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Development of Artificial Neural Networks Model to Determine Labor Rest Period Based on Environmental Ergonomics

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Abstract. Food SMEs (Small and Medium Enterprises) were examples of labor-intensive industry, which involved laborers in pursuing production activities. Food SMEs require complex processes in production activities. Support to increase work productivity and reduce ergonomic risks of the activities was needed. The study was conducted at Tofu SMEs. The determination of the rest period could be developed to give some recovery times to laborers. WBGT (Wet Bulb Globe Temperature) was estimated to determine the rest period. The rest period was determined by the workstation environment and workload labor. ANN (Artificial Neural Networks) model was carried out due to a nonlinear relationship. ANN was used to process the information from the data set and predict the amount of rest period and WBGT. ANN was trained using backpropagation. The backpropagation algorithm used the error value to change the weight with forward and backward propagation. The result showed that dry bulb temperature, heart rate, wet bulb temperature, and gender significantly impacted the rest period and WBGT. A total of 180 data sets from tofu SMEs were divided into training data (80%) and validation data (20%). The optimal ANN structure was determined by four input, four hidden, and two output neurons. The activation function was sigmoid for both layers. SSE (Sum of Squared Errors) was used to obtain the best structure. The value of R^2 was equal to above 0.900, which indicated that ANN could model the labor rest period based on environmental ergonomics.

Keywords: Artificial neural networks; Labor; Rest period; Wet bulb globe temperature

1. Introduction

SMEs had a vital role in developing the Indonesian economy. SMEs carry out most business organizations in Indonesia, with a total of 56.54 million units (Bank Indonesia and LPPI, 2015). SMEs also employed a considerable amount, more than 90% of labor (Bank Indonesia and LPPI, 2015). One of the characteristics of SMEs is labor-intensive. Food SMEs require complex processes to produce value-added products. Food product requires particular handling techniques due to their perishable characteristic. Ushada *et al.* (2017) mentioned some SMEs product delivery activities, such as boiling, steaming, frying, baking, and assembly. The activities were closely influenced by the workstation environment in SMEs.

Good management practices and Sustainable Manufacturing practices (Hami *et al.*, 2018) could increase eco-efficiency and labor productivity. The conditions were explored

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by Ushada *et al.* (2017), as shown in Table 1. Production activities with high temperatures could cause various effects on the body (Ushada *et al.*, 2017). Physical work combined with high temperature, radiation, and lousy air ventilation impacted losses in productivity (Yi and Chan, 2013). The body could experience muscle fatigue, decreased concentration, and heat stress. The temperature between SMEs (Table 1) was above 30°C. Thus, laborers could not perform activities effectively at 29.1°C due to heat discomfort (Ushada *et al.*, 2017). Working under thermal stress conditions had associated risks and consequences (Miller and Bates, 2007). Therefore, laborers needed sufficient rest periods under these circumstances.

Table 1 Environment temperature in SMEs (Ushada *et al.*, 2017)

SMEs	Environment Temperature (°C)
Nugget	30.1
Herbal Beverage	30.1
Fish Chip	31.1
Bakpia	33.1
Tempeh	34.2
Cracker	35.7

SMEs' work system was influenced by various factors and mainly by workplace environmental ergonomics (Ushada and Okayama, 2018). Determining the rest period could be adapted to reduce ergonomic risk at work (Tiacci, 2018). The determination of the rest period was pursued to provide recovery time to laborers. Recovery time gave laborers time to rest their bodies and restore the energy that comes out while working. Every activity in production had specific characteristics; therefore, rest period models, times, and frequencies were diverse and challenging to standardize (Negreiros *et al.*, 2019).

A Murell formula has been developed to determine the rest periods model (Iridiastadi and Yassierli, 2017). The Murell formula used work time and metabolic rate to determine rest time. Also, in a previous study, Yi and Chan (2013) optimized the rest time schedule for construction laborers in hot and humid working conditions. Ushada *et al.* (2017) developed an ANN model to determine food-based SMEs' set initial temperature values. Batubara and Dharmastiti (2017) stated that ergonomics intervention was used to improve work systems to reduce workload. Ushada *et al.* (2017) indicated the nonlinear relationship between worker ergonomics status and workplace environment. ANN (Artificial Neural Networks), as one of the Artificial Intelligence approaches could frame nonlinear structures based on the human brain system and were known as an estimator and could detect nonlinear relationships between variables (Vinoth *et al.*, 2016). Previous studies did not demonstrate a link between the WBGT and the rest period. Thus, an advanced rest period model using ANN was developed in this study, considering the environmental ergonomics, labor circumstances, and production times factor.

The study was conducted at SME tofu in five districts in the Special Region of Yogyakarta. Based on the preliminary research, the Special Region of Yogyakarta has a tofu SMEs center in each district as the representative. The research objectives were (1) to analyze the environmental workstation, labor workload, and rest period; and (2) to develop an ANN model for determining labor rest periods. Based on the objectives, the model could be expanded as an appropriate technology for sustainable, ergonomic application in food SMEs. Thus, the research would benefit the stakeholders in food SMEs, especially the owners, managers, and laborers.

2. Methods

2.1. *Tofu SMEs*

Figure 1 shows the conceptual model of this study. The parameters in this study were ergonomic parameters of labor and workstation environment in tofu SMEs. Ergonomic labor parameters were heart rate, weight, age, body temperature, and gender. The workstation environment parameters were dry bulb temperature, relative humidity, and wind velocity. Environmental ergonomics was defined as a relationship between the ergonomic parameters of labor and the workstation environment.

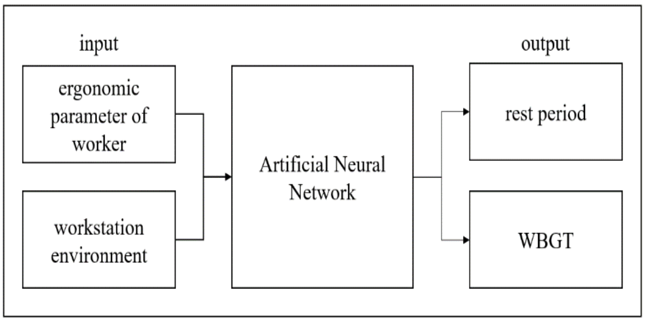


Figure 1 Conceptual modelling of the ergonomic parameters of the labor and workstation environment

The previous research by Li *et al*. (2016) showed that 14:00 to 15:00 was the high-risk time for laborers, while 07:00 to 08:00 was the non-hazardous time for laborers. Based on Li *et al*. (2016), the data were collected three times: initial, intermediate, and final labor shift.

2.2. *Rest Period and WBGT*

Metabolic rate (y) was determined by heart rate labor (x) in tofu SMEs. The metabolic rate was calculated using a formula from Astuti in Ushada and Okayama (2018), as shown in Equation 1.

$$y = 1{,}80411 - 0{,}0229038x + 4{,}71733 \times 10^{-4} \tag{1}$$

Rest period (R) was determined by labor work time (w), metabolic rate (b), and the threshold value of labor work time (s). The rest period was calculated using a Murell formula in Iridiastadi and Yassierli (2017), as shown in Equation 2.

$$\mathrm{R} = \frac{w(b-s)}{b-0{,}3} \tag{2}$$

WBGT was determined by effective temperature (ET) and wet bulb temperature. ET was obtained from Effective Temperature Chart, and wet bulb temperature from Psychrometric Chart. WBGT was calculated using Equation 3 (OSHA, 2012).

$$\mathrm{WBGT}\,(°F) = 1{,}102ET - 9{,}1 \tag{3}$$

Table 2 indicates the categories of metabolic rate and threshold for WBGT value based on the Indonesian government (Minister of Health Indonesia, 2016). Table 2 is a standard by the Minister of Health Indonesia (2016) compared with the actual condition in tofu SMEs.

Table 2 Work cycle and rest period in an hour

Work cycle and recovery	WBGT (°C)			
	Light	Moderate	Heavy	Very Heavy
75-100%	31.0	28.0	*	*
50-75%	31.0	29.0	27.5	*
25-50%	32.0	30.0	29.0	28.0
0-25%	32.5	31.5	30.0	30.0

*) prohibited due to physiological effects

2.3. *Development of ANN Model*

Based on Figure 1, the inputs of ANN were ergonomic parameters of labor and workstation environment. The predicted outputs were the rest period and WBGT. Data sets were divided into training data (n=144) and testing data (n=36). SSE (Sum of Squared Errors) was used as an error value to determine the optimal combination on the ANN model. SSE was minimized between the system output and the neural network model output (Janczak, 2005). The R^2 correlation was used to express the reliability of the ANN model. ANN was used to predict continuous variables, and a valuable measure of goodness of fit for each output was the coefficient of multiple determination (R^2) (Lingireddy and Brion, 2005).

ANN was trained based on the backpropagation algorithm. Backpropagation had a layered feed-forward neural network structure in which the nonlinear neurons were arranged in consecutive layers; afterward, the information passed from the input layer to the output layer through hidden layers (Vinoth *et al*., 2016). Ushada *et al*. (2017) found a nonlinear relationship between environmental ergonomics in Food SMEs. Thus, ANN could be a powerful computing approach for complex computations (Cavalieri, Maccarrone, and Pinto, 2004).

The training process was pursued to evaluate weights and biases in ANN (Argatov and Chai, 2019). The training process required a data set of experimentally measured input-output (Argatov and Chai, 2019). The training process was carried out in several stages as follows.

1. Training with variations in the number of neurons and hidden layers
2. Training with variations in the activation function
3. Training with variations in the value of the learning rate

3. Results and Discussion

3.1. *Respondents and Sample Location*

This study obtained sixty (60) respondents from laborers with three times different sampling times. A total sample of one hundred and eighty (180) data sets was obtained. The data samples were obtained from each district in the Special Region of Yogyakarta, such as Yogyakarta, Bantul, Kulon Progo, Gunungkidul, and Sleman. Table 3 indicates the demographic information of the respondents. The average age of the laborers in Tofu SMEs was 42.78 ± 13.64 years old, and the majority ranged from 31 to 40 years old and 41 to 50 years old. The majority gender of the laborers were men ($n = 39$), and the rest were women ($n = 21$). Based on the correlation test, age, and weight parameters had a value below 0.200, which indicated a low degree of correlation between the rest period and WBGT.

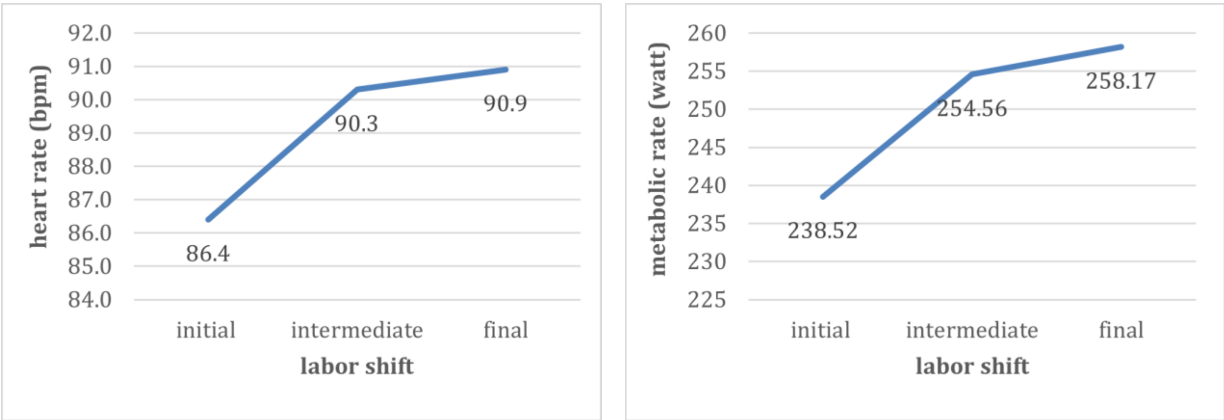
Table 3 Demographic Information

Demographic Categories	n	%	Demographic Categories	n	%
Gender			**Age**		
Male	39	0.65	21 to 30 years old	13	0.22
Female	21	0.35	31 to 40 years old	16	0.27
Weight			41 to 50 years old	16	0.27
31 to 40 kilograms	2	0.03	51 to 60 years old	7	0.12
41 to 50 kilograms	17	0.28	61 to 70 years old	8	0.13
51 to 60 kilograms	23	0.38	**District**		
61 to 70 kilograms	15	0.25	Kulonprogo	12	0.20
71 to 80 kilograms	3	0.05	Sleman	12	0.20
			Gunung Kidul	12	0.20
			Yogyakarta	12	0.20
			Bantul	12	0.20

3.2. Workload and Workstation Environment

Various tofu-making processes were generally carried out in several SMEs. The processes were soaking, milling, boiling, filtering, processing, solidifying, cutting, and frying. These processes were pursued in a batch continuously. The activities in the tofu production process can be categorized into potentials that cause physical workload (Widyanti *et al*., 2017). Thus, the activities affected the labor heart rate. Figure 2a shows a graph of labor heart rate, indicating an increase in labor heart rate from the initial to the final shift of the laborer.

Metabolic rate was counted from labor heart rate. The result indicated three (3) categories such as light, moderate, and heavy (Table 4). Figure 2b indicates an increase in metabolic rate from the initial to final labor shift.



(a) (b)

Figure 2 Labor condition: (a) Heart rate; and (b) Metabolic rate

Table 4 Metabolic categories of labor

Workload Categories	Percentage (%)	Metabolic rate (Watt)
Light	40.6	202.3
Moderate	55.6	275.5
Heavy	3.9	394.2

The workstation environment was where the laborers did some activities to process the tofu. The environment was observed during working time. The result showed dry bulb temperature increased during work time (Figure 3a).

The average WBGT value in tofu SME workstations was 26.39 °C. The value was still at the threshold for WBGT in the industry (Minister of Health Indonesia, 2016). Although it met the threshold, the value had a level of discomfort. WBGT value was included in the extremely hot environment category (Chowdhury, Hamada, and Ahmed, 2017). Based on Chowdhury, Hamada, and Ahmed (2017), it had the risk of discomfort, but there was no health risk. Work inconvenience at SMEs arose from 25.82 to 26.86 °C due to the extremely hot environment at the tofu SMEs workstation (Figure 3b). Tofu SMEs use heat sources in most of the process, which could impact increasing the temperature at the workstation.

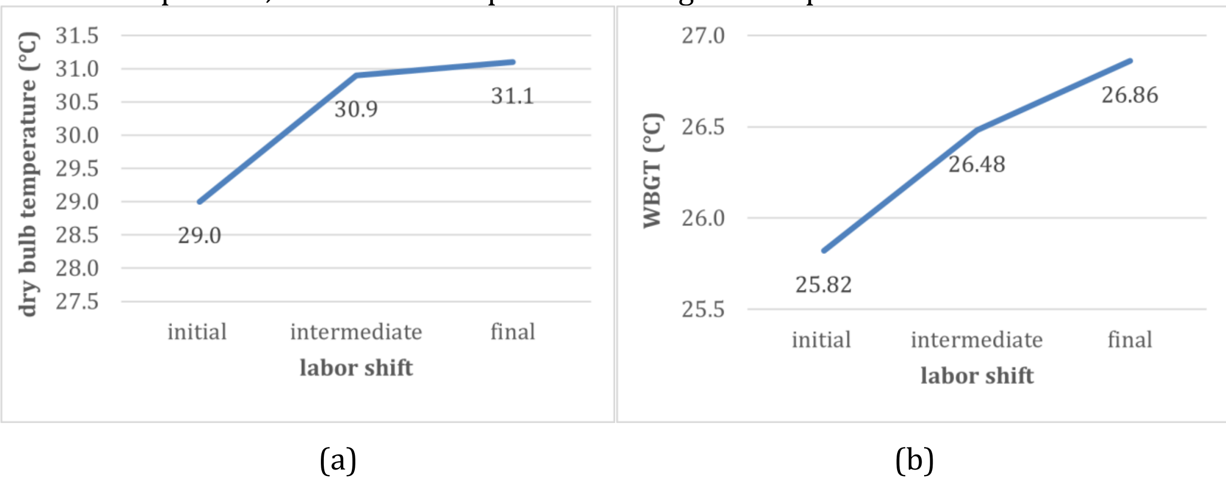


Figure 3 Workstation environment: (a) Dry bulb temperature; and (b) WBGT

Table 5 indicates one hundred and sixty-three (163) laborers with a positive WBGT gap. The positive value of the WBGT gap meant that WBGT in laborers did not exceed the threshold value. Laborers were still comfortable with the WBGT values and did well in their activities. On another side, the negative WBGT gap value was found in ten (10) laborers. If the WBGT gap was negative, the WBGT value exceeded the specified threshold. If the WBGT value exceeds the standard value, it could indicate high heat stress on laborers (Bolghanabadi, Ganjali, and Ghalehaskar 2019). Thus, during working hours, the activities increased, and performance did rise after the activities began.

Table 5 Gap of WBGT

WBGT Gap	Total
>0 (positive)	163
<0 (negative)	10
*	7

*) not allowed to work

3.3. Rest Period

The rest period was a scheduled break during a working day, and the laborers stopped their activities to rest, eat, and any other needs (ILO, 2019). The rest period was determined by metabolic rate labor during work time. Table 6 indicates the rest period of labor categorized by workload. Work breaks had a range from -44.3 to 11.3 minutes for an hour. The negative number said that laborers did not need an additional rest period because the workload was not too heavy. It could be interpreted that the labor had an extra rest period of 0 minutes to calculate negative numbers. In light and moderate workloads, the average additional rest period was obtained by a negative number, so laborers in tofu SMEs did not need extra work breaks. Labors in the heavy workload category had an average break time of 11.33 minutes. The results show the need for additional breaks of one hour for each work with heavy categories carried out in production activities. The work preferences related to the rest period length were not equal for every labor (Di-Pasquale *et al*., 2017). Research by Dababneh, Swanson, and Shell (2001) showed that frequent rest periods with short time would not decrease productivity.

Table 6 Rest period based on workload categories

Workload Categories	Average Rest period (minutes)
Light	-44.3
Moderate	-15.0
Heavy	11.3

The rest period depended on the situation in tofu SMEs. Production activities would affect the labor rest period. Activities increased during working hours, and performance increased 2 hours after starting work (Fahed, Ozkaymak, and Ahmed 2018). These conditions were similar to the workstation at tofu SMEs. Labors took a rest during the working day to take toilet breaks, prayer breaks or breaks to address other personal needs (ILO, 2019).

3.4. ANN Model

Data normalization was performed by the min-max normalization method. The method changed the data into a smaller range. The data changed to a 0 to 1 range. T-test, F-test, and correlation tests were performed. The result showed that dry bulb temperature (i_1), heart rate (i_2), gender (i_3), and wet bulb temperature (i_4) had a significant impact on the rest period (o_1) and WBGT (o_2). These parameters had a high correlation value toward dependent variables so that they could be used as an ANN input.

The result of the training process was an optimum structure for WBGT and the rest period, as shown in Figure 4. To improve the performance, ANN changed the weights between neurons in each layer to modify the structure of the training data (Darvishi *et al*., 2017). Training data with the lowest error value was at 4-4-2. The activation function for the between layers was sigmoid. The optimum learning rate was 0.01. That combination got SSE training 0.113 and SSE testing 0.037. The SSE indicated a low error.

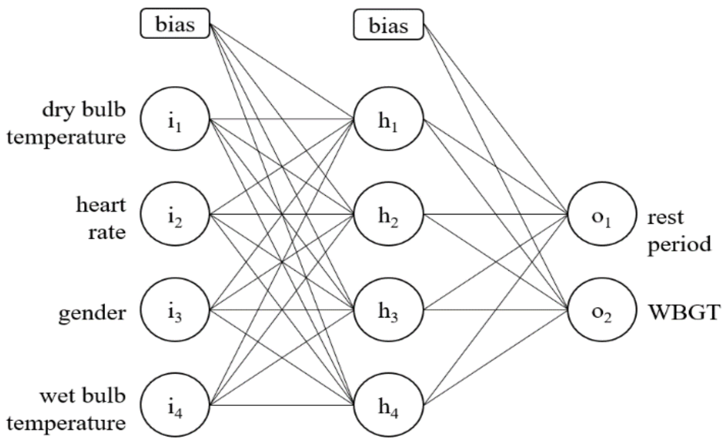
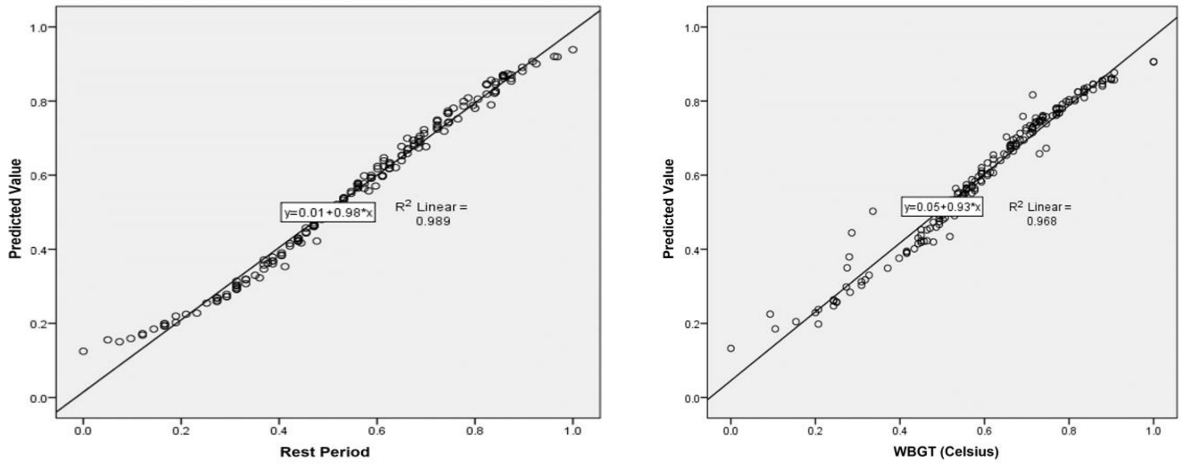


Figure 4 ANN structure for the rest period

The value of R^2 between the calculation and prediction of resting time was 0.989 (Figure 5a), while the value of R^2 between the calculation and prediction of WBGT was equal to 0.968 (Figure 5b). An R^2 value of 1.0 represented a perfect prediction (Lingireddy and Brion, 2005). The results indicated that the calculation of the rest period in explaining the variance of the predicted rest period value was 98.9%. The value showed that the prediction of the rest period could be explained well by calculating the rest period. The WBGT value calculation explains that the WBGT prediction value variance was 96.8%. The predicted WBGT value could be explained well by the WBGT value calculation. An appropriate rest period could reduce the risk caused by workload (Chen and Xie, 2014). Thus, the ANN model of rest period was developed using dry bulb temperature, heart rate, wet bulb temperature, and gender as the input with a rest period and WBGT as the output.



(a) (b)

Figure 5 R^2 Value for (a) Rest period; (b) WBGT

Murell formula (Equation 2) stated that the rest period was impacted by the labor work time and metabolic rate (Iridiastadi and Yassierli, 2017). Tofu SMEs utilize heat sources for most of the process, which affects the workstation's temperature. The results in this study indicated that the dry bulb temperature, heart rate, wet bulb temperature, and gender significantly impacted the rest period and WBGT, not only the work time and metabolic rate. Laborers needed more time to rest in a hot work environment since they were uncomfortable (Ushada *et al.*, 2017; Yi and Chan, 2013).

The novelty of the research was the relationship between labor, workload, environmental ergonomics, rest periods, and WBGT. The dry bulb temperature (i_1), heart rate (i_2), gender (i_3), and wet bulb temperature (i_4) demonstrated a strong impact on the rest periods (o_1) and WBGT (o_2) in the performance of production tasks. The ANN model of WBGT and rest periods were the best combination to solve the SME's issues. The rest periods could reduce the discomfort, whereas the WBGT displayed a temperature-based measure of work discomfort as the environment's temperature significantly impacted the rest periods.

3.5. Ergonomic Benefit and Practical Implication to SMEs

The model would benefit the stakeholders in food SMEs, especially the owners, managers, and laborers. The owners and managers could use it as a reminder for rest periods based on the condition of environmental ergonomics. The worker could use the rest period properly and feel comfortable while working.

The research results could be applied in SMEs or industries to determine the rest period and WBGT value. Weights and biases from the ANN model were used to calculate rest periods and WBGT. Weights and biases stored in programs could be managed using programming software. The input for the program consists of data sets of dry temperature, wet temperature, heart rate, and gender. The new data sets could be obtained from the workstation, so the rest period and WBGT values can be calculated.

4. Conclusions

The study results indicated that the workload in tofu SMEs had three categories: light, moderate, and heavy. The average threshold value of WBGT in tofu SMEs was 26.39 °C which was below the threshold. Thus, laborers still felt comfort in carrying out their activities. Additional rest periods for laborers in tofu SMEs are known to have a range from 0 to 11.3 minutes for every hour of work. The result showed that dry bulb temperature, heart rate, wet bulb temperature, and gender significantly impacted the rest period and WBGT. The best ANN model was a 4-4-2 network structure with four neurons in a hidden layer. The activation function used between the layers both were sigmoid. The best learning rate used was 0.01. The structure resulted in the value of SSE training at 0.113 and SSE testing at 0.037. The value of R^2 between the calculation and prediction of resting time was 0.989, while the value of R^2 between the calculation and prediction of WBGT was equal to 0.968. Thus, the model fits the performance and can be applied to calculate the rest period and WBGT using programming software. Therefore, the model could be used as a reminder for a rest period based on the condition of environmental ergonomics.

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