Fuzzy Cognitive Maps as a Tool for Modeling Construction Labor Productivity

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***Abstract*—Labor productivity is a fundamental building block of planning and controlling in construction, and therefore, predicting labor productivity levels for a given condition is very important in construction management. However, predicting labor productivity is extremely difficult due to a large number of factors that can affect productivity in perplexing ways. Another obstacle to predicting labor productivity is the qualitative nature and subjectivity of productivity factors. To address these issues, a soft computing technique called Fuzzy Cognitive Maps (FCMs) is proposed as a tool to model the complex inter-relationships between productivity factors based on expert knowledge, and for assessing the impact of the productivity factors on labor productivity. In this paper, the methodology for creating and using FCMs for this purpose is introduced, and then an exercise is presented for demonstration purposes. Additionally, issues identified from this exercise are described, and the way that FCMs can be practically used in the field for predicting labor productivity is also discussed in the paper.**

Keywords—Construction Labor Productivity; Fuzzy Cognitive Map (FCM); Knowledge representation; Soft computing

I. INTRODUCTION

Construction labor productivity is defined as man-hours per unit quantity (e.g., man-hours/m^3 for concrete, man-hours/ft^2 for formwork, and man-hour/ft for pipe rigging) [1]. Labor productivity tells us how much output can be/has been produced by a given labor input in construction processes. Labor productivity is a fundamental building block of construction planning and controlling, including cost estimating, scheduling, and performance tracking. Therefore, it is important to be able to reasonably predict labor productivity of construction processes to efficiently manage a construction project.

However, predicting labor productivity is extremely difficult, and this is mainly due to a large number of factors—whether known or unknown—that can affect labor productivity. The factors that have been verified to significantly affect labor productivity include weather [2], noise [3], health [4], motivation [5], skill level [6], fatigue [7], shift work [8], overtime [9], rework [10], communication method [11], material/equipment technology [12][13], material availability [14], congestion and crowding in workspace [15], change orders [16], supervision [5], to name a few. These factors may be different from project to project due to the uniqueness of construction projects. Furthermore, these factors often have inter-related causal relationships [17], and have a non-linear relationship with labor productivity [18].

Another problem in predicting labor productivity is the difficulty of quantifying the impact of productivity factors. For example, the impacts of workers' conditions like healthiness, motivation, skill level, fatigue, and site conditions like supervision, workspace congestion and crowding, are extremely difficult to quantify due to the subjectivity and uncertainty inherent in these factors [18]. Additionally, labor productivity is affected by both factors that are quantitative (e.g., temperature) and qualitative in nature (e.g., shift), and the combined effect that these factors have on labor productivity is even more difficult to predict. Hence, construction labor productivity is a complex phenomenon, and developing precise numerical models of construction productivity might not be feasible [19].

Given this background, the objective of this paper is to demonstrate the effectiveness of a soft computing technique called Fuzzy Cognitive Maps (FCM) as a tool for modeling construction labor productivity based on expert knowledge. The premise of this approach is that the knowledge of experts—who have prolonged experience in the field—on labor productivity is generalizable, reliable, and applicable to approximate reasoning and predicting the pattern of labor productivity and that this is especially true when multiple experts' knowledge is combined. As mentioned previously, construction labor productivity is dependent on many inter-related factors that are sometimes contradictory and/or can only be defined by subjective evaluations. Soft computing approaches can be a solution to capturing such elusive factors based on expert knowledge and representing and analyzing the dynamic behavior of a complex system while taking into account the nature of the variables in the real world—such as imprecision and uncertainty. Once constructed, FCMs can be used for conducting *thought experiments* for testing hypothetical scenarios—i.e., what-if analysis. Given that, this paper aims to demonstrate how FCMs can be used to model the complex inter-relationships among the productivity factors and to assess the impact of the factors on labor productivity.

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This paper is organized as follows: In the next section (section II), the previous efforts to computationally model labor productivity are reviewed. In the following sections (section III and IV), an overview of FCMs is provided, and then, the methodology used in this research to create an FCM of construction labor productivity is described. Then, the results of the FCM, discussion of the results, and conclusions follow in the subsequent sections (section V and VI).

II. Previous Efforts to Computationally Model Labor Productivity

A. Simulation

In computer simulation, the main components, processes, and factors of a system are modeled as variables and computational rules, such that simulation runs can reproduce the behavior of the system under investigation. To account for the various factors that affect labor productivity and to assess the impact of the factors on construction operations, several simulation approaches have been proposed. Among them, discrete-even simulation has been most widely used. In discrete-event simulation, the processes of construction operations are represented as an array of events, and factors that would affect the processes are modeled as input variables, which are often defined as a stochastic variable (i.e., random variable) to quantify the impact of a given factor on the entire system's performance in a statistical way.

Computer simulation has been used for analyzing different types of construction processes, including pile construction [20], steel fabrication [21][22], drainage operation maintenance [23], pavement construction [24], pipe spool fabrication [25], pipe line construction [26][27], bridge construction [28], concrete production in a plant [29], and tunnel construction [30]. The factors that were accounted for in these models include weather conditions, contractor experiences, equipment breakdown, site conditions, work hours, worker fatigue, schedule delays, shifts, overtime, worker experiences, and project management practices.

A major challenge in computer simulation for labor productivity is determining computational rules for the impact of productivity factors on labor productivity (e.g., the impact of experiences on an individual's production rate), and determining statistical parameters of the input variables for the productivity factors. In response to these difficulties, other approaches to model labor productivity have been proposed, including expert systems (e.g., fuzzy logic-based expert systems) and other artificial intelligence methods (e.g., artificial neural networks). Also, hybrid approaches combining the simulation modeling approach with others have been proposed, such as the simulation-based fuzzy logic approach [26].

B. Expert systems

An expert system is defined as a computer system that is designed to emulate the knowledge and the decision-making ability of human experts. In expert systems, the knowledge is acquired from domain experts, and the knowledge base is explicitly represented by a set of rules, and these rules are used to produce a solution to a given problem by reasoning (i.e., rule-based approach).

Fuzzy logic-based expert systems have been proposed several times as an approach to model construction productivity [19][26][31]. Problems in existing approaches to model labor productivity have been identified as: (1) the inability to deal with a large number of factors affecting productivity, (2) the inability to incorporate subjective variables, (3) the difficulties in obtaining data that is statistically significant, and (4) the difficulties in adapting models for different project contexts and factors [31]. It has been proposed that fuzzy expert system models can address these issues [31].

In fuzzy logic-based expert systems, knowledge about the factors affecting labor productivity can be obtained and expressed in linguistic forms, such as "if the supervision is *good*, labor productivity is *high*," and "if the weather conditions are *extremely bad*, labor productivity is *very low*," i.e., the same terminology that is used in daily construction management processes. Therefore, fuzzy logics deals with imprecision-inherent linguistic evaluations, and enables the processing of subjective variables in computerized decision support systems. However, identifying and obtaining the rules—which increase exponentially as the number of factors increase—has been identified as one of the main problems with this approach [31].

C. Artificial Neural Networks

Artificial Neural Network (ANN) approach is a data-driven modeling approach which is facilitated by learning algorithms mimicking the cognitive learning process of humans. Using such algorithms, an ANN can be automatically constructed from data through trial and error.

Due to its capability to learn patterns from historical data, ANN approach has been used for modeling the relationships between factors and labor productivity and for predicting labor productivity for a given condition. This approach has been applied to several different construction processes, and has shown promising results [18]. The construction processes that have been studied using this approach include formwork [32], concrete work [33], pipe installation [34], and pipe spool fabrication [18].

Although ANNs have found many applications, the main challenges in applying ANNs in estimating and predicting construction labor productivity are the extensive data collection required for a network to learn, and the time consuming experimentation with ANNs required to find satisfactory behavior of the ANN.

III. Fuzzy Cognitive Maps

An alternative to the approaches reviewed in the previous section is the Fuzzy Cognitive Map (FCM). FCM was introduced by Kosko (1986) [43], who enhanced the cognitive maps theory that had been used in social and political sciences to analyze social decision-making problems. An FCM is a signed digraph structure that consists of fuzzy concepts and causal feedback relationships. FCM originates from the combination of Fuzzy Logic and Neural Networks—i.e., a neuro-fuzzy system [35]. An FCM models a system's behavior in terms of interacting concepts. FCMs are built by experts using an interactive procedure of knowledge acquisition. The process of developing an FCM mimics the process of developing a cognitive map in human mind. Therefore, the development of an FCM is heavily dependent on the knowledge and judgment of experts. Once constructed, FCMs represent human knowledge, adapt the knowledge base, and allow for causal reasoning and predicting the system's behavior [36].

Figure 1 is a graphical illustration of an FCM. As shown in this figure, an FCM consists of nodes (C_i, C_j,…) representing a concept and edges (w_{ij}) representing a causal relationship between concepts. Each concept is a dimensionless, abstract variable that represents a state variable of the real system in question. The value of a concept can be determined by transforming a real value into an abstract value in the interval [0,1]. Therefore, modeling and simulating a system using FCMs has a qualitative nature. At time t, the state of an FCM is defined by the vector A_t of the values of the concepts ($A_t = [C_1, \ldots, C_n] \in [0,1]$), or in other words, a point in the fuzzy n-dimensional state space. An edge w_{ij} ($\in$ [-1,1]) defines causal flows $C_i \rightarrow C_j$ between the concepts. With 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/aggregated in the construction of the graph by adding or deleting an interconnection or a concept.

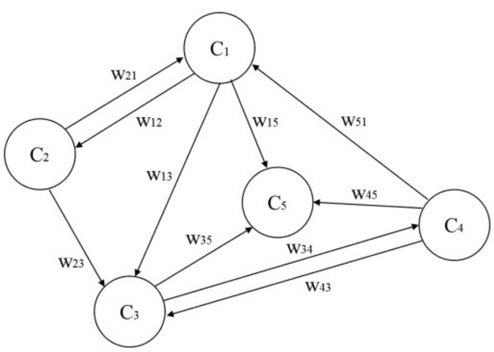

Fig. 1. A Fuzzy Cognitive Map Model

Experts' knowledge about the key principles/factors regarding the behavior of the system under investigation is critical in constructing FCMs. This knowledge determines the structure and the interconnections of the network. Since the concepts and interconnections can be defined in a fuzzy way, experts can use linguistic variables in order to describe the state and the inter-relationships of the concepts, and then the weights of the causal interconnections among concepts are determined by defuzzification [37].

Behind the graphical representation of the FCM, there is the mathematical model. The causal interconnections of an FCM 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 the n concepts in the FCM. The state of an FCM can be expressed by a $1 \times n$ vector A. Then, the dynamics of an FCM are dictated by these matrices.

The value for each concept is calculated at every time step by the following rule [38][39]:

$$A_i = f\Big(\sum_{\substack{j=1 \\ j \neq i}}^{n} A_j^{t-1} W_{ji} + A_i^{t-1}\Big) \qquad (1)$$

where A_i is the value of concept C_i at time t; A_i^{t-1} is the value of concept C_i at time t-1; W_{ji} is the interconnection from concept C_j to concept C_i, and f is a threshold function.

The unipolar sigmoid function is the most widely used threshold function in FCMs, and λ (> 0) determines the steepness of the continuous function f. The sigmoid function ensures that the calculated value of each concept will belong to the interval [0,1].

$$f(x) = \frac{1}{1+e^{-\lambda x}} \qquad (2)$$

In a vector algebra form, (1) can be rewritten as,

$$\mathbf{A}^t = f(\mathbf{A}^{t-1} \circ \mathbf{W} + \mathbf{A}^{t-1}) \qquad (3)$$

The new state vector $\mathbf{A}^t$ is computed by multiplying the state vector at time t-1 by the edge weight matrix $\mathbf{W}$. The new state vector holds the new values for the concepts after the interaction among concepts in the FCM. Values of concepts are continuously updated by this equation until the FCM reaches an equilibrium point or a limit cycle.

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 the concepts. Once constructed, FCMs can be used to qualitatively simulate the behavior of a system and perform the what-if analysis. Due to its effectiveness in representing a complex system's behavior, and the ease of use [40], FCMs have been applied to a wide range of areas, including business and management, education, environmental science, engineering, and medicine [41].

IV. Development of FCMs for Construction Labor Productivity

In order to demonstrate the effectiveness and practicality of FCMs for assessing the impacts of productivity factors on labor productivity, an exercise was conducted. In this exercise, three postdoctoral fellows in the domain of construction engineering and management at the University of Alberta acted as experts. The three postdoctoral fellows have each spent close to a decade in construction research, often in close collaboration on industry projects. The goal of this FCM was to model the general labor productivity phenomena in the construction industry.

Knowledge acquisition was performed in a sequential process: (1) the identification of the concepts, and (2) the identification of the influence weight between concepts. To avoid missing principal concepts in the FCM—which has been identified as one of the most serious problems in knowledge acquisition for developing FCMs [40], the three experts had a focus group session in which they listed the principal concepts to be included in the FCM for construction labor productivity. As a result, twelve concepts were identified, as shown in Table 1. As mentioned previously, each concept in FCMs is a dimensionless, abstract variable, and it is characterized by a value between 0 and 1. For example, 'Labor productivity level' represents the level of labor productivity between the highest and the lowest level of labor productivity observed and perceived in construction projects.

TABLE I. CONCEPTS IN THE FCM FOR CONSTRUCTION LABOR PRODUCTIVITY

Concepts	Description
Labor Productivity Level	Efficiency of task performance
Fatigue	Exhaustion from work
Morale	Feeling positive about work
Quality of Supervision	Supervisor-worker interaction
Adverse Work Environment	E.g., temperature, humidity, precipitation, noise
Competency of Workers	Workers' skill level and expertise
Overtime	Time spent outside regular working hours
Rework	Repetition of work due to errors in the previous work
Excessive Work Pressure	E.g., schedule pressure, cost-pressure, excessive workload
Interruptions	E.g., interruptions by material/equipment unavailability or safety problems
Work Complexity	Difficulty of tasks
Quality of Organizational Management	E.g., site layout, efficiency of schedule

Then, each of the three experts provided their linguistic evaluations on the causal influence between the concepts on a 9-point scale, based on their own knowledge: Positive very strong (μ_{pvs}), Positive strong (μ_{ps}), Positive moderate (μ_{pm}), Positive weak (μ_{pw}), Neutral (μ_z), Negative weak (μ_{nw}), Negative moderate (μ_{nm}), Negative strong (μ_{ns}), Negative very strong (μ_{nvs}). Fig. 2 shows the membership functions used for each linguistic response.

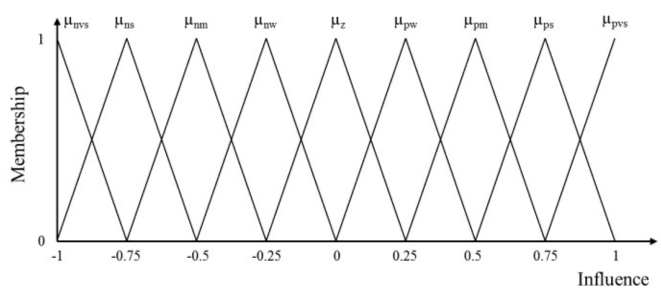

Fig. 2. Membership functions for the linguistic variable "influence"

Next, the linguistic inputs were aggregated using the fuzzy logic algorithm, SUM. For this, a *Java*-based FCM analysis software tool, *FCM Analyst v1.0*, developed by Margaritis et al. in 2002 [42], was 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 [42]. Additionally, the software tool allows users to enter both crisp values and fuzzy values—if it is a fuzzy value, the membership functions can be selected from triangular, Gaussian, and trapezoid functions, and aggregates the fuzzy values when multiple fuzzy values are entered—using either SUM or MAX method, and automatically produces the influence weights based on the fuzzy inputs using the defuzzification method of Center of Area or Bisector. Fig. 3 shows an illustration of how each individual expert's input is entered, and the multiple inputs are automatically aggregated and defuzzified in the software tool.

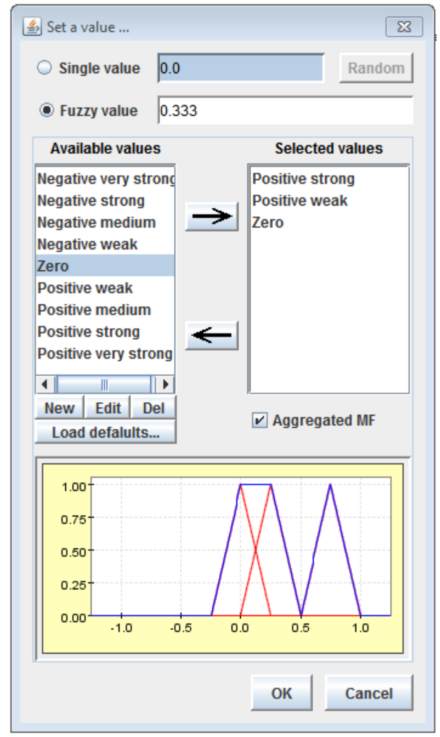

Fig. 3. Illustration of entering fuzzy inputs and automatic aggregation in *FCM Analyst* v1.0

The crisp values resulting from the defuzzification process represent the strength (i.e., weight) of causal influence between concepts. These values are expressed in a matrix form, where an entry w_{ij} of the matrix represents the causal influence from Concept i to Concept j (i.e., weight matrix W). The weight matrix W determined in this exercise is as below.

$$\mathbf{W} = \begin{bmatrix} 1 & 0 & 0.3 & 0 & 0 & 0 & 0 & 0 & -0.1 & 0 & 0 & 0 \\ -0.1 & 1 & -0.8 & 0 & 0 & 0 & 0 & 0.5 & 0 & 0.1 & 0 & 0 \\ 0.6 & 0 & 1 & 0 & 0 & 0 & 0 & -0.3 & 0 & 0 & 0 & 0 \\ 0.3 & 0 & 0.8 & 1 & 0 & 0 & -0.1 & -0.8 & 0 & -0.1 & 0 & 0 \\ 0.6 & 0 & 0.5 & 0 & 1 & 0 & -0.2 & 0 & 0 & -0.2 & 0 & 0 \\ 0.9 & 0 & 0 & 0 & 0 & 1 & -0.1 & -0.8 & 0 & -0.1 & 0 & 0 \\ -0.3 & 0.8 & -0.3 & 0 & 0 & 0 & 1 & 0.3 & -0.1 & 0 & 0 & 0 \\ -0.6 & 0.5 & -0.9 & 0 & 0 & 0 & 0.6 & 1 & 0.2 & 0.1 & 0 & 0 \\ -0.4 & 0.6 & -0.9 & 0 & 0 & 0 & 0.9 & 0.5 & 1 & 0 & 0 & 0 \\ -0.9 & 0 & -0.7 & 0 & 0 & 0 & 0.3 & 0 & 0.3 & 1 & 0 & 0 \\ -0.8 & 0 & -0.4 & 0 & 0 & 0 & 0.2 & 0.8 & 0.1 & 0 & 1 & 0 \\ 0.8 & 0 & 0.4 & 0 & 0.2 & 0 & -0.1 & -0.3 & -0.2 & -0.2 & -0.2 & 1 \end{bmatrix}$$

V. Results and Discussion

As a next step, what-if experiments with the FCM were conducted for demonstration purposes. Specifically, two scenarios were tested using the FCM model.

(1) Scenario 1: An extreme weather event occurs, and the overall worker skill level is lower than the standard, while other conditions are normal. This condition state is represented by:

A_0 =[0.5,0.5,0.5,0.5,1.0,0.2,0.5,0.5,0.5,0.5,0.5,0.5].

(2) Scenario 2: A sudden increase in work pressure develops wherein the required work is highly complex, and the quality of supervision is weak, while other conditions are normal. This condition state is represented by:

A_0 =[0.5,0.5,0.5,0.2,0.5,0.5,0.5,0.5,1.0,0.5,1.0,0.5]

In both scenarios, the values of the concepts stopped changing approximately after the 3rd iteration, and were therefore deemed to reach an equilibrium. Figs. 4 and 5 show the simulation results for the two scenarios. As shown in these figures, simulation results demonstrated that the FCM's behavior is interpretable; when a construction site is under adverse influences, such as extreme weather and low skill level (i.e., Scenario 1), or high level of work pressure and work complexity (i.e., Scenario 2), labor productivity will be significantly reduced, while undesirable situations such as rework and overtime will increase. The results of these scenarios will encourage future thought experiments among construction managers to identify ways to mitigate the adverse impacts of one or more factors. For example, one can experiment with the FCM to see to what extent the adverse impact can be mitigated by managerial efforts such as improved quality of supervision and/or reduced overtime and interruptions, using simulations.

This exercise demonstrated the potential usefulness of FCMs for assessing the impact of productivity factors and predicting the levels of labor productivity in the field. Firstly, the exercise showed that FCMs can be a useful means to obtain and formalize the existing knowledge about labor productivity factors and to use it for project planning and controlling in future projects (i.e., evolutionary progress of knowledge of labor productivity in the field). As noted by Taber (1991), perhaps the greatest strength of the FCM approach is ease of use [40]. Experts can make their knowledge explicit by listing the concepts and constructing the causal interconnections between the concepts, which usually requires much less effort than rule-based approaches. Furthermore, the FCM allows experts to input their knowledge using linguistic variables, which are used in their daily routines, and thereby are intuitive. Also, the FCM allows multiple experts to collaboratively contribute to an FCM, which enhances the confidence in using the FCM, and the scope of FCMs can be extended. Secondly, once constructed, FCMs can be used as a simulation model to conduct *what-if* experiments, and this can be done very efficiently, as demonstrated in the examples presented previously.

However, this exercise also demonstrated the requirements that have to be met to ensure the effectiveness and usefulness of the approach. Firstly, there is an issue of defining the concepts included in FCMs clearly enough to facilitate the effective communication of the represented knowledge. This is especially important when multiple experts collaboratively construct an FCM, and/or when FCMs are to be used by users other than the developers of the FCM. Therefore, great caution has to be exercised in the knowledge acquisition process, and if a data collection tool is used to elicit knowledge from experts, the tool has to be validated before use.

Another important issue is how to combine the FCMs developed by multiple experts—representing multiple experts' knowledge base—to construct one FCM that represents the collectively held knowledge base. Several researchers have paid significant attention to this issue [39][40]. These researchers suggested that when multiple FCMs are combined, *credibility weights* can be used to differentiate the level of expertise of each individual expert. The methods suggested by these researchers are based on the notion that credibility can be objectively derived from the level of consensus among experts and the distance between experts' suggestions in the FCMs. An experiment with randomly constructed FCMs demonstrated the effectiveness of the approach for distinguishing the "real knowledge" from the noise [40]. Although this method was not tested in our exercise due to the limited number of experts in this exercise, it would be strongly recommended to use this kind of method when more than three experts are involved in constructing an FCM.

Last but not least, the importance of having a specific scope for the FCM modeling has been recognized in the exercise. The reason is apparent: the causal relationship between two concepts—e.g., overtime and rework—may depend upon the specific context of the project type, of the region, or of the background culture. Therefore, the scope of an FCM modeling effort has to be clarified at the beginning, and the most suitable knowledge sources (i.e., domain experts) have to be identified—"A knowledge based reflects its sources."[40].

VI. Conclusions and Future work

In this paper, several different previous efforts to computationally model construction labor productivity have been reviewed, and based on the limitations observed in the previous approaches, the FCM has been proposed as an alternative. To demonstrate the effectiveness of FCMs for assessing the impacts of productivity factors and predicting the pattern of labor productivity in the field, an exercise has been presented. From the results of this exercise, it has been argued that FCMs can be a useful means of modeling the complex relationship between labor productivity factors, can be used for predicting labor productivity levels for a given condition, and also can be used for conducting experiments to find ways to improve labor productivity. FCMs essentially serve as a means by which industry practitioners' experiential knowledge is made explicit, retained, and utilized for managing future projects.

This paper has limitations that can be addressed in future research. Since the main objective of this paper is to demonstrate the effectiveness of FCMs as a tool for modeling construction labor productivity by showing an example, a simplistic approach was taken in the exercise with respect to the knowledge acquisition and the fuzzy logic processing. For example, simple assumed membership functions were used. More sophisticated methods to obtain membership functions for fuzzy variables are available in the literature, and these methods will need to be applied in the future. In addition, the sensitivity of the results to changes in the fuzzy operators was not tested in this research. This is another area this research will explore in the future. Additionally, the development of project type-specific FCMs for labor productivity will need to be pursued in the future.

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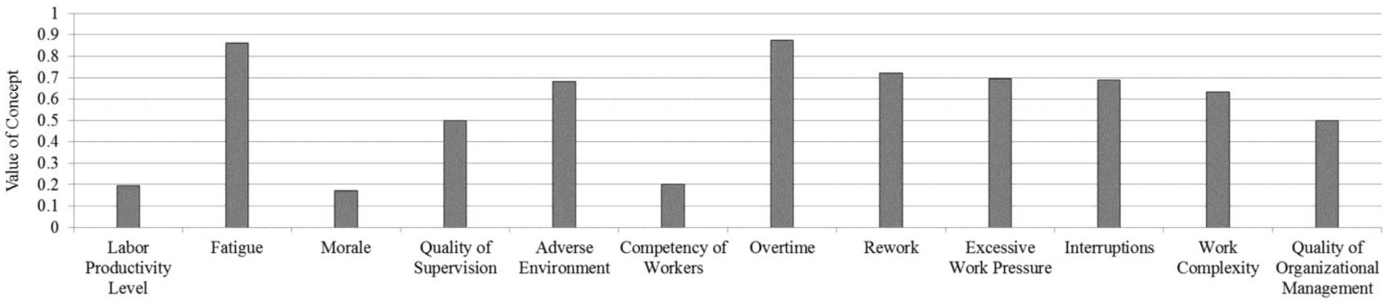

Fig. 4. The value of the concepts at the equilibrium in the simulation (Scenario 1)

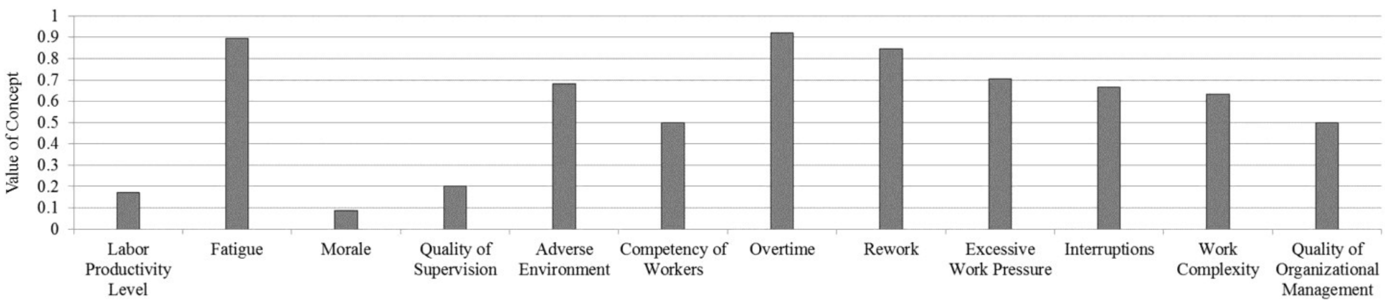

Fig. 5. The value of the concepts at the equilibrium in the simulation (Scenario 2)