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Incorporating Artificial Human Mentality (Kansei) in Intelligent Monitoring of Production Scheme for Customized Agro-industrial Produce

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Abstract: A novel Customized Agro-industrial Produce Design (CAPD) scheme is highlighted to monitor the plant factory production systems. The expected outcome is to provide every consumer with a produce that matches his or her unique mentality. The new challenges of CAPD are consisting of non-linear and complex interaction between the bio-response parameters and human mentality process involved. As the solution, the intelligent modeling of Bayesian Belief Network (BBN) and Artificial Neural Network (ANN) were proposed. Artificial human mentality was generated using BBN by *Kansei* approach. *Kansei* is defined as consumer mentalities which solicit their preferences reasoning. ANN was utilized to incorporate the mentality in the monitoring of production scheme. The implementation of CAPD scheme is demonstrated via a case study of Eco-produce of moss greening (*Rhacomitrium canescens*). The produce choices were harvested using the specific modules. The research objectives are: 1) to model the artificial human mentality using BBN by *Kansei* approach; 2) to incorporate the artificial human mentality in CAPD scheme using ANN. The result indicated that BBN attained satisfied accuracy. ANN was able to classify the modules using the mentality and choices. The modules were characterized by textural features and Likert scale's criteria. Both of the models were trained and validated based on benchmarking analysis (For BBN), sensitivity analysis (For ANN), minimum learning error and inspection data. Generally, the proposed CAPD is possibly applied for learning, mental simulation and monitoring in the early phase of customized produce development. Specifically it is applicable for Agro-industrial and Eco-produce design.

Keywords: Information technologies and ergonomics in agriculture, AI in agriculture, Plant factories.

1. INTRODUCTION

A significant success for introducing new customized agro-industrial produce depends on incorporating the desired consumer preferences in the monitoring of plant factory production scheme. In order to model the desired preferences, the consumer learning and reasoning method is required. For a new produce, more learning is required to understand the produce (Hoeffler, 2003). The Customized Agro-industrial Produce Design (CAPD) scheme involves the incorporation of their learning in the monitoring of production scheme.

Theories of learning most frequently cited in the literature include category-based learning, analogies, and mental simulation (Hoeffler, 2003). Mental simulation is learning strategy geared toward learning new information. Prior research has demonstrated that mental simulation help people deal with uncertainty and knowledge development (Taylor *et al.*, 1998). The new challenges of CAPD scheme are consisting of the non-linear and complex interaction between the bio-response and human mentality process involved.

As the solution, intelligent modelling of Bayesian Belief Network (BBN) and Artificial Neural Network (ANN) were proposed. As dealing with uncertainty and knowledge development, artificial human mentality was generated using BBN by *Kansei* approach. *Kansei* is defined as consumer mentalities which solicit their preferences reasoning. ANN was utilized to incorporate the mentality in the monitoring of production scheme.

The implementation of CAPD scheme is demonstrated via a case study of Eco-produce of moss greening (*Rhacomitrium canescens*). Moss plant has been used as an agro-industrial produce for building greening material in order to ease urban heat island effect (Murase and Ushada, 2006; Ushada and Murase, 2006) (Figs 1a and 1b). It is relatively a new produce and technological application. The produce choices were harvested using the specific modules. The modules were characterized by bio-response of textural images and water status (Ushada *et al.*, 2007).

(a) (b)

Fig. 1. Moss greening produce and technology; (a) Module of "Wet"; (b) Rooftop greening technology.

BBN has gained a reputation of being powerful technique for modelling complex reasoning problems involving expert knowledge and uncertain impact of causes (Henriksen *et al.*, 2007). ANN is applicable to model complex and non-linear relationship in bio-production systems (Ushada *et al.*, 2007). A novel CAPD scheme is highlighted combining BBN and ANN to monitor the production systems.

The research objectives are: 1) to model the artificial human mentality using BBN by *Kansei* approach 2) to incorporate the artificial human mentality in CAPD scheme using ANN. The expected outcome is to provide every consumer with a produce that matches his or her unique mentality. The plant factory could use the CAPD scheme to convert the produce choice in to the modules (bio-response parameters) (Fig. 2).

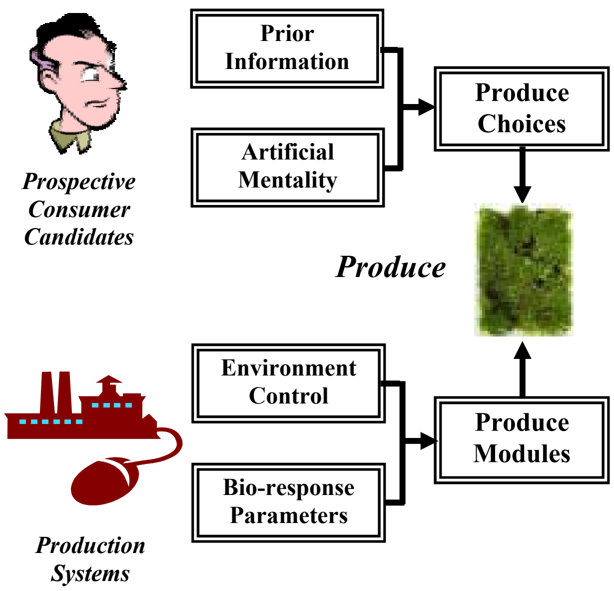

Fig. 2. CAPD scheme: incorporating artificial human mentality to monitor plant factory production systems.

2. MATERIAL AND METHODS

2.1 Questionnaire

A total of 98 prospective consumer candidates were selected as the respondent in the systematized psychological based-questionnaire. The questionnaire was pursued in the three languages that are Japanese, English and Indonesia. 39.8% of the respondents were Indonesian, 44.90% were Japanese and 15.30% were various foreign citizens who lived in Japan. The criteria to select the respondent are based on their limited prior information to the produce newness of moss. Only 10% of respondents who are familiar with the moss produce as shown in Fig. 3. The questionnaire was proposed using a developed approach. It combined the 5 categories of prior information and 24 preferences criteria. The prior information consists of demographic data, prior knowledge, and familiarity, agreement to the produce advantage and their interest to apply the produce.

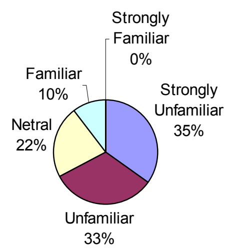

Fig. 3. Prior information of respondent to produce newness

2.2 CAPD Scheme

To incorporate the artificial mentality, a novel CAPD scheme was designed in 3 main sub-schemes. The sub-schemes consists of learning, mental simulation and monitoring as shown in Fig. 4. Learning involves the data acquisition of the developed questionnaire. Mental simulation involves the BBN reasoning to find the best knowledge sources and validated BBN to generate the artificial human mentality. Subsequently, monitoring deal with the classification of customized modules. ANN is utilized to incorporate mentality generated from BBN and produce choice measured from questionnaire by classifying the modules.

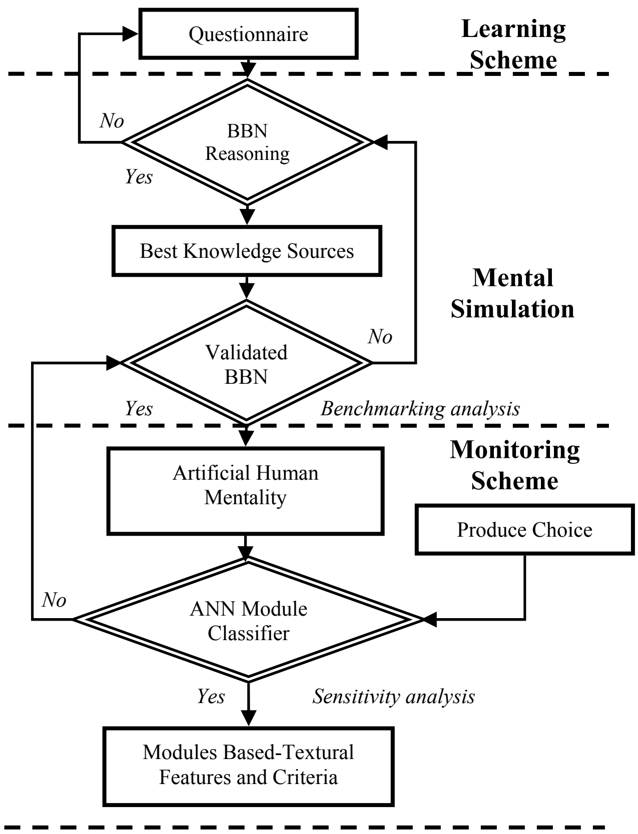

Fig. 4. A novel methodology of customized agro-industrial produce design scheme

2.3 Learning Scheme

The learning scheme in the questionnaire is defined as the following scenario: the respondents are first asked to state their demographic data based on social environment. Secondly they are asked about their prior knowledge and familiarity on new produce of moss. Thereby they are asked to determine their choice by viewing image of 4 (four) moss products.

In the next round, the respondents are then asked to evaluate their agreement on the functions of the related produce. In the light of this new information, they get the probability to change their mentality by making a new evaluation and generating their preferences criteria on produce. Finally they state their interest to apply the produce.

2.4 Artificial Human Mentality

Kansei is a Japanese term in information engineering which means a mixture of the concepts of human feeling, sensibility and emotion (Ishikawa *et al.*, 2003). The human mental simulation was developed using *Kansei* approach to BBN. The primary reason to use *Kansei* is that CAPD scheme should accommodate the consumer learning from questionnaire in the BBN. Artificial human mentality was defined as the probability combination of 5-point Likert scale to solicit specific preferences criteria. The probability of each Likert scale was derived from frequency of the 98 respondent's responses. For example, artificial mentality which solicits the consumer to prefer criteria of 'Produce Texture' has the probability as the following: consumer will prefer scale 1 of 'not very important' is 0.010, scale 2 of 'not important' is 0.041, scale 3 of 'moderate' is 0.388, scale 4 of 'important' is 0.388 and scale 5 of 'very important' is 0.173. The sum of probability must equal to 1.

2.5 Bayesian Belief Network (BBN)

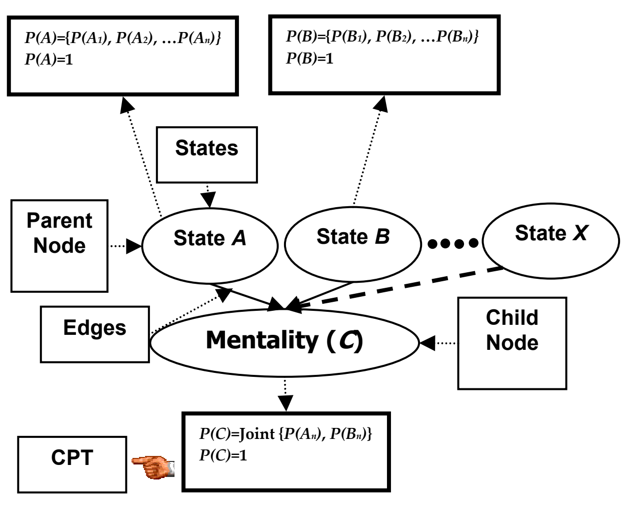

Fig. 5. Basic structure of Bayesian belief network for mentality reasoning

As shown in Fig. 5, the structure of BBN consists of parents (A, $B \ldots X$) and child node (Mentality), which represents variables, and edges, that connect nodes and represent relationship between nodes. The child node has an underlying Conditional Probability Table (CPT) that describes the probability distribution across the states of that specific node for each possible combination of (n) states of the parent nodes. An example of CPT structure with n child node C (Derived probabilities) being influenced by n parent nodes A, B (Prior probabilities) was described in Table 1.

Table 1. Basic structure of conditional probability table

A_n	B_n	C_1	C_2	C_n
A_1	B_n	$P(C_1 \vert A_1 B_n)$	$P(C_2 \vert A_1 B_n)$	$P(C_n \vert A_1 B_n)$
A_2	B_n	$P(C_1 \vert A_2 B_n)$	$P(C_2 \vert A_2 B_n)$	$P(C_n \vert A_2 B_n)$
A_n	B_1	$P(C_1 \vert A_n B_1)$	$P(C_2 \vert A_n B_1)$	$P(C_n \vert A_n B_1)$
A_n	B_2	$P(C_1 \vert A_n B_2)$	$P(C_2 \vert A_n B_2)$	$P(C_n \vert A_n B_2)$
A_n	B_n	$P(C_1 \vert A_n B_n)$	$P(C_2 \vert A_n B_n)$	$P(C_n \vert A_n B_n)$

2.6 Data Base of Moss Water Status

Data base of moss produce modules has been built in Table 2 (Ushada *et al.*, 2007). Temperature and relative humidity were measured each day and remained at approximately 15^{0}C and 80% to 90% respectively. The data were modelled in an intelligent monitoring model. The inputs are textural features and the output is water status fusion (Ushada *et al.*, 2007). The module could be customized based on its parameters.

Table 2. Data base of moss produce modules (Ushada *et al.*, 2007)

Class	Energy ($\times 10^{-4}$)	LH ($\times 10^{-1}$)	Contrast	Moisture Content (% d.b)	Leaf Area Index	Leaf Water Potential (MPa)
Soak	$X \geq 5.5$	$X \geq 1.13$	$X \leq 279$	$X \geq 490$	$X \geq 26$	$X \geq -1.69$
Wet	$3 \leq X < 5.5$	$0.72 \leq X < 1.13$	$279 < X \leq 514$	$243 \leq X < 490$	$15 \leq X < 26$	$-2.22 \leq X < -1.69$
Semi-Dry	$2 \leq X < 3$	$0.61 \leq X < 0.72$	$514 < X \leq 723$	$63 \leq X < 243$	$7 \leq X < 15$	$-2.67 \leq X < -2.22$
Dry	$X < 2$	$X < 0.61$	$X > 723$	$X < 63$	$X < 7$	$X < -2.67$

2.7 Artificial Neural Network

The architecture of network consisted of neuron units in input layer, neuron units in hidden layer and neuron units in output layer. The number of the hidden layer units was determined based on the minimization of output error and adjusting learning coefficient by sensitivity analysis. The training method was the back-propagation by generalized delta rule. The sigmoid function was used for the transfer function of the processing neural network. The training was terminated when the margin of error converged.

3. RESULTS AND DISCUSSION

3.1 BBN Reasoning by Kansei Approach

The *Kansei* analytical framework of BBN for human mental simulation was shown in Fig. 6. The inputs of the model are respondent's prior information. In this paper, the framework is used for modelling 24 preferences criteria. It is expected that by using the necessary prior information of prospective consumer candidate, artificial human mentality which solicit each of their preferences criteria could be generated.

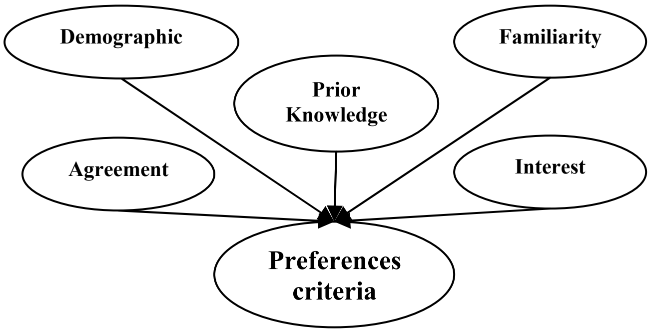

Fig. 6. *Kansei* analytical framework for BBN model

The component of prior information in Fig. 6 is described more clearly in Table 3. The criteria responses were mainly attained through Likert scale by open and closed questions.

Table 3. Prior information of respondent

Categories	Code	Criteria
Demographic	A,B	Age and Gender
	C,D	Education and Occupation
	E,F	Nationality and City
	G	Marital status
Prior Knowledge	H	Urban heat island
	I	Building greening
	J	Moss plant
Familiarity	K	Urban heat island effect
	L	Building greening
	M	Building greening moss plant
Interest	N	Building greening moss plant
Agreement	O	Improving building aesthetic
	P	Controlling the pollution
	Q	Reducing cooling cost
	R	Increasing lifespan of roof
	S	Lower lifetime cost
	T	Contributing better climate
	U	Reducing noise pollution
	V	Resale value of building

3.2 Benchmarking Analysis for Bayesian Belief Network

In this paper, the reasoning was built deterministically from questionnaire. The determined respondent's prior information was used to construct the BBN model. Benchmarking analysis was applied to test the performance of model. 4 BBN models were used in benchmarking analysis. Each of the BBN model has 24 sub-models describing the reasoning of each criterion. Benchmarking was done by varying the CPT method and prior information. BBN1 and BBN2 used the weighted random while BBN3 and BBN4 used the measured CPT. Due to the limited space, details of these two CPT methods can be found in other paper (Ushada and Murase, 2008). BBN 1 and BBN 3 used the artificial prior information from other BBN while BBN 2 and BBN 4 used the measured prior information from questionnaire. The BBN software was developed using C++ programming language.

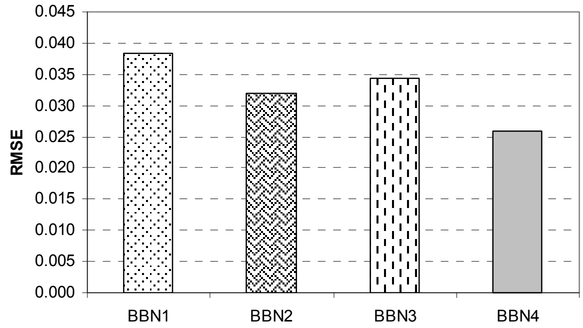

Fig. 7. Benchmarking analysis to attain the best BBN model

The minimum average value of Root Mean Square Error (RMSE) was attained by BBN4 compared to other models as shown in Fig. 7. The difference among them is not significant. Therefore the 4 BBN models are possible to be used. However due to the data originality, BBN4 was used. The satisfied accuracy was shown in Table 4 using the training and validation RMSE of BBN model. For inspection data, the sub-population from Indonesian's respondent was used. It could be concluded that 24 BBN models in BBN4 are possible and ready to be used in the CAPD scheme.

Table 4. Training and validation error of BBN

Code	Preferences criteria	Reasoning	Training Error	Validation Error
1	Texture	1 = *f* {J,N}	0.031	0.042
2	Colour	2 = *f* {O,N}	0.016	0.037
3	Endurance	3 = *f* {R,N}	0.014	0.019
4	Water content	4 = *f* {Q,K}	0.014	0.032
5	Price	5 = *f* {R,N}	0.009	0.024
6	Appearance	6 = *f* {1,O}	0.006	0.012
7	Eye catching	7 = *f* {23,O}	0.016	0.10
8	Moss quality	8 = *f* {M,N}	0.015	0.032
9	Waterproofing	9 = *f* {I,R}	0.007	0.035
10	Structure strength	10 = *f* {I,R}	0.016	0.018
11	Fitness architecture	11 = *f* {I,N}	0.014	0.011
12	Construction size	12 = *f* {I,N}	0.161	0.175
13	Construction slope	13 = *f* {I,P}	0.009	0.036
14	Directional	14 = *f* {I,P}	0.110	0.058
15	Construction height	15 = *f* {I,N}	0.022	0.039
16	Drainage	16= *f* {5,Q}	0.008	0.064
17	Maintenance cost	17= *f* {5,S}	0.005	0.029
18	Easy maintenance	18= *f* {S,N}	0.035	0.062
19	Comfortable	19= *f* {U,N}	0.016	0.054
20	Construction method	20= *f* {P,N}	0.024	0.041
21	Climate	21= *f* {K,T}	0.008	0.048
22	After sale	22= *f* {V,5}	0.052	0.048
23	Cleanness	23= *f* {B,N}	0.001	0.015
24	Ease of ordering	24= *f* {N}	0.001	0.055

The example of BBN to generate the mentality was shown in Fig. 8. It was tested on criteria of texture. The inputs are the consumer knowledge of moss plant and their interest. If a consumer has the neutral knowledge of moss plant and the usual interest to the moss produce, then it could be predicted that he or she will has mentality: 0.053 of not very important, 0.105 of not important, 0.579 of moderate, 0.211 of important and 0.053 of very important. The probability is necessary to be included in the planning matrix of produce design method such as Quality Function Deployment (QFD) (Cohen, 1995).

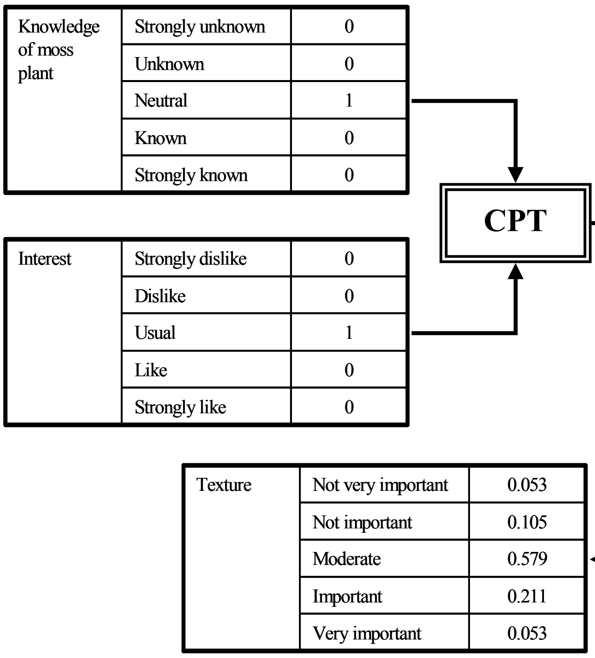

Fig. 8. Example of BBN structure for mentality which solicits criteria of 'Texture' (Code: 1)

3.3 Structure of Artificial Neural Network

The data was recapitulated into 83 set training data and 7 set inspection data. The total 90 set data described the consumer tendency to choose modules 2 (wet) and 3 (dry). The architecture of network was shown in Fig. 9.

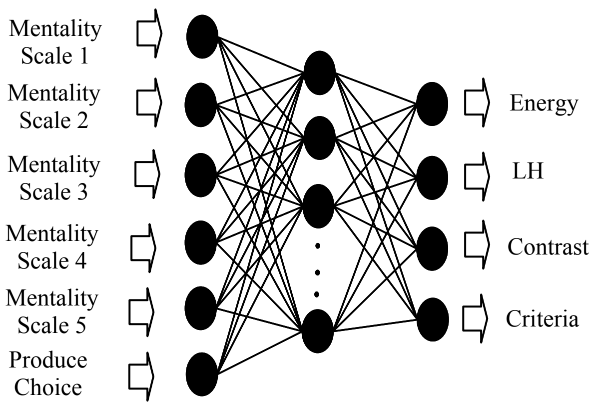

Fig. 9. Artificial neural network model for incorporating artificial human mentality

As the input, 5 scales of human mentality which is generated from the validated BBN and produce choice from questionnaire. The output is the harvested modules based on textural features and Likert's scale criteria in intelligent monitoring of production scheme. In this case study, only one criterion is used as 'Texture'. By using the same structure of ANN, the other 23 criteria are possible to be modelled.

3.4 Sensitivity Analysis for Artificial Neural Network

Table 5. Sensitivity analysis for artificial neural network model

No	Hidden Nodes	Learning Iteration	Training Error	Validation Error
1	4	10000	0.057	0.047
2	6	10000	0.053	0.047
3	8	10000	0.052	0.056
4	10	10000	0.053	0.048

Based on the sensitivity analysis of output error by trial and error basis (Table 5), 6 neurons in the hidden layer were determined. The architecture of network consisted of 6 neurons in the input layer, 6 neurons in the hidden layer and 4 neurons in the output layer (6-6-4).

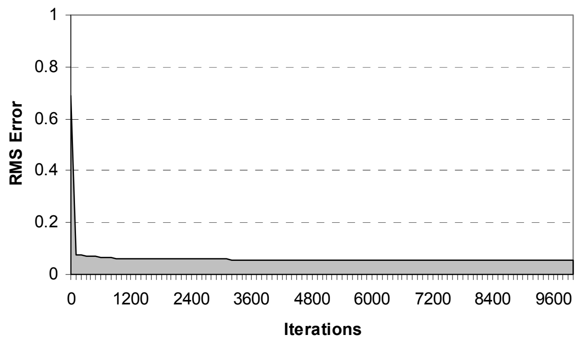

Fig. 10. Learning error of artificial neural network model

The training converged after 10000 iterations, learning coefficient of 0.1 and momentum of 0.9 (Fig. 10). RMSE of training and validation were 0.053 and 0.047 respectively. The result confirmed that using artificial mentality of one preference and the consumer choice, the module could be classified. Plant factory only required the respondent knowledge and their interest to classify the produce modules. By using hybrid method of validated ANN and BBN, plant factory could generate the decision for CAPD more efficient and faster by one criterion rather than collecting 24 criteria.

The comparison between predicted and measured value was shown in Table 6 to indicate the possibility to use it as a CAPD module classifier. By using these link weights from trained ANN, CAPD module can be classified using the artificial consumer mentality.

Table 6. Comparison between measured and predicted value for ANN output

Output Nodes	Measured Value	Predicted Value
Energy Feature	0.000301	0.000301
LH Feature	0.07181	0.07181
Contrast Feature	514.292	514.270
Criteria	4	4.1

Each of choice is possible to be converted in to the module consisted bio-response parameters of textural features, moisture content, leaf area index and leaf water potential using non-destructive sensing (Ushada *et al.*, 2007). The parameters are the main characteristic of agro-industrial produce. Therefore, it could be used as the control parameters in the closed environment systems.

4. CONCLUSIONS

Based on this research result, the following conclusions could be drawn:

1. BBN model by *Kansei* approach attained satisfied accuracy to generate the artificial human mentality. The accuracy was based on the benchmarking analysis, minimum learning error and inspection data.

2. ANN model shown the capability to classify the produce modules by using artificial human mentality. The capability was based on the sensitivity analysis, the minimum learning error and inspection data.

3. The proposed hybrid method of BBN and ANN is possible to model non-linear and complex interaction between bio-response and mentality for CAPD scheme.

4. The artificial human mentality is possible to be incorporated in intelligent monitoring of production scheme for customized agro-industrial produce.

5. Generally, the proposed CAPD scheme is possibly applied for learning, mental simulation and monitoring in the early phase of customized produce development.

6. Specifically, CAPD scheme is applicable for the Agro-industrial and Eco-produce design.

5. SUGGESTION AND FUTURE WORK

The data from questionnaire consists of produce and technological preferences. Therefore the future work is suggested to incorporate the customized technological preferences in a CAPD scheme.

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