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Research paper

Modeling labor productivity in high-rise building construction projects using neural networks

Duc Anh Nguyen[1], Dung Quang Tran[2], Thoan Ngoc Nguyen[3], Hai Hong Tran[4]

Abstract: Labor productivity in building construction has long been a focused research topic due to the high contribution of labor cost in the building total costs. This study, among a few studies that used scaled data that were collected directly from measuring equipment and onsite activities, utilized neural networks to model the productivity of two main construction tasks and influencing factors. The neural networks show their ability to predict the behaviors of labor productivity of the formwork and rebar tasks in a test case of a high-rise building. A multilayer perceptron that had two layers and used sigmoid as its activation function provided the best effectiveness in predicting the relations among data. Among eleven independent factors, weather (e.g., temperature, precipitation, sun) generally played the most important role while crew factors were distributed in the mid of the ranking and the site factor (working floor height) played a mild role. This study confirms the robustness of neural networks in productivity research problems and the importance of working environments to labor productivity in building construction. Managerial implications, including careful environmental factors and crew structure deliberation, evolved from the study when labor productivity improvement is considered.

Keywords: construction project, high-rise building, labor productivity, modeling, neural networks

[1]PhD., Hanoi University of Civil Engineering, Department of Building and Industrial Construction, 55 Giai Phong Street, Hanoi, Vietnam, e-mail: ducna@huce.edu.vn, ORCID: 0000-0001-5886-8310
[2]PhD., Hanoi University of Civil Engineering, Department of Building and Industrial Construction, 55 Giai Phong Street, Hanoi, Vietnam, e-mail: dungtq@huce.edu.vn, ORCID: 0000-0003-3928-0962
[3]MSc., Hanoi University of Civil Engineering, Department of Building and Industrial Construction, 55 Giai Phong Street, Hanoi, Vietnam, e-mail: thoannn@huce.edu.vn, ORCID: 0000-0002-5114-4130
[4]Prof., PhD., Hanoi University of Civil Engineering, Department of Building and Industrial Construction, 55 Giai Phong Street, Hanoi, Vietnam, e-mail: haith@huce.edu.vn, ORCID: 0000-0001-7766-5121

1. Introduction

Buildings are special products of the construction industry that are materials and resources (i.e., labor and machine) heavily consuming. Labor cost plays a key component in the total cost of a building, implying that construction is one of the most arduous industries in the economy [1, 2].

As a popular trend, more machines, even robotics, and artificial intelligence are gradually replacing the direct involvement of humans in the process of creating products. However, the nature of the construction industry slows down this replacement process. Therefore, at least in a near future, the proportion of direct labor in total construction costs will still be significant [3, 4]. Direct labor productivity will still be a critical success factor to building construction projects [2, 5].

To increase labor productivity, practitioners must understand its nature (e.g., impact factors) to make appropriate management decisions. Many scholars have focused on building models of independent variables and labor productivity. These independent variables have usually been selected from environmental, site, and management characteristics. Popular research methods include qualitative, inferential statistics, regression, and machine learning algorithms [6]. However, the topics still require much attention for the expectation of a better understanding of how labor productivity can be best enhanced.

This paper is a study that considered a few measurable variables (i.e., the weather, building characteristics, and crew structure) and how they affect labor productivity of two in the most important labor tasks: the formwork and rebar works. The weather variables were collected from a weather station near the site through a public request, while the other groups of variables were recorded onsite. The analysis method of the study was neural networks – a robust method to model many problems such as prediction in management because they relax many assumptions and can progressively learn by themselves.

After the introduction is the literature review, in which previous studies about construction labor productivity and independent factors, as well as analysis methods utilized. Next, fundamentals of neural networks are briefly introduced to explain how neural networks work and why neural networks are suitable for both linear and nonlinear problems. The methodology expresses the flow of research and present how data are collected from a high-rise building in seven months and are analyzed. Results and discussion follow with insights obtained from the study. Finally, the conclusion section summarizes the research.

2. Literature review

As discussed, labor productivity in construction is critical to the success of a construction project. Increase labor productivity has been a focused topic in the literature [6] Practitioners must understand the structure of the work and factors that impact the process of these works. Unfortunately, these factors vary from construction task to task. Therefore, many studies focused on a few tasks, using different methods, and generating mixed results.

Among many craft works, most popular labor tasks are formwork [1, 7], masonry [8], steel work (or rebar) [9, 10], pipe installation [11]. Methods of data analysis used have ranged from inferential statistical, linear regression, analytic hierarchy process (AHP), and neural networks. Table 1 synthesizes selected literature on the topic.

Table 1. Synthesis of related construction labor productivity modeling studies

Study	Construction task and type of input data	Method of data analysis	Independent factor
Jang et al. (2011) [1]	formwork, rebar, concrete; qualitative date	regression, AHP	equipment characteristics; worker characteristics; work method; work difficulty; design; management characteristics
Kazaz et al. (2016) [2]	craft work; qualitative data	inferential statistics	organizational; economical; socio-psychological; physical factors
Forsythe (2018) [3]	general construction works; qualitative data	inferential statistics	environmental; site; management; design factors
Shahtaheri et al. (2015) [5]	general construction works; qualitative data	neural network	project; site; weather; site; working condition; ground condition factors
El-Gohary et al. (2017) [12]	formwork, rebar; qualitative data	neural network	labor characteristics; weather; crew and management; project; working time; work difficulties
Golnaraghi et al. (2019) [7]	formwork; qualitative data	neural network	weather; labor; work type; floor level; work method
Juszczyk (2020) [9]	rebar; qualitative data	neural network	weather; working time; structures; work type; crew size and management
Umit Dikmen and Sonmez (2011) [13]	formwork; quantitative data	neural network	work quantity; crew size; management; height of work
Heravi and Eslamdoost (2015) [14]	foundation installation; qualitative data	neural network	crew and management; site; labor; schedule compression; change order; materials, tools and equipment deficiency; unfavorable external condition
Lu et al. (2000) [15], Abourizk et al. (2001) [16]	pipe installation; qualitative data	neural network	general project characteristics; site characteristics; labor characteristics (crew size. . .); equipment; difficulty; general activity; activity quantities; activity design; activity difficulty

Continued on next page

Table 1 – *Continued from previous page*

Study	Construction task and type of input data	Method of data analysis	Independent factor
Song and Abourizk (2008) [10]	steel drafting and fabrication; qualitative data	neural network	project; contract; structure; crew; organization; overtime; complexity; subcontract
Ezeldin and Sharara (2006) [17]	formwork, steel, concrete pouring; qualitative data	neural network	work quantity; crew size; management; labor skills; complexity; temperature; work type; overtime; materials
Moselhi and Khan (2012) [18]	formwork; qualitative and quantitative data	fuzzy subtractive clustering, regression, neural network	weather; crew; height of work; work type; work method
Jaśkowski et al. [19]	partitions, wiring, plasters, screeds, painting, and flooring	inferential statistics, scheduling techniques	task duration; buffer time; deadline

From literature, factors that affect labor productivity are recorded and include a few main groups: work nature (e.g., quantity, difficulty, type, method), worker capability (e.g., labor skills, crew size, crew structure), equipment, project characteristics (e.g., location), site characteristics (e.g., position, complexity), management (e.g., design, overtime), and environment (e.g., weather including temperature, wind, precipitation, humidity). Another observation is that most studies considered input as qualitative data, for instance subjective assessments from questionnaires.

Since it is impossible for all independent factors to be considered in any one study, this study includes collectible independent factors such as weather, crew structure, and working floor level, which will be detailed in the Methodology section. Future studies may add more independent factors to the input data and may or may not improve the model explanation.

Regarding data analysis method, regressions have been used commonly in engineering and management problems because the methods are intuitive and easy to interpret [20]. However, the use of regressions requires assumptions, whose violation can lead to misleading results [21, 22]. For example, the relations between independent and dependent data must be determined to be linear or nonlinear. In this study, while many independent variables seem to have a linear relation with dependent variables, temperature-productivity may follow a nonlinear relation. Specifically, there is an optimal range of temperature in which workers feel most comfortable, but in higher or lower range comfort reduces. Another assumption is the relatively linear behavior among independent variables [21]. But a reasonable argument would be temperature, sun, and radiation have some correlation.

These improprieties of regressions, if any, can be solved by the application of neural networks, which resides in artificial intelligent domain. Neural networks usually do not require strict assumptions such as linear/nonlinear and relatively independent relations. Neural network fundamentals are briefly presented in the next section.

3. Neural networks

Artificial neural networks, or neural networks, derived from the idea of mimicking the perception process of the human brain, though this process is highly complex and hard to be modelized. The research by McCulloch and Pitts [23] has intrigued the development of the technique class for a long time. Neural networks have useful capabilities to solve a lot of types of problems such as being nonlinear (hence can solve nonlinear problems, which are inappropriate for linear regressions), representing input-output mapping – good for both supervised and unsupervised learnings, adaptability (i.e., being versatile various classes of problems), and self-reinforcement, which means their robustness can be improved if the data are richer. Neural networks are suitable for many problems, including prediction, classification, and control [24] In construction management, neural networks have been used in diversified research including cost [25–27] productivity (e.g., El-Gohary et al. 2017), project management effectiveness (e.g., Apanavičienė and Juodis 2003), risk analysis and safety [29–31].

A neural network is a system of parallel processors made up of simple neurons – a typical neuron is depicted in Fig. 1 – that can store information and learn more knowledge through learning processes [32].

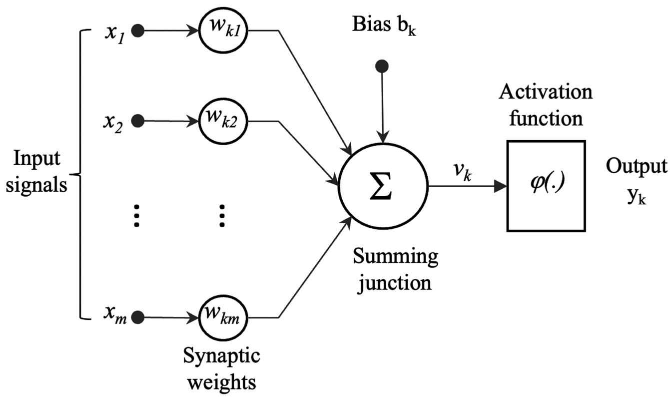

Fig. 1. The structure of a neuron [24]

Each input signal has its own synaptic weight when all signals and a bias input (b_k) will be summed into neuron k. The result then serves as the input of an activation function, whose range is limited (e.g., 0 to 1, –1 to 1) depending on the selected type of the function. An activation function, sometimes called a squashing function, limits the output of a function to some finite value. In the run of a neural network, the type of activation function is selected based on the type and the requirement of the problem. Two of the most used activation functions are *sigmoid* (Fig. 2) and *tansig* (Fig. 3).

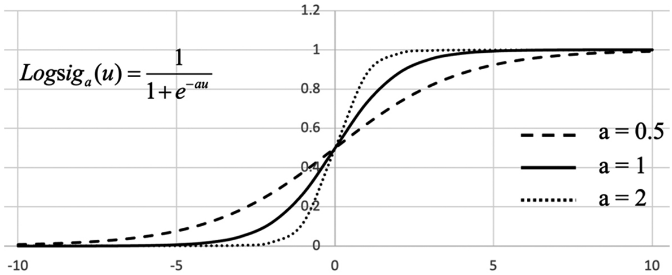

Fig. 2. Sigmoid graph with some different a values

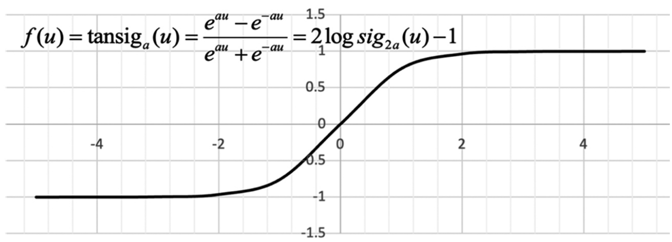

Fig. 3. Hyperbolic tangent graph with a = 1

A sigmoid function (log sig), whose range is [0;1], follows Formula (3.1):

$$\log \text{sig}\,(u) = \frac{1}{1 + e^{-au}} \tag{3.1}$$

A tansig function (hyperbolic tangent), whose range is $[-1;1]$, follows Formula (3.2):

$$f\,(u) = \tan \text{sig}_a\,(u) = \frac{e^{au} - e^{-au}}{a^{au} + e^{-au}} = 2\log \text{sig}_{2a}\,(u) - 1 \tag{3.2}$$

There are also other activation functions such as threshold function, purelin (pure linear function), and RELU (rectified linear unit). Each type works better in some classes of problems [33].

Most neural networks can be categorized into one of two groups: feed-forward and recurrent neural networks [34]. In the former one, the progression of calculation is forward only, while in the latter one, calculations happen in both directions to seek for best network structure and other parameters. A member of the feed-forward class, multilayer perceptron (MLP) is the most common and versatile neural network [35, 36]. In an MLP, there can be one hidden layer, two hidden layers, or many hidden layers. Fig. 4 and Fig. 5 depict a one-hidden-layer and a two-hidden-layer neural network examples.

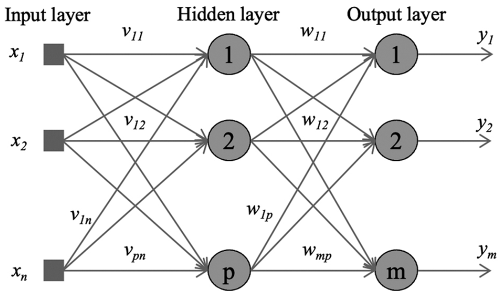

Fig. 4. One-hidden-layer neural network

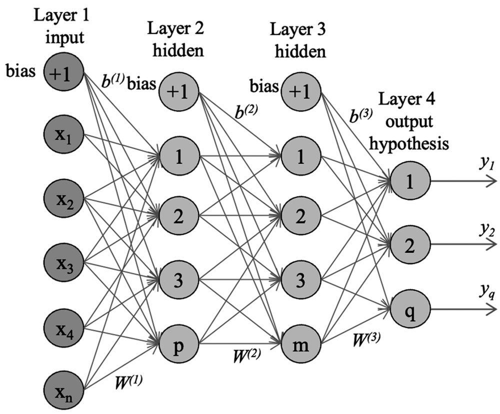

Fig. 5. Two-hidden-layer neural network

How a neural network learns

In the learning process of a supervised learning, outputs from a network are compared with actual observations. After a loss function is chosen, different algorithms can be applied to reach the loss function's minimum [37]. Two common examples of loss functions are sum of squares and mean of squared errors. Sum of squares (SSE) measures half the sum of the squared difference between the computed outputs and the actual output and is desired to be minimum (Formula 3.1):

$$\text{SSE} = \frac{1}{2}\sum_{i=1}^{p}(y_i - d_i)^2 \ \rightarrow \min \tag{3.3}$$

Whereas, mean square error (MSE) measures the average of squares of difference (Formula 3.4):

$$\text{MSE} = \frac{1}{p}\sum_{i=1}^{p}(y_i - d_i)^2 \ \rightarrow \min \tag{3.4}$$

Popular learning algorithms are Gradient Descent [38], Levenberg–Marquardt [39,40], Conjugate Gradient [41], Quasi Newton and Newton's method [42]. These algorithms are related to deriving the loss functions. The selection of these algorithms is usually a trial-and-error process, depending on the calculation goals of the users.

There are parameters that will not change during a calculation round of a neural network, such as number of hidden layers, activation function, synaptic change frequency (batch, mini-batch, or stochastic/online learning) [24]. These parameters are called hyperparameters [43, 44]. Users must manually set these hyperparameters and will observe the results to see if these hyperparameters yield desired results (e.g., errors, cost of computation).

4. Methodology

After a literature review, factors, or independent variables, that impact labor productivity, were synthesized. The authors analyzed data in discussions with project manager and foremen to figure out which data could be reliable. Fortunately, at the time of this study, the contractor was conducting research on construction processes and productivity so that it could establish its norms to improve its performance and reduce construction costs. Therefore, four engineers were designated with the task to work on a full-time basis. The engineers would cooperate with foremen and workers to collect input data, including crew gang size, gender structure of crew, and output data, including productivity of formwork and rebar tasks. Output data, or dependent variables, were measured by daily task plans, task status reports, shop drawings, material consumption tables, and other site reports. Other validation methods included footage from portable cameras and security cameras. These methods helped identify outliers in data, for instance, in cases of work stops by change order, tower crane maintenance, adverse weather that stopped construction completely, or work accidents. Designated engineers, foremen, and research participants discussed the data to keep or discard from further analysis.

Regarding weather data collection, the sources were provided after a public request. The weather observation station was 0.5km away from the construction site; therefore, observed data were assumed to represent those at the construction site. The data included seven factors: temperature (Celsius degree), moisture (percent), wind (m/s), sun (sunny time/hour), rain (mm), radiation (mJ/m^{2}h), atmospheric pressure (mb). After a screening, atmospheric pressure was discarded since its range was small, leading to trivial effect on productivity.

After all data were recorded, there was a screening phase to discard outliers. The designated engineers, the foremen, and the research participants discussed the data reports for their reliability.

In the analysis phase, neural networks were used while hyperparameters and parameters were adjusted during the analyses. These hyperparameters and parameters, along with the models' performance, were recorded. Finally, the models that had highest performance were analyzed in detail, while sensitivity analysis was conducted. SPSS version 26.0 [45] was used in this study for the neural network modelling.

5. Research results and discussion

The selected case was a 35-floor building with its typical floor area of 1,950 m^2. In the construction of a high-rise building, the duration was so long as to generate adequate data for machine learning approach. Indeed, both formwork and rebar jobs must be outdoor for clear observations. Plastic coated plywood formwork was used by the main contractor. Both formwork and rebar were fabricated on the ground and on the working floors. A tower crane was utilized to deliver materials to stock on the floors and sometimes to help assemble heavy components. All data were recorded in seven months, from the months of January to July. In the area, the weather in January, February, and the first half of March are usually cold; it gets hotter and more humid in the rest of the period. Table 2 depicts the descriptive statistics of the independent and dependent variables.

Table 2. Description of independent and dependent variables

Variable	Range	Minimum	Maximum	Mean	Std. Deviation
X1 – temperature (°C)	29.6	11.3	40.9	27.32	6.28
X2 – moisture (%)	70.0	30.0	100.0	72.06	15.96
X3 – wind (m/s)	5.0	0.0	5.0	2.01	1.02
X4 – sun (time/hour)	1.0	0.0	1.0	0.38	0.44
X5 – rain (mm)	35.8	0.0	35.8	0.12	1.52
X6 – radiation (10^{-2}mj/m^2h)	512.0	0.0	512.0	261.34	97.96
X7 – working floor height (m)	85.8	16.5	102.3	58.69	24.53
X8 – formwork gang size	57	43	100	70.36	9.24
X9 – rebar gang size	41	28	69	50.18	6.05
X10 – formwork gender (male ratio)	0.66	0.34	1.0	0.79	0.14
X11 – rebar gender (male ratio)	0.74	0.26	1.0	0.75	0.15
Y1 – formwork productivity (m^2) – normalized to man · day	2.8	3.8	6.6	5.38	0.46
Y2 – rebar productivity (kg) – normalized to man · day	37.9	72.8	110.7	91.43	7.61

Pearson correlation matrix among variables show some correlation in the weather group (e.g., sun-radiation, wind-rain), but not cross groups of weather-building-crew.

Data screening is necessary before results are analyzed to realize abnormal behaviors and to provide insights to interpret any models. Scatter distributions of each independent variable and dependent variables are plotted in Fig. 6 and Fig. 7.

Except for X_5–Y_1 and X_5–Y_2 (rain-productivity), data are scattered in a dense cluster in each plot. This promises the continuity of the prediction models. However, data appear in nonlinear shapes: most obviously in pairs of X_3–Y_1, X_4–Y_1, X_7–Y_1, X_{10}–Y_1, X_3–Y_2, X_{11}–Y_2. This observation ruled out the appropriateness of multiple linear regression, while neural networks can deal with these behaviors. Therefore, the data screening confirmed the

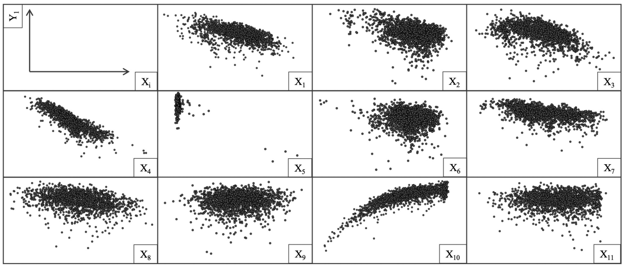

Fig. 6. Scatter plot of formwork productivity with each independent variable

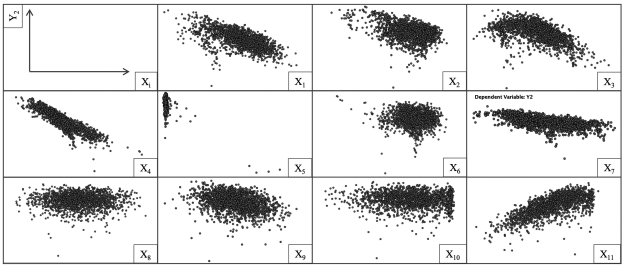

Fig. 7. Scatter plot of rebar productivity with each independent variable

hypothesis in the introduction section of this paper: neural networks are more appropriate than linear regression in this research.

Multiple settings of neural networks were calculated while their results were recorded and compared. Table 3 shows selected outputs from four settings.

Table 3. Results of selected settings of neural networks

Characteristics			NN1	NN2	NN3	NN4
Hidden Layer(s)	Number of Hidden Layers		1	1	2	2
	Activation Function		Hyperbolic tangent	Sigmoid	Hyperbolic tangent	Sigmoid
Output Layer	Activation Function		Hyperbolic tangent	Sigmoid	Hyperbolic tangent	Sigmoid
Training	Sum of Squares Error		27.757	6.743	29.12	6.657
	Ave. Overall Relative Error		0.138	0.143	0.138	0.139
	Relative Error for Scale Dependents	Y1	0.143	0.15	0.148	0.145
		Y2	0.135	0.138	0.132	0.135
Testing	Sum of Squares Error		7.025	1.912	7.185	1.664
	Ave. Overall Relative Error		0.127	0.143	0.14	0.13
	Relative Error for Scale Dependents	Y1	0.142	0.153	0.137	0.13
		Y2	0.118	0.137	0.142	0.129

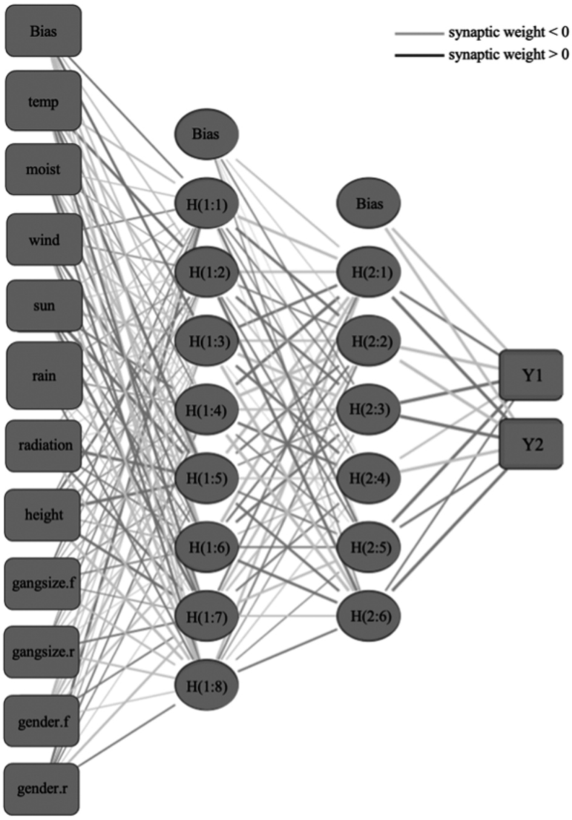

Fig. 8. Selected neural network for the construction labor productivity

Sum of squares error represents the precision of neural networks, and its minimum is sought by the model during training. The average overall error is the ratio of the SSE of Y1 and Y2 to the SSE for the *null* model (the mean values of Y1 and Y2 are used as the predicted values). The average overall relative error and relative errors are stable across the training and testing samples, inferring the confidence that the model is not overtrained, and that future will be close to this calculation. The network that had two hidden layers and that used sigmoid as activation function performed best and was selected for further analysis.

This neural network has two hidden layers, eight units in the first hidden layer, and six units in the second hidden layer (Fig. 8).

Figure 9 plots both predicted and actual values of formwork productivity. The trend should be close to a 45-degree line for a good prediction of the model. The plot does not show any outliers and the trend line shows a quite good convergence to the diagonal line. The data are not divided into different clusters but are continuous in one cloud. Maximum predicted-actual values were 6÷6.5 m^2/man · day, while minimum pairs of values were 4.2÷3.8 m^2/man · day. The model shows a reasonably good prediction ability.

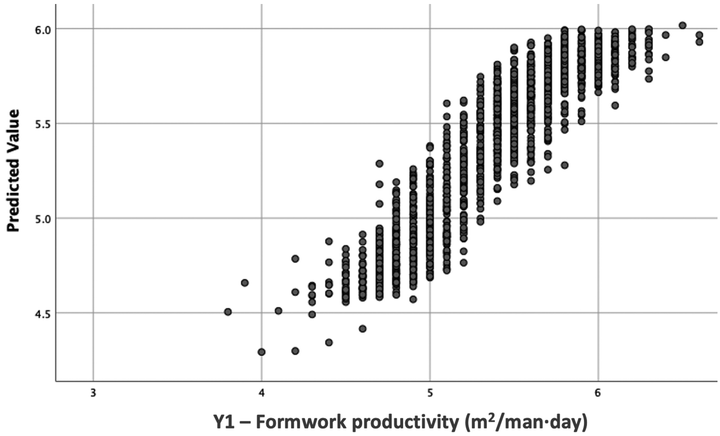

Fig. 9. Comparison chart between predicted and actual formwork productivity (Y1)

Residual errors of formwork productivity prediction are shown in Fig. 10. Residual errors were placed roughly like a normal distribution. The highest deviations were from two ends of the prediction range. On the lower end, the largest values were negative, meaning the observed were lower than predicted values. As recorded, construction tasks were abruptly stopped for some reasons that were not included as the models' inputs.

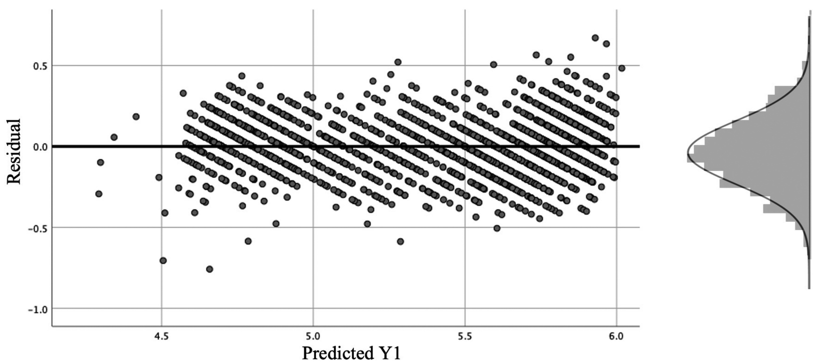

Fig. 10. Residual error chart of formwork productivity

Figure 11 plots both predicted and actual values of rebar productivity. Like formwork productivity, the rebar plot shows a quite good convergence to the diagonal line. The data points stay more densely in the two ends. This can be seen more clearly in Fig. 12 – residual error chart. The model is dense around a linear trend and shows almost no outliers, inferring a good prediction ability.

As the residual errors of formwork, these of rebar roughly follow a normal distribution. The larger the values predicted, the more residual errors are.

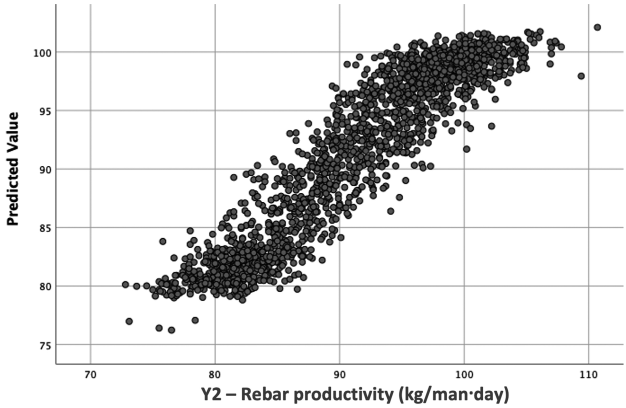

Fig. 11. Comparison chart between predicted and actual rebar productivity

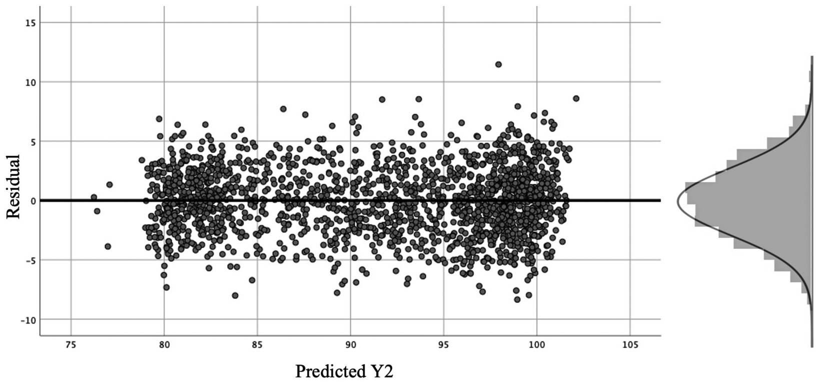

Fig. 12. Residual error chart of rebar productivity

5.1. Sensitivity analysis

In the neural network model, a sensitivity analysis was conducted to determine the importance of independent variables [46]. Sensitivity analysis evaluates the effect on model outputs by each independent variable while keeping all other input variables at their base-case values [47]. The outcome of this analysis presents how much each independent variable affect the model outputs (in this case, Y1 and Y2) or can be regarded as the *importance* of independent variables. Figure 13 depicts importance and normalized importance of independent variables. Normalized importance means that all other weights are scaled so that the most important variable becomes 100 percent.

Temperature is shown to be the most important variable that affects formwork and rebar productivity. During the recorded time of the construction, temperature ranged from 11.3 to 40.9°C, averaging 27.32°C. As recorded, construction tasks were minimized in hottest days: most workers perform their jobs on the ground, but not on the floors. Rain is the next most important variable (0 mm/h – no rain to 35.8 mm/h – the heaviest hourly rain

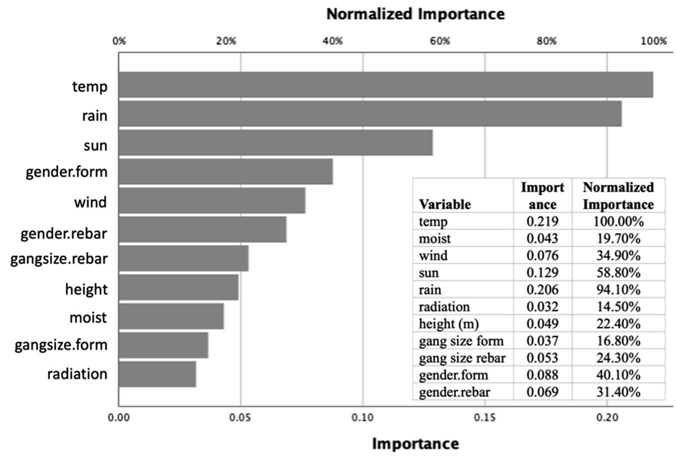

Fig. 13. Importance of independent variables to dependent variables

recorded in the year in the city). In reality, there is a threshold that if the rain magnitude surpasses it, all construction activities must stop. The next variable, also a weather variable, is sun – measured by sunny time/hour. It is noteworthy that sun is highly correlated with temperature: in the area, whenever there is sun, the temperature tends to be high; however, if there is no sun, it does not mean that it is always comfortable for the workers.

Next weather variables are wind (5^{th}), moisture (9^{th}), and radiation (11^{th}). Just like rain, if the wind is fast, then the construction tasks must stop. As observed, labor tasks, especially formwork was highly affected by wind. Moisture does not seem to impact productivity that much if compared to other weather factors. Vietnam is a tropical country and the moisture in the Northern is mostly high, except in short intervals in the year. Therefore, the workers are familiar with the conditions. The last ranked factor was the radiation by the sun. Workers who are exposed to high ultraviolet light might have skin burnt and corneal abrasions. However, workers were aware of this and covered themselves well from direct sunlight. This explains lowest impact of radiation on the productivity.

Interestingly, the variables in the crew group (i.e., gender structure and gang size of crew) has their importance distributed in the mid of the ranking. Gender of formwork crew (4^{th}) and gender of rebar crew (6^{th}) were placed a little higher than those of rebar gang size (7^{th}) and formwork gang size (10^{th}). The male ratios of formwork crew and rebar crew averaged 0.79 and 0.75 respectively. Construction tasks are heavy works and require good builds of bodies. Both formwork and rebar require workers to lift heavy objects at times. Being usually taller, male workers can raise objects higher, sometimes without the need of using scaffolds. Female workers, as observed, worked mostly with assembling forms and tying steel wire to secure bars. However, the details of gang size gender to productivity were not studied in this research. Both formwork and rebar tasks are space consuming, meaning if the area is too crowded, productivity will be negatively influenced. With the floor area approximates 1,950 m^2, the mean gang size was 70.36 and 50.18 for rebar and formwork respectively. However, on the most crowded days, the size reached 100 and 69 for each task. The data were captured through the contractor's daily registration and foremen's reports, so the numbers included both workers on the ground, working in the shops, and on the floors.

The only independent variable related to the building was the height of the working floor. This variable ranged from 16.5 m (5^{th} floor) to 102m (31^{st} floor). Many reasons can affect construction productivity so that *height of working floor* was only ranked 8^{th} in the importance ranking. For instance, parts of formwork and rebar were lifted by tower crane from the ground to the working floor. The cycle of the delivery therefore varied significantly. Moreover, wind speed was faster at higher floors, and wind impacted productivity, as analyzed.

6. Conclusions

In this study, a prediction model was established with the consideration of 11 independent variables included in 3 groups, i.e., work environment (weather), crew, and site and the relation with formwork and rebar productivity as dependent variables. This is one of a few studies in which all of independent and dependent variable data are of scaled and directly measured but not interval or categorical.

Data were collected in a 35-floor high-rise building in seven months during the structural construction phase. Specifically, weather data were obtained from reports of a national weather station closed to the project site. Other independent data were collected onsite through site observation and reports. Dependent data – productivity – were measured directly or indirectly by daily work plans, observations, hourly and daily reports by foremen and engineers, shop drawings, and material consumption table. Furthermore, footage from security cameras were used to discard outliers such as in case of special events, work incidents, or rainy days.

Neural networks were used for the prediction model and showed their effectiveness. The best built model was a two-layer MLP that used *sigmoid* as its activation function. This model generates good results with acceptable errors. Regarding the contribution of independent variables to the productivity of the formwork and rebar tasks, weather (e.g., temperature, precipitation, sun) generally played the most important roles while crew factors were distributed in the mid of the ranking and the working floor height played a mild role.

Neural networks, whose performance was observed in this study, confirmed the outcomes of previous studies, that these are appropriate and that these outperform regression in the modeling problems of construction labor productivity.

Due to the design of the study, the authors skipped many independent variables (e.g., other project, site, work characteristics) other than eleven variables included, though their contribution to labor productivity are certain. Moreover, data were collected from only one project in a period. However, the built neural networks could significantly explain dependent factors. Future studies can repeat with the same research design but with more independent factors, longer observation time, more projects, and more contractors. . . and enhance the body of knowledge about construction labor productivity, hence construction labor productivity itself.

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