Iranian Journal of Fuzzy Systems

Volume 17, Number 6, (2020), pp. 193-201

University of Sistan and Baluchestan

Probabilistic model development for estimating construction labor productivity optimization integrating with fuzzy logic approach systems

K. Nelsia Priya Dharsini[1] and M. C. Sashikkumar[2]

[1] *Department of Civil Engineering, University V.O.C. College of Engineering Thoothukudi, Tamil Nadu, India*
[2] *Department of Civil Engineering, University College of Engineering, Dindigul, Tamil Nadu, India*

nelsia.karunakaran@gmail.com, getsashi kumar@yahoo.com

Abstract

Construction labour productivity is a foremost tool used for data assessing, planning, budgeting and establishment of construction project. Influence of multi variation factors results in decrease of labour productivity in construction field. Still we are dependent on traditional technique comprises with reference published data or on the experience of estimators so as to estimate the construction labour productivity. The objective of this research is to recognize and map the association between identified factors affecting the construction labour productivity and individual productive rates through a systematic engineering model. This process comprises with calculation of productivity, collection of productivity information and using that information for designing construction model. Also, it intends to build up an optimized probabilistic model for construction industry. Initially, the raw data for instance labour cost, capital cost, and energy consumption has been considered as input so as to compute objective function and total productive factor. The membership function is developed and employed in fuzzy optimization algorithm to optimize the productivity rate in construction. The results through anticipated model prove to be more effective model with reasonable generalization capabilities compared to existing traditional work. Furthermore, this paper provides an insight of probabilistic model comprising internal in addition to external variable factors such as supervision, work rules, government rules and public labour unions.

Keywords: Fuzzy optimization algorithm, labour productivity, membership function, objective function, total productivity factor.

1 Introduction

Labour productivity plays a vital task in shaping the financial crisis arising due to construction industry. Construction framework comprises with various strategies of planning, design methodologies and financing, which initiates from project building to equipped for use [6]. The chief alarm in construction industry is the variation in construction productivity in accordance with labour productivity [14]. The disparity in the rapport among dominant factors and ensuing productivity can be measured using productivity models. These designed models should be effective in decision making, approximating, scheduling and planning future projects. The study on construction and productivity has been separated into two parts, existing method study and work measurement study. The survey on existing methods helps in finding better technique for productivity in construction field. Work measurement is used to forecast the usual time requirement to complete the particular task. The effective approach to evaluate and improve the performance of the productivity is through the effective work study and influence of various parameters affecting the competence of the construction system.

Productivity is termed as a significant parameter in the growth of national economic strength. Productivity measure in construction industry is validated using productivity model and tested at several conditions. Decision variables and objective function are used to resolve the unknowns required for developing a mathematical model and function for

Corresponding Author: K. Nelsia Priya Dharsini

Received: October 2019; Revised: January 2020; Accepted: July 2020.

decision makers [20]. The upshots of variability in the function of production can be reduced through the influence of buffers on sequential activities [12] [22] . There is an enormous requirement for design advancement and management of work in terms of buffers. In addition, approximate models such as discrete simulation [8], fuzzy logic [16], neural networks [21], statistics [1] and control theory [17] has been projected by different authors so as to address the issues regarding construction projects and optimization in construction projects. Construction of revenue forecasting model based on network mining and deep learning has been proposed by Shuhua Yan [25]. Another study uses cloud model to describe linguistic variable evaluation and process uncertainty from data source. C-TOPSIS (Cloud based TOPSIS) based on Minkowski distance function is established to improve the robustness of TOPSIS. An optimization algorithm is used to aggregate multi-period evaluation values to solve the problem that construction safety risks evolve with time [24].

2 Literature review

Watkins et al. [13] presented an agent-based modeling approach to assess the impact of congestion on construction labor productivity. Thomas and Ellis [26] investigated the average efficiency loss resulting from adverse weather conditions. Fundamental principles were then stated to mitigate the effects of unfavorable weather conditions. Moslehi et al. [4] proposed a neural network model to quantify the impact of change orders on construction productivity. The authorin [23] presented a system dynamics (SD)-based approach to model labor productivity. The complex inter-related structure of different factors affecting labor productivity was accounted in this research and the labor productivity was simulated considering the effects of all the influencing factors. The cited researches, however, face some major defects. Almost all of the previous researches did not account for the complex inter-related structure of different factors affecting the labor productivity.

A new Discrete Event Simulation (DES) technique has been discussed by author [5] to examine the consequences of unpredictability in the workflow model, which is caused owing to additional work or error work and fluctuations. An automated approach of production planning in the sphere of penalized construction environment has been suggested by author [3]. While simulating the fortified data of the building, DES model has been deployed to afford strong similarity. Furthermore, a new simulation based platform comprising DES, biochemical analysis for assessing workers muscle fatigue and increasing construction performance has been recommended by author [7]. A new statistical based technique has been discussed by author [19] for improving labour consumption measurement system on the basis of real time tracking in dam construction site. From the geographical map for the construction site study, the outcome attained provides the responsibility of the owner and supervisor in terms of labour usage with more accurate statistical prediction of the labour consumption [2].

Furthermore, with the advancements in artificial neural networks, a multilayer feed forward neural networks with the training obtained from back propagation neural networks has been used by author [11] for implementing labour productivity model. From the study, it has been examined that generalization performance is better contrast to premature stopping. A novel based approach comprising ANN to enhance and forecast productivity in construction labour has been recommended by author [15]. With the intention of achieving feasible economic investment and overcome the limitations in the construction productivity, a broad series of micro and macro level influencing issues has been considered. A novel technique comprising granular fuzzy logic approach for data transfer and developing granular generalized labour productivity model has been suggested by author [10]. This study shows that the granular fuzzy logic offers a cost efficient crew in converting the input data such as labour, equipment and material to efficient project outputs. Further, in order to evaluate and increase the motivation of the construction workers, a fuzzy rule based model comprising traditional expectancy theory has been offered by author [18]. The author [9] proposed a hybrid simulation based approach to progress the productivity in construction labour. Integrated fuzzy system with SD dynamic approach has been developed by author for modelling and to enhance labour productivity. From the above study, it has been examined that an effective probabilistic model needs to be developed to determine, optimize and enhance the rate of labour productivity in construction field.

3 Research methodology

This research intends in recognizing and mapping the association amid identified issues disturbing the construction labour productivity and individual productive rates through a methodical engineering model. This process comprises with calculation of productivity, collection of productivity information and using that information for designing construction probabilistic model. The block diagram of the proposed system is shown in Figure 1.

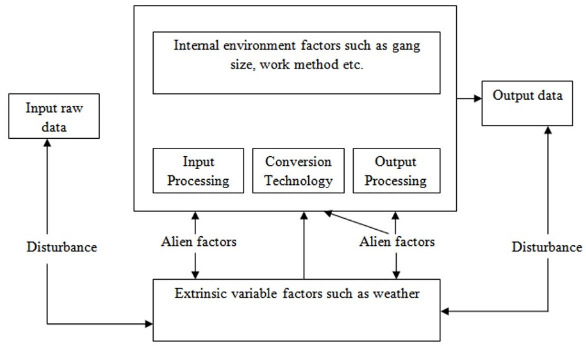

Figure 1: Block diagram of proposed system

The input raw data for construction comprises with various parameters such as labour cost, capital cost, energy consumption, material requirement and tools considered for analysis. The output data comprises with cost and time consumption. The total productivity defined by following factors is given by,

$$\text{Actual Productivity Factor(TPF)} = \frac{\text{Output Obtained}}{\text{Labour Cost+Material Requirement+Energy Consumption)}}. \tag{1}$$

3.1 Objective function

Objective function is used to define minimum construction requirement to complete the proposed task. The equation used to resolve the maximization and minimization in objective function are as follows,

$$Z_{max} = \sum_p u_p t_p, \tag{2}$$

$$Z_{max} = u_1 t_1 + u_2 t_2 +, ..., +u_n t_n, \tag{3}$$

where,
Z_{max} = Max objective function
U_p = Individual profit for product$P$.
t_p = Time considered to complete the task at interval p, where$(p = 1, 2, .n)$.

3.2 Productivity

The Total Productivity Factor (TFP) is defined as the ratio of number of weighted output to the number of input weighted counts. It is given by,

$$\text{Actual Productivity Factor(TPF)} = \frac{\text{f(scaled sum,number of output weight attributes)}}{\text{f(scaled sum,input weight attributes)}}. \tag{4}$$

Productivity is quantified as ratio of output by input, where input data comprises with the raw material data, tools, labour cost and time taken to complete the task. The output attained from the premised model is defined as the quantity of products yielded. Further this process is explained by considering a detailed example comprising five different kinds of products. The input variable xi represents the quantity of manufactured products in terms of 10^3 units. The variable function used to maximize the total productivity can be estimated as the summation of gain productivity, gi acquired from individual product and by considering applied discount d_i into account.

3.3 Membership function

The S-curve membership function suggested by author [11] is consideration productivity optimization. For value of m, the satisfaction degree $\mu_{\tilde{f}_{xy}}(m)$ for fuzzy coefficient $\tilde{f_{xy}}$ is defined by the membership function as shown in

$$\mu_{\tilde{f}xy}(m) = \begin{cases} 1 & m < f^l_{xy} \\ 0.99 & m < f^l_{xy} \\ \frac{B}{1+Ce^{\alpha}\left(\frac{m-f^1_{xy}}{f^h_x y - f^1_x y}\right)} & f^l_{xy} < m < f^h_{xy} \\ 0.001 & m = f^h_{xy} \\ 0 & m.f^h_{xy}. \end{cases} \tag{5}$$

$\mu =$ satisification value
$\tilde{f_{xy}} \mid_{\mu}=$ Fuzzy co-efficient
$f_{xy} \mid_{\mu}=$ value for fuzzy co-efficient. The crisp value is estimated by using

$$f_{xy}|_{\mu} = f^1_{xy} + \left[\frac{f^i_{xy} - f^l_{xy}}{\alpha}\right] \; In \, \frac{1}{A}\left[\frac{B}{\mu} - 1\right]. \tag{6}$$

The shape of the membership function is determined using vagueness factor α and A and B is estimated by using α in Eq. (7) and Eq. (8).

$$A = \frac{0.998}{(0.99 - 0.001e^{a})}. \tag{7}$$

$$B = 0.9(1 + A). \tag{8}$$

From the above equations, the membership function is calculated for different vagueness factor α. Further, fuzzy based system has been proposed in this research to solve the issues arising due to optimization.

3.4 Fuzzy optimization algorithm

Fuzzy logic optimization algorithm has showed to be an efficient and effective way for solving vague problems in construction industry. The fuzzy optimization algorithm comprises with five steps for construction optimization and they are as follows,

- Input layer fuzzification.
- Consideration of fuzzy logic operator such as AND or OR.
- Evaluation from precursor to resultant.
- Implication of consequent aggregation through rules.
- Defuzzification.

The block diagram for the proposed algorithm by considering five steps are shown in Figure 2. The parameters such as number of employees, skillset, availability of raw materials and time consumption is given as input parameters to the fuzzy system.

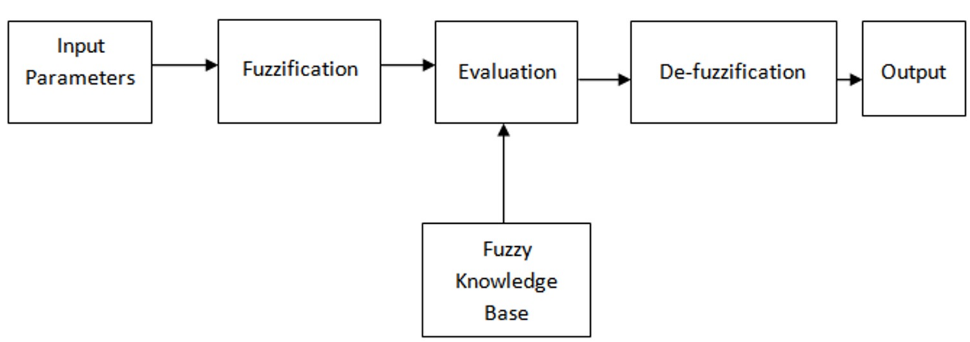

Figure 2: Block diagram of fuzzy system

Fuzzy C-Means algorithm (FCM) is widely-used algorithm is practically identical to the K-Means algorithm. Here, a data point can theoretically belong to all groups, with a membership function between 0 and 1, where: 0 is where the data point is at the farthest possible point from a clusters center and 1 is where the data point is closest to the center.

3.5 Experimental analysis and validation

The parameters which affect the productivity growth in construction industry such as work, the task has been choosed as input and collected through on-site observation and digitized monitoring system from Srivari Ananyaa, Thannerpandal and Diamond City, RS Puram. Concreting process over the entire period of 2 projects has been considered in this study.
Daily productivity of concreting process from site is obtained as actual productivity. Table 1 shows the input variables i.e the sample data obtained in terms of productivity in concrete pouring operation. The input comprises with 305 datasets and from the collected data, 80% is used for training purpose and 20% for testing and validation purpose. The cluster centres have been developed using FCM (Fuzzy C-Means algorithm) model and prioritized on account of ranking and MSE value. Table 2 shows the sample of cluster centroid co-ordinates followed by priority table, Table 3 distinguishes variables on the basis of ranking. Figure 4 predicts the model for calculating the estimated daily productivity. After clustering process through FCM method, the variable in each cluster comprising three set are processed multiplier block.
Further membership value is calculated for the corresponding input followed by multiplication of membership output with the input value and the index set value is added to obtain the estimated daily productivity. The formula for calculating estimated productivity is given by,

$$\text{Actual Productivity} = \frac{(Y_1 * W_1) + (Y_2 * W_2) + ...(Y_n * W_n)}{W_1 + W_2 + ...W_n}. \tag{12}$$

Table 4 shows the results obtained from the fuzzy based productivity model. Estimated productivity model is calculated as shown in Figure 3. and actual productivity through proposed FCM model.

$$\text{Actual Productivity} = \frac{\text{Total Work Quantities}}{\text{Total Hours Of Work}}. \tag{13}$$

The graph has been plotted as shown in Figure 4 by considering index value on X-axis and estimated and actual productivity value in Y axis.
From the graph, it has been revealed that the value of actual productivity in m^3/man-hour is lesser compared to estimated productivity because of the errors arising due to variables such as temperature, humidity and gang size. Further, the average Mean Square Error (MSE) is calculated for testing purpose and it is given by,

$$MSE_{TEST} = \sum_{I=1}^{61} \frac{(A_p - E_p)^2}{n} =\sim 0.1448. \tag{14}$$

$$MSE_{TRAIN} = \sum_{I=1}^{244} \frac{(A_p - E_p)^2}{n} =\sim 0.0362. \tag{15}$$

$$MSE_{AVG} = \frac{(0.0362 * 244) + (0.1448 * 61)}{305} =\sim 0.05792. \tag{16}$$

where,
$A_p =$ Actual Productivity.
$E_P =$ Estimated productivity.
$n =$ Total number of test samples.

Further, the effectiveness of the mathematical fuzzy model is calculated through average invalidity percent and average validity percent, which is given by,

Table 1: Sample variable data obtained from concrete pouring process

Temperature in 0c	Humidity	Wind speed Km/h	Precipitation	Gang size	Work Type	Method	Daily Productivity
33	24	20	0	45	2	1	2.67
32	58	17	0	40	2	1	2.55
35	54	20	0	20	1	1	0.40
33	34	12	0	45	2	1	2.24
35	54	20	0	100	3	1	2.50
26	90	13	0	50	1	1	0.62
29	68	11	0	50	1	1	0.70
28	72	12	0	70	2	1	1.11
28	57	17	0	50	1	1	0.62
30	53	14	0	50	1	1	0.70
29	58	11	0	70	3	1	0.49

Table 2: Cluster centroid developed through FCM method

Cluster	Humidity	Temperature	Precipitation	Wind speed	Work Type	Number of Workers	Method
C1	68.9	28.1	0	12	2	16	1
C2	65.5	30.2	0	15	3	35	1
C3	49.4	32.4	0	15	3	16	1
C4	50.1	32.2	0	20	2	10	2
C5	36.4	36	0	26	2	16	2

Table 3: Ranking of variables through MSE value

Sl.No.	Variable	MSE	Rank
1	Humidity	8.5	3
2	Temperature (0C)	6.4	2
3	Wind speed (Km/hr)	10.72	5
4	Precipitation	8.9	4
5	Method	13.5	6
6	Gang size	3.25	1

Table 4: Results obtained from fuzzy based productivity model

Index	Estimated Productivity on daily basis(m3/man-hour)	Actual Productivity on daily basis (m3/man-hour)
1	2.73	2.67
2	2.59	2.55
3	0.41	0.40
4	2.25	2.24
5	2.53	2.50
6	0.97	0.62
7	1.0	0.7
8	1.09	1.11
9	0.7	0.62
10	0.8	0.7
11	0.5	0.49
12	0.87	0.94

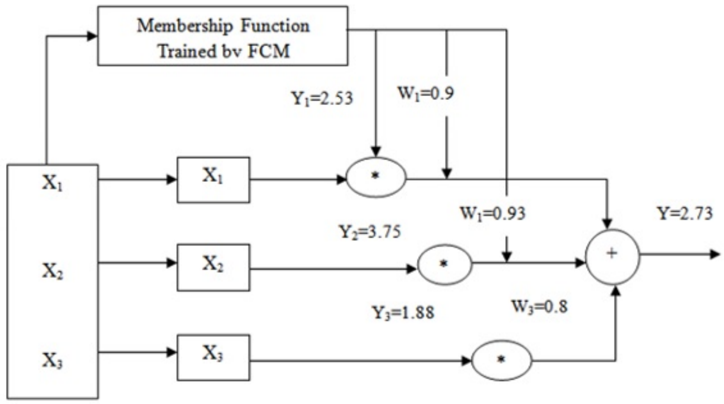

Figure 3: Model for calculating estimated daily productivity

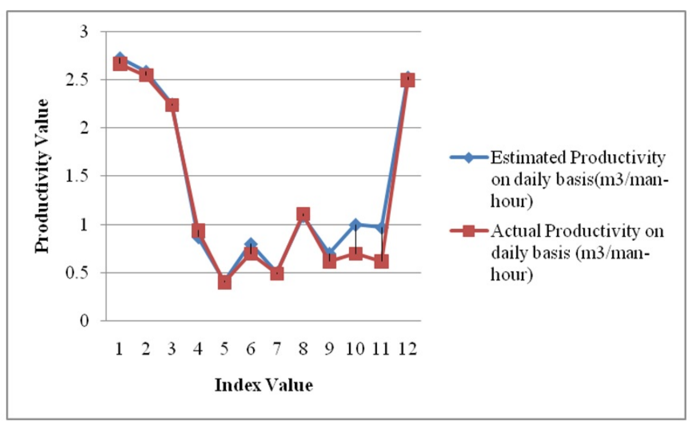

Figure 4: Productivity Graph

$$AIP = \left(\sum_{i=1}^{n} |1 - \left[\frac{E_{Pi}}{A_{pi}} \right] | * \frac{100}{n} \right) = 0.7811. \tag{17}$$

From the proposed system, Average Invalidity Percent (AIP) has been calculated for the testing set. The value of the AIP should be as closer to zero for effective design. The AIP value obtained from this research is 0.977, which is less contrast to other existing systems. Further, Average Validity Percentage (AVP) is calculated, which is given by,

$$AVP = 100 - AIP. \tag{18}$$

$$AVP = 100 - 0.7811 = 99.22.$$

The result attained from the calculation of Average Validity Percent is 99.22, which shows that the designed fuzzy system is acceptable and accurate in predicting the productivity of the work task.

4 Conclusion

This research aims in developing an optimization model in construction industry using probabilistic technique and fuzzy based systems. Nine critical parameters such as temperature, humidity, precipitation, number of workers etc. has been extracted from construction industry through onsite observation and data from Srivari Ananyaa and Diamond City. A novel based fuzzy system and membership function has been considered to calculate productivity in construction industry and the predicted results obtained will help managers to take necessary actions and enhance the productivity. The proposed research shows significant improvement in predicting the effectiveness of qualitative and quantitative variables on individual task durations. The proposed model is validated on the basis of MSE, AIP and AVP and results obtained shows that average validity percentage of 99.22 is obtained, which is high compared to other existing techniques. Furthermore, the proposed fuzzy system benefits researchers and civil practitioners because of its robust knowledge database and effectiveness in predicting related task productivity in construction activities.

References

[1] L. F. Alarcon, D. B. Ashley, *Playing games: Evaluating the impact of lean production strategies on project cost and schedule*, In Proceedings of the 7th Annual Conference of the International Group for Lean Construction, (1999), 263-274.

[2] M. R. Arashpour, M. Arashpour, *Analysis of workflow variability and its impacts on productivity and performance in construction of multistory buildings*, Journal of Management in Engineering, **31**(6) (2015), 04015006.

[3] V. Benjaoran, N. Dawood, *Intelligence approach to production planning system for bespoke precast concrete products*, Automation in Construction, **15**(6) (2006), 737-745.

[4] K. M. El-Gohary, R. F. Aziz, H. A. Abdel-Khalek, *Engineering approach using ANN to improve and predict construction labor productivity under different influences*, Journal of Construction Engineering and Management, **143**(8) (2017), doi.org/10.1061/(ASCE)CO.1943-7862.0001340.

[5] M. A. M. Farag, *A bridge between increasing reliability and reducing variability in construction work flow: A fuzzy-based sizing buffer model*, Journal of Advanced Management Science, **2**(4) (2014), doi: 10.12720/joams.2.4.287-294.

[6] R. A. Fleming, H. J. Barclay, J. N. Candau, *Scaling-up an autoregressive time-series model (of spruce budworm population dynamics) changes its qualitative behaviour*, Ecological Modelling, **149**(1-2) (2002), 127-142.

[7] V. González, L. F. Alarcón, T. W. Yiu, *Integrated methodology to design and manage work-in-process buffers in repetitive building projects*, Journal of the Operational Research Society, **64**(8) (2013), 1182-1193.

[8] A. S. Hanna, *Quantifying the impact of change orders on electrical and mechanical labor productivity*, Research Rep. No. 158-11, Construction Industry Institute, Austin, TX, 2001.

[9] G. Heravi, E. Eslamdoost, *Applying artificial neural networks for measuring and predicting construction-labor productivity*, Journal of Construction Engineering and Management, **141**(10) (2015), doi.org/10.1061/(ASCE)CO.1943-7862.0001006.

[10] H. Jiang, P. Lin, M. Qiang, Q. Fan, *A labor consumption measurement system based on real-time tracking technology for dam construction site*, Automation in Construction, **52** (2015), 1-15.

[11] H. Liu, M. S. Altaf, Z. Lei, M. Lu, M. Al-Hussein, *Automated production planning in panelized construction enabled by integrating discrete-event simulation and BIM*, In 5th International/11th Construction Specialty Conference, (2015), 8-10.

[12] B. McTague, G. Jergeas, *Productivity improvements on Alberta major construction projects: Phase I-back to basics*, Alberta Economic Development, 2002, 130 pages.

[13] P. Nojedehi, F. Nasirzadeh, *A hybrid simulation approach to model and improve construction labor productivity*, KSCE Journal of Civil Engineering, **21**(5) (2017), 1516-1524.

[14] J. Podani, *Multivariate data analysis in ecology and systematics*,SPB Academic Publisher, the University of Michigan, 1994.

[15] J. Seo, S. Lee, J. Seo, *Simulation-based assessment of workers muscle fatigue and its impact on construction operations*, Journal of Construction Engineering and Management, **142**(11) (2016), doi.org/10.1061/(ASCE)CO.1943-7862.0001182.

[16] L. Song, S. M. Abourizk, *Measuring and modeling labor productivity using historical data*, Journal of Construction Engineering and Management, **134**(10) (2008), 786-794.

[17] L. Song, D. Liang, *Lean construction implementation and its implication on sustainability: A contractors case study*, Canadian Journal of Civil Engineering, **38**(3) (2011), 350-359.

[18] L. Sveikauskas, S. Rowe, J. Mildenberger, J. Price, A. Young, *Productivity growth in construction*, Journal of Construction Engineering and Management, **142**(10) (2016), doi.org/10.1061/(ASCE)CO.1943-7862.0001138.

[19] H. R. Thomas, W. F. Maloney, R. M. W. Horner, G. R. Smith, V. K. Handa, S. R. Sanders, *Modeling construction labor productivity*, Journal of Construction Engineering and Management, **116**(4) (1990), 705-726.

[20] J. N. Thompson, *Insect diversity and the trophic structure of communities*, In: Huffaker, C. B. (ed.) Ecological Entomology. Wiley-Interscience, New York, 1984.

[21] I. D. Tommelein, D. R. Riley, G. A. Howell, *Parade game: Impact of work flow variability on trade performance*, Journal of Construction Engineering and Management, **125**(5) (1999), 304-310.

[22] B. Tóthmérész, *Comparison of different methods for diversity ordering*, Journal of Vegetation Science, **6** (1995), 283-290.

[23] A. A. Tsehayae, W. Pedrycz, A. R. Fayek, *Application of granular fuzzy modeling for abstracting labour productivity knowledge bases*, In IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS), (2013), 1096-1101.

[24] L. Tzu-Ping, *A multi-period comprehensive evaluation method of construction safety risk based on TOPSIS and cloud model*, Journal of Intelligent and Fuzzy Systems, (2019), 1-13, doi: 10.3233/JIFS-190076.

[25] S. Yan, L. Guo, *Construction of industry configuration model for network emotion mining and fundamental research based on deep learning*, Journal of Intelligent and Fuzzy Systems, (2019), 1-8.

[26] M. Yeheyis, B. Reza, K. Hewage, J. Y. Ruwanpura, R. Sadiq, *Evaluating motivation of construction workers: A comparison of fuzzy rule-based model with the traditional expectancy theory*, Journal of Civil Engineering and Management, **22**(7) (2016), 862-873.

Iranian Journal of Fuzzy Systems
Volume 17, Number 6 (2020), pp. 218

Probabilistic model development for estimating construction labor productivity optimization integrating with fuzzy logic approach systems

K. Nelsia Priya Dharsini and M. C. Sashikkumar

توسعه مدل احتمالی جهت برآورد بهینه سازی بهره وری نیروی کار ساختمانی با تلفیق سیستم رویکرد منطق فازی

چکیده. بهره‌وری نیروی کار ساختمانی یک وسیله در درجه نخست جهت تشخیص داده‌ها، برنامه‌ریزی و بودجه بندی و تأسیس پروژه ساخت می‌باشد. تأثیر فاکتورهای چند متغیره به کاهش بهره‌وری نیروی کار در زمینه ساخت منجر می‌شود. ما هنوز به تکنیک سنتی متضمن داده‌های انتشار یافته مرجع یا تجربه ارزیاب، جهت برآورد بهره‌وری نیروی کار ساختمانی وابسته‌ایم. هدف این تحقیق تشخیص و ترسیم مشارکت بین فاکتورهای شناسایی شده تأثیر پذیر بر بهره‌وری نیروی کار ساختمانی و میزان تولید فردی از طریق یک مدل مهندسی سیستماتیک است. این فرآیند شامل محاسبه بهره وری مجموعه اطلاعات بهره‌وری و استفاده از اطلاعات جهت طراحی مدل ساخت می‌باشد. همچنین قصد آن ساخت یک مدل احتمالی بهینه‌سازی شده برای صنعت ساخت می‌باشد. مقدمتاً، داده‌های خام، برای هزینه ساخت نمونه، هزینه سرمایه، و مصرف انرژی به عنوان ورودی، جهت محاسبه تابع هدف و فاکتور مولد کل درنظر گرفته شده‌اند. جهت بهینه‌سازی میزان بهره‌وری در ساخت، تابع عضویت توسعه یافته و در الگوریتم بهینه‌سازی فازی بخدمت گرفته شده‌است. نتایج حاصل از طریق مدل پیش‌بینی شده نشان می دهد که این مدل در مقایسه با کار سنتی موجود، از توانایی گسترده‌تر معقولی برخوردار است. بعلاوه، این مقاله علاوه بر فاکتورهای متغیر خارجی، مانند نظارت، قوانین کار، قوانین دولت و اتحادیه‌های کار همگانی، یک بینشی درونی از مدل احتمالی فراهم می‌آورد.