# Decision-Making with Probabilistic Reasoning in Engineering Design

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**Abstract.** The goal of decision making is to select the most suitable option from a number of possible alternatives. Which is easy, if all possible alternatives are known and evaluated. This case is rarely encountered in practice; especially in product development, decisions often have to be made under uncertainty. As uncertainty cannot be avoided or eliminated, actions have to be taken to deal with it. In this paper a tool from the field of artificial intelligence, decision networks, is used. Decision networks utilize probabilistic reasoning to model uncertainties with probabilities. If the influence of uncertainty cannot be avoided, a variation of the product is necessary so that it adjusts optimally to the changed situation. In contrast, robust products are insensitive to the influence of uncertainties. An application example from the engineering design has shown, that a conclusion about the robustness of a product for possible scenarios can be made by the usage of the decision network. It turned out that decision networks can support the designer well in making decisions under uncertainty.

**Keywords:** Probabilistic reasoning · Decision-making · Engineering design · Decision network · Bayesian network

## 1 Introduction

For the development of robust products, which are insensitive to uncertainties, it is important to assess possible effects of decisions made in the development process and to consider the relevant influencing factors of tolerances, environments and use cases [1]. Handling uncertainties in this context, e.g. by identifying design rules and learning about sensitivities is a major part in the management of product complexity [2]. Systems that support the designer in the decision-making process have to reduce the uncertainty by providing knowledge or help to estimate possible scenarios, so that the products are robust against possible uncertainties. But almost all computer aids like computer-aided design require discreet parameters [3]. Knowledge-based engineering systems are often used in the late phases of the development process, e.g. to derive variants quickly and check them for validity by tables and rules [4]. Knowledge-based engineering is also beneficial for the conservation of engineering knowledge which is accessible then for later design projects so that uncertainty can be tackled with experience [5].


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In this paper, another approach is investigated, targeting at conditional probabilities that arise in the management of requirements that impact the design. In probabilistic reasoning, uncertainties can be represented by probabilities. For this purpose, Bayesian networks and decision networks will be examined in more detail. The structure of this paper is organized as follows: Sect. 2 describes decision making, uncertainty and probabilistic reasoning in engineering design. In Sect. 3 a decision network for the application example of a rotary valve is built. Section 4 provides a summary and describes approaches for further research.

## 2 Related Work

In the development of products, decisions often have to be made under uncertainty. A tool from the field of artificial intelligence, probabilistic reasoning, offers the possibility to model uncertainties by using probabilities.

### 2.1 Decision-Making in Product Development

In general, the goal of decision making is to select the most suitable option from a number of possible alternatives [6]. Decisions have to be made by the designer during the entire product development process which may be divided in *task clarification*, *concept*, *embodiment design* and *detailed design*. Since it encompasses an initial requirement management, *task clarification* has a major influence on the later stages, especially on *embodiment design* where first geometric considerations are made and the shape is defined [7]. Decisions in the development of a new product must take into account a selection of different criteria [9], which lead to different scopes of change in the product. Due to time pressure, decisions are often made at short notice in practice, which can lead to significant negative consequences, such as delays in deadlines, limitations in functionality, cost overruns and product quality defects [8]. Therefore, tools that support the designer in decision making have to quickly assess possible consequences.

### 2.2 Uncertainty in Engineering Design

Uncertainty cannot be avoided or eliminated within the product development process, therefore it is necessary to consider and react to uncertainty [10]. Kreye et al. [11] differentiate four types of manifestation of uncertainty: *context uncertainty*, *data uncertainty*, *model uncertainty* and *phenomenological uncertainty*. When creating a system, uncertainties arise from the input (data uncertainty), the used model (model uncertainty) and the results of the system (phenomenological uncertainty). Context uncertainty, in contrast, describes the influence of the environment on the system. It can be divided into *endogenous uncertainties*, which arise within the system and can be controlled, and *exogenous uncertainties*, which lie outside the system and typically arise during use of the product [12]. Despite their random occurrence, exogenous variables can be seen as a key to assessing the value of a design, because they reflect the way in which the engineer handles variables that cannot be controlled by himself [6].

According to Chalupnik et al. [13], there are different ways to deal with uncertainty. On the one hand, the uncertainty can be reduced by aiming for an increase in knowledge about the system. On the other hand, the system can be protected from the influence of uncertainty. *Active protection* ensures that the system adapts to uncertain situations. Where, in contrast, *passive protection* ensures that the system withstands the influence of uncertainty and therefore no changes need to be made [13]. Robust products are those that are insensitive to uncontrollable factors [14].

### 2.3 Modeling Uncertainty with Probabilistic Reasoning

Reasoning with uncertainty given limited resources is part of many technical applications in artificial intelligence [15]. Graph-based models have proven to be an important tool for dealing with uncertainty and complexity, as they build a complex system by combining simpler parts [16].

**Bayesian Networks.** Probabilities are very suitable for the modelling of reasoning with uncertainty [15]. Bayesian networks use the so-called Bayesian rule (1), because evidence is often perceived as an effect of an unknown cause and the goal is to determine the cause [17].

$$\text{P(cause} \mid \text{effect)} = \frac{\text{P(effect} \mid \text{cause) P(cause)}}{\text{P(effect)}} \tag{1}$$

The Bayesian rule is explained using a simplified application example for the dosing of powder for the preparation of hot drinks. To support the understanding, the system is reduced to one effect-cause pair. In practice, many effects have very different causes; the multi-causal relationships are discussed in more detail in Sect. 3.2.

In this example the following problem was noticed: the hot drink tastes watery. A possible cause was identified by an insufficient dosage of the powder. For the further solution of the problem it would be helpful to know with which probability the low dosage is the cause for the problem or effect. Based on a statistical analysis, the probability of the effect is P(watery) = 0.2. Since the dosing is carried out automatically, a sensor measures the required powder quantity, which is below its reference value with a probability of P(low) = 0.1. The probability that the hot drink tastes watery if too little powder is dosed is P(watery | low) = 0.8, because the taste is subjective. Based on the information obtained, the Bayesian rule can be used to determine the probability that the low dose of powder is the cause of the watery taste P(low | watery) = 0.4. This leads to the following conclusion that the insufficient dosage of the powder is with a probability of 40% the cause for the watery taste of the hot drink.

According to Russel and Norvig [17], the structure of a Bayesian network can be described by a directed acyclic graph (DAG) in which each node is annotated quantitative probability information. Figure 1 shows a Bayesian network with four nodes, which represents the probabilities for a *watery hot drink* in case of an *incorrect mixing ratio* of a machine for preparing hot drinks due to a *blocked powder supply* or *defective flow sensor* for liquids. The probabilities of the nodes *blocked powder supply* and *defective flow sensor* reflect the probability of their occurrence. The *incorrect mixing ratio* node has the nodes *blocked powder supply* and *defective flow sensor* as parent nodes, so the probability is described in a conditional probability table (CPT) depending on the probability of the parent nodes. The *watery hot drink* node describes the probability of a watery taste of a hot drink depending on the probability of an *incorrect mixing ratio*.

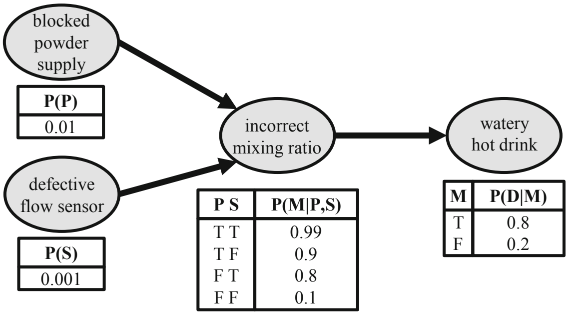


**Fig. 1.** Simple example for a Bayesian network for a watery hot drink

In a Bayesian network, the direct influences can be displayed by arcs without having to specify each probability manually [17]. The arcs in the DAG specify causal relations between the nodes [18], therefore the Bayesian rule can be applied. The main usage of Bayesian networks is inference, which involves updating the probability distribution of unobserved variables as new evidence or observed variables become available [19].

**Decision Networks.** A directed acyclic graph (DAG) model that combines chance nodes from a Bayesian network with additional node types for actions and utilities is called a decision network [17]. In general, decision networks can be used for optimal decision making, even if only partial observations of the world are given [20]. According to Zhu [18], a decision network represents the knowledge about an uncertain problem domain, as well as the available actions and desirability of each state. The following three node types, chance nodes, decision nodes and utility nodes form the basic structure of a decision network [17]:

- *Chance Nodes*: random variables as they are used in a Bayesian network, where each node is connected to a conditional distribution indexed by the state of the parent node
- *Decision Nodes*: points where the engineer has a choice of actions to make a decision
- *Utility Nodes*: points with a utility function that describes the preferred outcomes.

Actions are selected based on the evaluation of the decision network for each possible setting of the decision node [17]. Once a decision node is set, the probabilities of the parent nodes of the utility node are calculated by using a standard probabilistic inference algorithm [17]. As a result, the action that has the most added value based on the utility function is selected.

# 3 Application of Probabilistic Reasoning in Engineering Design

As an application for probabilistic reasoning, an example from engineering design is used to demonstrate a possible handling of uncertainty for the development of robust products.

## 3.1 Rotary Valve as Application Example

A rotary valve is to be used for the dosing of bulk food for hot drinks. Rotary valves or metering feeders are generally used for metering and conveying free-flowing bulk materials [21]. Figure 2 shows a rotary valve with its components. In this case, the rotary valve is driven via the shaft and receives and transports bulk food through the rotary valve pocket per rotation. To avoid bulk food being drawn in or jammed between the rotary valve and the housing, the gap between the rotary valve and the housing is kept as small as possible.

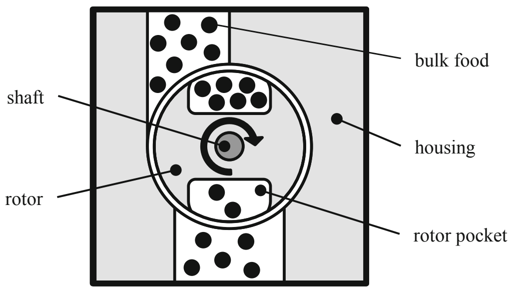


**Fig. 2.** Rotary valve for the dosing of bulk food

The rotary valve has many advantages in application, as it is easy to handle and provides reproducible results. On the other hand, the dimensioning or design of the rotary valve requires adaptation to the bulk material properties [21]. Especially for discontinuous and quantitative dosing, the rotor pocket size is decisive, which should also be filled as completely as possible during dosing.

The rotary valve in this application example is integrated in a machine for the preparation of various hot drinks. Each hot drink requires a different amount of bulk food to be dosed. In addition, the machine is to be placed at different locations, such as in the home kitchen, the office or a café. These boundary conditions result in uncertainties that cannot be influenced by the engineer. The aim for the engineer is to cover as many possible and probable scenarios with one size of the rotor pocket.

## 3.2 Modelling of a Decision Network for the Application Example

To support the design engineer in the decision making process for the optimal rotor pocket size, a decision network was established which also represents the given uncertainties due to the boundary conditions.

The decision network (Fig. 3) of the application example consists of a Bayesian network with six chance nodes. The nodes bulk food and place of use form the initial nodes. The nodes weight and density depend on the selected bulk food. Depending on the place of use, a different quantity of liquid is required for the hot drinks, because the number of hot drinks needed is different. The dosing volume depends on the weight and density of the bulk food, and on the required quantity of liquid. The additional chance node filling level represents the uncertainty when filling the rotor pocket size with bulk food. The decision node rotor pocket size represents the different pocket sizes which are available as possible actions. The utility node utility function represents the preferred outcomes, where design conditions are also included.

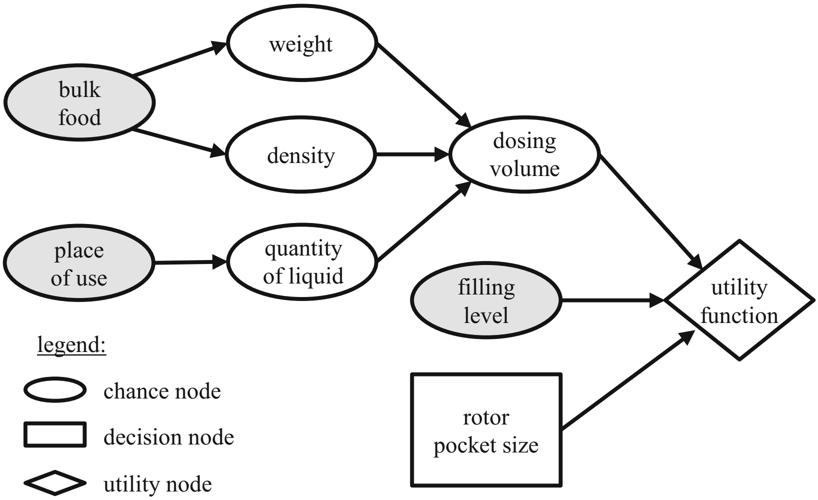


**Fig. 3.** Decision Network for rotary pocket size

The decision network for the application example was built within Matlab using an open-source package for directed graphical models called Bayes Net Toolbox (BNT). A great strength of BNT is the variety of implemented inference algorithms [20]. In addition, Matlab is very suitable for rapid prototyping, because the Matlab code is high level and easy to read [20].

In the first step, the Bayesian network was represented by six chance nodes (Fig. 4). For the chance nodes *bulk food* and *location* the occurrence probabilities were stored. For the chance nodes *weight*, *density* and *quantity of liquid* the probabilities were stored with conditional probability tables (CPT). CPTs were used, because the application example contains only discrete variables and thus the inference was simplified. The probability values are taken from a similar project and were determined empirically.

For the selection of the possible rotor pocket size, in addition to the possible dosing volumes, the filling level of the rotor pocket size has to be considered. For this purpose, the following assumptions are made that the rotor pocket size has a filling level of 0.9 at 80% and that filling levels 1.0 and 0.8 occur with a probability of 10%. To determine the possible rotor pocket sizes, all divisors with one decimal place of the possible dosing

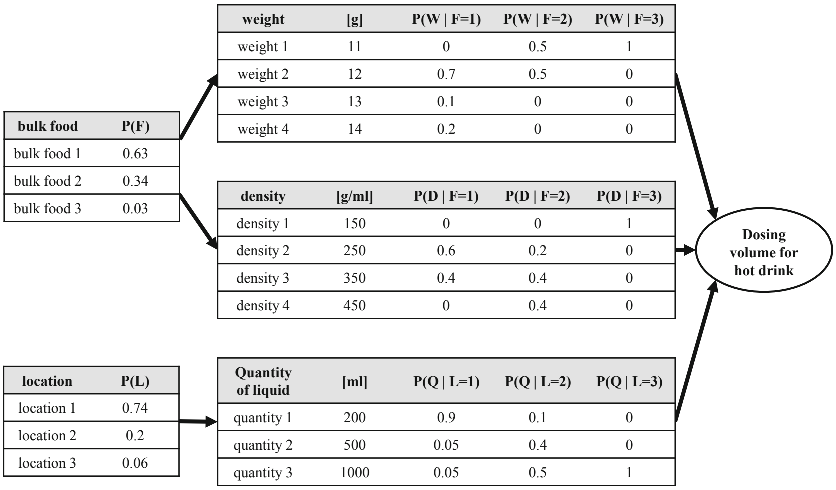


**Fig. 4.** Bayesian network for dosage in the preparation of hot drinks

volumes were determined. This ensures that all rotor pocket sizes are considered for the required dosing volume.

The general utility function describes the sum of the utilities of all possible outcomes, weighted according to their probability of occurrence [6]. As this general utility function also contains results that lead to an unsuitable layout of the design, the following conditions are also represented in the utility function:

- *High Variability*: One rotor pocket size should be able to cover many different dosing volumes
- *Fast Dosing*: The time for dosing should not take longer than the heating time of the liquid for the hot drink
- *Exact Dosage*: the rotor pocket size should dose exactly the required dosage volume.

The listed conditions lead to conflicts which have to be resolved by the algorithm. For example, high variability leads to the smallest possible rotor pocket size, whereas fast dosing requires the largest possible rotor pocket size. In the following Sect. 3.3 the results of the algorithm for the application example are presented and discussed.

### 3.3 Results of the Decision Network

The aim of the application example is to support the engineer with a decision network in the selection of the optimum rotor pocket size. Table 1 shows the results of the decision network in Matlab at different information levels. The column known information represents the different levels of evidence or observation for the decision network. The column rotor pocket size shows the optimal rotor pocket size for the given evidence, which is the best choice for dosing the most likely dosing volumes. The column utility probability describes the added probabilities of the dosing volumes, which can be dosed with the rotor pocket size depending on the filling level. For the situation where no further information is available, the optimum rotor pocket size is 10.7 ml with a utility probability of 15.26%. It can also be noticed that a higher information level does not necessarily lead to a higher utility probability, as this depends on the uncertainty or diversity of the probabilities of the chance nodes. This can also be shown by comparing the utility probabilities of no known information with 15.26% and bulk food 2 with 15.16%.

**Table 1.** Results for the optimal rotary pocket size with utility probabilities

| Known information | Rotor pocket size [ml] | Utility probability [%] |
|---|---|---|
| No known information | 10.7 | 15.26 |
| Bulk food 1 | 10.7 | 23.38 |
| Bulk food 2 | 1.0 | 15.16 |
| Bulk food 3 | 16.3 | 70.64 |
| Place 1 | 10.7 | 19.75 |
| Place 2 | 1.0 | 16.84 |
| Place 3 | 53.3 | 21.80 |
| Bulk food 1 & Place 1 | 10.7 | 30.38 |
| Bulk food 1 & Place 2 | 1.0 | 20.84 |
| Bulk food 1 & Place 3 | 53.3 | 33.60 |
| Bulk food 2 & Place 1 | 1.0 | 17.30 |
| Bulk food 2 & Place 2 | 0.8 | 24.00 |
| Bulk food 2 & Place 3 | 0.8 | 34.00 |
| Bulk food 3 & Place 1 | 16.3 | 76.00 |
| Bulk food 3 & Place 2 | 16.3 | 48.00 |
| Bulk food 3 & Place 3 | 81.5 | 80.00 |

In addition, the decision network can support the engineer in making decisions under uncertainty by allowing the utility probability to make a prediction about the robustness of a product:

- *High utility probability*: If a value has a high utility probability, it can be assumed that this value is a suitable solution for as many scenarios as possible and therefore no further changes are necessary. Furthermore, it can be concluded that the described uncertainty within the decision network has little influence on the outcome and therefore it represents a robust product.
- *Low utility probability*: With a low utility probability, only a part of the possible scenarios can be covered with one value. This indicates a high diversity within the decision network, which may be due to a higher influence of uncertainty. For this

reason, the product have to be adaptable to different conditions, i.e. it should have a high variability or modifiability.

The aim of the decision network is to minimize or even avoid the need for design changes at a late stage of product development or in the use phase. If the utility probability is high, the most robust variant is chosen as the solution, because it is insensitive to the assumed uncertainties. If the utility probability is low, a variant cannot cover the whole spectrum of possible results. In this case, a portfolio of variants can be compiled to cover as many scenarios as possible. This portfolio enables a fast reaction to changing conditions.

## 4 Conclusion and Future Research

Decisions in the product development process often have to be made under uncertainty. Uncertainties can occur during product development or arise from the environment when the product is used. There are two possibilities for dealing with uncertainty. On the one hand, the uncertainty can be reduced by increasing knowledge, on the other hand, the product can be protected from the influence of the uncertainty. To be able to react to the influence of uncertainty, the requirements have to be compared with the behavior of the product during production and use. Especially with a large number of requirements and broad requirement corridors, this requires a great effort from the engineers.

The method presented in this paper supports the engineer in decision-making by representing the uncertainties in a decision network using probabilities. With sensitivities, i.e. the minimum and maximum of a requirement corridor, possible use cases are determined with their probability of occurrence. Based on these, statements about the robustness of the product can be made. Furthermore, they enable a feedback with product management to improve product variety, as possible application scenarios and market segments of the product are already checked.

For future research, it is necessary to investigate how suitable the method with the decision network is for selecting appropriate variants. In addition, the volume of a rotor pocket size was exclusively used as the basis for the application example. For the variation of the rotor, the number of pockets on the circumference or a combination of two pocket sizes could also be interesting. For the illustration of different variants with given uncertainty a coupling between a decision network and a knowledge-based system (KBS) would also be conceivable. Here the requirements with their probabilities of occurrence could be represented in a decision network and the most probable result is transferred to the knowledge-based system for the configuration of the product.

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