ii)* CSA 22.2 No. 301-16, *(iii)* UL 508A, *(iv)* NFPA 79, *(v)* IEC 61439-1, *(vi)* ISO 9001:2000, and *(vii)* NEMA (Flierl 2017, The Panel Shop Inc. 2017).

	DP 0: 120-volt AC control panel	DP 1: Backplate	DP 2: Electrical devices	DP 2.1: AC terminal blocks (TBS)	DP 2.2: Main circuit breaker	DP 2.3: Power supply unit (PSU)	DP 2.4: Programmable Logic Controller (PLC)	DP 2.5: Contactor and relays	DP 2.6: DC terminal blocks	DP 2.7: DIN rails	DP 2.8: Ethernet switch	DP 2.9: Grounding	DP 2.9.1: AC grounding	DP 2.9.2: Instrument grounding	DP 2.10: Segregation/shielding	DP 2.10.1: Grey wire duct for AC wires	DP 2.10.2: White wire duct for DC wires	DP 2.11: Component/wire labeling	DP 3: Device layout plan	DP 4: Wiring layout plan	DP 5: Enclosure conforming to the area classification	DP 5.1: NEMA-compliant enclosure	DP 5.2: Cooling system	DP 6: CSA/UL/ISO certifications	DP 7: Arc flash label
FR 0: Build an electrical enclosure conforming to standards/best practice	X																								
FR 1: Provide means of mounting of devices		X																							
FR 2: Provide the components of the system to be enclosed			X																						
FR 2.1: Provide a means of terminating AC field wires				X																					
FR 2.2: Provide a means of disconnection and electrical safety protection					X																				
FR 2.3: Provide a system to energize field devices						X																			
FR 2.4: Provide the machine control system							X																		
FR 2.5: Provide a means of protecting users and field devices								X																	
FR 2.6: Provide a means of terminating DC field wires									X																
FR 2.7: Provide a means of mounting the components in the enclosure										X															
FR 2.8: Provide a means of communication with field devices/sensors											X														
FR 2.9: Provide grounding												X													
FR 2.9.1: Provide AC grounding													X												
FR 2.9.2: Provide instrument grounding														X											
FR 2.10: Provide segregation/shielding															X										
FR 2.10.1: Provide a systematic wiring for AC devices																X									
FR 2.10.2: Provide a systematic wiring for DC wires																	X								
FR 2.11: Provide a system to facilitate maintenance and troubleshooting																		X							
FR 3: Provide a system for laying out the devices in the enclosure																			X						
FR 4: Provide a system for wiring the devices in the enclosure																				X					
FR 5: Build an enclosure appropriate to the environment																					X				
FR 5.1: Provide a standard-compliant enclosure																						X			
FR 5.2: Provide cooling																							X		
FR 6: Provide CSA/UL/ISO certifications																								X	
FR 7: Provide arc flash label																									X

Figure 5.3. Control panel design matrix

5.4.2 Building the interaction matrix

Forming the interaction view of the IFM requires completing the DSM. Since the DM is square, the DSM is obtained by following the steps presented in Figure 5.1. These DPs become actors in the interaction view. Users are incorporated as actors as well since they affect and are affected by the processes. In addition to the actors, the following operands are provided: (i) electricity, and (ii) environment. Operands are specifications of energy, material, and signals to the system (Eisenbart et al. 2012). Electricians are considered as users of the control panel. They play the role of maintaining the integrity and reliability of every electrical component of the system. Electricity is an operand, since the control panel

is required to be energized with 120 V AC. Wires transmit electricity throughout the electrical system. With respect to the control panel, electrical devices listed as actors in the interaction view are interconnected with wires. Electrical energy affects the environment through electromagnetic interference (EMI), heat, and hazards within the control panel. Interactions of these actors and operands of the control panel form the interaction view in the IFM stage are shown in Figure 5.1.

5.4.3 Completing the integrated function modelling

Using the interaction view, the standards and best practices are applied to the design of the control panel. For an in-depth discussion on control panel best practices see Control Design (2015), Al-Abeediah (2008), IEEE 1100 (2005), and Ennulat (2013). The control panel design follows a sequence of processes: (P1) provide energy to the system, (P2) process input and output signals, and (P3) transmit signals to and from the field. These processes are depicted in the process flow view of the IFM. Actors affecting and affected by the processes are indicated as 'X' and 'O', respectively, in the actor's view. Figure 5.4 presents the state, interaction, use case, process flow, and actors view of the control panel design. A linear time complex algorithm is discussed in the next section to illustrate the use of standards and best practices to address the interaction of actors and operands of the IFM in planning the device layout and wiring of the control panel. Mechanical aspects of the control panel design will not be explored in this paper. Meller and Deshazo (2001) provide greater details in the mechanical design of electrical box and enclosures. It should be noted that the interaction of the actors and operands involves the safety aspect of control panel design. Thus, a safe environment is one which conforms to the NFPA 70E standard Control

Design (2010), which addresses arc flash hazards, hazard risk assessment, and arc flash labeling for the purpose of protecting the users of the control panel.

5.5 Control panel design algorithm

This section provides an algorithm for planning the layout and wiring of a control panel. This algorithm, as previously indicated, utilizes control panel design best practices and mainly comprises: (1) input-output declaration, panel partitioning, and placement of devices; (2) placement of wireways; and (3) wire connections. In the absence of information, the lower bound of recommended allowances for future expansion can be used to arrive at a reasonably sized control panel. Aside from the cooling requirement provided in Figure 5.4, heat dissipation and ergonomics are considered in the recommended spacing given in control panel design best practices.

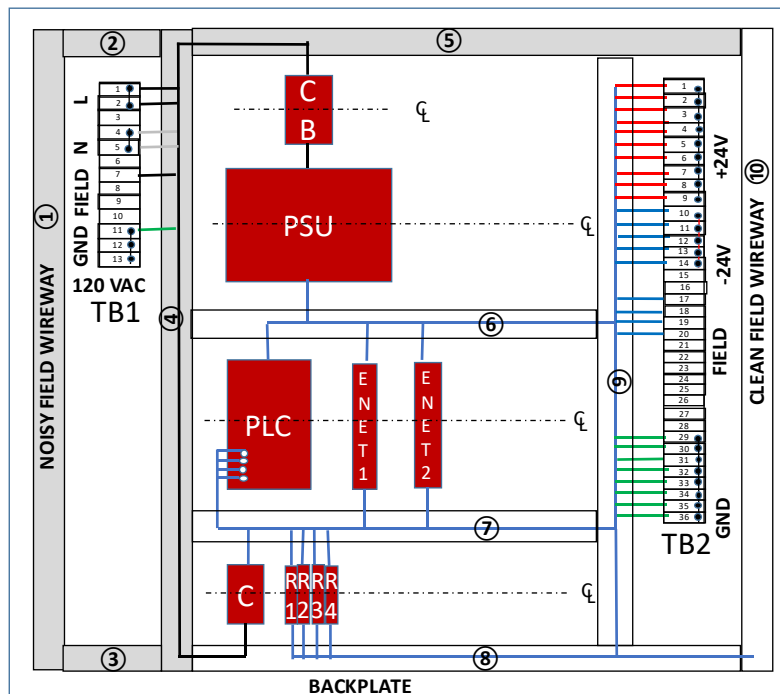


Figure 5.4. Layout of control panel and its wiring

Inputs to the algorithm comprise high voltage and low voltage devices. These devices are classified into power supply unit (PSU), circuit breaker (CB), low voltage devices (LV) such as a relay (R) and an ethernet switch (ENET), and low voltage devices that have both high and low voltage terminals (DLV) such as a contactor (C). Distinct from these live inputs are the passive components, i.e., clean and noisy wireways and terminal blocks (TBs). Having defined the inputs, the objective of the algorithm can then be carried out, which is to lay out these inputs into the *left_{section}*, *middle_{section}*, and *right_{section}* of the control panel. The middle section is further divided into *top_{row}*, *mid_{row}*, and *bot_{row}*, where the devices are placed and spaced using the functions *Placedevice*, and *Aligndevice*. Control panel design best practices are applied as follows: (i) place the high voltage devices in the top row, *top_{row}*, and (ii) facilitate the calculation of the top row area, *TopRow_{area}*, that defines the height and the common width of the top and subsequent rows. Similarly, the height of the subsequent rows is obtained from the calculated areas *MidRow_{area}*, and *BotRow_{area}*, for the mid and bottom rows, respectively. If the row width is known, low voltage devices are placed from largest to smallest in the middle row and the remaining devices that cannot fit in this row are placed in the bottom row. Devices are mounted on DIN rails whose positions are determined in the *Aligndevice* function. In the calculation of the area of each section, the physical dimensions of horizontal wireways are considered. A device is subtracted from the set of devices, defined at the beginning of the algorithm, after it is placed on the panel.

Having dimensioned the middle section, the remaining wireways and TBs are placed for the high and low voltage sides while honoring best practices and standards on ergonomic spacing and EMI segregation. EMI segregation is performed by ensuring that 120 V AC

and 24 V DC wires are run separately in noisy and clean wireways, respectively. Similarly, the left and right sections of the panel should only contain 120 V AC and 24 V DC TBs, respectively. Part 2 of the algorithm is executed by the function *Placewireways*. For conciseness, the remaining functions are presented at a high level in the algorithm; however, enough details will be provided to describe these functions. *Placewireways* begins with the declaration of the set of wireways and wires and the initialization of the left and right TB variables. This initialization of variables ensures that only one set of TBs is placed in the left or right section of the panel. As in Part 1, wireway positions are determined and a wireway is subtracted from the set of previously defined wireways.

Finally, Part 3 of the algorithm involves connecting wires with the function *Connectwires*, which ensures that wires are run and terminated according to (i) the correct classification of devices, i.e., CB, PSU, LV or DLV; (ii) the correct and shortest wireway, i.e., clean or noisy; and (iii) the correct TBs, i.e., 120 V AC TB (*leftTB*) or 24 V DC TB (*rightTB*). *Connectwires* follows best practices to run wires along their designated wireways and to prevent crisscrossing of noisy and clean wires. These wires are terminated at (1) the device, and (2) TBs and another device identified as inputs to the function. It should be noted that for the control panel presented by Tamayo et al. (2017), 120 V AC and 24 V DC are considered high-voltage and low-voltage, respectively. Figure 5.4 illustrates an application of the algorithm, where wireways are numbered and colored to distinguish the clean from the noisy.

A summary of the steps required to develop Algorithm 1 for the design automation of control panels for automated modular construction machines is presented below.

Algorithm 1 Control Panel Layout

```
1:  $Panel_{area} \leftarrow \langle left_{section}, middle_{section}, right_{section} \rangle$ ;  
2:  $Left_{area} \leftarrow \mathbb{R}$ ;  
3:  $Right_{area} \leftarrow \mathbb{R}$ ;  
  
4:  $HighVoltageDevices \leftarrow \{set\ of\ high\ voltage\ devices\}$ ;  
5:  $LowVoltageDevices \leftarrow \{set\ of\ low\ voltage\ devices\}$ ;  
6:  $middle_{section} \leftarrow \langle top_{row}, mid_{row}, bot_{row} \rangle$ ;  
7:  $MiddleTop_{area} \leftarrow \mathbb{R}$ ;  
8:  $MiddleMid_{area} \leftarrow \mathbb{R}$ ;  
9:  $MiddleBot_{area} \leftarrow \mathbb{R}$ ;  
10: while  
11:    $(\exists device \in HighVoltageDevices \wedge (middle_{section} = top_{row}))$  do  
12:   Placedevice(device);  
13:    $HighVoltageDevices \leftarrow HighVoltageDevices \setminus device$ ;  
14:   Aligndevice(device);  
15:    $MiddleTop_{area} \leftarrow Calculatedarea()$ ;  
16: end while  
17: while  
18:    $(\exists device \in LowVoltageDevices \wedge (middle_{section} = mid_{row}) \wedge (Middlemid_{area} \leq MiddleTop_{area}))$  do  
19:   Placedevice(device);  
20:    $LowVoltageDevices \leftarrow LowVoltageDevices \setminus device$ ;  
21:   Aligndevice();  
22:    $MiddleMid_{area} \leftarrow Calculatedarea()$ ;  
23: end while  
24: while  
25:    $(\exists device \in LowVoltageDevices \wedge (Panel_{area} = middle_{section}) \wedge (MiddleMid_{area} > MiddleTop_{area}))$  do  
26:   Placedevice(device);  
27:    $LowVoltageDevices \leftarrow LowVoltageDevices \setminus device$ ;  
28:   Aligndevice(device);  
29:    $MiddleBot_{area} \leftarrow Calculatedarea()$ ;  
30: end while  
31: Placewireway(wireway);  
32: Connectwires(wires, leftTB, rightTB, device);
```

► Part 1 of the algorithm: Placing devices on the control panel surface

► Part 2 of the algorithm: Placing wireways and TBs

► Part 3: Connecting devices and TBs with wires

Figure 5.5 depicts the same control panel shown in Figure 5.4 without the use of standards and best practices contained in the algorithm. These two figures represent the qualitative validation of the presented conceptual design process.

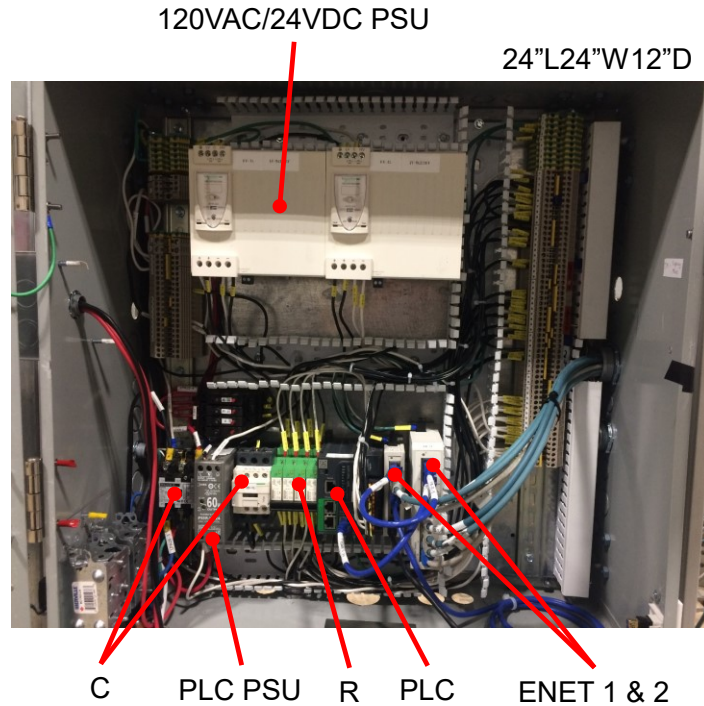


Figure 5.5. The same control panel in Figure 5.4 without the use of the conceptual design framework.

5.6 Conclusion

IFM combined with AD and DSM results in a conceptual design methodology for automated modular construction machines that is systematic, visual, iterative, and transdisciplinary, and due to the mathematical basis of AD and DSM, the resulting integrated design approach also inherits a scientific property. The research presented in this paper illustrates that the integrated design methodology can be applied to the design of an associated component such as a control panel of an automated modular construction system. Control panels are important subsystems given that they *(i)* house the devices that constitute the control system, *(ii)* facilitate the upkeep of the control system, and most importantly, *(iii)* account, in the design process, for safety hazards that affect the users and the environment. Interactions among elements of the system, such as electricity and the environment, are clearly communicated across disciplines through a matrix-based

interaction view of the integrated design methodology. A linear time complex algorithm is introduced for planning the control panel device and wiring layouts; an algorithm that embodies best practices complements the computer-aided design of the control panel at the detailed design stage.

Chapter 6 Conclusion

6.1 Research Summary

The increasing demand for modular construction in Canada offers an opportunity for automation. In this growing area of the building construction industry, building components are manufactured offsite and then transported to the construction site for assembly. In North America, the utilization of automated modular wall frame fabrication methods for residential and commercial buildings has increased. Extraneous physical work is reduced when steel or wood panelized frames are produced in a factory environment that is conducive to safer work conditions and automation. Furthermore, transport and assembly of factory-manufactured wall frames results in an overall reduction in construction cycle time. Given these benefits, automated modular wall frame fabrication for either wood or steel structures is in high demand in Canada.

In consideration of automated modular construction manufacturing systems, this research deals with the integrated conceptual design of complex systems in a transdisciplinary environment. Conceptual design is emphasized to address the issue of costly design errors depicted in the Macleamy curve. Designing a manufacturing system involves multiple technical disciplines consisting primarily of mechanical, electrical, and instrumentation and control engineers. A functional modelling methodology in conceptual design ensures that the various disciplines work toward a common design intent. A systematic approach to efficiently capturing the design intent promotes interdisciplinary communication, clarity, and early systematic determination of a functional design that fulfills customer needs. An integrated function modelling methodology that combines the advantages of

axiomatic design, design structure matrix, and integrated function modelling is proposed and the methodology is applied to the design of an automated steel wall framing machine. At the conceptual design phase, the product design team is not only faced with the challenge of avoiding design errors but with that of reducing design complexity due to a significant number of FRs. An important aspect of the conceptual design is at the customer requirement (CR) definition stage, where an optimal number of FRs are specified with the application of QFD. To facilitate a systematic specification of FRs, state-of-the-art unsupervised machine learning techniques will be introduced in the feature selection of FRs. However, the scarcity of references in the literature with respect to unsupervised feature selection reflects the difficulty associated with this topic. At the CR definition phase, three techniques have been proposed for selecting FRs, namely (a) principal component analysis, (b) forward orthogonal search, and (c) Kohonen self-organizing map neural network.

Without a methodology, the practice of control system design for automated modular construction machines mainly depends on experience and trial and error. The implementation of controllers requires planning at the conceptual design phase. AD has been introduced in developing control solutions. A methodology is proposed to formalize the conceptual design of a controller with the use of QFD as a design and an analysis tool. The controller design approach using QFD has been applied to the automated steel wall framing machine and to a 2-DOF robotic arm, which can be readily extended to n-DOF robotic manipulators. The analysis and decoupling techniques for controller design presented in this research differ from those used in traditional AD. QFD for controller

design provides continuous transfer functions to represent relationships and mathematical decoupling that is easily implemented in software.

Automation of modular construction machines consists of not only the machines but also the supportive electrical and pneumatic systems, which, regardless of the design approaches used for automated machines, can be applied to the design of their associated systems. To avoid costly design changes, there is a clear need for a systematic and iterative design methodology at the conceptual design stage. For the control panel, the conceptual design method introduced in this paper facilitates the subsequent computer-aided design to be performed at the detailed design stage. Integrated function modelling, combined with axiomatic design and design structure matrix, constitutes the conceptual design approach for the control panel. In this work, linear time complex algorithm is developed for automating the layout of the electrical devices and wiring connections in order to facilitate computer-aided design implementation in the detailed design phase. Furthermore, the control panel guidelines and standards that constitute the prior knowledge of the design process are embedded in the algorithm.

6.2 Research contributions

The contributions of this research can be summarized as follows:

1. Methodology for building the IFM framework using CRs, AD, and DSM: This research developed an integrated approach to the conceptual design of an automated modular construction manufacturing system that is basically a three-stage approach consisting of AD, DSM, and IFM. The integrated approach was then applied to the conceptual design of an automated steel wall framing machine.

2. Two-prong approach to the development of a mathematical formulation for IFM: ,
This research first identified the DSM portion of IFM and built the DSM from AD, thereby leveraging the mathematical framework that comes with AD and DSM. Second, using the procedures for building the IFM and the structure of the framework itself, the mathematical expressions of the overall IFM framework were derived. Furthermore, first order logic was introduced in mathematically expressing the process flow view of a specific application. The mathematical expressions developed for the IFM, moreover, provide the necessary foundation for the framework as a systematic and scientific approach.
3. Use of machine learning techniques in the CR determination phase of conceptual design: A comprehensive set of unsupervised machine learning tools has been introduced to address the limitations, indicated in the literature, of existing methods in systematically selecting FRs from a QFD matrix. Determination of the suitable machine learning techniques was achieved based on identification of the FR optimization problem as unsupervised learning. Furthermore, a process of ranking the techniques using evolutionary computational concepts was developed.
4. Reduction of the integrated design approach to the conceptual design of an automated modular construction manufacturing system to a repeated use of QFD: This research incorporated dynamics into QFD, developed a systematic approach to the conceptual design of controllers, demonstrated the use of P-canonical or V-canonical forms of QFD to control the MIMO automation process, described the decoupling techniques associated with each form, and incorporated simulation into the conceptual design.

5. Development of a design methodology: This research introduced an integrated conceptual approach to the design automation of a control panel for automated modular construction machines and developed an algorithm for design automation of a control panel.

6.3 Research limitations

This research is subject to the following limitations:

1. Mapping of CRs to FRs and the determination of the optimal number of FRs can be time consuming if it is not done systematically. An automated implementation of the proposed methodology to the conceptual design of the steel wall framing machine could have facilitated the thinking process more efficiently.
2. Microsoft Excel has been used to implement the integrated design of the automated steel wall framing machine.
3. Quantization error is used to measure the fitness in the SOM wrapper algorithm.
4. The emphasis on decoupling a QFD matrix limits the strategy to linear decoupling.
5. Design automation and simulation have been introduced but not formalized as part of the presented integrated conceptual design methodology.

6.4 Future research

The research methodology serves as a foundation for automated panel manufacturing. The following areas require further research:

1. Future projects can benefit from the application of the proposed design methodology with the aid of other software tools. Moreover, the mapping of CRs to FRs and the determination of the optimal number of FRs can be efficiently

- automated in the future using state-of-the-art techniques to achieve QFD during brainstorming sessions.
2. Other measures such as entropy, Davies-Bouldin Index, and Gini Index can be explored as to the optimal selection of FRs and the automated integrated conceptual design package for future research.
 3. Another consideration for future research should include extending the application of the proposed feature selection methods to online CR or FR identification, design alternatives selection, project management, contract management, and marketing. Along with this consideration, a software interface should also be developed.
 4. Although the emphasis on decoupling a QFD matrix limits the strategy to linear decoupling, the framework developed in this thesis can be extended to incorporate nonlinear feedforward and adaptive linear feedforward strategies for future work.
 5. Further research is required to formally incorporate these aspects into the integrated framework and into the software implementation of the methodology for product design teams to use as an automated design framework.

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