SUPERVISORY FCM SIMULATION IN TUNNEL CONSTRUCTION

Limao Zhang[a], A. J. Antony Chettupuzha[b], Seungjun Ahn[c], Stephen Hague[d], Chrysostomos D. Stylios[e], Simaan M. AbouRizk[f]

[a],[b],[c],[d],[f] Department of Civil and Environmental Engineering, University of Alberta, Edmonton, Canada
[e] Department of Computer Engineering, Technological Educational Institute of Epirus, Arta, Greece

[a] limao@ualberta.ca, [b] chettupu@ualberta.ca, [c] seungjun@ualberta.ca,
[d] steve.hague@ualberta.ca, [e] cdstylios@gmail.com, [f] abourizk@ualberta.ca

ABSTRACT
This paper presents a Fuzzy Cognitive Map (FCM) approach for controlling the Tunnel Boring Machine (TBM) operation in tunnel construction. The fuzzy logic based approach is used to capture the construction experience and knowledge from domain experts in creating FCMs. A supervisory FCM model is developed to represent the cause-effect relationships among the variables involved in the operation of a TBM. The developed model can be used to test what-if scenarios and to perform a real-time control of operational variables in response to the changing environment. A tunneling project in China is used as an example case study to demonstrate the applicability of the developed approach. This example case study shows that the TBM performance is influenced by a variety of geological and operational variables, and that FCMs can provide guidance on adjusting operational parameters in tunnel construction. The proposed approach can be used as a decision support tool for ensuring satisfactory performance of TBMs, and thus increases efficiency of tunnel construction projects.

Keywords: Simulation; Fuzzy Cognitive Map (FCM); TBM Performance; Supervisory System

1. INTRODUCTION

In recent years, the construction of subway systems and underground utilities has dramatically increased due to the increasing population and lack of surface space. The tunnel boring machine (TBM) technique has found widespread application in tunnel construction, and is used for excavating tunnels in nearly all types of rock masses and geological conditions. However, occurrences of shield cutter-head failure, and even catastrophic failures of drive motors are frequently observed in real projects. In general, there is concern that a decrease in performance of the TBM due to a component failure leads to unacceptable equipment damage, and can significantly adversely impact the overall productivity of tunnel projects.

Often, a failure in the TBM occurs due to the mismatch between the geological variables (e.g., soil density) and the operational variables (e.g., gross thrust of the TBM). Therefore, timely and appropriate responses to the changing underground conditions are very important in TBM operations. However, precisely predicting the geological conditions for every location in tunnel construction is impossible. Hence, real time sensing and monitoring of the geological conditions is required in tunnel construction as the TBM advances.

Complex systems, like TBM operations, are usually characterized by high dimensions, and involve many different kinds of variables or subsystems that are strongly interconnected and mutually dependent. A large number of complex processes are not fully understood, but their operation is “tuned” successfully through experience, rather than through the application of pure mathematic principles (Stylios & Groumpos, 2000, 2004). In this situation, effectively and efficiently capturing and utilizing experts’ knowledge can provide a solution to develop and improve complex system models (Tianfield, 2001; Wu & Cai, 2000). Soft computing techniques have been proposed to create a platform to capture and integrate experts’ knowledge in an effective and efficient manner. Fuzzy cognitive map (FCM) approach is one of the soft computing modeling techniques. The implementation of FCM for modeling supervisory control systems is a promising area, since FCMs can integrate all kinds of relevant knowledge from domain experts, and simulate thinking processes of human experts by using a more abstract representation of the cause-effect mechanism, general control knowledge and adaptation heuristics, and enhance the performance of the whole complex system (Stylios & Groumpos, 2004).

The supervisory FCM is an augmented model of the complex system, which represents the relationships among the actual systems and their models. The supervisory FCM monitors and organizes all the subsystems in order to accomplish a task, to help the operator make decisions, to plan strategically and to detect and analyze failures (Stylios & Groumpos, 2000). A supervisory FCM for complex systems provides decision support and is efficient in examining what will happen if a state of the system changes (Stylios & Groumpos, 2004).

This paper investigates the potential of using supervisory FCM as a tool to model and simulate the TBM system, as well as assist operators in ensuring satisfactory performance during the TBM operation. A supervisory FCM model for controlling TBM performance is developed. The developed model provides further understanding on how the system behavior evolves quantitatively in the case of changes in variables, and assists engineers (the operators of the system) in adjusting relevant variables to ensure the satisfactory performance of the TBM operation. Also, the dynamic nature of a complex system over time is considered in the developed supervisory FCM models, in order to accurately illustrate the dynamic features of variables in the real world. A tunnel case in China is used to demonstrate the effectiveness of the proposed approach, as well as its application potential.

2. METHODOLOGY

FCM is a modeling methodology for complex systems, which originated from the combination of fuzzy logic and neural networks. The graphical illustration is a signed fuzzy graph with feedback, consisting of nodes and weighted interconnections. Figure 1 illustrates a simple FCM model. Nodes of the graph stand for concepts that are used to describe mainly behavioral characteristics of the system. Nodes are connected by signed and weighted arcs representing the causal relationships that exist among concepts. This simple illustration provides thoughts and suggestions in reconstructing FCM, in regards to adding or deleting interconnections or concepts. In conclusion, an FCM is a fuzzy-graph structure, which allows systematic causal propagation, in particular, forward and backward chaining. Based on the unique reasoning technique of FCM, a systematic decision approach to supervise the TBM performance in tunnel construction is developed in this research, which consists of the following four steps.

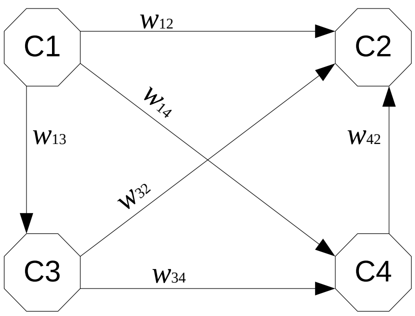

Figure 1: A Simple FCM Model

2.1. Representation of Concepts

FCMs are dynamic systems that have the topology of a directed fuzzy graph (see Figure 1) consisting of nodes and edges and permitting cycles and feedback. Nodes of the graph stand for the concepts that are used to describe the behavior of the system and they are connected by signed and weighted arcs representing the causal relationships that exist among concepts. It must be mentioned that all the values in the graph are fuzzy, indicating the concept nodes *Ci* have a fuzzy nature. In the FCM framework, each concept, defined by C_i with an interval of [-1, +1], represents a characteristic of the system (e.g., events, actions, goals, values or trends of the system). Relationships and interdependencies among concepts are represented by the arcs (i.e., interconnections) among concepts in FCM models, as shown in Figure 1.

Concepts in FCMs (C_i, C_j,…, C_n) represent the state of a system. At time t, the state of an FCM is defined by the vector A_t of the values of the concepts ($A_t = [C_1, \ldots, C_n] \in [-1,+1]$), or in other words, a point in the fuzzy n-dimensional state space. An edge e_{ij} ($\in [-1,+1]$) defines causal flows $C_i \rightarrow C_j$ between the concepts. Based upon the graphical representation, it becomes clear which concept influences other concepts, and the degree of the influence. Therefore, the FCM approach permits thoughts and suggestions to be collected or aggregated in the construction of the graph by adding or deleting an interconnection or a concept.

2.2. Fuzzy Weight Determination

Given an FCM model with N concepts, a weight from the concept C_i to the concept C_j ($1 \le i, j \le N$, $i \ne j$), defined by W_{ij}, is the relative influence from concept C_i that determines the value of concept C_j. These are fuzzy weights that describe the degree of the causal interconnection among concept nodes. To be specific, there are three types of causal interconnections between concepts that represent the degree of influence from one concept to the other:

- $W_{ij}>0$: means the weight of the arc from C_i to C_j would be positive. An increase in the value of C_i leads to the increase of the value of C_j, and a decrease in the value of C_i leads to the decrease of the value of C_j.
- $W_{ij}<0$: means the weight of the arc from C_i to C_j would be negative. An increase in the value of C_i leads to the decrease of the value of C_j, and vice versa.
- $W_{ij}=0$: means that there is no relationship between C_i and C_j.

The causal interrelationships among concepts are declared using a linguistic variable which takes values in the universe U = [-1, +1]. It is known that the number of linguistic intervals can largely affect the reliability of the estimation. Specifically, short intervals (or a great number of variables) indicate that the statistic is precisely known, while wide intervals (or a small number of variables) indicate great uncertainty. In order to reach the high precision of the influence estimation among concepts, it is better to conduct a group of short intervals, rather than wide intervals. According to Dawes' (2008) experiment, the use of 5-9 point scales is likely to produce slightly higher mean scores relative to the highest possible attainable score, and besides, a larger number is usually impractical. Thus, in this research, a 9-point linguistic scale is used to provide a basis for an expert to describe in detail the influence of one concept on another based on his/her knowledge, and then discern between different degrees of influence. Figure 2 illustrates the corresponding membership functions for these 9 linguistic terms: negatively very strong (μ_{nvs}), negatively strong (μ_{ns}), negatively moderate (μ_{nm}), negatively weak (μ_{nw}), zero (μ_z), positively weak (μ_{pk}), positively moderate (μ_{pm}), positively strong (μ_{ps}), positively very strong (μ_{pvs}).

In order to exploit the knowledge and experience of experts on the description and modeling of a complex system, it is supposed that there are *M* experts who evaluate every interconnection and describe it with a fuzzy rule inferring a linguistic weight. The credibility weight for every expert is introduced to increase the objectivity of the FCM developing method, accepting that initially, all the experts are equally credible and have the same credibility weight. Generally, at least *M*/3 of the experts have to fully agree with their suggestions, thus, an average weight of the interconnection is calculated using Equation 1. Otherwise, the credibility weight of an expert should be reduced by r% every time there is a wrong suggestion for an interconnection. Next, the suggested linguistic weights for an interconnection may be aggregated in accordance with the well-known fuzzy logic method of "SUM," which can be used to produce an aggregated linguistic weight. Finally, the defuzzification method of center of gravity (COG) is applied, and a numerical weight for the interconnection is calculated (Jang, Sun, & Mizutani, 1997; Nie & Linkens, 1995):

$$W_{ij} = \frac{\sum_{k=1}^{M}\left(b_k \times W_{ij}^{k}\right)}{M} \tag{1}$$

where, W_{ij} stands for the aggregated fuzzy weight from C_i to C_j; *M* stands for the total number of the participating experts; b_k stands for the credibility weight of the *k*th expert; and W_{ij}^{k} stands for the fuzzy weight from C_i to C_j based on the judgement of the *k*th expert.

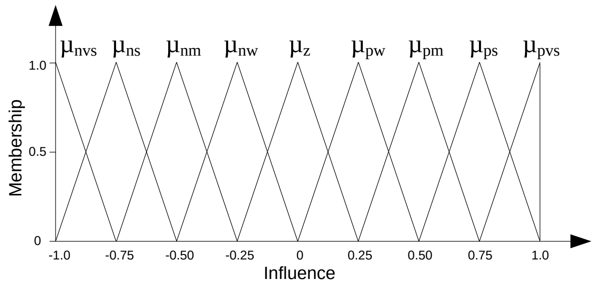

Figure 2: Membership Functions for the 9-point Linguistic Scale Regarding Influence between Concepts.

2.3. Dynamics of FCM

Behind the graphical representation of FCM, there is the mathematical model. The causal interconnections of an FCM model can be expressed by an $n \times n$ matrix *W*, which contains all of the n^2 rules or pathways in the causal web between *n* concepts in the FCM. The state of an FCM model can be expressed by a $1{\times}n$ vector *A*. Then, the dynamics of the FCM model are dictated by these matrices, and can be updated through iteration with other concepts and with its own value. Equation 2 drives this interaction where the strength of the causal relationships is represented by the weight of the summation (Stylios & Georgoulas, 2011; Stylios & Groumpos, 2004). After some iterations, the values of the concepts will evolve until stabilized at a fixed point or a cycle limit.

$$A_i\left(t+1\right) = f\left(A_i(t) + \sum_{j=1,\, j\neq i}^{n}\left(W_{ji} \times A_j(t)\right)\right) \tag{2}$$

In Equation 2, *t* stands for the interaction index; $A_i(t+1)$ stands for the value of concept C_i at time $t+1$; $A_i(t)$ and $A_j(t)$ stands for the value of concept C_i and C_j at time *t*, respectively; W_{ji} stands for the interconnection weight from concept C_j to concept C_i; and $f(\bullet)$ stands for a threshold function.

Generally, there are two kinds of threshold functions used in the FCM framework. One is the unipolar sigmoid function, where $\lambda>0$ determines the steepness of the continuous function $f(\bullet)$, and squashes the content of the function in the interval [0,1], as shown in Equation 3. Another threshold function can be used to transform the content of the function into the interval [-1, +1], as shown in Equation 4. The selection of the threshold function depends on the method that is used to describe the concepts. In this research, we attempt to assess the impacts of root causes of the reliability of the target event in terms of "positive influence" and "negative influence." As a result, the threshold function as shown in Equation 4 is selected for this research, and presented later in a case study.

$$f(x) = \frac{1}{1+e^{-\lambda x}} \tag{3}$$

$$f(x) = \tanh\left(x\right) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{4}$$

2.4. FCM-based Analysis

An FCM represents human knowledge about the dynamic behavior of a complex system. In other words, an FCM is a model about a system's dynamic behavior in term of concepts and interrelationships among concepts. Once constructed, FCMs can be used to simulate the behavior of a system and perform what-if analysis, due to its effectiveness in representing a complex system's behaviors, and the ease of use (Taber, 1991).

There is a cause behind every failure or problem, and localization and elimination of its causes should be of the utmost significance, in order to avoid failure occurrence. Predictive analysis aims to forecast the future outcome or effect of an event in light of some evidence being available. It can be used to address the problem or non-conformance by localizing the true cause and implementing corrective action to prevent recurrence of the problem (Rooney & Heuvel, 2004). Several variables may be involved in the occurrence of a failure; however, what the contributions of those variables are is unknown. In the FCM framework, as shown in Figure 1, at least one concept should represent the target event (decision concept), and some concepts should represent the potential root causes. Causal analysis is able to identify the relationship between the causes and effects of a target event, and further perform predictive analysis. More details regarding the predictive analysis of the TBM performance can be seen later in the tunnel case study.

3. FCM MODELING OF TBM PERFORMANCE

3.1. Concepts Involved in TBM Operation

A TBM is a machine used to excavate tunnels with a circular cross section through a variety of soil and rock strata. TBMs have the advantage of limiting the disturbance to the surrounding ground and producing a smooth tunnel wall, which significantly reduces the cost of lining the tunnel, and makes them suitable to use in heavily urbanized areas. In soft ground, there are two main types of TBMs, earth pressure balance (EPB) and slurry TBM. Compared with the slurry TBM, the EPB TBM is relatively inexpensive and does not need a large amount of space, and thus, is commonly used for a broad range of applications, especially in the construction of urban rail transport systems (Copur et al., 2014).

Generally, TBM performance is measured in terms of *Advance Rate* (C_T), which is the actual excavating and supporting distance divided by the total time, including downtime for TBM maintenance, machine breakdown and tunnel failure (Alber, 1996). The advance rate depends on various types of factors ranging from machine design to geological features. Therefore it may not be possible to capture this complex relationship in an explicit mathematical expression (Zhao, Gong, Zhang, & Zhao, 2007). In accordance with an extensive review of literature, the most important parameters that would be used in TBM performance studies can be divided into two major categories, as follows:

- Geological variables: The construction of a tunnel project is very sensitive to geological conditions due to complex tunnel-soil interactions. Some particular geological features may increase the hazardous nature of the TBM advance process. *Soil Cohesion* (C_1), *Friction Angle* (C_2), *Compression Modulus* (C_3) and *Soil Density* (C_4) are four variables frequently used to illustrate the geological features.
- Operational variables: In the process of the TBM-driven tunneling excavation, some pressure and speed sensors are installed on the top and middle of the cutter head in advance, and engineers pay close attention to the measurement of those operational variables, in order to maintain the face stability of the excavation and minimize risk (Ding, Wang, Luo, Yu, & Wu, 2013). Rational and appropriate *Gross Thrust* (C_5), *Cuter Torque* (C_6), *Earth Pressure* (C_7) and *Grouting Speed* (C_8) are considered very important technical variables in tunnel construction practice, which can also be further adjusted to guarantee satisfactory performance in the excavation process.

In total, nine concepts C_i (i=1, 2,...,8, T) are created in order to model the complex system of TBM performance. Table 1 illustrates the definitions of the above nine concepts. Due to the imprecise and uncertain nature of the variables in the real world, measurement of the initial values of those concepts remains a problem. Although many models for the prediction of TBM performance have been presented, as mentioned above, a commonly accepted model that can be used in every case regardless of geological conditions has not been reached. One significant reason is that the scope of favorable or unfavorable geological/operational variables varies greatly among different tunnel cases in different areas, leading to challenges in determining the value of a specific concept representing a corresponding geological or operational variable due to uncertainty.

In order to solve this problem, a 5-point linguistic scale provides a basis for an expert to describe in detail the favorability of a specific concept in response to the TBM performance based on his/her knowledge. Figure 3 illustrates the corresponding membership functions for these 5 terms: negatively very unfavorable (δ_{nvu}), negatively unfavorable (δ_{nu}), favorable (δ_n), positively unfavorable (δ_{pu}) and positively very unfavorable (δ_{pvu}). Given several experts are involved in the measurement of concepts in a specific project, the credibility weight for every expert is also introduced to increase the objectivity during the integration of expert knowledge from varying backgrounds, as well as to enhance the confidence in using the FCM. In a similar way as shown above in the section of fuzzy weight determination, both the well-known fuzzy logic method of SUM, and the defuzzification method of COG, are then applied to obtain a crisp value of a specific concept. For instance, if the concept C_1 has a value of 0, it means C_1 lies in a very favorable range in response to the TBM performance. Contrary to that, if the concept C_1 has a value of -1 (or 1), it means C_1 lies in a negatively very unfavorable (or negatively unfavorable) range in response to the TBM performance.

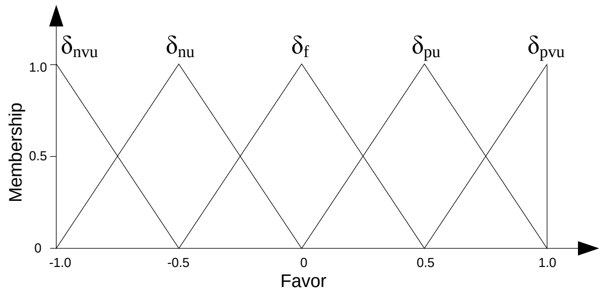

Figure 3: Membership Functions for the 5-point Linguistic Scale Regarding Concept Measurement

3.2. Model Construction

In order to demonstrate the effectiveness and practicality of FCM for supervising the TBM performance, a tunnel project, the Metro Line 7 (ML7) in the Wuhan metro system in China, is used as a case study. A questionnaire was prepared and distributed among ten experts who participated in the construction of ML7, including seven domain experts with at least five years of working experience and three professors in this field. The experts were asked to evaluate the influence/weight between the concept C_i and C_j (i, j=1, 2, ...,8,T; $i \neq j$) using the 9-point linguistic terms, as shown in Figure 2. In accordance with the methodology, as mentioned in Section II, the linguistic inputs from the experts were then transformed into crisp values using the fuzzy logic algorithm SUM and the defuzzification method of COG.

Table 1: Definitions of Nine Concepts Involved in TBM Operation

Items	Concepts	Descriptions
C_1	*Soil Cohesion*	Component of shear strength of a soil
C_2	*Friction Angle*	Force that resists the relative motion of solid surfaces, fluid layers, and material elements sliding against each other
C_3	*Compressive Modulus*	Capacity of a material or structure to withstand loads tending to reduce size
C_4	*Soil Density*	Mass of many particles of the soil divided by the total volume they occupy
C_5	*Gross Thrust*	Total thrust during the TBM operation
C_6	*Cuter Torque*	Torque of the cutter disk during the TBM operation
C_7	*Earth Pressure*	Pressure at the face of the TBM to remain a balanced performance
C_8	*Grouting Speed*	Speed of the concrete grouting at the shield tail
C_T	*Advance Rate*	Actual excavating and supporting distance divided by the total time in TBM operation

In order to support the computations, a *Java*-based FCM analysis software tool, *FCM Analyst v1.0*, developed by Margaritis et al. (2002), is used. This software tool has capabilities for creating an FCM, such as creating concept nodes and interconnections between concept nodes, manipulating the concepts/weights matrices, and running simulations to show the behavior of the FCM model. Taking the determination of the influence weight from concept C_1 to C_T as an example, there are five experts who have a judgement of negatively weak (μ_{nw}), two experts have a judgement of negatively moderate (μ_{nm}), and only one expert has a judgement of zero (μ_z). Figure 4 shows an illustration of how each individual expert's input is entered, and multiple inputs are automatically aggregated and defuzzified in the software tool. The weight of W_{1T} is then determined to be -0.275. With knowledge from all the participating experts integrated in an effective manner, Figure 5 depicts a graphical representation of the FCM model that is used to describe, model and supervise the TBM performance in tunnel construction.

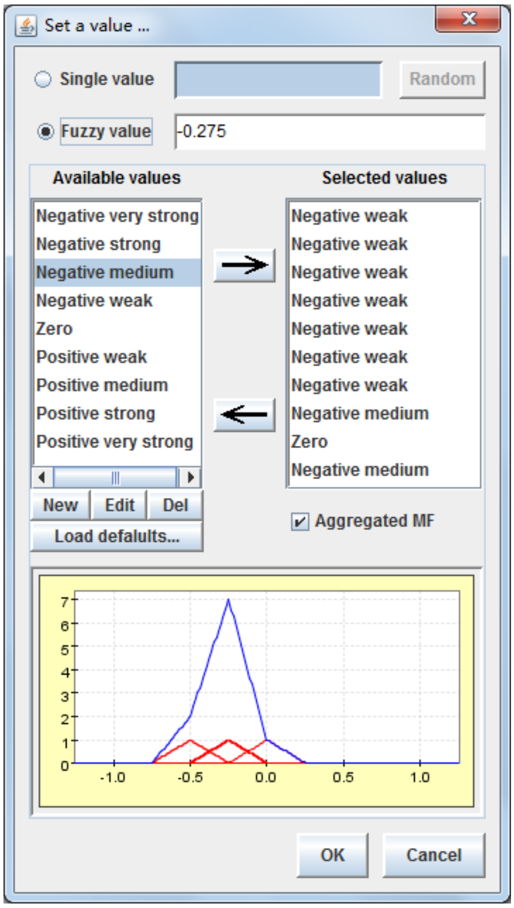

Figure 4: Illustration of Fuzzy Weight Calculation in *FCM Analyst v1.0*

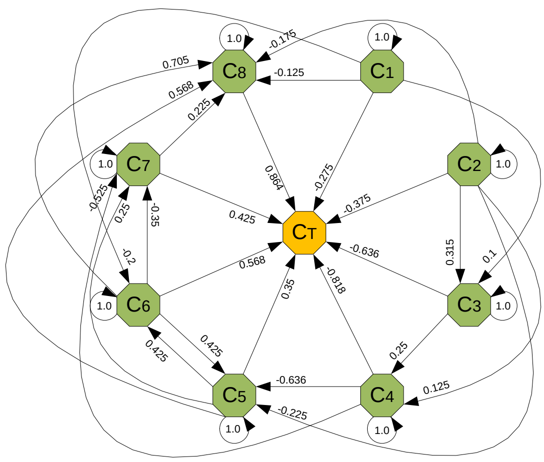

Figure 5: Graphical Representation of the FCM Model for the TBM Performance

4. SAMPLE EXPERIMENTS

Once an FCM is built, many what-if experiments can be conducted for exploring the cause-effect interaction of the TBM performance. In this paper, we present a sample experiment for predictive analysis of the TBM performance in tunnel construction. Predictive analysis aims to forecast the future outcome when evidence of a variable/concept is available. In the FCM framework, the propagation of evidence of a variable allows an update of the outcome of the other variables in the network in light of the newly found evidence. As mentioned above, the values of concepts correspond to real measurements that have been transformed in the interval [-1, +1] using the 5-point linguistic scale (see Figure 3). The concept has a value of 0 (-1 or +1), indicating it lies in a very favorable (negatively very unfavorable or positively very unfavorable) range in response to the TBM performance. Hence, when evidence is set on a specific concept in the FCM model, as shown in Figure 5, the evidence will propagate to the other concepts in the network, and cause the outcome of the affected concept nodes to change. Figure 6 illustrates impacts of variations of different concepts/causes on the TBM performance in the predictive analysis. In other words, this analysis shows the prediction of consequences if a concept (C_1-C_8) has a non-favorable condition while other concepts remain in the favorable range.

Taking into account the knowledge from domain experts, the developed FCM (see Figure 5) can be used as a tool to supervise TBM performance. It can be used to examine what will happen if a scenario is running, and what the consequences will be for the whole process if a state of the system changes. In general, the geological concepts C_1, C_2, C_3 and C_4 all perform markedly negative corrections with the concept C_{T}, while the operational concepts C_5, C_6, C_7 and C_8 all perform markedly positive corrections with the concept C_{T}. With respect to the measurement of this kind of correction among different concepts, the concept C_4 displays a strongest negative correction with the concept C_{T}; while the concept C_8 displays the strongest positive correction with the concept C_{T}. That is to say, the concepts C_4 and C_8 are both very sensitive to ensuring satisfactory performance of the TBM operation, and thus, should be given significant attention in tunneling excavation. This is consistent with observed construction practice, indicating the established FCM model is valid to some extent. As a matter of fact, to maintain the face stability of the excavation and minimize risk, engineers need to adjust the operational parameters continuously during the TBM operation so as to fit the surrounding geological conditions in a dynamic manner. The results achieved from the predictive analysis can provide more understanding on how the TBM performance evolves quantitatively in case either the geological or operational variables suffer a change, which can offer insights on the guidance for the reasonable adjustment of operational parameters in tunnel construction.

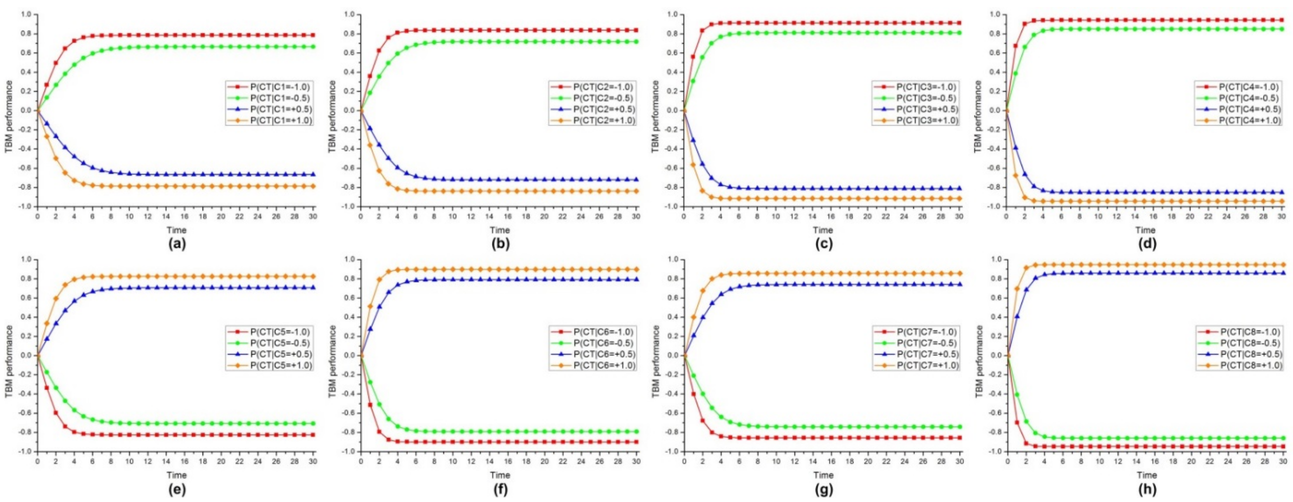

Figure 6: Impacts of variations of different concepts/causes on the TBM performance in the predictive analysis: (a) the concept C_1; (b) the concept C_2; (c) the concept C_3; (d) the concept C_4; (e) the concept C_5; (f) the concept C_6; (g) the concept C_7; and (h) the concept C_8

5. DISCUSSION

The FCM model that has been described in this paper takes into consideration expert feedback on the interrelationships between concepts that impact the performance of a TBM. An improved understanding of the relationships between these concepts can extend this theoretical model to practical applications in tunneling construction. One such potential application could be using the FCM as an intelligent automated supervisor that assesses and reacts to changing conditions.

FCMs integrated as an Intelligent Supervisor System have been previously proposed as a method to model a supervisory control system for dynamic environments (Stylios & Groumpos, 2000). If we were to consider a range of optimal TBM advancement rate as an objective, it is possible to design a supervisory FCM based on this model. This would be very useful when the tunneling area under consideration consists of several different kinds of soil types that are unevenly distributed. Traditionally, engineers would have to conduct rigorous surveys and determine operational parameters for every instance of soil variation and then provide these values integrated with a schedule to the TBM driver. However, if the TBM were equipped with sensors that detect these geological conditions, the FCM could automate this process with greater considerations for the interactions between all the concepts, and provide operational parameters for an optimized TBM advancement rate.

6. CONCLUSIONS AND FUTURE WORK

The operation of TBM systems is very complicated, since various kinds of variables are involved. Balancing the interaction among all the variables as to ensure satisfactory performance of the TBM operation becomes a challenging task. In this research, an FCM-based model is developed to supervise the TBM performance in tunnel construction, with construction experience and knowledge from domain experts taken into account. The developed approach is capable of performing predictive analysis given that an observation of change is available, providing insights into how the system should be adjusted over time. The obtained simulation results for the TBM performance illustrate the feasibility of the proposed approach, as well as its application potential in the modeling and controlling of complex systems in other areas.

The developed FCM-based approach also has some limitations. FCM provides an immediate understanding of causal knowledge in an intuitive way because of its simplicity. It is very helpful in the decision-making processes; however, constructing an FCM causal model by means of knowledge acquisition from experts is time-consuming. In addition, domain experts are generally considered scarce resources, especially in the construction industry, and finding experts in certain domains is challenging. Our subsequent research work would focus on the data mining technique in the knowledge engineering process, as well as the future application of FCM in the construction industry.

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