Bayesian Networks for Estimating the User's Interests in the Context of a Configuration Task

Wilken Schütz, Ralph Schäfer[1]

DFKI GmbH, Stuhlsatzenhausweg 3, 66123 Saarbrücken, Germany
Wilken.Schuetz@dfki.de, Ralph.Schaefer@dfki.de

Abstract. Nowadays, many configurable products and services are sold via web. For supporting a customer in configuring the desired product, the interaction with the configurator has to be personalised according to the user's interests. In this paper, we show how these interests can be estimated. In an idealisation, we ascribe the Multi-Attribute Utility Theory as evaluation process to the user. Based on this assumption, Bayesian networks are described which are able to interpret the user's observable behaviour in situations which typically occur in a configuration session, for example setting / changing a parameter value or accepting / rejecting a solution.

Keywords. Bayesian network, estimation of user interests

1 Introduction

Today, many companies offer to their customers the possibility to configure individually tailored products via the Web. A configuration can be seen as a special kind of design, where the configured product is composed of instances of a set of predefined components, which interact in certain ways [SW98]. Configuring products can be a very complex task if a large number of parts has to be determined. The number of legal configurations is usually restricted by functional criteria, limitations of technical nature and the customer's requirements and interests, that may be unique to each individual configuration process [Stu97].

When customers are offered to configure the products themselves, the problem is that many products are so complex that the system has to assist the customer (also called the user of the system) in fulfilling the configuration task. For example, the system could select the values of parameters for the user or provide her[2] with default values. For this purpose, the system has to know the user's interests. The problem is how to estimate these interests? During the configuration, there are several typical situations in which the user's behaviour can be observed:

- In the beginning, the system may ask the user about her interests and the user assesses herself. However, this self assessment should not be taken for granted, because there could be a misunderstanding about the meaning of certain terms.

---

[1] This work takes place with support of the IST-Programme of the European Union (Contract: IST-1999-10688 CAWICOMS). The project Web page is `http://www.cawicoms.org`.

[2] In the following we use female pronouns for the user.

- Before the configuration starts and during the configuration process, the user has the option to specify values for some parameters.
- After the system has calculated a valid configuration, this configuration will be presented to the user. Then, she has to decide whether she accepts the solution and finishes the configuration process.
- The user also can change values in a configuration and resubmit it for a reconfiguration.

The question is, how these observations can be used in order to estimate the user's interests. This raises the following issues: What does it mean, if the user

- expresses some interest in an interest dimension such as reliability of a product;
- selects a parameter and specifies a value;
- accepts (or rejects) a configured product;
- changes a parameter's value in a configuration?

The problem is that in the above described situations, the user's interest can only be estimated with uncertainty. So, there is a necessity for an inference mechanism which is able to deal with uncertainty. Here, we will show, that Bayesian networks are an adequate inference mechanism and describe how to solve the above mentioned problems with them.[3]

2 Context: Configuration Workbench CAWICOMS

The focus of CAWICOMS[4] is to enable businesses to market complex customisable products and services by the new methods of electronic commerce. For this purpose, CAWICOMS aims at the following two main goals:

- Enabling integration and collaboration of distributed, heterogeneous Web based configurators.
- Providing adaptation and personalisation of user interactions with the new generation of distributed configurators.

A prototype workbench for configurators achieving those goals has to be developed. On a very abstract architectural level, it is split into the *Backend*, to allow distributed configuration, and the *Frontend*, to provide a personalised interaction with the user (see [CC00]).

Personalisation is realised by using different personalisation strategies, which are represented in form of rules. To decide which strategy to use, the model of the current user is critical, because it allows assumptions about knowledge level, preferences and interests of the user. The user model is created and adapted during the whole

[3] Another approach to support the user of a Web-based configuration system on the basis of high level properties is the application of case-based reasoning (CBR) as shown in [WB98]. The advantage of that method is that the behaviour of the system is more independent on the initially modeled knowledge and there is no need to know completely which properties influence which parameters. However, our approach is much more efficient, because there is no need to store a large set of cases. Another advantage is that the uncertainty of the interpretations of the user's observable behaviour is taken into account.

[4] CAWICOMS is the acronym for „**C**ustomer-**A**daptive **W**eb **I**nterface for the **Co**nfiguration of Products and Services with **M**ultiple **S**uppliers".

interaction process. In this paper, we concentrate on the updating of the part of user model which represents the user's interests.

To realise and test the CAWICOMS workbench, guiding application scenarios were defined. They are realistic, practical problems of the project's industrial partners. One scenario, which is used for illustration purposes in this paper, deals with the configuration of telecommunication switches (TeComs) according to the customer's needs. The basic switching functionality has to be provided as like as additional features like Voice-Mail and add-on hard- and software to fulfil the whole needed functionality.

3 MAUT as Idealisation of the User's Evaluation Process

In an idealisation, we ascribe to the user the Multi-Attribute Utility Theory (MAUT) (see [WE86]) as evaluation process (cf. [JSS+95]). In this section, we will describe MAUT and show how it can be applied in the telecommunication switch domain.

According to MAUT, the overall evaluation *v(x)* of an object *x* is obtained by a weighted addition[5] of its evaluation with respect to its relevant *value dimensions* [WE86]. For example, a telecommunication switch can be evaluated on the value dimensions *fastness*, *reliability*, *extensibility*, and *economy.* This is expressed in the following *overall value function*:

$$v(x) = \sum_{i=1}^{n} w_i v_i(x) .$$

Here, $v_i(x)$ is the evaluation of the object on the *i*-th value dimension d_i and w_i the weight determining the impact of the *i*-th value dimension on the overall evaluation (also called the *relative importance* of a dimension), *n* is the number of different value dimensions, and $\sum_{i=1}^{n} w_i = 1$.

For example, in Table 1 the ratings of different configurations of a TeCom are shown. According to the user's interest shown in Fig. 1, TeCom A would be evaluated as 5*0.3+6*0.15+4*0.15+1*0.4 = 3.4, whereas TeCom B would get a better evaluation with 2*0.3+3*0.15+2*0.3+3*0.15+10*0.4 = 5.4.

Dimension	Rating of TeCom A	Rating of TeCom B
Fastness	5	2
Reliability	6	3
Extensibility	4	3
Economy	1	10

Table 1. Ratings of different configurations of a TeCom

The evaluation on a value dimension is obtained by a weighted aggregation of the evaluation of the relevant attributes. In order to evaluate attributes, it is necessary to

[5] There are other possibilities for aggregation which are described by [WE86].

construct a scale representing the properties of the *levels (values)* of an attribute (parameter). Very often there is already a natural scale. For example, a scale representing the levels of the attribute '*hard disc capacity'* of the TeCom object would simply measure the '*hard disc capacity'* in MB. Within a given interval of values - we use the interval from 0 to 10 - each value of the parameter is assigned a *rating*[6]. Higher values represent higher preferences. In this way a *value function* is constructed. For example on dimension reliability, a higher '*hard disc capacity'* is more valuable than a lower one.
The overall evaluation scheme can be visualised by a *value tree* (see Fig. 1 and Fig. 2 for an example).

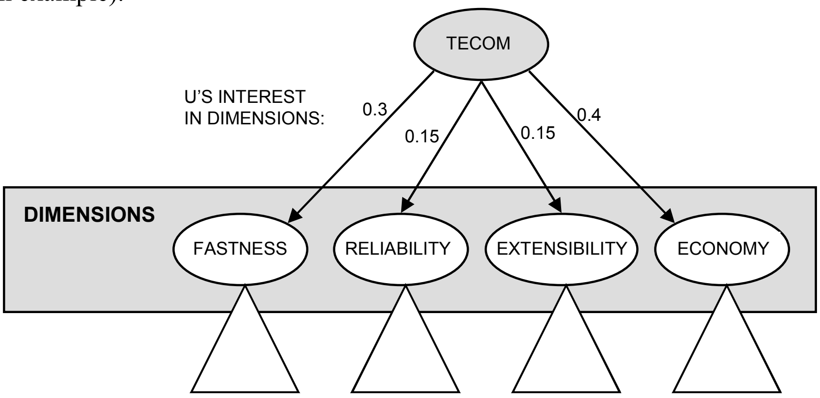

Fig. 1. Simplified value tree for the evaluation of a telecommunication switch.

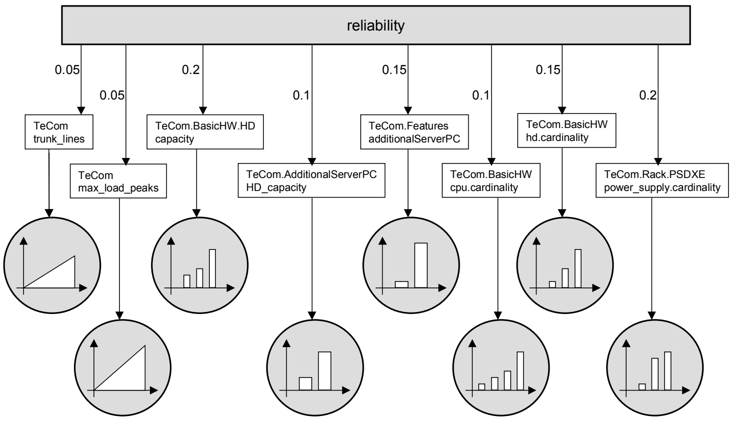

Fig. 2. Fragment of a value tree for the evaluation of a TeCom on dimension "reliability".

---

[6] Usually, one speaks of assigning a value as the result of the evaluation. However, the term "value" is used within this context to refer to the "value of a parameter", which corresponds to the "level of an attribute".

For each value dimension d_i the evaluation $v_i(x)$ is obtained analogously by the evaluation of the relevant attributes:

$$v_i(x) = \sum_{a \in A_i}^{n} w_{ai} v_{ai}((l(a)).$$

Here A_i is the set of all attributes relevant for value dimension d_i, $v_{ai}(l(a))$ is the evaluation of the actual level (or value) *l(a)* of attribute (or parameter) a on dimension d_i. w_{ai} is the weight determining the impact of the evaluation of attribute *a* on value dimension d_i. w_{ai} is also called *relative importance of attribute a* for d_i. For all d_i *(i=1,...,n)* holds $\sum_{a \in A_i}^{n} w_{ai} = 1$. In our application, we assume that the evaluation of the value of an attribute a $v_{ai}(l(a))$ is the same for all users. We also employ the simplifying assumption that all w_{ai} are the same for all users.

Since we assume that the evaluation functions are the same for all users and also the weights of the attributes for their relevant dimensions, we can calculate the evaluation of a product (v_i) on a dimension for a given user.

The model described here for obtaining an overall evaluation is an idealisation. However, using a model representing the user's evaluation technique would not be desirable for two reasons:

- The evaluation process of a person is usually not very well structured. On the one hand, the outcome of the evaluation often turns out to be unsatisfying for the evaluator. For example, people often buy products which they do not find as useful as they thought before, because they did not take into account all relevant information for evaluation. Using a model which reflects such an evaluation process would not help the user in really finding the appropriate product, but only a product of which she thinks at the moment of choosing that it would be appropriate. On the other hand, if a company has to decide whether it will buy a costly product, it will evaluate this product very thoroughly in order to make the right decision. For supporting such evaluation processes, MAUT was developed.
- The user modelling application in CAWICOMS must be able to process many users at a time. Therefore, it is necessary to simplify the assumed evaluation process.

There are other evaluation schemes which also take into account dimensions for evaluation of objects. For example, VDI 2225 is used for technical, economical evaluation of objects in constructing domains. However, VDI 2225 does usually not take into account weights and requires that the dimensions are chosen in a way that they have the same impact on the overall evaluation [Ste99]. This criterion is quite artificial and does not reflect the user's evaluation process.

The information about evaluating the domain objects is represented in an *ontology*. This information is closely related to the configuration model, which contains the needed information for solving the intrinsic configuration task. So, we provide an ontology that adds the necessary knowledge for user modelling to the configuration model.

In additio, we define dimensions and specify relations between those dimensions and parameters of the configuration model. Besides the identification of the dimension and the related parameter, such a relation comprises the specification of the relative weight of the parameter for the dimension. Furthermore, a function is defined, which maps the values of the parameter to a value for the dimension.

4 Stereotypes for Initialisation of the User Model

Using stereotypes is a common way to handle user models. A stereotype defines a class of users with particular properties and allows to infer knowledge about the user.
A stereotype contains a body where values are specified for certain elements of the user model. These values are usually true for a user to whom that stereotype is applied. In a configuration system, a typical example for information, that is assigned to a stereotype, are default values or value ranges of a parameter. Also triggers are comprised in the definition of stereotypes. A trigger specifies inputs or events that cause the assignment of a stereotype to the user. The set of stereotypes are organised in form of a generalisation hierarchy. Sub-stereotypes inherit every information from their ancestors in that hierarchy, except for values which are explicitly overridden [Ric88].
In our context, we are particularly interested in the user's interests in different dimensions, so a stereotype's body specifies these interests. For example, the stereotype could be defined dependent on the growth of the company. A fast growing company would be very interested in extensibility whereas a non-growing company would not be interest in extensibility.
Using simple stereotypes is not enough in the configuration context, because there is much uncertainty. Therefore, the stereotypes specified here are used for defining the a priori probabilities of Bayesian networks (see Sections 5 and 6).
At the moment we only consider a fix set of stereotypes and then adapt the estimated interests during every dialogue. But in the future it will be an interesting task to adapt the stereotypes themselves (i.e. the triggers and the inferred estimations) over a longer time and many different dialogues.

5 Bayesian Networks as Inference Mechanism

A *Bayesian network* (BN) is a kind of a probabilistic network represented as directed acyclic graph (see [Pea88]). The *nodes* of this graph represent random variables, which consist of a set of mutually exclusive and exhaustive propositions which are called *hypotheses*. For each of these hypotheses, the probability of being true is maintained. All these probabilities together are called a *probability distribution,* also named the *belief of a node*. The dependencies between the propositions are represented by the *links* between the nodes. A *conditional probability table* (CPT) expresses such a dependency.
For the root nodes, a priori probabilities must be defined. The belief of a node that is not a root node can be predicted on the basis of the parent nodes' beliefs. Observed

evidence will be interpreted and used to update the beliefs of the nodes of the network. This process is called *solving the network*. A detailed description of this process can be found in [Pea88].

6 Interpretation of the User's Actions

In this section, we will describe Bayesian networks which can be used for learning the user's interests. In CAWICOMS, there will be also networks to interpret the user's actions which are relevant for estimating the user's expertise (or knowledgeability). These networks are not described here, since they are out of scope of this article. In the networks presented here, we assume that the user knows the implications of the attribute on all relevant dimensions. By combining the networks for estimation the user's knowledgeability this assumption can be relaxed. However, the networks would be more complex (cf. [Sch98]).

Currently, the CPTs are being defined by the designers of the networks. Therefore, some are only a rough estimate, they can be refined, for example by using an empirical study in the future. Within the project CAWICOMS, an evaluation of the whole system is planned. The results of these evaluations will also be used for refining the CPTs.

6.1 Self Assessment

6.1.1 Description of the Situation

The user gives a self assessment of her interests in the different value dimensions. Here, the user has to rate her interests on a scale from 0 to 1. Although it seems that in this way it may be very easy to get a fairly correct estimate of the user's interests by an interview, there are some problems:

- The user may not understand correctly the implications of the dimensions, and therefore gives a false self assessment.
- If explicitly asked, the user may wish to hide her real interests.

There are other methods with which better results can be obtained than a mere rating. However, even there much uncertainty is involved.

6.1.2 Meaning of the Situation

The user's self assessment gives at least some qualitative hints about her interests. Nevertheless, they should not be taken for granted. It is probable, not sure, that the assessment given by the user reflects her real interests.

6.1.3 Bayesian Network for Handling the Situation

The network for handling a user's self assessment is illustrated in Fig. 3. The higher the user's interest in a dimension is (see node U'S INTEREST IN DIMENSION D), the higher her given rating of her interest in this dimension will be (see node U'S SELF ASSESSMENT OF HER INTEREST IN DIMENSION D). The a priori probabilities for U'S INTEREST IN DIMENSION D are defined by the user model using stereotypes (see Section 4). By instantiating node U'S SELF ASSESSMENT OF HER INTEREST IN DIMENSION D and solving the network, the estimates of the user's interest will be updated.

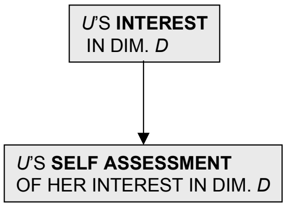

Fig. 3. Fragment of a value tree for the evaluation of a TeCom on dimension "reliability".

6.2 Accepting or Rejecting a Solution

6.2.1 Description of the Situation

When the system has configured a product, the product will be presented to the user. She then has the choice to accept this solution or to reject it. Besides a simple rejection, the user has the possibility to change the instantiated values of some of the parameters (see section 6.3).

6.2.2 Meaning of the Situation

If the user accepts a solution, she is most probably content with the configured product. In addition, she usually will be convinced that it is very difficult to configure an even better product. The better the product is evaluated, the more she will be convinced. That means, the better a product is evaluated by a user the more probable it is that she will accept the solution.
If she rejects the configuration, it will be probably a bad solution, where she assumes that changing some of the parameters' values should result in a solution which has a higher evaluation according to her interests.

6.2.3 Bayesian Network for Handling the Situation

Fig. 4 depicts the BN for the interpretation of the user's acceptance of a configured product. The following description holds for all dimensions d_i (i=1,...,n.). Instead of d_i, we will simply use d in our description. The estimate of U'S INTEREST IN DIMENSION D is obtained from the user model. The evaluation of the current configuration c of the product on dimension d (see node EVALUATION OF C ON D) is calculated with help of the knowledge which is stored in the ontology. The evaluation is done according to MAUT as described in Section 3. U'S WEIGHTED

EVALUATION OF C ON D results from multiplying U'S INTEREST IN DIMENSION D and EVALUATION OF C ON D.
By adding U'S WEIGHTED EVALUATION OF C ON D for all dimensions U'S OVERALL EVALUATION OF C ON D is estimated. The better U'S OVERALL EVALUATION OF C ON D is the more probable an ACCEPTANCE OF C BY U will be.

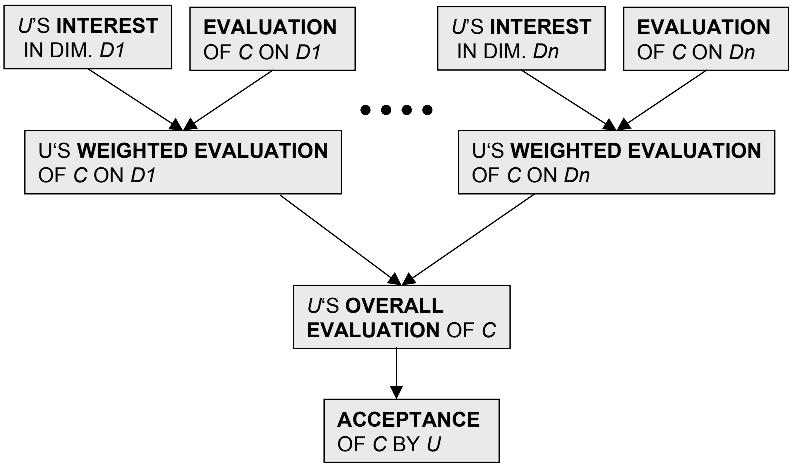

Fig. 4. BN for processing the acceptance /rejection of a solution by the user.

There are two possibilities for using this network in the configuration context:

- Prediction: If the system has to decide which instances of a set of configurations should be presented to the user, it can use the network to predict whether the user will probably accept a configuration or not. Then, the system could present the configuration where it is most probable that the user will accept it.
- Interpretation: If it is observed that the user accepts (rejects) the configuration, the node ACCEPTANCE OF C BY U is instantiated with "yes" ("no"). By solving the network the beliefs of the nodes (especially of U'S INTEREST IN DIMENSION D) are updated.

6.3 Changing a Parameter's Value

6.3.1 Description of the Situation

The system presents a configured product/service to the user. Then, the user changes one or more parameters. After each change, the system has to update its estimate of the user's interests.

6.3.2 Meaning of the Situation

The user's motivation to change a parameter's value comes from the idea that the configured product will be better than if the parameter is left unchanged. Changing a parameter also implies a risk for the user, because she cannot be sure that this change will lead to a change in another parameter and thus neutralising or even worsening the currently configured product. So, if the gain in the overall evaluation of the product is high, then the change most probably will be made. Otherwise, it is less probable that the user will change the parameter.

6.3.3 Bayesian Network for Handling the Situation

The network for handling this situation is depicted in Fig. 5. It is similar to the network in Fig. 4, but the difference here is that we have to estimate the evaluation shift on dimension d caused by the change of the parameter from its original value v_1 to its new value v_2 (see node EVALUATION SHIFT OF P ON D). This results from calculating the absolute difference of the evaluations of v_1 and v_2. Those two single evaluations are done according to MAUT as described in Section 3. As described in Section 6.2.3, the estimate of U'S INTEREST IN DIMENSION D is obtained from the user model. U'S WEIGHTED EVALUATION SHIFT OF P ON D is calculated by multiplying U'S INTEREST IN DIMENSION D and EVALUATION SHIFT OF P ON D. Also U'S OVERALL EVALUATION OF C ON D results by adding the weighted evaluation shifts.

The higher U'S OVERALL EVALUATION SHIFT OF C ON D is, the more probable it will be that the user really changes the value of the parameter from v_1 to v_2 (see node VALUE CHANGE OF P BY U).

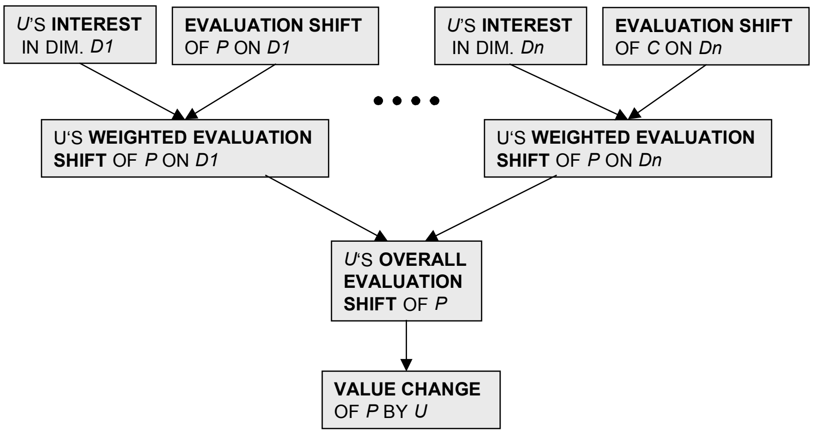

Fig. 5. BN for prediction/interpretation of a change of a parameter value by the user.

6.4 Specification of a Parameter's Value

6.4.1 Description of the Situation

In the beginning and also during the configuration process, the user has the option to specify an up to now unspecified parameter.

6.4.2 Meaning of the Situation

The motivation for selecting a parameter value is twofold:

- First, the user does not want the system to decide about this parameter, because the influence on the overall evaluation is very big. On the one hand, if the user would left the parameter unchanged, she would risk that she would get a product which is unsatisfying. On the other hand, she would not specify too many parameters, because in this way, she would risk to overspecify the product, resulting in a contradiction. Therefore, most probably she will only specify the parameters which have a big impact on the overall evaluation of the product.
- Second, the user expects that the chosen value for the parameter results in an acceptable overall evaluation of the product.

6.4.3 Bayesian Network for Handling the Situation

The interpretation of the user's behaviour as presented in section 6.4.2 is handled by two different Bayesian networks: The first one interprets the fact that the user explicitly *selects a parameter* and the second one interprets the *specific parameter's value* specified by the user.

The Bayesian network (see Fig. 6) for the first case interprets the impact that a parameter has on the total evaluation of a configured product, dependent on the user's interests.

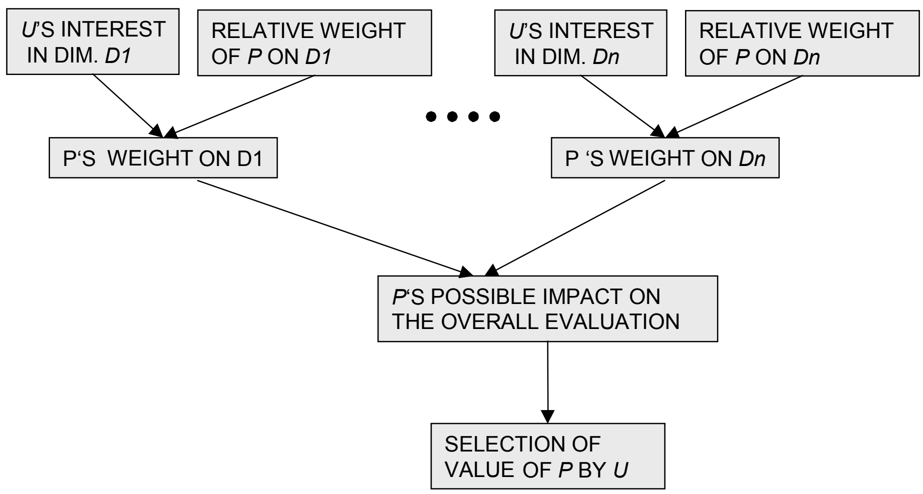

Fig. 6: BN for processing the specification of a parameter's value by the user based on the impact of the parameter.

For a dimension D, P'S WEIGHT ON D is defined as multiplication of the U'S INTEREST IN DIMENSION D and the RELATIVE WEIGHT OF P ON D.
For defining the possible impact of the evaluation of the parameter on the overall evaluation, we have to take into account the value function of all relevant dimensions for this parameter. These functions could either compensate or reinforce each other. The degree of compensation or reinforcement depends on the weight of the parameter on the value functions. In this way, P'S POSSIBLE IMPACT ON THE OVERALL EVALUATION depends on P'S WEIGHT ON D_I for all value dimensions d_i (i=1, ..n) and is the difference between best and worst evaluation.
If the impact is very high, it is more probable that the user will specify the parameter herself. This is expressed in the dependency between P'S POSSIBLE IMPACT ON THE OVERALL EVALUATION and the SELECTION OF P'S VALUE BY U.
For the second case, we can use a Bayesian network (see Fig. 7) which resembles the Bayesian network for the interpretation of the change of a parameter's value (see Section 6.3). The only difference is, that here we use the shift between the rating of the specified value and the rating which the user expects if she would let the system define the parameter's value EVALUATION SHIFT OF P (REGARDING EXPECTED VALUE) ON D.

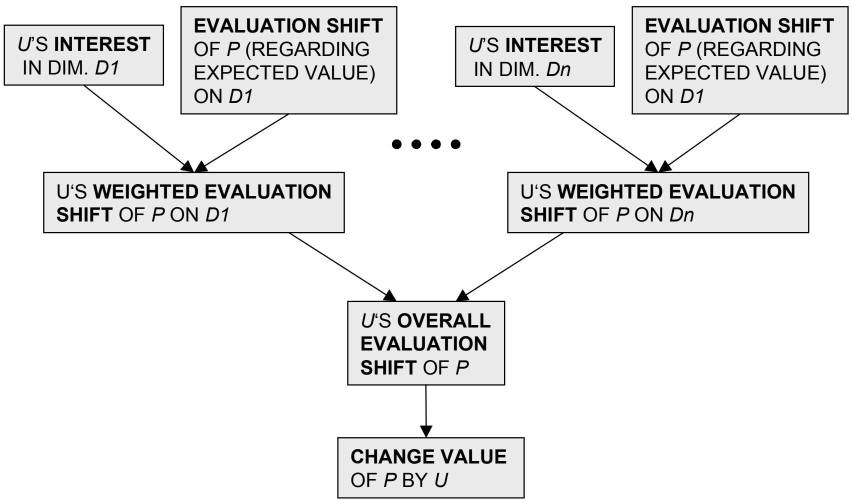

Fig. 7. BN for processing the specification of a parameter's value by the user.

7 Dynamic Aspects

Up to now, isolated BNs were introduced with which the user's observable behaviour can be interpreted. In the following we explain, how they are connected to each other. The user's interests may vary over time. However, during a single configuration session, it is very unlikely that the interests vary. Therefore we assume that the

interests can be considered as static, which allows to connect the networks in the following way:
After the interpretation of evidence, the beliefs of the nodes we are interested in (namely the nodes representing the user's interests) are used as a priori probabilities for nodes representing the user's interests of the network to be used for interpretation of the next situation. In this way, the networks can be seen as part of a dynamic Bayesian network[7].
Another problem is the normalisation of the weights representing the user's interests (corresponding to the nodes U'S INTEREST IN DIM. D). The networks described in Section 6 do not guarantee that the weights always sum up to 1. A solution of this problem is to introduce a node which represents the sum of all weights. Then, we "observe" that the sum is 1. By solving the network, the probability distribution of the interest nodes will be set so that their values sum up to 1.
If we introduce the node in the above described networks, their solving will be more costly. In the current form they are single-connected, which means that they can be solved by a propagation algorithm. Otherwise, they will be multiply-connected, because there will be more than one path between the nodes representing the user's interests: For example, in Fig. 6 one path would go through node U'S EVALUATION SHIFT OF P, whereas the other path would go via the newly introduced node. Such networks will require more costly solving algorithms. An alternative would be to apply the network for normalising the values after the network for interpretation of the user's behaviour, but in this case the results would not be absolutely correct, because this normalisation has to be done in the networks for interpreting the user's behaviour. It has to be examined what is the better alternative.

8 Conclusion

In many domains, configuration is a very complex task. So it is important to help the user of a configuration system, to adapt the interaction to her needs, interests, and knowledge. Such a personalisation requires the modelling of the user's needs, interests, and knowledge. We have shown that Bayesian networks can be used for modelling these characteristics. Here, we focused on estimating the user's interests. For this purpose, we have identified typical situations which occur during such a task and specified networks which are able to interpret the user's behaviour.
The quality of the estimates depends on the quality of modelling the value dimensions and the BN's CPTs.
Currently, the networks are being implemented. In the next step, we will analyse the behaviour of them and examine whether a fine tuning is necessary.

[7] An introduction to dynamic Bayesian networks can be found for example in [RN95].

9 References

[CC00] Cawicoms Consortium (2000). *Deliverable D01 – Requirements, Application Scenarios, Overall architecture, and Test Specification.*

[JSS+95] Jameson, A., Schäfer, R., Simons, and J. Weis. T. (1995). Adaptive provision of evaluation-oriented information: Tasks and techniques. In C.S. Mellish (ed.), *Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence*, pp. 1886 – 1893.

[Pea88] Pearl, J. (1988). *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference.* San Meteo, CA: Morgan Kaufmann.

[Ric88] Rich, E. (1988). *Stereotypes and user modelling,* in User Models in Dialog Systems, Kobsa, A., and Wahlster, W. (eds.), Springer-Verlag, pp. 35-51.

[RN95] Russel, S., and Norvig, P. (1995). *Artificial Intelligence - A modern approach,* Prentice Hall, Englewood Cliffs.

[Sch98] Schäfer, R. (1998). *Benutzermodellierung mit dynamischen Bayes'schen Netzen als Grundlage adaptiver Dialogsysteme*, Ph.D. thesis, Universität des Saarlandes, Saarbrücken.

[Ste99] Steinschaden, M. (1999). *Lehrgang Konstruktionsmethodik*, http://www.staff.fh-vorarlberg.ac.at/hs/Konstruktionsmethodik/Kap_00/KMethod.htm.

[Stu97] Stumptner, M. (1997). *An overview of knowledge-based configuration*, in AI Communications, 10(2).

[SW98] Sabin, D., and Weigel, R. (1998). *Product configuration frameworks – a survey,* in Special Issue on Configuration of IEEE Intelligent Systems, 13(4), pp. 42-49.

[WB98] Wilke, W. and Bergmann R. (1998). *Techniques and Knowledge Used for Adaptation During Case-Based Problem Solving*, on the 11th International Conference On Industrial and Engineering Applications of Artificial Intelligence and Expertsystems, IEA-1998.

[WE86] Winterfeld, D. von and Edwards, W. (1986). *Decision analysis and behavioral research*. Cambridge, England: Cambridge UniversityPress.