Proceeding of International Conference on Electrical Engineering, Computer Science and Informatics (EECSI 2014), Yogyakarta, Indonesia, 20-21 August 2014

# Combining Kansei Engineering and Artificial Neural Network to Assess Worker Capacity in Small-Medium Food Industry

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***Abstract*—This paper highlighted a new method for worker capacity assessment in Indonesian small-medium food industry. The sustainable and productivity of Indonesian food industry should be maintained based on the workers capacity. The status of worker capacity could be categorized as normal, capacity constrained worker and bottleneck. By using Kansei Engineering, worker capacity can be assessed using verbal response of profile of mood states, non-verbal response of heart rate in a given workplace environmental parameters. Fusing various Kansei Engineering parameters of worker capacity requires a robust modeling tool. Artificial Neural Network (ANN) is required to assess worker capacity. The model was demonstrated via a case study of Tempe Industry. The trained ANN model generated satisfied accuracy and minimum error. The research results concluded the possibility to assess worker capacity in Indonesian small-medium food industry by combining Kansei Engineering and ANN.**

***Keywords—artificial neural network; bottleneck; capacity constrained worker; kansei engineering; tempe industry;***

## I. Introduction

There is more than 54.6 million small-medium industry includes Small-Medium Food Industry (SMFI) who use the man power almost 97.2% [1]. The sustainable and productivity of SMFI should be maintained based on the workers capacity [1]. As shown in Fig. 1, the condition of workplace for the worker is complex and possible to influence the worker capacity. The status of worker capacity could be categorized as normal, capacity constrained worker and bottleneck [2].

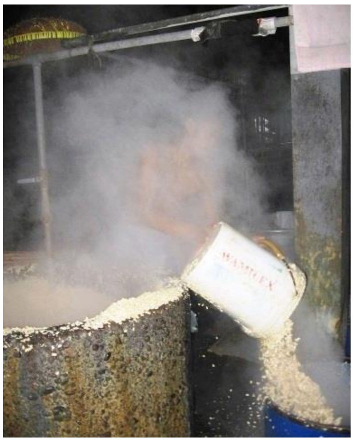

Fig.1. Workplace condition in Tempe Industry

Bottleneck is a worker which has capacity (unit /minutes) larger than the arrival rate of material (unit/minutes) in a production flow which cause any disruption to the schedule and decreases output. Deriving production bottleneck are essential to maintain the planned product flow in each work station [2,3]. Bottleneck is difficult to be derived due to the complexity of motion study to measure the status of worker capacity.

Kansei Engineering approach is applicable to model the human sensibility factors using comparison between verbal and non verbal responses [4, 5]. Ushada and Murase [6] has utilized diagram method of Kansei Engineering flow from the zero-level concept to extract the Kansei words. The others potential method to apply Kansei words is using Profile of

Mood States (POMS). It measures the affective mood state fluctuation in a wide variety of populations. The POMS identifies and assesses transient and fluctuating affective mood states of human [7].

In this research we formulate the worker capacity using Kansei Engineering as shown in Eq.1 and Fig. 2:

Worker Capacity = f {C, VR, NVR, WE} (1)

C = Work response capacity (Unit/minute)
VR = Verbal response of mood
NVR =Non-verbal response of heart rate (Pulse/minute)
WE = Workplace environment

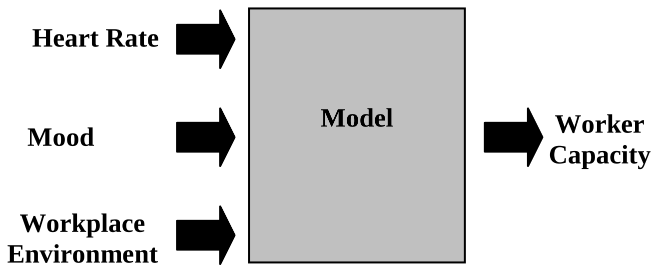


Fig. 2. Conceptual model of worker capacity assessment

Nowadays, various method was developed to improve productivity in SMFI. Seonwoo *et al.* [8] has defined the relationship between physiological and biomechanical response during cherry tomato harvesting in greenhouse. Silalahi *et al.* [9] has developed the assessment method of worker workload in tomato production greenhouse using body temperature and heart rate reserve. Seonwoo *et al.* [8] and Silalahi *et al.* [9] did not use the Kansei Engineering to formulate the research problem. Zhang et al. [10] has used Kansei Engineering in product form identification technology.

Fusing various parameters of verbal, non-verbal responses, workplace environmental parameters and worker capacity requires a robust modeling tool. Silalahi *et al.* [9] concluded that worker assesment in a case study of greenhouse were not linear. Therefore, Artificial Neural Network (ANN) is required to assess worker capacity. It is due to its capability to model large number of non linear parameters in biosystems [11, 12].

The research objective is: 1) To identify the worker capacity in small-medium food industry using Kansei Engineering ; 2) To develop an artificial neural network model to assess worker capacity.

Worker capacity status can be used to prevent capacity constrained worker shifting to bottleneck, improving capacity constrained worker for being normal status and shifting the existing bottleneck to capacity constrained worker.

## II. Materials and Methods

### A. Case Study

The case study of the research is in Industry of `Tempe` `Muchlar`, Bantul, Yogyakarta Special Province. `Tempe` is made from cooked and slightly fermented soybeans and formed into a patty, similar to a very firm veggie burger. This industry produced half fermented `Tempe”. The industry supplies the product to other division in Sleman region to be a final `Tempe` product.

### B. Data Acquisition

Data acquisition was required for training and validation data for ANN model. The data acquisition consists of worker capacity, motion and time study, profile of mood states, heart rate and workplace environment.

#### 1) Worker Capacity

Worker capacity status was assesed using utility as defined in Eq. 2:

$$U = \frac{\lambda}{\mu} \qquad (2)$$

U = Worker utility

ʎ = Arrival rate of material (unit/minutes)

μ = Worker capacity (unit/minutes)

Bottleneck worker is a worker which has μ Capacity (unit/minutes) > the ʎ arrival rate of material (unit/minutes) in a production flow which cause any disruption to the schedule and decreases output (utility ʎ/ μ x 100% is less than 50%). Capacity Constrained Worker (CCW) is a worker which has μ < ʎ (Utility ʎ/ μ x 100% is more than 100%). Normal worker is a worker which has μ close or equal to ʎ (Utility ʎ/ μ x 100% is between 50% and 100%). Arrival rate of material was measured using data of production target per day. Worker capacity was measured using motion and time study.

#### 2) Motion and Time Study

Motion and time study is an effective method to measure the leanness of a production system [13]. Motion and time study were used to calculate the worker capacity status. When an operator is observed for a period of time, the number of units produced during this time, along with the performance rating, gives Eq.3:

$$t_N = \frac{t_0}{N} \times PR \qquad (3)$$

$t_N$ = Time worked

$t_0$ = Number of units produced

$PR$ = Performance rating

A standard time is derived by adding to normal time for personal needs (such as washroom and coffee breaks), unavoidable work delays (such as equipment breakdown or lack of materials), and worker fatigue (physical or mental). The buffer is indicated in Eq.4:

$$t_s = t_N + (AF \times t_N) \tag{4}$$

$t_s$ = Standard time

$AF$ = Allowances Factor

### 3) *Profile of Mood States*

In this research, Profile of Mood States (POMS) are proposed to measure seven identifiable mood or affective states. Questionnaire result is analyzed using *T* score or known as Total Mood Disturbance (TMD) in Eq.5:

$$TMD = TA + D + AH + F + C - V - F \tag{5}$$

| | | |
|---|---|---|
| $TA$ | = Tension－Anxiety | $V$= Vigor |
| $D$ | = Depression－Dejection | $F$= Fatigue |
| $AH$ | = Anger－Hostility | $C$= Confusion. |
| $F$ | = Friendliness | |

### 4) *Heart Rate*

Heart Rate (HR) was selected as physiological criteria because it is simple, reliable, and provides good accuracy on manual measurement [14]. HR was measured using finger pulseoxymeter during 6 days of work. These 6 days represents the normal day of working in the bioproduction system. In each day we measured the HR every hours with the periods of 07.00 (Befor working) and 14.00 pm (After working).

### 5) *Workplace Environment*

The treatment of temperature, dew point, wet bulb , mixing ratio and relative humidity was measured using Thermo Recorder (Extech RH520 Data Logger). Light intensity was measured using Lightmeter (Lutron LX-101). The noise was measured using Multifunctional Environmental Meter (Krisbow KW 06-291).

### 6) *Artificial Neural Network*

An artificial neural network model is defined as a black box relationship between worker capacity status and workplace environmental parameters. Its function for deriving worker capacity status can be defined as dynamic variation of profile of mood states, heart rate in a given workplace environmental parameters. Thus, these relationships were modeled using a three layered ANN as shown in Fig.3.

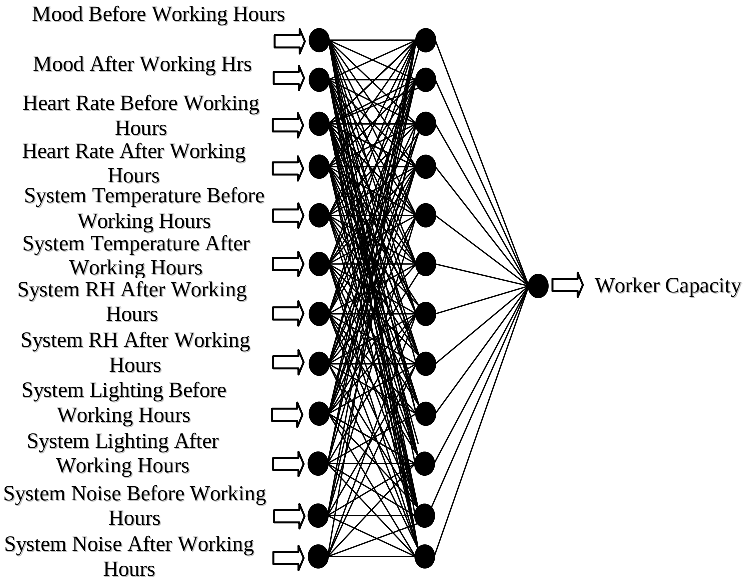


Fig. 3. Artificial neural network model

The inputs were total mood disturbance, heart rate, workplace temperature, relative humidity, lighting and noise, which were measure before and after working. The outputs was worker capacity status of normal, CCW and bottleneck. The software of ANN was used [15]. Worker capacity status is expected as the feedbacks for workplace environmental control system in SMFI.

## III. RESULTS AND DISCUSSIONS

### A. *Worker Status Assessment*

Worker status classification can be defined in Table 3. Utility 1 indicated the first utility measurement. Utility 2 indicated the second utility measurement. Status 1 indicated the first status classification. Status 2 indicated the second status classification. Table 3 indicated the dynamic worker capacity status during the different period of measurement. There are various worker capacity status within the same arrival rate of production target. Workers 1 of threshing and 7 of soaking II indicated the different capacity status during the different period of measurement. The industrial management confirmed that there are low capacity of threshing machine which caused the dynamic worker 1 status. The high TMD and HR before and after working caused the dynamic worker 2 status.

TABLE 1. WORKER STATUS CLASSIFICATION

| Worker | Arrival Rate (Kg/Min) | Utility 1 | Utility 2 | Status 1 | Status 2 |
|---|---|---|---|---|---|
| 1 | 26.6 | 0.23 | 0.69 | Bottleneck | Normal |
| 2 | 16.9 | 1.15 | 1.23 | CCW | CCW |
| 3 | 30 | 0.63 | 0.51 | Normal | Normal |
| 4 | 29.9 | 0.81 | 0.6 | Normal | Normal |
| 5 | 29.2 | 1.72 | 1.6 | CCW | CCW |
| 6 | 20.4 | 2.70 | 1.91 | CCW | CCW |
| 7 | 39.3 | 1.25 | 0.98 | CCW | Normal |
| 8 | 18.2 | 0.33 | 0.25 | Bottleneck | Bottleneck |
| 9 | 26 | 2.60 | 1.57 | CCW | CCW |
| 10 | 28.4 | 1.71 | 1.48 | CCW | CCW |

### B. *Artificial Neural Network*

The data included multiparameters was defined using mood efficiency, heart rate, capacity, temperature, dew point, wet bulb, mixing ratio, RH, noise and light intensity. The experimental and questionnaire results are recapitulated in to 120 set data. The 108 set data were used in training ANN model, while the remains were used in inspection data. Table 2 indicated examples of three set training data and Table 3 for the output.

TABLE 2. THREE EXAMPLES OF SET INPUT TRAINING DATA

| No | Inputs | Set 1 | Set 2 | Set 3 |
|---|---|---|---|---|
| 1 | TMD before working | 5.85 | 8.95 | 8.03 |
| 2 | TMD after working | 9.80 | 9.13 | 7.36 |
| 3 | HR before working | 72 | 74 | 86 |
| 4 | HR after working | 79 | 75 | 86 |
| 5 | System temperature before working | 31.6 | 29.4 | 29.6 |
| 6 | System temperature after working | 30.9 | 34.6 | 31.6 |
| 7 | System RH before working | 72 | 59 | 78 |
| 8 | System RH after working | 75 | 57 | 69 |
| 9 | System lighting before working | 225 | 335 | 316 |
| 10 | System lighting after working | 215 | 370 | 360 |
| 11 | System noise before working | 67 | 80 | 82.5 |
| 12 | System noise after working | 60 | 80 | 87 |

TABLE 3. EXAMPLES OF OUTPUT SET TRAINING DATA

| No | Worker Capacity Status | Value |
|---|---|---|
| 1 | Bottleneck | -1 |
| 2 | CCW | 0 |
| 3 | Normal | 1 |

Based on sensitivity analysis of output error by trial and error basis (Table 4), twelve neurons in the hidden layer were determined. The architecture of network consisted of twelve neurons in the input layer, twelve neurons in the hidden layer and one neuron in the output layer (12-12-1).

TABLE 4. SENSITIVITY ANALYSIS FOR ANN MODEL

| Learning coefficient | Momentum | Hidden nodes | Learning iteration | Mean RMSE |
|---|---|---|---|---|
| 0.1 | 0.9 | 12 | 14,000 | 0.076 |
| 0.1 | 0.9 | 12 | 16,000 | 0.075 |
| 0.1 | 0.9 | 12 | 18,000 | 0.104 |
| 0.1 | 0.9 | 12 | 19,000 | 0.061[a)] |

[a)]minimum RMSE

The training converged after approximately 19,000 iterations, learning coefficient of 0.1 and momentum 0.9.The mean value of Root Mean Square Error (RMSE) of training and inspection data was 0.061 and 0.24 respectively. Learning iteration has tough convergence with 75% accuracy and 25% misclassified. The research results indicate the possibility to use trained ANN model. By using these link weights from trained ANN, worker capacity status are derived.

## IV. CONCLUSSIONS

The research results in a case study of Tempe industry concluded the possibility to assess the worker capacity status using Artificial Neural Network (ANN) and Kansei Engineering. An ANN model were tested successfully described the relationship between verbal parameter of worker mood, non-verbal parameter of heart rate , worker capacity and workplace environment using back-propagation supervised learning method and inspection data. The trained ANN model generated satisfied 75% accuracy and 25% misclassified. It is suggested that the worker capacity status can be assessed by appropriate selection of ANN architecture. The research results concluded the possibility to assess worker capacity in Indonesian small-medium food industry by combining Kansei Engineering and ANN.

For the future work, this research results are used to develop Kansei Engineering-based watchdog model to assess worker capacity in Indonesian Small-Medium Food Industry.

## ACKNOWLEDGMENT

We would like to acknowledge the financial support Hitachi Scholarship Graduate Support Program, Japan for the 2013 Research Program and Directorate General for Higher Education, Indonesian Ministry of Education and Culture for 2014 International Collaboration Competitive Research Grant for International Publication of Universitas Gadjah Mada No: LPPM-UGM/1008/LIT/2014

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