Modeling consumer preference for greening material using Bayesian Belief Network and Particle Swarm Optimization

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Abstract: This paper presents research on modeling consumer preference regarding the uses of plant as greening material. This kind of plant is produced in a plant factory for the application of building greening. The objectives of the paper were: 1) To propose modeling consumer preference for greening material by predicting its attributes importance using mentality constraints; 2) To develop the modeling by hybridizing Bayesian Belief Network (BBN) model and Particle Swarm Optimization (PSO). When greening attributes are measured, they can be considered as process parameters in a plant factory control system. The inputs of modeling were a set of consumer mentality constraints as different demographic, their prior knowledge, familiarity, agreement to material function and interest. The output was a predicted attribute importance. BBN and PSO were hybridized to take the advantage of both methods. BBN was used to identify the probability-based reasoning. PSO was used to maximize the satisfaction using the analogy between the consumer preference and social behavior of animal swarm. The modeling was demonstrated on a case study of Sunagoke moss (Rhacomitrium japonicum). These plants were promoted to the respondents using designed questionnaires. A 24 simple BBN model was used to predict each attribute importance. PSO was used to optimize BBN models using a satisfaction function. Hybrid modeling of BBN and PSO has indicated the performance improvement compared to single modeling of BBN. The improvement was based on satisfied correlation and minimum error between measured and predicted value. It was concluded that consumer mentality constraints are possible to be used as inputs to predict an attribute importance of greening material.

Keywords: attribute importance, Bayesian Belief Network, greening material, Particle Swarm Optimization, reasoning

1 Introduction

1.1 Greening material

The merits of plants as greening materials are considered in many studies for the application of building greening. Greening materials have positive effects such as combat environmental problems efficiently (Kivimaa and Mickwitz, 2006), reduce urban heat islands and microclimatic benefit (Ushada and Murase, 2006). A significant success for introducing a new greening material depends on modeling consumer preferences. Modeling consumer preference during product development processes is critical to develop a mass customization (Tseng and Jiao, 1996). The expected outcome is as part of decision support system for mass customization system in a plant factory. Preferences of greening material can be especially complex, unfamiliar, and morally charged (Irwin and Scattone, 1997). The valuation of these special commodities has become an interesting researched area (Ushada, Murase and Fukuda, 2006a). Only a few researches related to preferences of greening material (Emilsson et al., 2007).

1.2 Hypothesis of consumer preference

The current problem of the research in consumer preferences is the difficulty to predict the attribute importance accurately (Horsky, Nelson and Posavac, 2004; Tabatabaei, 2004). An attribute importance is obtained by asking the consumers to evaluate its importance among a given set of materials preference (Barlas, 2003). It is an instrument in evaluating tradeoffs between conflicting attributes of alternative materials, in searching for relevant information for a decision, and interpersonal-communication of preferences (Barlas, 2003). Attribute importance has received remarkable attention in the literature because of its central role in reasoning process (Barlas, 2003).

In the case of greening material, it involves the technical term of attributes which considered being difficult for the new consumer (Emilsson et al., 2007; Irwin and Scattone, 1997). When greening attributes are measured, they can be considered as process parameters in a plant factory control system. The question of importance is considered complex and confusing for consumer (Horsky, Nelson and Posavac, 2004). A complex questionnaire survey was considered relatively inefficient and time consuming. Attributes importance of CBGM remain difficult to be predicted from consumers accurately. The modeling is expected as a solution to predict CBGM attributes importance easily and accurately. There were various researches related to consumer preference for agricultural engineering problems (Adapa et al., 2007; Clarke, L. J, 2000; Cros et al., 2003; Tooy and Murase, 2007) and none of them is related to greening material.

Problems may arise in preference study, such as in gathering a real data, which is timely and costly and deals with the complex factor of the people observed, and in analyzing and simulating complex data (Tooy and Murase, 2007). A modeling technique is required in analyzing and simulating complex data of consumer preference. In this research, modeling is defined as the prediction and optimization of attributes importance. The hypothesis is an attribute importance can be predicted using the consumer mentality constraints. A number theory of human decision has been reviewed to describe the contribution of mentality constraint which controls modeling attribute importance (Alba and Hutchinson, 2000; Doyle, 1987). Prior research demonstrated that mentality help people deal with uncertainty and reasoning (Taylor et al., 1998). A consumer preference model is proposed to simplify the complex questionnaire as shown in Figure 1. Modeling is assumed as a function of an attribute importance and mentality constraints. The inputs are the consumer mentality constraints. The output is a predicted attribute importance.

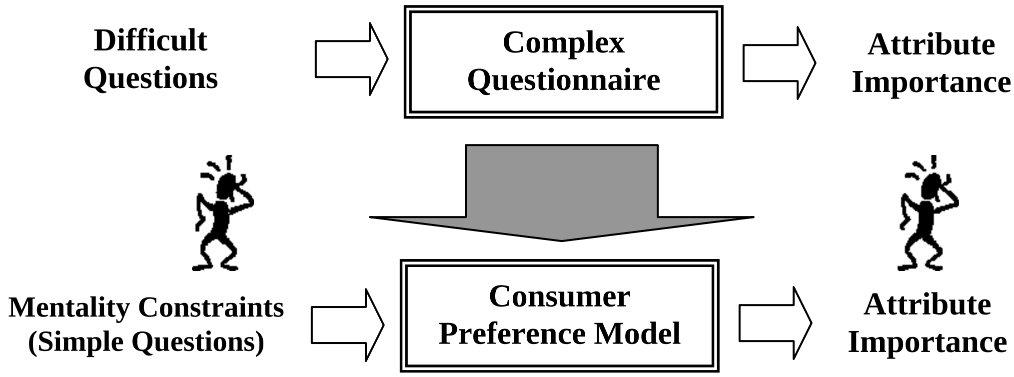


Figure 1 Conceptual model for consumer preference of greening material

1.3 Solution by prediction model

Bayesian Belief Network (BBN) is a type of artificial intelligence based on the probability theory. It is a modeling platform that connects variables through a series of conditional dependences. It allows the use of all available information in identification of reasoning (Bacon, Cain and Howard, 2002). Pomerol (1997) has declared the relationship between reasoning and subjective probabilities. BBN is selected to predict the attributes importance because they have gained a reputation of being powerful technique for modeling probability-based reasoning problems involving expert knowledge and uncertain impact of causes (Bacon, Cain and Howard, 2002).

1.4 Solution by optimization model

A satisfaction function is required to model consumer preferences (Ajzen, 1996). Satisfaction can be categorized as a NP-hard and highly multi-modal complex problem. NP-hard is defined that the time needed to solve the problem increases at a much higher rate than the increase in the size of problem (Kaul and Rao, 1995). Predicting the attributes importance by BBN, makes the plant factory to maximize the preference model based on its mentality constraint.

Originally, Kennedy and Eberhart (1995) proposed the Particle Swarm Optimization (PSO) algorithm, one of the most recent Meta heuristics artificial intelligence, which is inspired from the swarming behavior of animals and human social behavior. It is conceptually based on the social behavior of groups of organism, such as herds, school and flocks. In this paper, PSO is used to maximize the consumer satisfaction using the analogy between consumer preference and social behavior of animal swarm. PSO is required to optimize the BBN. PSO is selected because it has become the alternative to solve NP-hard problem due to the limitations of the exact methods (Liao, Tseng and Luarn, 2007; Jarboui et al., 2008).

1.5 Research objectives

The objectives were: 1) to propose modeling consumer preference for greening material by predicting its attributes importance using mentality constraints; 2) to develop the modeling by hybridizing Bayesian Belief Network model and Particle Swarm Optimization. The modeling was demonstrated on a case study of Sunagoke moss (Rhacomitrium japonicum). The paper is organized as follows: in Section 2, Sunagoke moss and the questionnaire are explained. In section 3, the hybrid modeling of BBN and PSO is highlighted to solve the problem in Section 1. The results are described in Section 4, and it is discussed in Section 5. Finally the paper is concluded in Section 6.

2 Materials

2.1 Respondents and material

A total of 102 consumer candidates from the Japanese, Indonesian and Foreigners were selected as respondents. Each respondent received a souvenir as a compliment to their participation. The foreigners represented the noise segment. The noise condition is considered as the ideal situation related to mentality constraint as defined by Doyle (1987). The noise possibly occurred as the effect of social environment around the respondent. The respondents were clustered into two segments: 51 respondents who choose the wet moss and 51 who choose semi-dry moss.

Sunagoke moss was produced from the plant factory by controlling the water status parameters (Ushada, Murase, and Fukuda 2006b; Ushada, Murase and Fukuda, 2007). It has been used as a building greening material in order to ease urban heat island effect (Murase and Ushada, 2006; Ushada and Murase, 2006). Sunagoke moss was promoted to the respondents using designed questionnaires. The data were acquired as attributes importance and respondent's mentality constraints of a preferred material. The questionnaire provided image visualization of two material as shown in Figures 2a and 2b.

(a) (b)

Figure 2 Visual imaginary of Sunagoke moss used in the questionnaire: (a) Wet moss; (b) Semi-dry moss

2.2 Questionnaire of attributes importance

The questionnaire offered the 24 attributes importance as shown in Table 1.

Table 1 Attributes of moss greening material

Code	Attributes	Information User	Code	Attributes	Information User
1	Texture	Plant Factory	13	Construction slope	Greening Technology
2	Color	Plant Factory	14	Directional	Greening Technology
3	Endurance	Plant Factory	15	Construction height	Greening Technology
4	Water content	Plant Factory	16	Drainage	Greening Technology
5	Price	Greening Technology	17	Maintenance cost	Greening Technology
6	Appearance	Plant Factory	18	Easy maintenance	Plant Factory
7	Eye catching	Greening Technology	19	Comfortable	Greening Technology
8	Moss quality	Plant Factory	20	Construction method	Greening Technology
9	Waterproofing	Greening Technology	21	Climate	Greening Technology
10	Structure strength	Greening Technology	22	After sale	Greening Technology
11	Fitness with architecture	Greening Technology	23	Cleanness	Greening Technology
12	Construction size	Greening Technology	24	Ease of ordering	Greening Technology

When greening attributes are measured, they can be considered as process parameters in a plant factory control system. The Likert scale is equivalent to the absolute importance (Cohen, 1995). The definition of importance is used to determine how important each of design attribute is to the consumer (Cohen, 1995). The entries are chosen from a scaled selection of importance. The number of points on such a scale has been known to range from three to ten (Cohen, 1995). Importance values are obtained by a questionnaire in which respondents are asked to rate the importance of each attributes on 5-point response provided. In this research, 5-point Likert scale is used as follows:

1 = Not at all important to the consumer
2 = Minor importance to the consumer
3 = Moderate importance to the consumer
4 = Very important to the consumer
5 = Highest importance to the consumer

2.3 Questionnaire of mentality constraints

The questionnaire attained respondent mentality constraints as shown in Table 2. The constraint consists of demographic data, prior knowledge, and familiarity, agreement to the material, advantage and their interest to apply the material. The questionnaire was arranged as follows: the respondents were first asked to state their demographic data and their social environment. Secondly they were asked about their prior knowledge and familiarity of moss. Thereby they were asked to determine their choice by viewing the image of materials. In the next round, the respondents were then asked to evaluate their agreement on the functions of the related material. In the light of this new information, they got the probability to make a new evaluation and reasoning the attributes importance. Finally they stated their interest to use the material.

Table 2 Mentality constraints of consumer

Categories	Code	Constraints
Demographic	B	Gender
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

Alba and Hutchinson (2000), Doyle (1987) and Emilsson et al. (2007) suggested some mentality constraints related to consumer knowledge, familiarity, interest and positive effects of the greening material. Mentality constraints are defined as the state of environment which limited the consumer to rate the attributes importance as follows:

- Prior knowledge: a statement of a knowledge that a consumer knows, or could know, or might know a material. As an example of questions: "How could you rank your knowledge of the moss plant".
- Familiarity: a statement of a familiarity that a consumer is familiar, or could be familiar, or might be familiar, with a material. As an example of questions: "How could you rank your familiarity with building greening".
- Agreement to material functions: a statement of an agreement that consumer agrees, or could agree, or might agree, with the function of a material. As an example of questions: "Please indicate how much you agree/disagree with the following function of moss greening".
- Interest: a statement of interest that consumer is likely, or could be likely, or might be likely, to use a material. As an example of questions: "How likely are you to use the building greening using moss plant".

The criteria to select the respondent are based on their limited mentality constraint to the newness of moss greening. As indicated in Figure 3, only 11% of respondents who are familiar with the moss plant as a greening material.

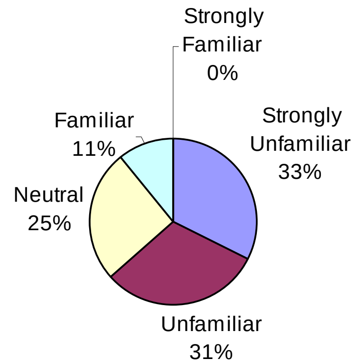


Figure 3 Respondent's familiarity to moss plant as a greening material

3 Methodology

3.1 Consumer preference model

Figure 4 presents a methodology for modeling consumer preference. The modeling was proposed to predict the attribute importance using the mentality constraint. Subsequently, it optimizes the importance using the satisfaction function. The questionnaire provided the learning data for BBN. Prediction was demonstrated using BBN. The inputs of a BBN model are mentality constraints. The output is the predicted importance. Finally, optimization was demonstrated using PSO to maximize the consumer satisfaction. This optimized importance is used as the feedback information for product development in the plant factory.

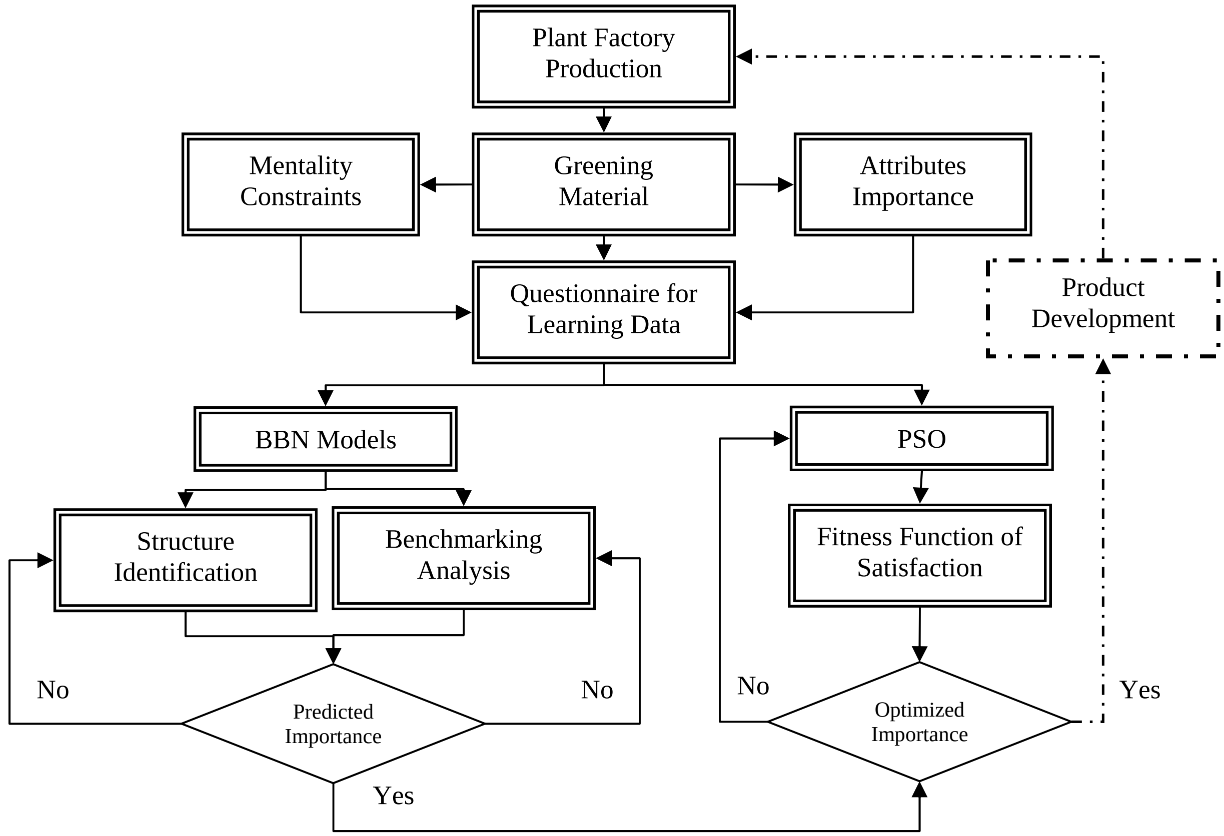


Figure 4 Modeling consumer preference of a greening material

3.2 Bayesian Belief Networks (BBN)

The two steps in developing a BBN are structure learning and prior conditional probability estimation (Heckerman, 1999; Gupta and Kim, 2008). As shown in Figure 5, the structure of BBN consists of independent parents (*A*, *B*…*X*) and child node (An attribute importance), 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.

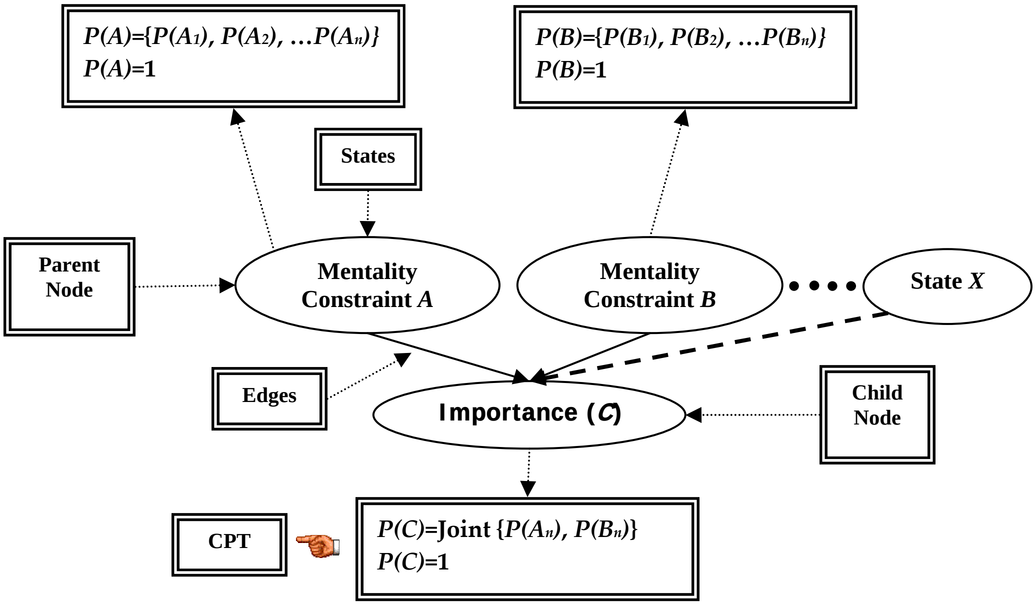


Figure 5 Structure of Bayesian Belief Network for prediction model.

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 3. CPT is a knowledge representation to control the reasoning in BBN. Basic structure of CPT in Table 3 was derived from structure in Figure 5. In this paper, 98 respondents were selected for building the learning CPT algorithm of BBN. Benchmarking analysis is pursued to attain the best CPT. BBN software was developed using C++ computer programming language.

Table 3 Basic structure of conditional probability table

A_n	B_n	C_1	C_2	C_n
A_1	B_n	$P(C_1\|A_1B_n)$	$P(C_2\|A_1B_n)$	$P(C_n\|A_1B_n)$
A_2	B_n	$P(C_1\|A_2B_n)$	$P(C_2\|A_2B_n)$	$P(C_n\|A_2B_n)$
A_n	B_1	$P(C_1\|A_nB_1)$	$P(C_2\|A_nB_1)$	$P(C_n\|A_nB_1)$
A_n	B_2	$P(C_1\|A_nB_2)$	$P(C_2\|A_nB_2)$	$P(C_n\|A_nB_2)$
A_n	B_n	$P(C_1\|A_nB_n)$	$P(C_2\|A_nB_n)$	$P(C_n\|A_nB_n)$

Consumer preference can be modeled by the Bayesian concept as follows:
If a respondent rated an attribute importance x_{ij} which was assumed to be controlled by their mentality constraint y_{ij}, then the probability of an attribute x_k can be formulated in Eq. (1):

$$P(x_k \mid x_{ij}) = \frac{P(x_{ij} \mid x_k)P(x_k)}{\sum_{k=1}^{l} P(x_{ij} \mid x_k)P(x_k)} \quad (1).$$

From the basic mathematical model in Eq. (1), modeling an attribute importance can be formulated as the tradeoffs of 5-point Likert response. The importance and constraints were represented by the probability of each response. The probability of each Likert scale was derived from frequency of each respondent who choose the same material. For example, the importance of `Texture` attribute has the probability as follows: 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 be equal to 1.

3.3 Maximization problem of satisfaction function

In order to use PSO for optimizing BBN, a satisfaction function is defined. Typically a consumer does not have perfect information about the greening material in his or her mentality set. The consumer incorporates this uncertainty and its related constraint by maximizing their satisfaction (Ajzen, 1996). The output of BBN is optimized to attain the Likert responses that are best suited to consumer satisfaction for each attribute.

The maximization problem of satisfaction is defined in a function Eq. (2):

$$U_m(A) = Max\left(\sum_{m=0} CX_{m,1} + CX_{m,2} + CX_{m,3} + CX_{m,4} + CX_{m,5} \right) \qquad (2).$$

This problem is formulated to find the tradeoffs of Likert response for attributes importance that generates the maximum satisfaction of consumer. The satisfaction function is defined as the sum of the tradeoffs of the given Likert scale. *U* is satisfaction of each initial attribute, *A* is notation of importance, *C* is probability of Likert response, *m* is notation of mentality constraint and *X* represents Likert response (5-point scale). In this function, each *C* of an attribute importance was maximized based on limited mentality constraints. The function summed the scores from each single attribute to provide an overall satisfaction score.

3.4 Particle Swarm Optimization algorithm

The optimization of BBN can be modeled using the movement of particle to search the satisfaction function. In this paper, the particle is defined as a candidate solution of the probability of an attribute importance *xk*. The mentality constraint is represented by an m-dimensional real-valued vector, where m is the number of probability of Likert scale which was generated from the BBN model. The proposed PSO algorithm was implemented in C++ computer programming language. The PSO algorithm can be summarized as following steps:

3.4.1 Generate an initial random population

At *n*-th iteration, the *i*-th particle $\varphi_i(n)$ can be described in Eq. (3):

$$\varphi_i(n) = [\sigma_{i,1}(n), \sigma_{i,2}(n), \ldots, \sigma_{i,m}(n)] \qquad (3).$$

Where $\sigma_{i,j}(n)$ represents the position of the *i*-th particle with respect to the *j*-th dimension.
Many particles form a population and it is assumed here that as a set of *Q* particles forms a population as $[\varphi_1, \varphi_2, \ldots, \varphi_Q]^T$. It is the moving velocity of a particle $\varphi(n)$ represented also by an

m-dimensional real-valued vector. At n-th iteration, the i-th particle velocity $V_i(n)$ is expressed in Eq. (4):

$$V_i(n) = \left[v_{i,1}(n), v_{i,2}(n), \ldots, v_{i,m}(n)\right] \quad (4).$$

3.4.2 Termination condition

There are two general conditions to terminate the PSO algorithm: (a) the objective function of the global best is less than a pre-specified value or (b) the number of iterations achieves the maximum allowable number n_{max}. In this study, the second criterion is adopted to terminate the search process.

3.4.3 Finding the individual and global best position

As a particle moves through the search space, it compares its current objective function with the best that it has ever attained so far. The best position associated with the best objective function is called the individual best $P(n)$. For each particle in the population, $P(n)$ is determined and updated during the search. To solve a maximization problem of the BBN model, the individual best $P_i(n)$ of the i-th particle can be determined such that $x_k\left(P_i(n)\right) > x_k\left(\varphi_i(\sigma)\right)$, for $\sigma \le n$. Also, the individual best $P_i(n)$ can be expressed in Eq. (5):

$$P_i(n) = \left[p_{i,1}(n), p_{i,2}(n), \ldots, p_{i,m}(n)\right] \quad (5).$$

Where $p_{i,j}(n)$ is the position of the individual best of the i-th particle with respect to the j-th dimension. The global best is referred to as the best position among all the individual best positions achieved so far. At n-th iteration, the global best $G(n) = \left[g_1(n), g_2(n), \ldots, g_m(n)\right]$ is determined such that $x_k\left(G(n)\right) > x_k\left(P_i(n)\right)$, i = 1,2,…, Q.

3.4.4 Velocity and position updating

According to the above individual best and global best, the i-th particle velocity with respect to the j-th dimension is updated by Eq. (6):

$$v_{i,j}(n+1) = K(\omega \times v_{i,j}(n) + \mu_1 R_1(p_{i,j}(n) - \sigma_{i,j}(n)) \quad + \mu_2 R_2(G_j(n) - \sigma_{i,j}(n)) \quad (6).$$

In this paper iteration wise the inertia weight ω as the function of initial and final weights ω_{min} , ω_{max} and maximum iterations n_{max} in Eq. (7):

$$\omega = \omega - (\omega_{min} - \omega_{max}) / n_{max} \quad (7).$$

It is given by a constant, μ_1 and μ_2 are the positive acceleration coefficients that pull each particle toward the individual best and global best positions, respectively, R_1 and R_2 are uniformly random numbers chosen from the interval $[0,1]$.

For the whole experiments, ω_{max} and ω_{min} were selected as 0.9 and 0.4, respectively. Constants μ_1 and μ_2 were selected as 2.0 and 2.1, respectively. The constriction factor *K* value was set as 0.729. In this paper, *K* and ω were combined in order to make the convergence faster. After obtaining the velocity updating formula, each particle moves its corresponding position according to the following updating in Eq. (8):

$$\sigma_{i,j}(n+1) = \sigma_{i,j}(n) + v_{i,j}(n+1) \qquad (8).$$

3.4.5 Boundary of the velocity and search interval

To prevent the velocity explosion, a parameter maximum velocity V_{max} was used. The value was set as 2.0. Basically if the velocity value exceeds $\pm V_{max}$, it gets reset to $\pm V_{max}$ accordingly. In this approach, the 5-point Likert response is formulated as randomly generated within a pre-specified upper and lower bound limit. The elements of individual response are generated by generating random digits between *C* response of attribute *A* and its *m* constraint. The searching interval $[\sigma_{min}, \sigma_{max}]$ is set for each position element σ. As the boundary, if any resulting parameter violates the constrained interval during search process, set it the corresponding bound in Eq. (9):

[(σ_{min} =0), (σ_{max} = upper limit of *A or m*)], if $A = m$

[(σ_{min} = Lower limit of *A*), (σ_{max} = upper limit of *m*)], if $A < m$

[(σ_{min} =Lower limit of *m*), (σ_{max} = upper limit of *A*)], if $A > m$ (9).

As the maximum value of satisfaction should equal to 1, the feasible solution was normalized.

3.5 Weighted average importance index

Each importance generated from PSO was quantified using Weighted Average Importance Index (WAII). WAII in Eq. (10) is the index of perception of consumer on how important the offered material is meeting their satisfaction:

$$WAII = \frac{\sum_{k}\left[\left(N_A \times k\right)\right]}{N_t} \qquad (10).$$

Where *NA* is number of respondents at importance value *k*, *NT* is total number of respondents, and *k* is grade of importance (1, 2, 3, 4 and 5 of Likert response). If almost all respondent answered a question with the same value, then the reaction of the respondent base would be homogenous with respect to their satisfaction. However, there is a possibility that the answers may not cluster around a single value.

3.6 Performance of the model

In order to know the performance of the preference model, the Root Mean Square Error (RMSE) was used as shown in Eq. (11):

$$E_{rms} = \sqrt{\frac{1}{N}\sum_{i=0}^{N}\left[\hat{Y}_m(x_i) - Y_m(x_i)\right]^2} \quad (11).$$

where: E_{rms} is root mean square value, the subscript m indicating the m^{th} pattern in considering a group of patterns; N is the number of data; $\hat{Y}_m(x_i)$ is the predicted value; $Y_m(x_i)$ is the real value of the output and i is iteration for number of data.

4 Results

4.1 Structure identification of Bayesian belief network

24 modeling structures were identified and were statistically independent as shown in Table 4 (mean Intercorelation = 0.15; range = 0 to 0.352). Simple BBN structure was selected in order to proactive clarify likely changes and the development of reasoning as reported in Bacon, Cain and Howard (2002). The simple structures of BBN were built based on the low correlation of the involved variable in the reasoning.

Table 4 Independence test of variable inputs based on R^2

Code	Attributes importance	Reasoning	R^2 Inputs	Correlation
1	Texture	1 = *f* {J,N}	0.1238	0.352
2	Colour	2 = *f* {O,N}	0.0971	0.312
3	Endurance	3 = *f* {R,N}	0.0424	0.206
4	Water content	4 = *f* {Q,K}	0.0155	0.124
5	Price	5 = *f* {R,N}	0.0424	0.206
6	Appearance	6 = *f* {1,O}	0.00008	0.0089
7	Eye catching	7 = *f* {23,O}	0.002	0.044
8	Moss quality	8 = *f* {M,N}	0.0224	0.15
9	Waterproofing	9 = *f* {I,R}	0.01	0.1
10	Structure strength	10 = *f* {I,R}	0.01	0.1
11	Fitness architecture	11 = *f* {I,N}	0.0536	0.231
12	Construction size	12 = *f* {I,N}	0.0536	0.231
13	Construction slope	13 = *f* {I,P}	0.0107	0.10344
14	Directional	14 = *f* {I,P}	0.0107	0.10344
15	Construction height	15 = *f* {I,N}	0.0536	0.231
16	Drainage	16= *f* {5,Q}	0.0055	0.074
17	Maintenance cost	17= *f* {5,S}	0.005	0.0707
18	Easy maintenance	18= *f* {S,N}	0.0047	0.068
19	Comfortable	19= *f* {U,N}	0.1121	0.334
20	Construction method	20= *f* {P,N}	0.0974	0.312
21	Climate	21= *f* {K,T}	0.0111	0.105
22	After sale	22= *f* {V,5}	0.0124	0.111
23	Cleanness	23= *f* {B,N}	0.0009	0.03
24	Ease of ordering	24= *f* {N}	0	0
	Mean		**0.03**	**0.15**
	Range		**0 to 0.1238**	**0 to 0.352**

4.2 Benchmarking analysis of conditional probability table

Benchmarking analysis was applied to test the performance of CPT. Four CPT were used. CPT1 and CPT2 used the weighted random data while CPT3 and CPT4 used the measured data from questionnaire. Details of these CPT methods can be found in other paper (Ushada and Murase, 2008). The minimum average value of RMSE was attained by CPT4 compared to other models as shown in Figure 6. The difference among them is not significant. Therefore the four CPT are possible to be used. CPT4 was used in 24 simple BBN models due to the measured data.

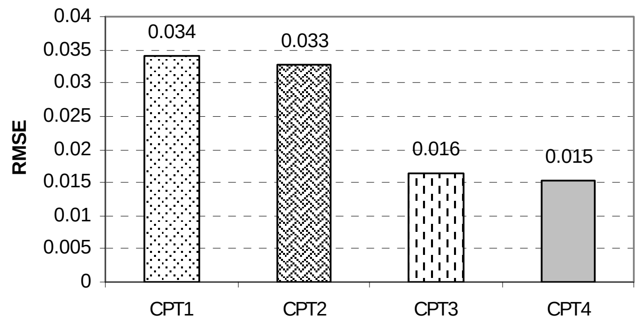


Figure 6 Benchmarking analysis to attain the best CPT

4.3 Prediction Model of Bayesian Belief Network

The example of BBN to predict an attribute importance was shown in Figure 7. The importance of texture attribute (Code: 1) is predicted using the respondent knowledge of the moss plant (Code: J) and their interest (Code: N). If a respondent has the `Neutral` knowledge of moss plant and the `Usual` interest to the moss greening, then it could be predicted that he or she has probability of reasoning the attribute: 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`.

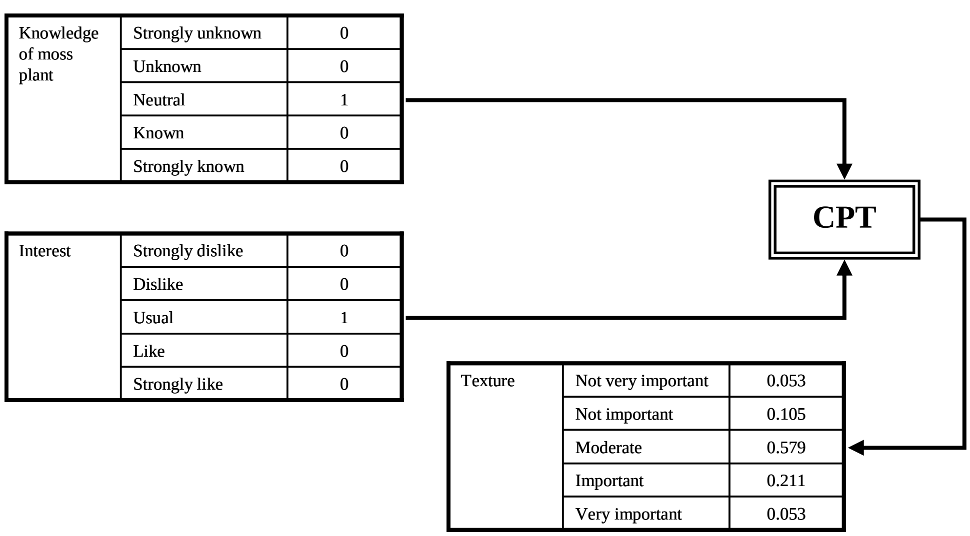


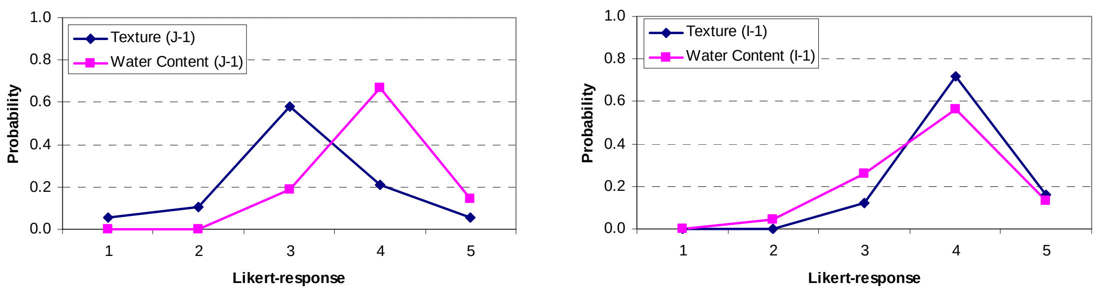
Figure 7 Example of BBN structure for the importance of “Texture”

Satisfied accuracy of 24 BBN models were indicated in Table 5 based on RMSE of learning and validation. For the validation, Sub-populations from Indonesian's and Japanese's respondent were used.

Table 5 Learning and validation error of BBN

Code	Reasoning	Learning Error	Validation Error For Japanese	Validation Error for Indonesian
1	1 = *f* {J,N}	0.031	0.049	0.042
2	2 = *f* {O,N}	0.016	0.049	0.037
3	3 = *f* {R,N}	0.014	0.041	0.019
4	4 = *f* {Q,K}	0.014	0.038	0.032
5	5 = *f* {R,N}	0.009	0.018	0.024
6	6 = *f* {1,O}	0.006	0.029	0.012
7	7 = *f* {23,O}	0.016	0.078	0.10
8	8 = *f* {M,N}	0.015	0.026	0.032
9	9 = *f* {I,R}	0.007	0.035	0.035
10	10 = *f* {I,R}	0.016	0.021	0.018
11	11 = *f* {I,N}	0.014	0.021	0.011
12	12 = *f* {I,N}	0.002	0.031	0.039
13	13 = *f* {I,P}	0.009	0.074	0.036
14	14 = *f* {I,P}	0.023	0.080	0.058
15	15 = *f* {I,N}	0.022	0.029	0.039
16	16= *f* {5,Q}	0.008	0.055	0.064
17	17= *f* {5,S}	0.005	0.027	0.029
18	18= *f* {S,N}	0.035	0.015	0.062
19	19= *f* {U,N}	0.016	0.033	0.054
20	20= *f* {P,N}	0.024	0.010	0.041
21	21= *f* {K,T}	0.008	0.046	0.048
22	22= *f* {V,5}	0.052	0.097	0.048
23	23= *f* {B,N}	0.001	0.008	0.015
24	24= *f* {N}	0.001	0.031	0.055

For the inspection data, the attributes importance was predicted by using validated BBN. The inspection data was intended to customize the preference between the Japanese and Indonesian respondents as shown in Figure 8. The inspection data were applied to the attribute "Texture" and "Water content" of the greening material. By using BBN model, the consumer preference could be customized for different segments using its attributes importance.

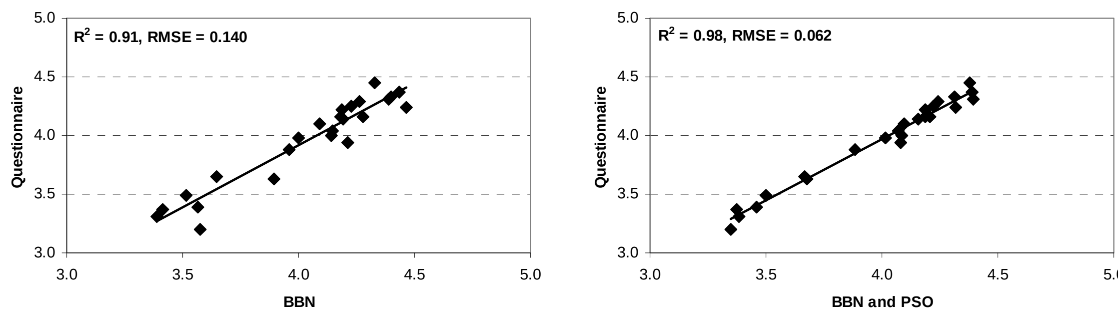


(a) (b)

Figure 8 Predicted attribute importance; (a) Japanese; (b) Indonesian

4.4 Particle Swarm Optimization

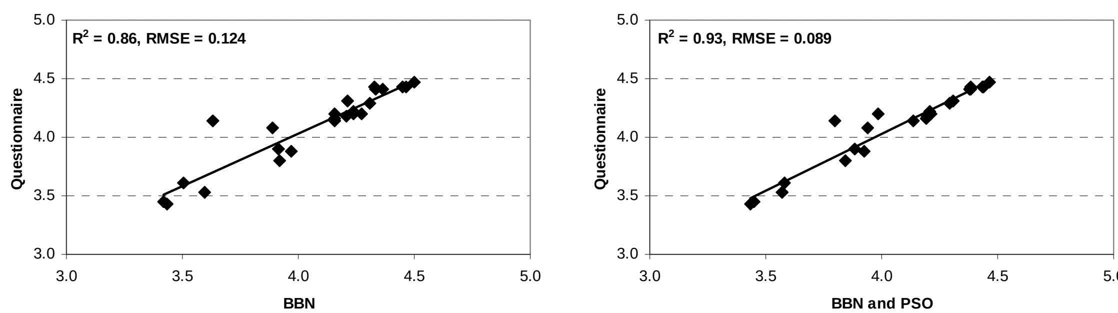
Hybrid of BBN and PSO has indicated better performance compared to single modeling of BBN. Figure 9 indicates that PSO can improve the performance of BBN to predict the attributes importance of wet moss. There is an improvement of R^2 WAII value from 0.91 to 0.98 between measured and predicted values. Mean value of RMSE 24 attributes improved from 0.140 to 0.062.



(a) (b)

Figure 9 Improvement of R^2 WAII for wet moss; (a) BBN model; (b) Hybrid model of BBN and PSO

Figure 10 indicates that PSO can improve the performance of BBN to predict the attributes importance of semi-dry moss. There is an improvement of R^2 WAII value from 0.86 to 0.93 between measured and predicted values. Mean value of RMSE 24 attributes improved from 0.124 to 0.089.



(a) (b)

Figure 10 Improvement of R^2 WAII value for semi-dry moss; (a) BBN model; (b) Hybrid model of BBN and PSO

5 Discussion

5.1 Prediction using Bayesian Belief Network

Model of consumer preference was identified using a probabilistic-based reasoning of 24 simple BBN models. A significant benefit is that mentality constraints can become a critical input for a reasoning model designed to maximize the satisfaction. In these BBN models, uncertainty preference variables were incorporated as probability of Likert response.

In order to generate the accurate reasoning structure, an independence test for variable input. The independence test generated the correlation values of 24 BBN structure ranged from 0 to 0.352. The entire correlation confirmed with Srivastava, Connoly and Beach (1997) that the lower value of correlation less than 0.5 is necessary to minimize the subjectivity in preference. Some of the attributes importance is inferred from other attributes as appearance (Code: 6), eye catching (Code: 7), drainage (Code: 16), maintenance cost (Code: 17) and after sale (Code: 22). However, one of the parent nodes from these attributes reasoning is the other attribute which is inferred from the mentality constraints. As an example, the appearance attribute can be predicted using texture attribute (Code: 1) and mentality constraint stated how far the agreement to the function of moss material can improve building aesthetic (Code: O). In other side, the texture attribute can be predicted by knowing the respondent knowledge constraint of the moss plant (Code: J) and their interest (Code: N). This kind of reasoning structure is confirmed and as reported in Bech-Larsen and Nielsen (1999).

The 24 BBN models generated the satisfied performance with the minimum RMSE of learning and validation. By using BBN, preference reasoning can be modeled with satisfied accuracy. Mentality constraints are possible to be used to predict the attributes importance in preference reasoning. Therefore in the subsequent application, the plant factory can offer the simple questions of mentality constraints to attain the complex information of attributes importance.

5.2 Optimization of BBN using Particle Swarm Optimization

A 24 BBN models was optimized using PSO. When selecting a PSO for an optimization problem, the needs of the specific problem formulation should be addressed. Maximizing satisfaction is one of the optimization problems in consumer preference (Kaul and Rao 1995). Hence for the PSO, the satisfaction function was used as a fitness function. Problem of maximizing satisfaction was confirmed by Albritton and McMullen (2007). They reported that modeling consumer preference can focus upon a wide variety of areas. The extant marketing and psychology theory suggests that consumer create preferences based on their perceptions and will inevitably make the decision for a given product (Kaul and Rao 1995). In this paper, the perceptions are defined as attributes importance. It is possible that consumer satisfaction directly affect reasoning the most important attribute. Hence, optimization problem is required to maximize the satisfaction function.

PSO is used to make an analogy between the consumer preference and animal swarm behavior which move as particles (For example as a bird in the nature). After the initialization of position and velocity from the particle, the search process begins. As stated in Eq. (5), the search process for a single particle is based on the personal best. A particle makes “decisions” based on their experience. Here, a particle will go through the various position based on satisfaction function of each attribute. To reiterate, the satisfaction function in Eq. (9) is based on probability distribution from not very important (Scale 1) to very important (Scale 5). Each time a particle is faced with a decision regarding the fitness function, a particle with exchange this personal decision to other particle until the global best decision is generated. In this term, the global best is an attribute importance consists of optimal tradeoffs of Likert response.

The same mechanism is assumed on consumer satisfaction in the reasoning an attribute importance of greening material. The complexity of greening material as reported in Irwin and Scattone (1997) should be solved by pursuing the tradeoffs of consumer response (Barlas 2003). Hence, we assumed that the consumer will act like as if they were particle swarm. This assumption confirmed with the theory of social context reported from Barlas (2003). Most decisions are made within social contexts and/or require tradeoffs. However, Barlas (2003) stated that a decision maker may place importance on the attributes in such a way as to protect and enhance her self-image and approval from others. In PSO, we used the opposite analogy from Barlas (2003). PSO algorithm simulated as if the consumer exchanges their personal experience each other to attain the same satisfaction.

In the modeling of wet and semi-dry moss, the improvement of R^2 of WAII and mean value of RMSE indicated that consumer satisfaction in reasoning the importance can be maximized using PSO. By hybridizing BBN model and PSO algorithm, the preferences could be customized using its attributes importance.

5.3 Limitations and directions for future research

A main limitation of this research is the limited variety of greening material to distinguish the different preferences. The variety is essential for the research which wants to explore more about greening material. The originality of our research focus on predicting and optimizing an attribute importance based on the consumer mentality constraints. There is an opportunity to strengthen the current study by extending this modeling to other agricultural products. Irwin and Scattone (1997) have reported that greening material is relatively difficult to be modeled due to the complexity of attributes. This research is possible to be applied to other agricultural products which have same or less complexity.

6 Conclusions

The research results concluded that mentality constraints are possible to be used as input to predict an attribute importance in modeling consumer preference of greening material. It is indicated from the satisfied performance of the 24 simple Bayesian Belief Network (BBN) models. The structures of model were determined based on the independence test and benchmarking analysis of conditional probability table. The performance was based on minimum root mean square error of validation and inspection data. Furthermore, the inspection data has indicated that the attributes importance could be customized between the Japanese and Indonesian preference. By using the mentality constraints, the attributes importance of a preferred material could be customized into different consumers.

On the other side, hybrid modeling of BBN and Particle Swarm Optimization (PSO) is a feasible method to model consumer preference. PSO has indicated the capability to optimize the 24 simple BBN models for different greening materials. The coefficient of determination (R^2) and mean value of RMSE between measured and predicted attribute importance was improved by hybridizing BBN and PSO. It indicated that hybrid modeling of BBN and PSO perform better compared to single modeling of BBN. The modeling is applicable to simplify the complex questionnaire in data acquisition of consumer preference.

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