Neuro-Fuzzy System Dynamics Technique for Modeling Construction Systems

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Abstract

The performance of construction systems (e.g., activities, operations, projects) is commonly measured using different indicators, such as productivity or production rate. The accurate prediction of performance, which is an important concern of construction researchers and practitioners, requires effective techniques for construction modeling. However, the complexity of construction systems creates three challenges for construction modeling: (1) construction systems are affected by numerous interacting factors, (2) the factors that affect construction systems often exhibit both probabilistic and non-probabilistic uncertainty, and (3) construction systems are dynamic. Fuzzy system dynamics (FSD) is a simulation technique used for modeling construction systems with the potential to address the three aforementioned challenges. However, the application of FSD technique in construction is still limited due to its low accuracy for modeling the non-linear, complex and highly-dimensional relationships between the different variables of construction systems (i.e., system relationships), since in current applications of FSD, system relationships are often defined by linear regression due its computational simplicity. This paper introduces a new hybrid technique — neuro-fuzzy system dynamics (N-FSD) — by integrating FSD and hybrid neuro-fuzzy systems. In N-FSD, hybrid neuro-fuzzy systems are

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used to define the non-linear and complex relationships between the different variables of the FSD model. The use of hybrid neuro fuzzy systems for defining system relationships, rather than linear regression, can improve the accuracy of FSD models in construction applications. The applicability of the N-FSD technique is tested through a construction case study by modeling the production rate of earthmoving operations.

Keywords: construction modeling, hybrid technique, fuzzy logic, neuro-fuzzy systems, system dynamics

1. Introduction

Construction projects are complex systems, and their performance levels are constantly changing under the effect of numerous interacting factors. Predicting performance is challenging for several reasons. First, there are numerous interactions between the factors that affect the performance of construction systems (e.g., time, cost, quality); these interactions may affect individual factors as well as overall project performance [1]. Therefore, an appropriate modeling technique needs to capture the interactions between factors along with each factor's individual impact on the performance of construction projects. Second, factors that influence the performance of construction projects exhibit probabilistic and non-probabilistic uncertainty, so an appropriate modeling technique needs to capture both types of uncertainties. Third, the behavior of construction systems and the factors influencing their performance are dynamic (i.e., they change over time); therefore, dynamic modeling techniques (i.e., techniques that are capable of tracking the changes of real-world systems over time) are superior to static techniques for modeling construction systems [1,2].

Various techniques are used for construction modeling to overcome the three aforementioned challenges. Simulation techniques are one type of modeling technique capable of overcoming some of these challenges, as they predict the behavior of construction projects by running them virtually using computer-based models [3]. System dynamics (SD) is a simulation technique developed by Forrester [4] for modeling complex industrial systems. SD is capable of capturing the dynamism of construction systems as well as the interactions between the factors that affect the performance of these systems. However, SD cannot capture the non-probabilistic uncertainties (i.e., uncertainties caused by subjective or imprecise information) of the factors that affect construction systems. In order to address this limitation, Levary [5] hybridized SD with fuzzy logic, which is an artificial intelligence (AI) technique developed for modeling subjective, imprecise, and linguistically expressed information (i.e., non-probabilistic uncertainties). The resulting hybrid simulation technique, fuzzy system dynamics (FSD), is a powerful technique for modeling the performance of construction projects, and it has been applied to a variety of construction problems such as construction risk management [6,7], construction productivity [2,8], and construction quality management [9].

To develop SD/FSD models, modelers first need to quantitatively define the relationships between the different factors that affect the system—called system relationships—and then the SD/FSD models can simulate the behavior of a real-world system and predict its output. Theoretically, system relationships can be defined using any input-output predictive modeling technique (e.g., linear regression, artificial neural networks [ANN], Gaussian process regression, fuzzy rule-based systems [FRBS], and neuro-fuzzy systems) [10–16]. Each predictive modeling technique used for defining system relationships in SD/FSD models has some advantages and disadvantages over the other modeling techniques. As an instance, the linear regression technique is commonly used in different applications due to its computational simplicity; however, this technique lacks the capacity to learn from data and model non-linear system relationships [8]. As one of the most commonly used predictive modeling techniques in engineering context, ANN has the capacity to learn from data and model the non-linear relationships between the input and output variables; however, this technique lacks the capacity to capture the non-probabilistic uncertainty of the input and output variables and this technique solely relies on historical data for modeling and validation purposes [17]. Accordingly, the choice of modeling technique used for defining system relationships is a critical task in the process of developing SD/FSD models, since the accuracy of the SD/FSD models relies on the accuracy of the modeling technique used for defining these relationships. Table 1 presents an overview of the modeling techniques used for defining system relationships in recent applications of SD/FSD in construction context.

Table 1. Classification of system variables of the N-FSD model of the earthmoving operation rate.

Variable Type	System Variables	No. of Variables
Objective system variables	Soil type, groundwater level, number of equipment, equipment capacity, absenteeism, absenteeism rate, hauling distance, equipment per labor, overtime work, crew size, temperature, precipitation, snow on ground, wind speed, total volume of work, daily working time, crew composition, production rate	18
Subjective system variables	Soil moisture, crew motivation, crew experience, operator experience, schedule compression, site restrictions	6

As shown in Table 1, in existing applications of SD and FSD, the technique most commonly used to define system relationships is linear regression, due to its computational simplicity. However, the application of linear regression for defining system relationships decreases the accuracy of SD and FSD techniques in construction applications for two reasons. First, the relationships between the factors affecting construction systems are usually non-linear and cannot be accurately modeled by linear regression [18]. Second, linear regression often has low prediction accuracy in construction applications due to limited availability of data. According to Table 1, the expert-driven FRBSs (i.e., FRBSs developed by expert knowledge) are also used for modeling system relationships in FSD models, however, this modeling technique lacks the capacity to learn from data; and according to Zadeh's principle of incompatibility [19], this technique is not appropriate for modeling highly dimensional relationships, in which a large number of input variables are mapped to the output(s). Accordingly, there is a gap in the existing body of knowledge on FSD modeling in construction for identifying an appropriate and accurate technique for defining the non-linear, complex and highly-dimensional relationships between the different variables of construction systems. This research gap is addressed in this paper by hybridizing neuro-fuzzy systems with an FSD technique to develop a new modeling technique, called the neuro-fuzzy system dynamics (N-FSD) technique. The hybridization of neuro-fuzzy systems with FSD can increase the accuracy of the FSD technique in construction applications because (1) hybrid neuro-fuzzy systems can model the non-linear relationships between the factors that affect construction systems more accurately than linear regression [18]; (2) hybrid neuro-fuzzy systems has the capacity to capture the non-probabilistic uncertainty exhibited of the input and output variables; (3) hybrid neuro-fuzzy systems has the capacity to learn from data and outperform statistical techniques if limited data is available for modeling [20]; and (4) hybrid neuro-fuzzy systems outperform the expert-driven FRBSs for defining highly dimensional system relationships [19].

The rest of this paper is organized as follows. Section 2 presents a brief literature review on FSD and neuro-fuzzy systems and their applications in construction modeling. Section 3 presents the methodologies for integrating neuro-fuzzy systems and the FSD technique and for developing N-FSD models. In Section 4, the N-FSD technique is applied to a construction case study to predict the production rate of earthmoving operations, and the accuracy of this technique is compared to a conventional FSD technique in order to illustrate how hybridization of FSD and neuro-fuzzy systems (i.e., the N-FSD technique) can improve the accuracy of the FSD technique. Finally, Section 5 presents research conclusions and areas of future research.

2. Research Background

2.1. Fuzzy System Dynamics Technique in Construction Applications

The FSD technique is a hybrid simulation technique, developed by integrating SD and fuzzy logic, for modeling real-world systems that exhibit both probabilistic and non-probabilistic uncertainty [5]. Nasirzadeh et al. [21] developed an FSD model for construction risk management in which the magnitudes and probabilities of the risk factors are subjectively assessed by expert knowledge (rather than historical data). Khanzadi et al. [22] developed an FSD model to predict the cost performance of infrastructure projects over their life cycles in order to determine the concession period of build-operate-transfer (BOT) contracts for such projects. Gerami Seresht and Fayek [8] used FSD to capture the non-probabilistic uncertainties of numerous factors affecting construction systems to predict the multi-factor productivity of equipment-intensive activities. Siraj and Fayek [7] presented an application of the FSD technique in construction risk management for analyzing the impacts of interrelated and interacting risk and opportunity events on work package cost and determining work package and project contingencies; in this application, the probability and impact of risk and opportunity events and the causal relationships between them were assessed by experts using natural language.

The development of FSD models starts with the identification of all the factors that affect a particular real-world system, hereafter called system variables, and the relationships between these factors. There are two categories of system variables in construction systems, which can be distinguished based on their scale of measure [12]: (1) objective system variables that are defined by crisp numbers (e.g., 40°C for temperature) and (2) subjective system variables that are defined by subjective scales or linguistic terms (e.g., high crew motivation) [8]. After the system variables are identified, the relationships between the system variables are identified and defined quantitatively. According to Coyle [23], there are two types of system relationships in FSD models: hard system relationships, for which the mathematical form of the relationship is known, and soft system relationships, for which the mathematical form of the relationship is unknown. Since the mathematical form of hard relationships is known, these relationships are always defined using mathematical equations. Unlike hard system relationships, the mathematical form of soft system relationships is unknown; these relationships therefore need to be defined by an input-output predictive modeling technique. In existing applications of FSD in construction, soft relationships are usually defined either by linear regression, when historical data are available [8,22,24], or by expert-driven fuzzy rule-based systems (FRBSs), when historical data are not available.

While soft system relationships can be defined by any input-output modeling technique, in existing applications of FSD, linear regression is commonly used to define these relationships for the sake of computational simplicity [10]. In a recent paper, Gerami Seresht and Fayek [8] compared linear regression and the fuzzy *c*-means (FCM) clustering technique [25] in terms of their accuracy in defining soft system relationships and concluded that in some cases, FCM clustering outperforms linear regression. However, in the comparison conducted by Gerami Seresht and Fayek [8], neither of the two techniques (i.e., linear regression or FCM clustering) was universally the best technique for defining soft system relationships in their FSD model. Moreover, the accuracy of the FCM clustering technique decreases as the dimensionality of the relationships increases (i.e., the number of input and/or output variables increases) [26], which hinders the application of this technique for defining highly dimensional soft system relationships (i.e., systems having numerous input and/or output variables). There is a gap in the research on identifying an appropriate predictive modeling technique for defining soft system relationships in construction applications. Such a technique should be capable of modeling the non-linear relationships between system variables, handling the limited data availability often found in construction, and handling the high dimensionality of system relationships in construction applications. This research gap is addressed in this paper by integrating the FSD technique with neuro-fuzzy systems, the latter of which are used to define soft system relationships in FSD models. This new hybrid modeling technique, hereafter called the neuro-fuzzy system dynamics (N-FSD) technique, can potentially outperform the FSD technique for predicting the behavior of construction systems, since the use of neuro-fuzzy systems rather than linear regression improves accuracy when modeling non-linear system relationships [18] and enables the modeling technique to learn from historical data [27].

2.2. Neuro-Fuzzy Systems for Predictive Modeling in Construction Applications

Neuro-fuzzy systems are input-output modeling techniques developed by integrating two common AI techniques: ANNs and FRBSs [17,28]. Despite the wide application of ANNs in construction modeling, this technique has two limitations: (1) an ANN cannot capture the non-probabilistic uncertainty exhibited by the factors that affect construction systems and (2) the reasoning process of an ANN is not transparent. On the other hand, an FRBS is a predictive modeling technique with the capability of processing non-probabilistic uncertainties and mimicking human reasoning processes, though it lacks the capacity to learn from historical data. The limitations of these two techniques are addressed by integrating them, thereby developing neuro-fuzzy systems. The reasoning process of neuro-fuzzy systems is transparent and has the capacity to process non-probabilistic uncertainty because it uses the human-like reasoning process of the FRBS technique, and by using the learning algorithm of the ANN technique, neuro-fuzzy systems have the capacity to learn from data and improve the accuracy of their predictions by training.

Neuro-fuzzy systems consist of five data processing layers [27]: (1) the input layer, where the inputs are entered as crisp numbers; (2) the fuzzification layer, where the membership value for each input is determined; (3) the inference layer, where the FRBS component predicts the output of the system based on the inputs; (4) the defuzzification layer, where the outputs of the FRBS are defuzzified; and (5) the output layer, which delivers the final output of the hybrid neuro-fuzzy system. A learning algorithm (e.g., a backpropagation learning algorithm) is used to adjust the different features of the system, including the shape and/or number of fuzzy membership functions of the input and output variables and the number of fuzzy rules and rule weights [17]. There are different types of neuro-fuzzy systems, which are categorized based on three characteristics: (1) the structure of their FRBS component (i.e., Mamdani or Sugeno); (2) their learning algorithm (e.g., backpropagation, random, supervised or unsupervised learning); and (3) the features of the system, which are adjusted by the learning algorithm (e.g., the shape of membership functions, rule weights) [29]. The adaptive network-based fuzzy inference system (ANFIS) [30] and the evolutionary fuzzy neural inference model (EFNIM) [31] are two types of neuro-fuzzy systems commonly used in construction applications.

The ANFIS neuro-fuzzy systems technique has a Sugeno-type FRBS, and learning algorithms are used to tune both the weights of the rules of the FRBS and the shapes of the membership functions that represent the inputs and the outputs of the system. The ANFIS has been applied to a variety of construction problems, including strength prediction of construction materials [32] and hydraulic structure design [17]. Despite the extensive use of the ANFIS in different engineering applications, this technique is limited in terms of learning algorithms and the features of the system that are tuned by learning [29]. The learning algorithm of the ANFIS technique requires differentials to implement the learning process; therefore, those features of the system that are not differentiable (e.g., the number of rules of the rule base) cannot be optimized by the learning algorithm of the ANFIS technique [29]. In order to address this limitation, population-based neuro-fuzzy systems are introduced, which combine neuro-fuzzy systems with a population-based optimization technique (e.g., a genetic algorithm [GA] or particle swarm optimization [PSO]) so that those features of the system that are not differentiable can be optimized by the optimization component [29,33,34]. Moreover, the ANFIS technique is a static neuro-fuzzy system, which means the structure of the system (i.e., the number of membership functions and rules of the system) cannot be optimized by the learning process [29]. As opposed to static neuro-fuzzy systems, self-organizing neuro-fuzzy systems are capable of optimizing the structure of the system through the learning process by determining the optimum number of membership functions that represent the input and output variables or the number of rules of the FRBS. Self-organizing neuro-fuzzy systems can be developed by hybridizing a neuro-fuzzy system (e.g., the ANFIS) with a fuzzy clustering technique [17,29,34]. Hybridization of the ANFIS with subtractive clustering [17], FCM clustering [35], and grid partitioning [36] are a few examples of such hybrid neuro-fuzzy systems. In the case of the N-FSD technique, the soft system relationships are defined using a population-based hybrid neuro-fuzzy system, which combines the capabilities of the subtractive clustering, PSO, and ANFIS techniques for developing predictive models.

3. Methodology for Developing Neuro-Fuzzy System Dynamic Models

This section presents the research methodology for hybridizing the FSD technique with neuro-fuzzy systems and developing N-FSD models. The development of N-FSD models consists of three major steps: qualitative modeling, quantitative modeling, and model validation, as presented in Fig. 1.

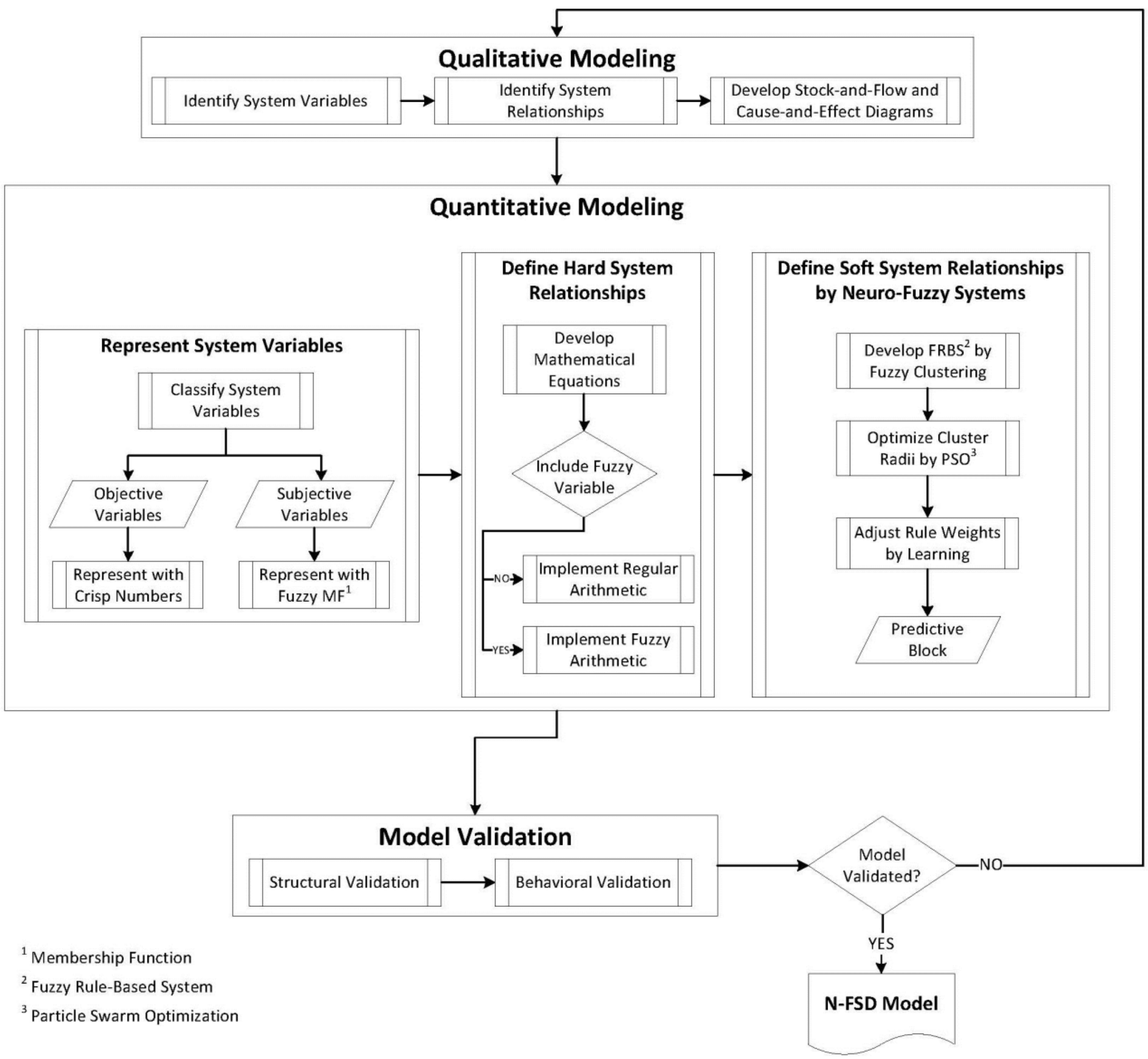

Fig. 1. Methodology for developing N-FSD models.

3.1. Qualitative N-FSD Modeling

Qualitative N-FSD modeling is accomplished by following steps similar to those used for the FSD technique, which are briefly discussed in this section. Qualitative FSD modeling is discussed in more detail by Gerami Seresht and Fayek [8] and Nasirzadeh et al. [2]. In the first step, all the factors that affect the real-world system are identified through a literature review and/or based on the knowledge of the modeler about the real-world system [37]. Hereafter, these factors are called system variables. In the second step, system variables are represented using one of the four different types of variables in N-FSD models: stock variables, flow variables, dynamic variables, and static variables (or constants). Stock variables are those variables that accumulate over time (e.g., total volume of soil excavated). Flow variables represent the rate of increase/decrease in stock variables (e.g., daily production). Dynamic variables are those that change in value (e.g., temperature, crew size), and static variables (or constants) are those whose value does not change throughout the simulation run (e.g., total volume of work).

In the third step, the relationships between system variables, called system relationships, are identified. There are two types of system relationships in N-FSD models: hard system relationships and soft system relationships. Since the mathematical form of hard system relationships is known, these relationships are identified using the mathematical equation that defines the relationship. For example, the relationship between the total cost of an activity (TC) and its unit cost (UC) and the total volume of work (V) is evident from the mathematical equation that defines the relationship ($TC = UC \times V$). On the other hand, the mathematical form of soft relationships is unknown, as is the case, for example, with the relationship between the precipitation level and the production rate of an earthmoving operation. These relationships therefore need to be identified using existing knowledge about the real-world system, which is acquired through a literature review or expert knowledge [37]. Finally, qualitative modeling is accomplished by representing system variables and system relationships graphically in stock-and-flow and cause-and-effect diagrams.

3.2. Quantitative N-FSD Modeling

The process of quantitative N-FSD modeling consists of two steps: (1) representing the values of system variables and (2) defining system relationships quantitatively. To represent the values of system variables, which are identified in qualitative modeling, they are classified as either objective or subjective, based on their scale of measure [8,12]. Next, the values of the objective system variables are represented by crisp numbers, and the values of the subjective system variables are represented by fuzzy membership functions, which are developed using one of the few data-driven techniques, such as FCM clustering or subtractive clustering [38].

Once the values of the system relationships are represented, the hard system relationships are defined quantitatively. Hard system relationships are always defined using mathematical equations, and arithmetic is implemented to determine the outputs of these equations at each time step of the simulation run. Conventional (i.e., regular) arithmetic is used for those equations, which include only objective system variables, and fuzzy arithmetic is used for the equations that include subjective system variables [39]. Fuzzy arithmetic operations may be implemented using one of the two approaches introduced in the literature: (1) the α-cut approach, which uses horizontal discretization of the input fuzzy numbers and interval calculations [40], or (2) the extension principle approach, which is an extension of arithmetic operations on crisp numbers applied by the extension principle of fuzzy sets and using any give fuzzy *t*-norm [41]. Both approaches for implementing fuzzy arithmetic have advantages and disadvantages. Implementing fuzzy arithmetic using the α-cut approach is advantageous because of its computational simplicity and the low sensitivity of the outputs to changes in the input variables [39,41]. The disadvantage of the α-cut approach is the overestimation of uncertainty in simulation results [8,39,41,42], which reduces the ability of the user to accurately predict the output of the real-world system and hinders the process of decision-making using simulation results [43]. On the other hand, the advantage of implementing fuzzy arithmetic by the extension principle approach is its flexibility in using different t-norms, which can reduce the overestimation of uncertainty in simulation results compared to the α-cut approach. However, implementing fuzzy arithmetic by the extension principle approach is computationally complex, and there only a few computational methods established for this approach using the drastic product *t*-norm [43] and the product and Lukasiewicz *t*-norms [41]. Accordingly, the appropriate approach for implementing fuzzy arithmetic in N-FSD models needs to be selected by the modeler while considering the advantages and disadvantages of each approach.

After defining the hard system relationships, the soft system relationships are defined quantitatively using an input-output modeling technique. This is an important step in FSD and N-FSD modeling because the accuracy of the simulation model heavily relies on the accuracy of the technique used to define the soft system relationships [23]. Since the mathematical form of hard system relationships is known, they are always defined with maximum accuracy (i.e., with no error), so it is the input-output modeling technique used for defining the soft system relationships that is responsible for the accuracy of the simulation model. In the case of the N-FSD technique, soft system relationships are defined using neuro-fuzzy systems, whose methodology is presented in Fig. 2. As a result, each soft system relationship of N-FSD models is defined by a neuro-fuzzy system, which is hereafter called a predictive block.

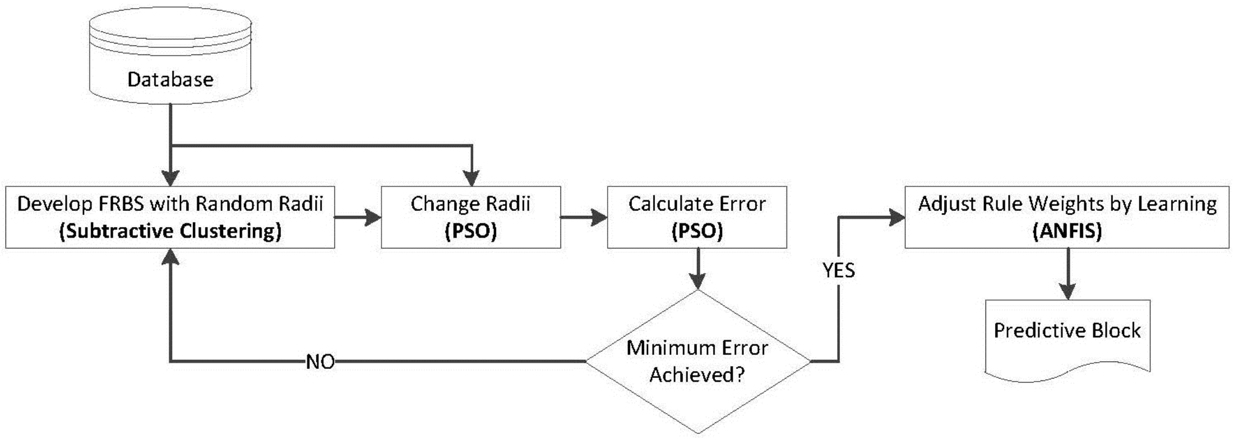

Fig. 2. Methodology for defining soft system relationships using EFNIM models.

To develop predictive blocks, a Sugeno-type FRBS is first developed using the subtractive clustering technique. Sugeno-type FRBSs can transform the complex and non-linear relationships between input and output variables into a set of linear relationships [18], which can increase the accuracy of the FRBS as a predictive model and improve the computational efficiency of the model. While FRBSs can be developed using any fuzzy clustering technique, the use of subtractive clustering is preferred over the other fuzzy clustering techniques for N-FSD in order to facilitate the use of PSO for optimizing the structure of the FRBS. The user-defined parameter for subtractive clustering (as discussed below) is continuous, unlike the FCM clustering technique; the PSO technique, which is an appropriate technique for optimizing continuous variables [44], can therefore effectively optimize the user-defined parameter for subtractive clustering. The user-defined clustering parameter for subtractive clustering is called the cluster radius, and it determines the minimum Euclidean distance between any two cluster centers. In subtractive clustering, each data point is considered to be a potential cluster center, and the potential of each data point to become a cluster center (P_i) is determined using Equation 1 [17].

$$P_i = \sum_{j=1}^{n} e^{-\alpha}\left\|x_i - x_j\right\|^2 \,, \qquad \alpha = \left(\frac{2}{r_a}\right)^2 \tag{1}$$

where r_a stands for the predefined cluster radius and $\|.\|$ stands for the Euclidean distance. Next, the data point with the highest potential for becoming a cluster center (i.e., the point with the largest value of P_i) is selected as the first cluster center and then P_i is recalculated for all the remaining points using Equation 2 [17].

$$P_i \Leftarrow P_i - P_1^*.\, e^{-\beta\|x_i - x_1^*\|^2}, \qquad \beta = \left(\frac{2}{r_b}\right)^2 \tag{2}$$

where r_b is a positive constant called the squash factor, which ensures that the potential for all the points neighboring the first cluster center is reduced significantly, so that the occurrence of developing two clusters with extremely close cluster centers will be avoided. The value of the squash factor is suggested to be $r_b = 1.25 \times r_a$ [17]. In Equation 2, P_1^* is largest value P_i calculated in the previous step (refer to Equation 1) and x_1^* is the location of the first cluster center. This process for calculating the potential of each data point for becoming the next cluster center and selecting the point with the highest potential is repeated until the potential of all remaining points (i.e., P_i in Equation 2) is less than 15% of the potential for the first cluster center (i.e., P_1^* in Equation 2) [38,45]. In subtractive clustering, the value of the cluster radius of each input and output variable is determined by the user [38,45]. This approach enables the user to change the weights of the input or output variables for the development of the FRBS in order to improve its accuracy. Decreasing the cluster radius of an input or output variable decreases its weight for the development of the FRBS and vice versa.

After developing an initial FRBS using randomly selected cluster radii, the PSO technique is used to determine the optimum value of the cluster radius for each input and output variable of the FRBS, taking into consideration the minimization of the root mean square error (RMSE) of the predictions made by the FRBS. Equation 3 presents the mathematical form of the optimization problem solved by the PSO technique.

$$\min_{r_a^i} \sqrt{\frac{\sum_{t=1}^{t=T}(\hat{y}_t - y_t)}{T}}, \qquad subject\ to{:}\, r_a^i \in (0,1), i = 1,2, \dots, k \qquad 3$$

where $\hat{y}$ is the actual data, y_t is the predicted output of the FRBS, T is the total number of historical data points used for testing, and r_a^i stands for the cluster radius of the input/output variable i, and k stands for the total number of input and output variables. Next, the FRBS developed using the optimum values of the cluster radii is trained using the learning algorithm of the ANFIS technique in order to improve the accuracy of the predictive block [17]. This learning algorithm improves accuracy by determining the rule weights of the FRBS. The details of the learning algorithm used in the ANFIS technique are discussed extensively in the literature [27,29,30]. The population-based hybrid neuro-fuzzy system used for developing the predictive blocks of N-FSD models has the capacity to learn from historical data (i.e., using the ANFIS learning algorithm), as well as the ability to optimize the structure of the neuro-fuzzy system using PSO and subtractive clustering techniques.

3.3. Validation of N-FSD Models

The validity of N-FSD models is tested using two types of validation tests: (1) structural validation tests, which validate the qualitative modeling step where the system variables and system relationships are identified, and (2) behavioral validation tests, which validate the quantitative modeling step where the values of the system variables are determined and the system relationships are defined quantitatively. The structural validity of N-FSD models can be determined through a variety of tests, including structure verification, dimensional consistency, and parameter verification tests [46–49]. The structure verification test determines if the structure of the N-FSD model complies with the available knowledge about the real-world system, which may be obtained by reviewing the literature or acquiring expert knowledge [46,49]. The dimensional consistency test ascertains whether the units of measure on both sides of the system relationships are consistent [8,46,50]. The dimensional consistency test can be implemented only on hard system relationships, where the mathematical form of the relationships is known [8]. Finally, the parameter verification test determines whether the constants of the system are consistent with those of the real-world system [49]. Thus, the structural validation tests determine if the qualitative N-FSD model provides the user with an accurate understanding of the factors that affect the real-world system being studied and the interactions between these variables.

The behavioral validation tests of the N-FSD models determine whether the N-FSD model can accurately replicate the behavior of the real-world system in different situations [46–49]. The behavioral validity of N-FSD models can be determined through a variety of tests, including prediction accuracy tests, the extreme conditions test, and the pattern verification test [8,46,49]. Prediction accuracy tests are commonly used for all different predictive modeling techniques; in these tests, model outputs (i.e., predictions) are compared to empirical data using different error measures in order to determine the accuracy of the predictions made by the model. For the validation of SD and N-FSD models using prediction accuracy tests, Barlas [46] suggested using the mean absolute percentage error (MAPE), where a MAPE of 30% or below confirms the validity of the model. Although prediction accuracy tests are necessary for validating predictive modeling techniques, including the SD and N-FSD techniques, these tests alone cannot confirm the behavioral validity of the N-FSD models [46,50]. The extreme conditions test is a behavior validation test that sets the value of some system variables at their extremes (i.e., their lower or upper bounds) and determines whether or not the N-FSD model behaves in a manner similar to the real-world system in extreme conditions [49]. Finally, the pattern verification test compares model outputs to empirical data to ascertain whether the N-FSD model can accurately replicate different aspects of the patterns of empirical data, for example, predicting the extremum points (i.e., minimums and maximums) of system outputs, predicting the frequency of repeated values in system outputs, and predicting increasing and decreasing trends in system outputs [8,46]. Thus, the structural validation tests ascertain whether the quantitative N-FSD model can accurately mimic the behavior of the real-word system and provide the user with accurate predictions of system outputs.

4. Construction Application of the N-FSD Technique

In this section, the application of the N-FSD technique for modeling the production rate of an earthmoving operation is presented in order to illustrate the applicability of this technique to construction problems. In addition, the N-FSD technique is compared to the conventional FSD technique in terms of the accuracy of simulation results to illustrate how the hybridization of neuro-fuzzy systems with the FSD technique can improve the accuracy of the FSD technique. The N-FSD model of the earthmoving production rate is developed through the qualitative and quantitative modeling steps discussed in Sections 3.1 and 3.2. The qualitative N-FSD modeling is accomplished by identifying system variables, identifying system relationships, and finally developing the cause-and-effect diagram. In this paper, system variables (i.e., those factors that affect the production rate of the earthmoving operation) are identified through a literature review [8,13,51,52]. Next, the relationships between the system variables are identified based on knowledge of the real-world system. Finally, all the system variables and system relationships are presented in the cause-and-effect diagram and the qualitative N-FSD model of the earthmoving production rate is developed as presented in Fig. 3.

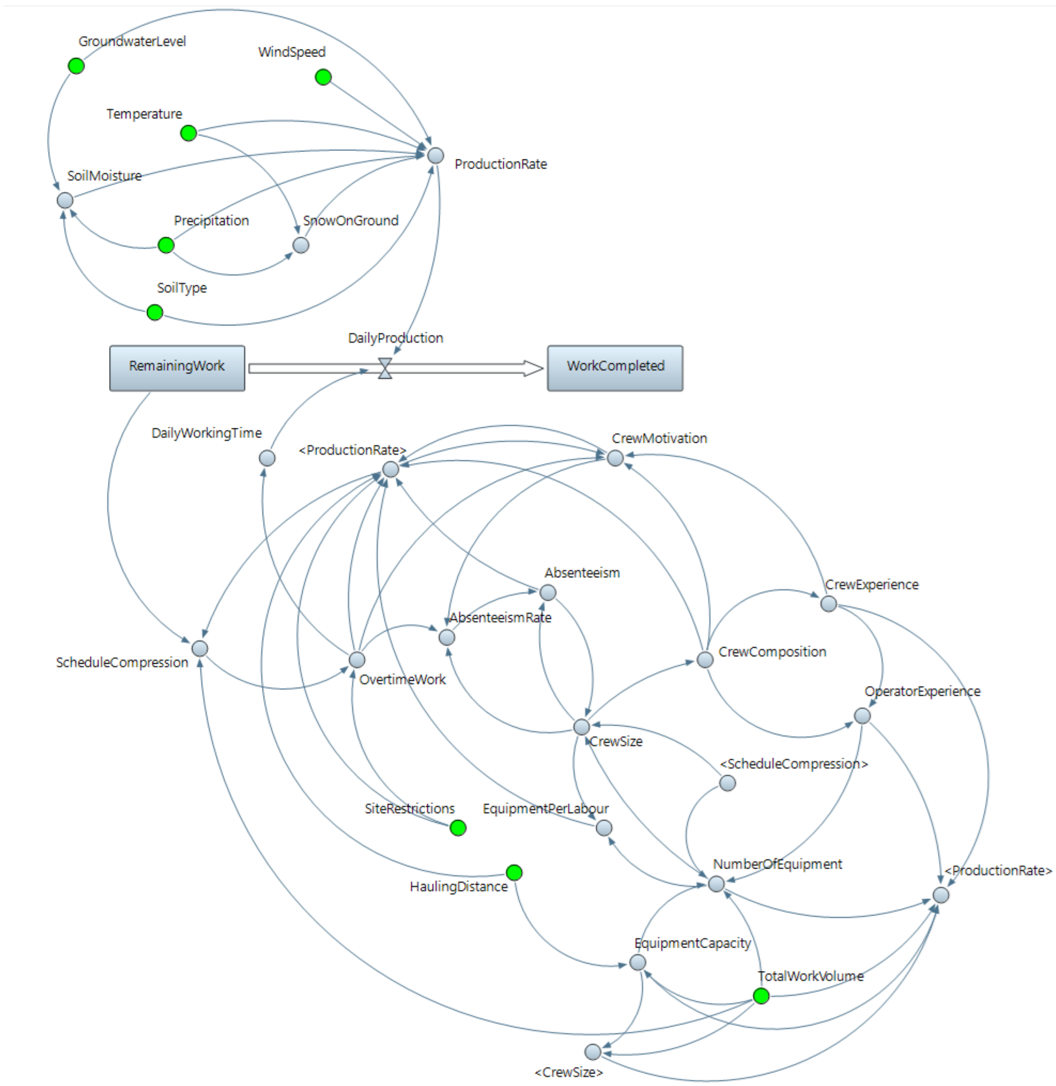

Fig. 3. Qualitative N-FSD model of earthmoving production rate.

The qualitative N-FSD model of the earthmoving production rate is developed using AnyLogic® software. In the model, there are 24 dynamic system variables, two stock variables, and one flow variable. Out of the 24 dynamic system variables represented in Fig. 3, there are seven independent variables, shown in green: groundwater level, temperature, wind speed, precipitation, soil type, site restrictions, hauling distance and total work volume. The independent system variables are those system variables that are not affected by any other system variables (i.e., there are no arrows to show system relationship ends for these variables).

Following the development of the qualitative N-FSD model, the first step for developing the quantitative N-FSD model is classifying the system variables into objective and subjective system variables, as presented in Table 1.

The values of the objective system variables are represented by crisp numbers (e.g., 4°C for temperature) and the values of the subjective system variables are represented by fuzzy numbers (e.g., high crew motivation). Fuzzy numbers are a specific type of fuzzy membership functions that (1) have bounded support; (2) are normal (i.e., they possess at least one point in the universe of discourse with the membership value of 1); and (3) are convex [53,54]. Fuzzy numbers can be used to represent the values of real-world parameters when exact values are not measurable due to subjectivity [41,54]. While in most cases the system variables are classified as objective or subjective based on their scale of measure [12], in some cases, the measuring technique used to determine the values of the system variables needs to be taken into account, as well. For example, soil moisture can be an objective system variable if it is measured numerically using soil tests, or it can be a subjective system variable if it is measured subjectively through expert judgment. The values of subjective system variables are represented using fuzzy numbers, which are developed using the subtractive clustering technique, as illustrated in the quantitative definition of soft system relationships below.

After classifying the system variables, the hard system relationships are defined using mathematical equations. As discussed in Section 3.2, hard system relationships are identified based on the fact that the mathematical form of these relationships is known. In this case study, there are four hard system relationships, as presented in Equations 4 to 7.

$$Absenteeism = Absenteeism\ Rate \times Crew\ Size \quad (4)$$

$$Equipment\ Per\ Labor = \frac{Number\ of\ Equipment}{Crew\ Size} \quad (5)$$

$$Total\ Daily\ Work\ Hours = Planned\ Working\ Hours + Overtime\ Work \quad (6)$$

$$Daily\ Production = Total\ Daily\ Work\ Hours \times Production\ Rate \quad (7)$$

Next, the soft system relationships are defined quantitatively by developing predictive blocks using the population-based hybrid neuro-fuzzy system discussed in Section 3.2. Table 2 presents the soft system relationships of the N-FSD model of the earthmoving production rate.

Table 2. Input and output variables of the soft system relationships.

#	Output system variable	Input system variables
1	Snow on ground	Precipitation, temperature
2	Soil moisture	Precipitation, soil type, groundwater level
3	Schedule compression	Remaining work, production rate, total work volume
4	Absenteeism rate	Crew size, overtime work, crew motivation
5	Crew size	Number of equipment, absenteeism, schedule compression, total volume of work
6	Number of equipment	Schedule compression, equipment capacity, total volume of work
7	Operator experience	Crew composition, crew experience
8	Crew experience	Crew composition
9	Crew composition	Crew size
10	Crew motivation	Production rate, overtime work, crew experience, crew composition
11	Equipment capacity	Hauling distance, total volume of work
12	Production rate	Crew motivation, precipitation, temperature, groundwater level, soil type, soil moisture, snow on ground, wind speed, hauling distance, site restrictions, equipment per labor, overtime work, absenteeism, crew composition, crew motivation, crew experience, operator experience, equipment capacity, crew size, number of equipment

Developing predictive blocks using neuro-fuzzy systems for defining soft system relationships is the unique characteristic of the N-FSD technique that distinguishes it from the conventional FSD technique. The methodology for developing predictive blocks is illustrated in detail using a numerical example of the soft system relationship between the production rate and the 20 input system variables (refer to Table 2). First, the input and output variables for each soft relationship are determined as presented in Table 2. Next, using a random set of cluster radii $\{r_a^i \,|\, i = 1,2,\ldots,21 \textit{ and } r_a^i \in (0,1)\}$, an initial FRBS is developed using the subtractive clustering technique to define the soft relationships between the production rate and the 20 input variables. Fig. 4 shows the structure of the initial FRBS developed for the production rate.

As shown in Fig. 4, the FRBS developed for the production rate has five layers: (1) the input layer, where the values of the 20 input variables are entered in the system; (2) the fuzzification layer, where the values of the input variables are fuzzified; (3) the inference layer, where the rule-base of the FRBS is located; (4) the defuzzification layer, which determines the membership value for each membership function of the output (i.e., the production rate); and (5) the output layer, which determines the final output of the system by aggregating all the membership functions of the output (refer to Section 2.2).

In the next step, the PSO component is used to optimize the cluster radius for each input and output variable of the relationship. The mathematical formulation of the optimization problem is presented in Equation 3. Fig. 5 shows the results of optimization using the PSO technique.

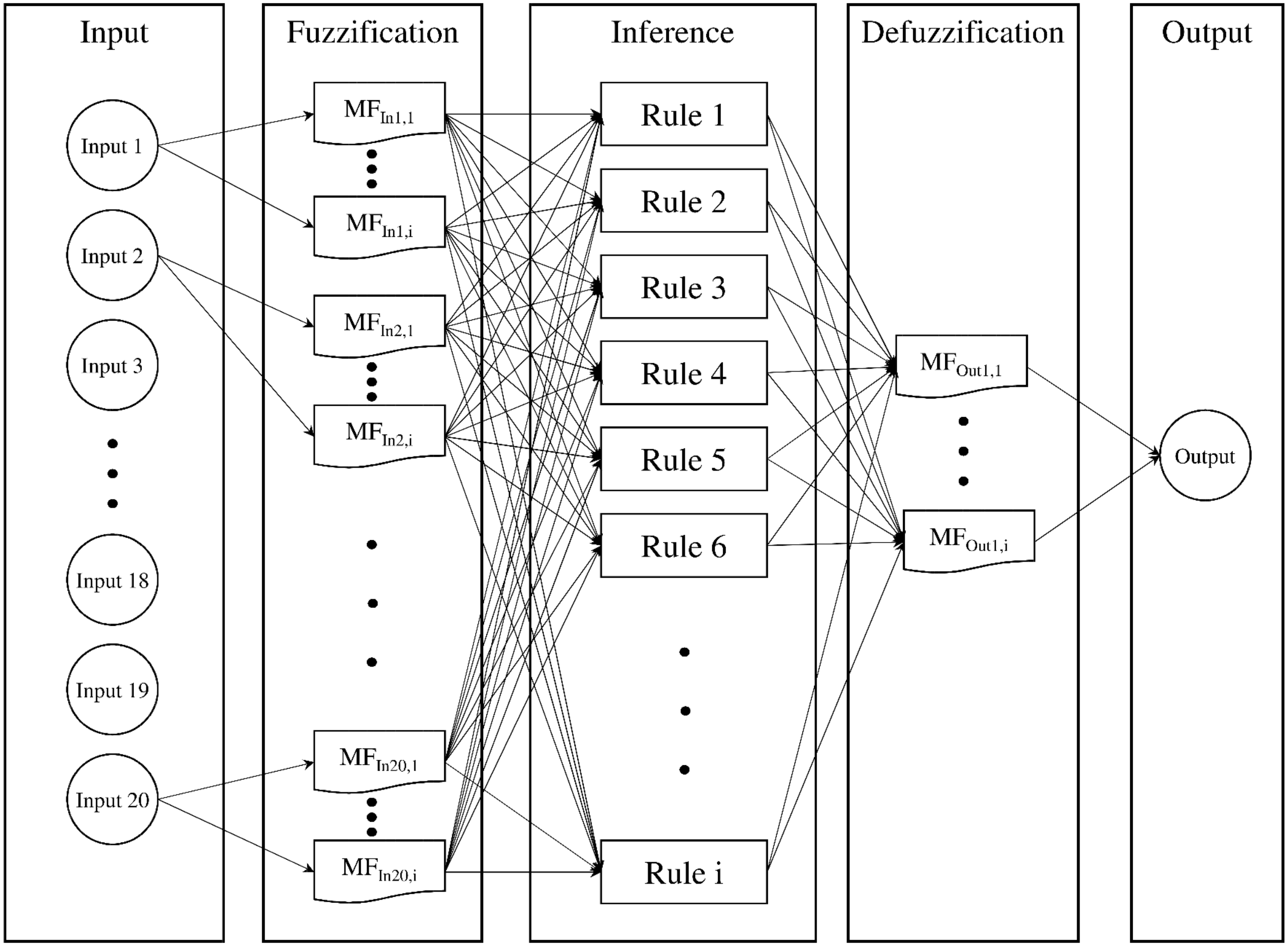

Fig. 4. Initial FRBS structure for production rate developed by subtractive clustering.

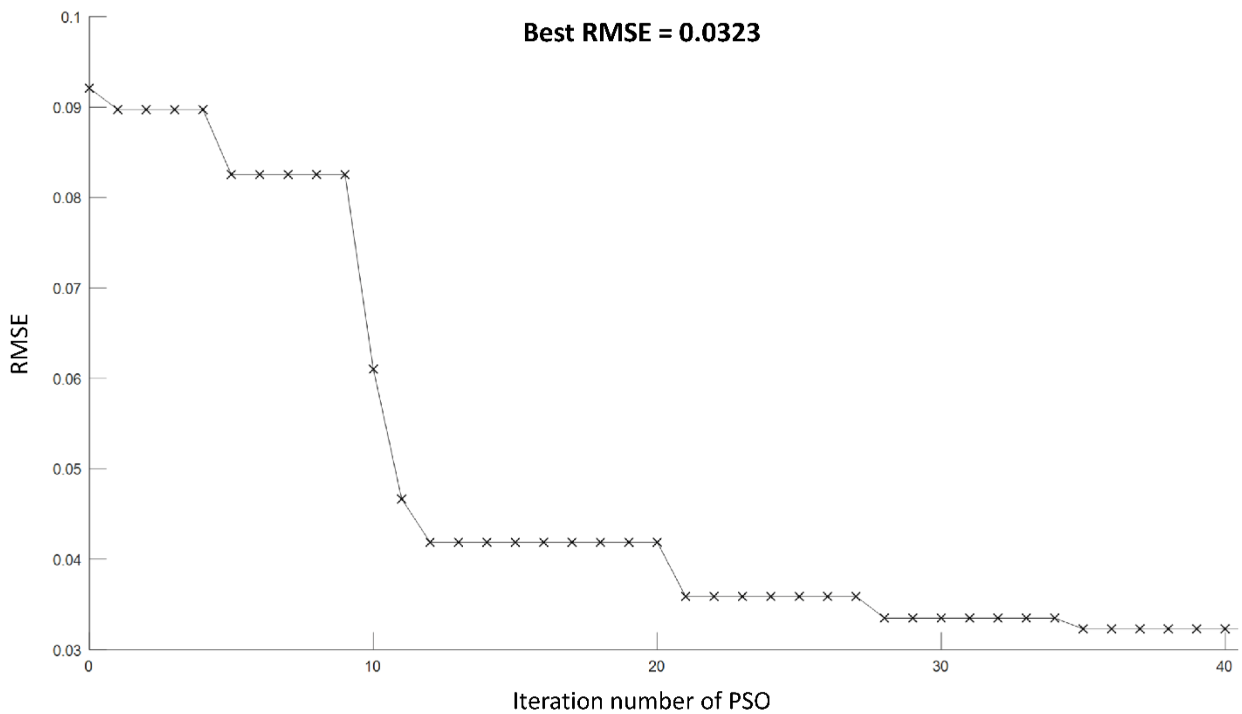

Fig. 5. PSO optimization results for optimizing the cluster radii for subtractive clustering.

In Fig. 5, the vertical axis shows the value of the RMSE of the FRBS for predicting the production rate using actual field data (refer to Equation 3) and the horizontal axis shows the number of iterations of the PSO technique. As shown in Fig. 5, the minimum value of $RMSE = 0.0323$ is obtained through the optimization process. In other words, in each iteration, the PSO optimization technique changes the value of the cluster radius for each input and output variable and consequently develops new FRBSs and determines the RMSE of the developed FRBSs. Finally, the optimum value of the cluster radius for each input and output variable is determined, yielding the FRBS with the minimum value of the RMSE. Table 3 presents the optimum cluster radii for all the variables of the soft relationships that predict the value of the production rate (i.e., the output variable is the production rate).

Table 3. Optimum cluster radii for the variables of the soft relationships that predict production rate

Variable Name	Cluster Radius	Variable Name	Cluster Radius
Temperature	0.892119	Total volume of work	0.354266
Precipitation	1.00E-20	Site restriction	0.307102
Snow on ground	0.496825	Soil type	0.201373
Wind speed	0.914398	Hauling distance	0.842654
Crew size	0.651692	Crew motivation	0.025542
Crew composition	0.000871	Operator experience	0.034076
Crew experience	0.820244	Groundwater level	1.00E-20
Overtime work	0.316029	Soil type	1.00E-20
Absenteeism	0.705813	Soil moisture	1.00E-20
Equipment per labor	0.998841	Equipment capacity	1.00E-20
Production rate	**0.831932**		

After determining the optimum cluster radii and developing the optimum FRBS (i.e., the FRBS with the minimum RMSE) using the PSO technique, the learning algorithm of the ANFIS technique is used to improve the accuracy of the predictive block by tuning the rule weights. Thus, the predictive block for defining the soft system relationship that predicts the value of the production rate using the 20 input variables, presented in Table 2, is developed. Using the same methodology, the other soft system relationships of the N-FSD model (refer to Table 2) are defined by developing a predictive block for each relationship.

4.1. Validation of the N-FSD Model of Earthmoving Production Rate

The structural validity of the N-FSD model is tested using dimensional consistency and structure verification tests. The dimensional consistency test is implemented through dimensional analysis of the mathematical equations that define the hard system relationships of the system [8]. Dimensional analysis of the mathematical equations that define the hard system relationships of the N-FSD model (Equations 4–7) confirms that the four hard system relationships of the N-FSD model are dimensionally consistent. The factors that affect the production rate of earthmoving operations are extracted from the literature [8,52,55–57], and their relationships with the production rate are confirmed with a structure verification test through a literature review.

Next, the validity of the N-FSD model needs to be tested using behavioral validation tests, which compare the simulation results to actual field data. In this paper, the behavioral validity of the N-FSD model is tested by running the simulation model for a 30-day period and comparing the results to actual field data. The actual field data were collected from a case study of earthmoving operations on a pipeline maintenance project in Alberta, Canada [8]. This project included 79 work packages (i.e., digs), each of which includes the following activities: excavation, sandblasting, welding, coating, and backfilling. The case study presented in this paper is focused on the earthmoving activities (i.e., excavation and backfilling), which were executed by eight earthmoving crews. Field data were collected for these two activities by documenting the value of the factors that influence the production rate and the actual daily production rate of the earthmoving operations.

In order to illustrate how hybridizing FSD with neuro-fuzzy systems improves the ability of the N-FSD technique to predict the behavior of real-world systems, the accuracy of N-FSD and FSD models are compared using this case study. The errors of the two techniques (i.e., FSD and N-FSD) in predicting the production rate of the earthmoving operation are calculated using actual field data and compared to one another. While all soft system relationships are defined by hybrid neuro-fuzzy systems in the N-FSD mode, in the FSD model these relationships are defined by linear regression as practiced in the recent applications of SD/FSD techniques in construction (refer to Table 1), including the FSD model of construction productivity by Gerami Seresht and Fayek [8], the construction labor productivity model developed by Nasirzadeh et al. [2] and the SD model for assessing the environmental impacts of cement industry by Ekinci et al.

[58]. The simulation results of the N-FSD and FSD techniques and the actual field data are numerically shown in Table 4 and graphically presented in Fig. 6. Due to confidentiality constraints, all field data presented in Table 4~~2~~ are normalized within the range of [0,1] using Equation 8.

$$V_i^N = \frac{V_i - min(V_i)}{max(V_i) - min(V_i)} \quad (8)$$

where V_i^N stands for the normalized value of any system variable, V_i stands for the original value of the system variable.

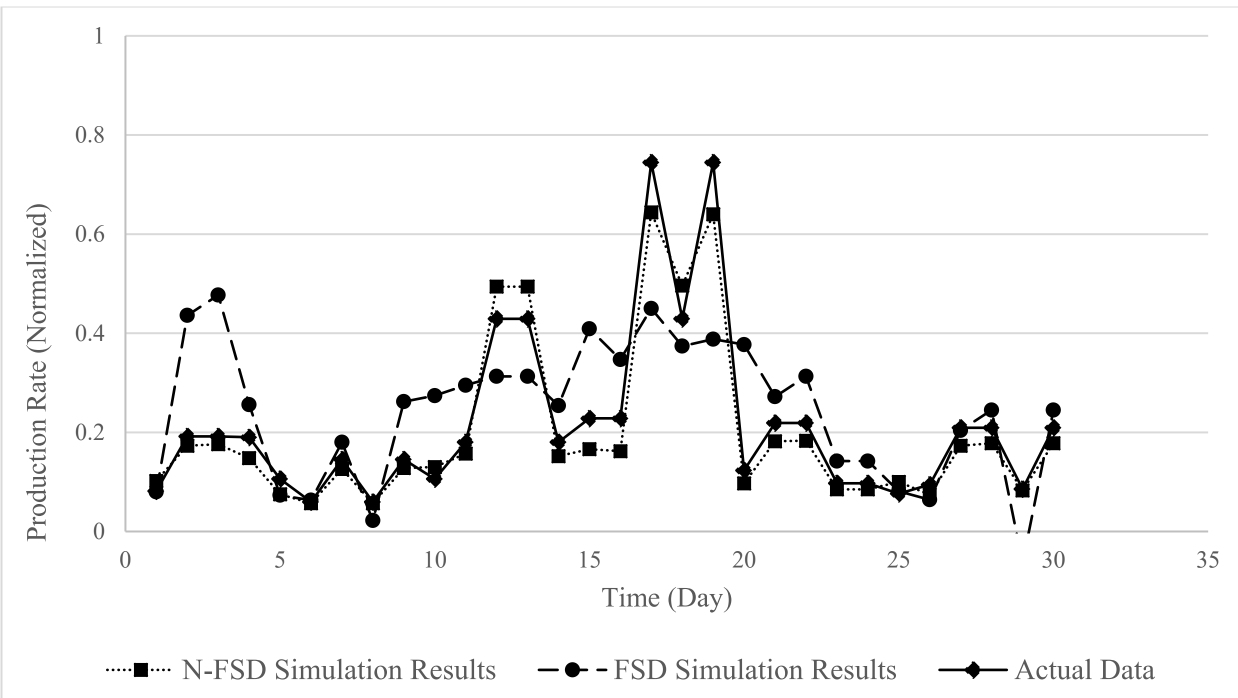

Figure 6. Simulation results for production rate in comparison to actual field data.

Table 4. N-FSD and FSD simulation results and actual field data for production rate

Time (Day)	**N-FSD Result**	**FSD Result**	**Actual Data**	**N-FSD Error** $\frac{(\text{Actual} - \text{Result})}{\text{Actual}}$	**FSD Error** $\frac{(\text{Actual} - \text{Result})}{\text{Actual}}$
1	0.102	0.08	0.082	0.249	0.020
2	0.173	0.436	0.192	0.098	1.273
3	0.176	0.477	0.192	0.083	1.486
4	0.148	0.256	0.190	0.222	0.346
5	0.075	0.073	0.106	0.293	0.312
6	0.057	0.063	0.060	0.044	0.056
7	0.126	0.18	0.145	0.133	0.239
8	0.057	0.022	0.060	0.044	0.631
9	0.128	0.262	0.145	0.119	0.803
10	0.13	0.274	0.106	0.225	1.583
11	0.157	0.295	0.180	0.129	0.636
12	0.494	0.313	0.429	0.151	0.271
13	0.494	0.313	0.429	0.151	0.271
14	0.152	0.254	0.180	0.157	0.409
15	0.166	0.409	0.228	0.273	0.792
16	0.162	0.347	0.228	0.290	0.520
17	0.644	0.45	0.745	0.135	0.396
18	0.496	0.374	0.429	0.156	0.129
19	0.64	0.388	0.745	0.140	0.479
20	0.097	0.377	0.123	0.213	2.060
21	0.182	0.272	0.219	0.169	0.242
22	0.183	0.313	0.219	0.165	0.429
23	0.085	0.142	0.097	0.126	0.459
24	0.085	0.142	0.097	0.126	0.459
25	0.1	0.081	0.076	0.311	0.062
26	0.074	0.064	0.095	0.217	0.323
27	0.173	0.204	0.209	0.173	0.025
28	0.178	0.245	0.209	0.150	0.171
29	0.083	-0.063	0.086	0.031	1.735
30	0.178	0.245	0.209	0.150	0.171
MAPE				**16.42%**	**55.96%**

As shown in Table 4, the N-FSD technique outperforms the FSD technique in terms of accuracy, as the MAPE for the N-FSD technique is 16.42% and for the FSD technique it is 55.96%. The ability of the two simulation techniques (i.e., FSD and N-FSD) to predict the behavior of constructions systems is compared using behavioral validity tests (refer to Section 3.3) and the following conclusions are drawn based on the simulation results presented in Fig. 6:

- The N-FSD technique outperforms the FSD technique in predicting trends in the behavior of construction systems. Trends in the production rate (i.e., an increase or decrease in the value of the production rate between any two consecutive points) are correctly predicted by the N-FSD model in 28 out of 29 cases (96%), while the FSD model predicted these trends correctly in 20 out of 29 cases (69%).
- The N-FSD technique outperforms the FSD technique in predicting the behavior of construction systems in extreme conditions. The extreme conditions (i.e., where the value of the production rate reaches its minimum or maximum values) are predicted by the N-FSD mode correctly in all cases (days 8, 22, and 23 for the minimum value and days 17 and 19 for the maximum value), while the FSD model predicted these extreme conditions correctly only in one out of five cases (day 8 for the minimum value).

Thus, the results of the comparison show that the N-FSD technique can more accurately predict the behavior of construction systems than the FSD technique.

4.2. Research Limitations and Future Directions

The construction case study presented in this section reveals that the N-FSD technique also has some limitations for modeling construction systems, which need to be addressed in future research. First, there two types of uncertainties exhibited by the different variables in construction systems, the probabilistic uncertainties and non-probabilistic uncertainties. The N-FSD technique has the capacity to capture the non-probabilistic uncertainties of construction systems, however, this modeling technique cannot capture the probabilistic uncertainties of these systems. While there are numerous system variables in construction systems that exhibit probabilistic uncertainty (e.g., temperature or level of precipitation), in future applications, it is necessary to integrate the N-FSD with Monte Carlo simulation to capture the non-probabilistic uncertainty of construction systems. Such integration delivers a comprehensive modeling technique, with the capacity to capture all the different types of uncertainty in construction systems and increases the applicability of this technique in different engineering contexts. The second limitation of the N-FSD technique lies in its high computational cost, as compared to the SD/FSD techniques, and the lack of a commercial software package for developing N-FSD models. The N-FSD model of earthmoving operations presented in this paper has been developed in AnyLogic® and by establishing an online connection to MATLAB®. In such architecture of the model, at each time step of simulation, AnyLogic® sends the value of input variables for each system relationship (i.e., defined by hybrid neuro fuzzy systems) to MATLAB®; next, the MATLAB® determines the outputs of the system relationships and returns the results to AnyLogic®. Establishing the connection for exchanging information between the two software packages increases the computational cost of this modeling technique significantly, as compared to the FSD model of earthmoving operations presented in this section (i.e., two hours of simulation runtime for N-FSD model as compared to five minutes simulation runtime for FSD model). The high computational cost of N-FSD technique may limit the application of this technique for modeling construction systems with larger scope of modeling (i.e., including numerous system variables); and to address this limitation, evaluating the outputs of neuro-fuzzy systems should be accomplished within the simulation framework, AnyLogic® in this case, by defining new functions for hybrid neuro-fuzzy systems in the sub-class of system relationships.

5. Conclusions and Future Work

The complexity of construction projects makes it challenging to develop models for predicting projects' performance, which is an essential task for several managerial practices. In this paper, a new hybrid modeling technique, called neuro-fuzzy system dynamics (N-FSD), has been introduced by hybridizing FSD with neuro-fuzzy systems. The N-FSD technique has the capacity to capture the dynamic and interacting structure of construction systems and the non-probabilistic uncertainty of the factors influencing construction systems. The application of the N-FSD technique for modeling construction systems is tested through a case study by modeling the production rate of earthmoving operations and comparing the results to the FSD technique. The results show that the hybridization of FSD with neuro-fuzzy systems (in the N-FSD technique) improves the applicability of the FSD technique in construction, since (1) N-FSD is more accurate than FSD in terms of predicting the value of the production rate; (2) N-FSD is more accurate than FSD in terms of predicting the trends of the system output (i.e., an increase or decrease in the value of the production rate between any two consecutive points); and (3) N-FSD is more accurate than FSD in terms of predicting the behavior of the system in extreme conditions (i.e., when the system output reaches its minimum or maximum values). The contribution of this paper is introducing a new hybrid modeling technique — N-FSD technique — to address the following challenges associated with modeling construction systems: (1) capturing the impact of numerous interacting factors that affect construction systems; (2) capturing the non-probabilistic uncertainty exhibited by the variables affect construction systems, (3) addressing the dynamism of construction systems; and (4) modeling the non-linear and highly-dimensional relationships between the variables of construction systems accurately. This paper also contributes to the state of the art in FSD modeling by hybridizing this technique with machine learning (i.e., neuro-fuzzy systems) to enable this technique to learn from historical data.. Finally, this paper contributes to construction practice by providing a new technique for developing predictive models for construction systems that will support construction practitioners in their managerial practices. In future research, the N-FSD technique will be used to model different aspects of construction systems, such as managing construction risk or predicting different performance indicators of construction systems (e.g., productivity, cost performance). Moreover, in future research, the N-FSD technique will be extended by integrating it with Monte Carlo simulation in order to model the probabilistic uncertainty of the factors that affect construction systems.

6. Declaration of Competing Interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work.

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