# An Approach to Improve the Efficiency of Configurators

Yue Wang, Mitchell M. Tseng
Advanced Manufacturing Institute, The Hong Kong University of Science and Technology, Hong Kong

*Abstract* - **Configurators have been generally accepted as important tools to bridge the gap between customers' needs and company offerings in the form of specific instances of product platform. To date, improving the efficiency of configurators is a big challenge for both the academic research and the current practice in the competitive global marketplace. In this paper, a new configurator design approach is presented to tackle the configuration task in an efficient manner by providing adaptive and customized configuring sequence for individual customers to best match his preference towards the products. To represent and manipulate the probabilistic nature of customers' preferences, Bayesian network is deployed to reflect the product physical structure and the likelihood of the customers' potential preferences among components. The configuring process is modeled as an uncertainty elimination process and an information theory based algorithm is applied to obtain customers' targeted configuration. The idea is to sequentially select the component with most relevant information for a customer to configure from the remaining components pool based on his previous steps' specification. A case study is reported to demonstrate the feasibility and potential of the proposed method.**

*Keywords* – **configurator, Bayesian network, product design.**

## I. INTRODUCTION

Configurators have been generally accepted as powerful tools to capture customers' requirements. A product configurator consists of a set of predefined components for customers to choose. Some constraints on these components are also included to ensure that the selected components work compatibly. It takes customers' needs as inputs and the output is the desired product, i.e. the configuration. In the studies of customers' decision making processes, it has shown that customers have higher satisfaction with configuring process than traditional selection process, not only in the results of decision but also the decision process [1]. Therefore, configuration has been applied to bridge the gap between customers' needs and company offerings.

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The authors are with Advanced Manufacturing Institute, The Hong Kong University of Science and Technology, Hong Kong (e-mail: yacewang@ust.hk; tseng@ust.hk).

To date, configurators are connected with mass customization intimately in that they facilitate the objective of capturing customer's needs and providing tailored products so that the service level is improved and profit can be increased. Especially due to the development of internet, it is possible for companies to acquire immediate information about customer's requirement and meet them by delivering customized products or related information in real time. Well-known examples of such configuration system can be found in the homepage of some cell phone, lap top and automobile companies etc.

But now there are still some limitations and shortcomings which haven't been paid enough attention in previous research [2]. Among them the efficiency is a big challenge for the research. The manual configurator can be tedious and time consuming when the product is complex. As for online configurators, because it has been widely acknowledged that online customers are impatient [3], it is crucial to develop a configurator which can capture customers' needs quickly and be less demanding for customers' attention and time. To overcome this problem, a method is proposed in this paper to improve the efficiency of configurators. A probability based configurator is designed to deal with the task of configuring under uncertainty and incomplete information. The constructs include products represented with a Bayesian network which reflects the likelihood of the physical constraints and customers' potential preferences between components/attributes. Thus the new method takes into considerations both products' physical structure and customers' preferences. In addition, due to the nature of customers' preferences, the configuration task is tackled in the probabilistic domain rather than deterministic domain which is unique from the previous research. An information theory based algorithm is provided to obtain customers targeted configuration efficiently and with less input. The idea is to select the most informative component to specify and as a result, the uncertainty can be eliminated once customers' requirements are configured. The intent of this new approach is to equip configurators with adaptive and customized configuring sequence for individual customers to specify what they want based on their inputs in prior steps. In other word, each customer has a customized configurator which best match his preference towards the components.

## II. LITERATURE REVIEW

Since 1970s, the research on configuration system has drawn much attention due to its advantage of speeding the assembly and manufacturing process, increasing customer satisfaction, and reducing technical error etc. Digital Equipment Corporation (DEC) developed a program called R1 (also called XCON internally) in 1978 to configure VAX computer systems to customer specification [4]. It was first put to use in 1980 and by 1986, it had processed 80,000 orders, achieving 95-98% accuracy. Ever since then, a large number of configuration expert systems had been developed and put into use, such as Cossack [5], BLADES [6] and MICON [7]. All these systems are rule based reasoning systems which derive solutions in a forward chaining manner. But this kind of systems often suffers from the maintenance due to the lack of separation between domain knowledge and control strategy and the spread of information on a particular attribute over several rules especially when the configurator system is complex.

Mittal and Frayman first treated configuration task as the constraint satisfaction problem [8]. In their framework, a configuration task is to assign values to all the variables without violating any constraints. To make configurator function under dynamically changing environment, Mittal and Falkenhainer also modeled the configuration task as a sequence of dynamic Constraint Satisfaction Problems (CSP) in which both the ports and variables are considered as variables in a CSP domain [9]. Both compatibility constraints and activity constraints were introduced into the extension to specify conditions under which configuration can dynamically include or exclude component based on current selections. D. Sabin and E. Freuder proposed an idea that represented the configuration task as a new class of nonstandard constraint satisfaction problem called composite CSP. It provided a more comprehensive and efficient basis for formulating and solving configuration problems [10]. They also provided methods to detect redundancies and inconsistencies in activity constraint as a further research [11]. Gelle and Faltings developed a general framework to deal with the *mixed* and *conditional CSP* problems [12]. In this method, both discrete and continuous variables were considered. Xie et al proposed *Dependent CSP* [13] in which variables are classified into two groups, dependent variables and independent variables. Dependent variables are eliminated to improve the efficiency of configuration searching strategy.

Based on previous study on configurator design, the configuration task involves two basic steps, representation of the domain knowledge in which a configurator functions and the solving algorithms which drive the configurator to produce a solution. This paper also follows these two steps. In section 3, the probability based domain knowledge representation is introduced. It also discusses the configuring algorithm. An example is shown in section 4 to illustrate the approach. The last part is the concluding remarks.

## III. METHODOLOGY

### A. *Domain knowledge representation*

Before the configuring process, it is impossible to know what a customer wants for each component since individual customers may have different requirements and tastes. Hence the customers' preferences are random variables and the knowledge cannot be represented in the deterministic domain properly. This paper uses Bayesian network to represent customers' preferences and the physical structure of the product. Customers' preferences towards the components and their influence relationships are depicted by the conditional probabilities. The hard constraints among components can also be revealed by Boolean conditional probabilities with value 0 or 1. Customers' preferences information can be obtained from customers' survey, previous customers' configuration data or even domain expert.

A Bayesian network is a directed acyclic graph in which each node is annotated with quantitative probability information. In a formal language, a Bayesian network is a triplet *(V, A, P)* in which

- *V* is a variable set. In the network, the variables are represented by nodes.
- *A* is a set of arcs which connect the nodes. *V* and *A* constitute a directed acyclic graph $G = (V, A)$.
- *P* is a conditional probability set. $P = \{P(X \mid parent(X)) : X \in V\}$. Here *parent(X)* is the set of parents nodes of *X*.

Two methods can be applied to construct a Bayesian network. If enough data are available, the relationships among different nodes can be discovered by statistical learning approaches [14]. Otherwise, to deep understand the influence relationships among the variables, domain experts are indispensable for building a Bayesian network. When constructing Bayesian network, we require not only that each variable be directly influenced by only a few others, but also that the network topology actually reflect those direct influences with the appropriate set of parents. Therefore, the appropriate order in which to build a Bayesian network is to add the root causes node first, then the variables they influence and so on until we reach the leaves which have no direct causal influence on other variables [15].

For a configuration system, one can identify some key components that are crucial to implement some functions in many design domains. For example, an audio card is important for a computer audio processing PC. These key components can be used as the root nodes when building a Bayesian Network. What is more, customers' special interests which are not commonly captured can also be used as key components. Provided enough data, the Bayesian Network can also be built from statistical learning which is more suitable for the case that little domain knowledge is known [14]. The conditional probabilities associated with the nodes in the network can be calculated as follows:

$$P(N_i = v_{ik} \mid \Pi_{N_i} = w_{ij}) = \frac{N_{ijk}+1}{N_{ij}+r_i} \quad (1)$$

where $v_{ik}$ is a value of variable $N_i$, $w_{ij}$ is an instantiation of the parent set $\Pi_{N_i}$, $r_i$ is the number of different values of variable $N_i$, $N_{ijk}$ is the number of cases with variable $N_i$ having the value $v_{ik}$, and $\Pi_{N_i}$ is instantiated as $w_{ij}$ with $N_{ij} = \sum_{k=1}^{r_i} N_{ijk}$.

The Bayesian network structure can also be generated through knowledge elicitation from experts if the historical data on the quantitative aspect of the BN are hard to find. Actually this method is more common for the BN construction. Accordingly, the parameters can be assessed by experts as well. Currently, many methods have been proposed for the probability assessment like the assessment scale developed by Renooij et al [16].

### B. *Product configuring process*

In the Bayesian network based mechanism, a configurator is modeled as a sequence of components proposed to customers to specify the values. An efficient configurator should sequentially select the most informative component in the remaining components pool and add it to the sequence. The "most informative component" means the component which can provide the most information and eliminate most uncertainty. In this paper, some concepts and techniques from information theory are used to develop the method.

The concept of entropy in information theory describes how much information or uncertainty there is in a signal or random event. For a discrete random event x, with possible states 1,…,n, its entropy can be defined as follow:

$$H(x) = -\sum_{i=1}^{n} p_i \log_2 p_i \quad (2)$$

Here $p_i$ is the probability that x is in state *i*.

During the configuring process, new evidences (component alternative) are revealed step by step. The new evidence will affect the probability distribution of unrevealed components. In information theory, the value of a random variable Y provides information to another random variable X whenever it change the probability distribution of variable X from the prior one {P(X)} to the posterior one {P(X|Y=y)}. The measure of this information is defined as $f(X \mid Y = y)$, i.e., the additional information received from the value of another variable. Based on Shannon's work [17], the expectation of $f(X \mid Y = y)$ when average over y should be the mutual information of X and Y, i.e.,

$$E\left[f(X \mid Y = y)\right] = I(X;Y) \quad (3)$$

In Blachman's paper [18], he showed that the form of $f(X \mid Y = y)$ is not unique based on different additional conditions. Two information measures of the function are proposed which are referred as $I(X;Y)$ and $J(X;Y)$. The definitions are:

$$\begin{aligned} I(X;Y) &= H(X) - H(X \mid Y = y) \\ &= \sum_x p(x)\log\frac{1}{p(x)} - \sum_x p(x \mid y)\log\frac{1}{p(x \mid y)} \end{aligned} \quad (4)$$

$$J(X;Y) = \sum_x p(x \mid y)\log\frac{p(x \mid y)}{p(x)} \quad (5)$$

The first measure represents the difference of the *a priori* and *a posteriori* entropies of X, i.e., the reduction in uncertainty about X given value y. The latter one is the expected relative entropy between event $x_i$ and $y$ regarding the *a posterior* probability distribution of X. It represents the dissimilarity of the *a priori* and *a posteriori* belief about X. Usually, a high degree of dissimilarity indicates useful evidence. Blachman also proved that $J(X;Y)$ is unique as a non-negative information measure satisfying (3). Along with other properties, it is more important and useful of the two measures. In this paper, $J(X;Y)$ is adopted as the metric to evaluate the usefulness of the new evidence, i.e., the value of the component. Formally, the selected component is defined as:

$$\begin{aligned} Y^* &= \arg\max_Y I(X;Y) \\ &= \arg\max_Y E[J(X;Y)]. \\ &= \arg\max_Y \sum_{y \in Y}\sum_x p(x \mid y)\log\frac{p(x \mid y)}{p(x)} \end{aligned} \quad (6)$$

In summary, the configuring algorithm is as follows:

Step 1: Based on the Bayesian network structure, set all the nodes having no predecessors in the candidate set C.

Step 2: Compute the relative entropy of each component in the candidate set by equation (6).

Step 3: Find the node that has the biggest information gain in set C and remove it to the solved set S. If there are ties between the nodes, arbitrarily choose one.

Step 4: Remove the newly found node's (in step 3) direct successors to the candidate set C if all the successor's predecessors are in the solved set.

Step 5: Update the probability distribution according to equation (1) or other means.

Step 6: If the candidate set is empty, stop. Otherwise, go to step 2.

It should be noted that the components configuring order of different customers may differ a lot because different specification of one component will lead to distinct subspace within which the final configuration should be found. Therefore this is a customized configurator tailored to customers' preferences.

## IV. CASE STUDY

This section is to illustrate the approaches proposed in this paper with an example of a simplified personal computer configurator to demonstrate the configuring process. A set of PC components and alternatives are listed in Table 1. And we also get 41 customers' preferred configurations. To simulate the real market situation, the 41 "customers" are asked to select the basic level, entertainment level and high performance PC respectively based on their preferences. The configuration results are list in appendix.

TABLE I
LIST OF COMPONENTS AND THEIR ALTERNATIVES FOR PC

| Component | Code | Description |
|---|---|---|
| Processor (A) | A1 | Pentium E2160 1.8G |
| | A2 | Pentium E2180 2.0G |
| | A3 | AMD Athlon™ 64 X2 |
| | A4 | Intel Core 2 Duo E4300 1.8G |
| | A5 | Intel Core 2 Duo E4500 2.2G |
| | A6 | Intel Core 2 Duo E4600 2.4G |
| Memory (B) | B1 | 512MB DDR2 |
| | B2 | 1GB*DDR2 |
| | B3 | 2GB*DDR2 dual channel |
| Monitor (C) | C1 | 17' LCD |
| | C2 | 19' LCD |
| | C3 | 20' LCD and above |
| Hard Disk (D) | D1 | 80GB |
| | D2 | 160GB |
| | D3 | 250GB |
| Disk Driver (E) | E1 | 24X CD-RW/DVD* Combo |
| | E2 | 48X CD-RW/DVD* Combo |
| | E3 | 8X DVD+/-RW* |
| | E4 | 16X DVD+/-RW* |
| Display Card (F) | F1 | NVIDIA® GeForce® 6150 |
| | F2 | Intel® Graphics Media Accelerator 3000 |
| | F3 | Intel® Graphics Media Accelerator |
| | F4 | 128MB PCIe™ x16 ATI Radeon™ |
| | F5 | 256MB PCIe™ x16 nVidia® GeForce® |

Several experts are consulted to help build the Bayesian network of home used PC which is shown in figure 1. It should be noted that for other uses like the scientific computing or large workstation, the Bayesian network may vary a lot. While this paper only focuses on home PC. The conditional probabilities can also be calculated from the configuration data based on (1) which are omitted here.

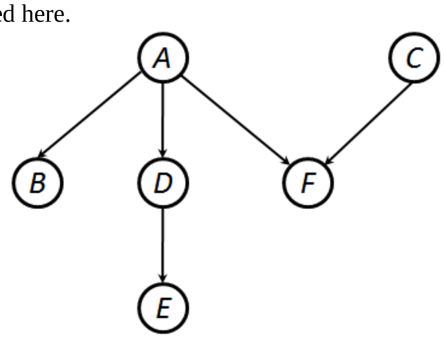


Fig 1. The Bayesian network of home PC

In the first step, the candidate set is {A, C}. From (6), $E[J(X;Y=A)] = 4.78$ and $E[J(X;Y=C)] = 2.01$. Thus component A (processor) should be configured first and the updated candidate set is {B, C, D}. Suppose one customer has the preference set {A4, B2, C1, D3, E3, F3}. Then we can also compute the relative entropy of the second round. $E[J(X \setminus A, A = A4; Y = B)] = 0.61$, $E[J(X \setminus A, A4; Y = C)] = 0.61$ and $E[J(X \setminus A, A4; Y = D)] = 0.69$. Then the second configured component is D. By the same method, the following components configuring sequence are E, B, C, F. Thus for this customer, the configuring order is A, D, E, B, C, F.

If another customer's preference is {A1, B2, C1, D2, E2, F1}, the corresponding configuring order is A, C, B, D, E, F.

Form this example we can see that different preferences will lead to different configuring order. Thus the configurator is an adaptive and customized one. In this simplified example, the advantage may not be obvious. But for the complicated product which has more components to be configured, this mechanism can guarantee a more efficient configuring procedure. With a fixed number of specified components, this approach can eliminate more uncertainty.

## V. CONCLUSION

In this paper, a new configurator framework is proposed. It bridges the gap between current academic research and practical configurators. The main contributions are as follows:

- The framework takes both product physical structure and customers' preferences into consideration. Because configurators are the link between customers and product family, it should not only be manufacturing oriented but also customer-orientated. However, little attention has been paid in previous research. This paper does some exploration in this new direction.
- Previous research on configurators is mostly in deterministic domain. The Bayesian networks enable not only to represent but also to provide the necessary tools to manipulate the probabilistic nature of customers' preferences in configuration process. Thus, the likelihood of the customers' potential preferences among components can then be taken into consideration in addition to the product physical structure of product family.
- The configuring process is considered as an uncertainty elimination process. The new configurator mechanism chooses the next most informative component from the remaining components pool and as a result, it guarantees that each time a customer input a specification, more uncertainty can be eliminated. Customized questions sequence catered to individuals can then be proposed according to customer's information gathering during the

configuration process. Consequently, different customers may have different set of questions and their sequences. It is expected that redundant questions can be reduced. As a result, customers can get what they want quickly and with fewer burdens.

## APPENDIX

TABLE II
CUSTOMERS' CONFIGURAITON DATA

| Customer | Processor | Memory | Monitor | Hard | Disk | Display |
|---|---|---|---|---|---|---|
| 1 | A1 | B2 | C1 | D1 | E3 | F2 |
| 2 | A1 | B2 | C1 | D1 | E1 | F1 |
| 3 | A1 | B1 | C1 | D1 | E2 | F1 |
| 4 | A1 | B2 | C1 | D2 | E2 | F2 |
| 5 | A1 | B2 | C1 | D2 | E1 | F1 |
| 6 | A1 | B1 | C1 | D2 | E2 | F2 |
| 7 | A1 | B2 | C1 | D2 | E2 | F1 |
| 8 | A1 | B2 | C1 | D2 | E1 | F2 |
| 9 | A1 | B2 | C2 | D2 | E2 | F2 |
| 10 | A2 | B2 | C1 | D2 | E2 | F1 |
| 11 | A2 | B2 | C1 | D2 | E3 | F1 |
| 12 | A2 | B2 | C1 | D2 | E2 | F2 |
| 13 | A2 | B2 | C1 | D2 | E3 | F2 |
| 14 | A2 | B2 | C1 | D3 | E2 | F1 |
| 15 | A2 | B2 | C1 | D3 | E3 | F1 |
| 16 | A2 | B3 | C1 | D3 | E2 | F1 |
| 17 | A2 | B2 | C2 | D3 | E2 | F2 |
| 18 | A2 | B3 | C2 | D3 | E2 | F3 |
| 19 | A3 | B2 | C1 | D2 | E2 | F2 |
| 20 | A3 | B2 | C1 | D2 | E3 | F2 |
| 21 | A3 | B3 | C1 | D2 | E2 | F3 |
| 22 | A3 | B2 | C2 | D2 | E3 | F2 |
| 23 | A3 | B2 | C1 | D3 | E2 | F2 |
| 24 | A3 | B2 | C2 | D3 | E3 | F3 |
| 25 | A3 | B3 | C2 | D3 | E2 | F3 |
| 26 | A4 | B2 | C1 | D2 | E2 | F2 |
| 27 | A4 | B2 | C1 | D2 | E3 | F3 |
| 28 | A4 | B2 | C1 | D3 | E2 | F3 |
| 29 | A4 | B3 | C1 | D3 | E2 | F2 |
| 30 | A4 | B2 | C2 | D3 | E3 | F4 |
| 31 | A4 | B3 | C2 | D3 | E3 | F4 |
| 32 | A4 | B3 | C2 | D3 | E4 | F4 |
| 33 | A5 | B2 | C1 | D2 | E3 | F3 |
| 34 | A5 | B3 | C1 | D3 | E3 | F4 |
| 35 | A5 | B2 | C2 | D3 | E3 | F4 |
| 36 | A5 | B3 | C2 | D3 | E4 | F5 |
| 37 | A5 | B3 | C3 | D3 | E4 | F5 |
| 38 | A6 | B2 | C1 | D3 | E3 | F4 |
| 39 | A6 | B3 | C2 | D3 | E4 | F4 |
| 40 | A6 | B3 | C2 | D3 | E4 | F5 |
| 41 | A6 | B3 | C3 | D3 | E4 | F5 |

## REFERENCES


[1] S. H. Kurniawan, M. M. Tseng and R. H. Y. So, "Consumer Decision Making Process in Mass Customization," In *Proceedings of the 2003 World Congress on Mass Customization and Personalization*, F. Piller, R. Reichward and M. Tseng eds. 2003, pp. 267-282

[2] M. M. Tseng, and F. Piller, "New Direction for mass Customization," In *The Customer Centric Enterprise*, F. Piller, R. Reichward and M. Tseng eds. 2003, pp. 519-535.

[3] L. Enos, "Report: Five Keys for E-Tail Success" [online]. E-Commerce Times. Avalible from: http://www.ecommercetimes.com/story/7743.html

[4] J. McDermott, "R1: An Expert in the Computer Systems Domain". In: Proceedings of the 1st Annual National Conference on Artificial Intelligence, Stanford University, California: Stanford University, 1980, pp269-271.

[5] F. Frayman and S. Mittal, "Cossack: A Constraint based expert system for configuration task," In *Knowledge-based Expert Systems in Engineering: Planning and Design.* Boston: Computational Mechanics Publication, Sriram, D. and Adey, R. ed. 1987, pp143-166.

[6] F. Elturky, and R. Nordin, "BLADES: an expert system for analog circuit design," In *Proceeding of the IEEE Symposium on Circuit and System*, San Jose, CA, 1986, pp552-555.

[7] W. Birmingham, A. Brennan and D. Siewiorek, "MICON: A single board computer synthesis tool," IEEE Circuits and Devices Magazine, vol 4, no. 1, pp37-46. 1988

[8] S. Mittal, and F. Frayman, "Towards a generic model of configuration task," In *Proceedings of International Joint Conference on Artificial Intelligence*, Calilfornia: Morgan Kaufmann, 1989, pp1395-1401.

[9] S. Mittal, and B. Falkenhainer, "Dynamic Constraint Satisfaction Problems," In *Proceedings of American Association for Artificial Intelligence*, Boston, MA 1990, pp25-32.

[10] D. Sabin, and E. Freuder, "Configuration as Composite Constraint Satisfaction," In *Proceedings of the first Artificial Intelligence and Manufacturing Research Planning Workshop*, AAAI Press. G. F. Luger, eds. 1996, pp153-161.

[11] D. Sabin, and E. Freuder, "Detecting and resolving inconsistency and redundancy in conditional constraint satisfaction problems," [online]. Available from: http://citeseer.ist.psu.edu/sabin98detecting.html

[12] E. Gelle, and B. Faltings, "Solving mixed and conditional constraint satisfaction problems," *Constraint*, vol 8. no.2, pp107-141.2003

[13] H. Xie, P. Henderson, J. Neelamkavil, and J. Li, "A systematic search strategy for product configuration," In *Proceedings of the 17th international conference on Innovations in applied artificial intelligence.* Springer, pp718-727. 2004

[14] F. Jensen, *Bayesian networks and decision graphs.* New York: Springer. 2001

[15] S. Russell, and P. Norvig, *Artificial Intelligence, A Modern Approach*. NJ: Prentice Hall. 2003

[16] S. Renooij, and C. L. M. Witteman, "Talking probabilities: communicating probabilistic information with words and numbers,". *International Journal of Approximate Reasoning.* 22(3), 169-194. 1999

[17] C.E. Shannon, "A mathematical theory of communication," *Bell Sys. Tech. J.*, vol. 27, pp.379-423, July 1948

[18] N. M. Blachman, "The amount of information that y gives about X," *IEEE Trans. Inform. Theory*, vol. IT-14, no. 1, pp. 27-31, Jan. 1968

[19] S. Mittal, and B. Falkenhainer, "Dynamic Constraint Satisfaction Problems," In *Proceedings of American Association for Artificial Intelligence*, Boston, MA 1990, pp25-32.