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Estimating Production and Warranty Cost at the Early Stage of a New Product Development Project

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Abstract: The paper is concerned with estimating the cost of production and warranty in the context a new product development project. All possible variants of the trade-off between costs are sought within the company's resources and requirements for a product development project. A company and its projects can be specified in terms of variables and constraints that constitute the systems approach for a problem related to cost optimization. This problem is described in the form of a constraint satisfaction problem and implemented with the use of parametric modelling and constraint programming techniques. The paper also presents a method for estimating the cost of prototyping, faulty products in manufacturing and the after-sales stage, and simulating variants that ensure the desirable level of costs. An example shows the applicability of the proposed approach in the context of a product development project.

Keywords: business analytics, computational intelligence for business, data-driven decision making, decision support and control, project management.

1. INTRODUCTION

The new products development (NPD) process is one of the most important activities in today's companies, taking into account shortening product life cycles and strong competition. Moreover, shorter time for developing new products and the limited resources impel companies towards greater effort and attention in managing the NPD projects. Increasing competition and customers' requirements impose more frequent product launches on the market within the target time and costs related to a new product. Launching a new product before competitors, customer satisfaction, and controllable costs are prerequisites for the product success. If the total costs related to product development, production, and warranty are not acceptable for decision makers, then they can be interested in obtaining information of possible variants for NPD project performance that could reduce the costs.

The identification of possible variants of project performance requires the specification of variables, their domains and constraints, including the mentioned relationships between variables. This specification can be formulated in terms of a constraint satisfaction problem (CSP). A CSP which generally belongs to combinatorial problems may be solved using constraint programming (CP) techniques (Liu and Wang 2011). CP includes search strategies that are crucial for improving search efficiency of solving a wide range of problems, for instance, scheduling (Liu and Wang 2011; Bożejko et al. 2017; Sobaszek et al. 2017; Bocewicz et al. 2020), planning (Booth et al. 2016), manufacturing (Soto et al. 2012; Rudnik 2018; Sitek and Wikarek 2018), and resource allocation (Hladik et al. 2008; Zeballos 2010). In the context of product development, the CSP paradigm has been mainly applied to product design (Yannou and Harmel 2004; Yang and Dong 2012). Taking into account cost estimation and simulations, the CSP paradigm has been used in the NPD cost and unit production cost (Relich et al. 2020), and advertising and promotional cost (Relich and Świć 2020). The contribution of this study is the development of a model of cost estimation towards incorporating the cost of faulty products in manufacturing and the after-sales stage. The cost of prototype tests of a new product increases with the number of tests. On the other hand, more prototype tests can reduce the cost of faulty products in manufacturing and warranty. This study develops previous research in the context of using the CSP paradigm to finding the trade-off between the mentioned costs.

The NPD costs are related to market research, generating concepts of a new product, its design and tests. Testing prototypes of a new product is often a long-term and costly process which absorbs the majority of the NPD budget. In turn, prototyping costs are usually low (if not negligible) in comparison to the overall cost of production (Rayna and Striukova 2016). Moreover, the number of prototype tests affects product reliability, and finally, the costs related to faulty products in manufacturing and the after-sales stage. The low product reliability can reduce customer satisfaction and increase the warranty cost. Companies usually tend to

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seek the trade-off between the prototyping cost (often also the time, taking into account the actions of competitors) and costs related to production and warranty. Cost estimation can use relationships between variables that are identified by parametric models. These relationships are also used to reduction of the number of faulty products and return of goods, and the identification of possible variants of NPD project performance, if any.

The proposed approach aims to develop a method for estimating the cost related to production and warranty at the early stage of an NPD project. Moreover, this approach verifies the possibility of such changes at the early stage of an NPD project (e.g. in the number of prototype tests), for which the production and warranty cost could be reduced. The research includes three main targets. Firstly, a cost estimation model is developed towards incorporating the cost of faulty products in manufacturing and the after-sales stage. Secondly, a method for cost parametric estimation is proposed using databases of project-oriented enterprises, in order to identify the possibility of cost reduction of the total product cost. Thirdly, this study presents the use of CP techniques to identify possible variants of NPD project performance.

The paper is organised as follows: Section 2 presents problem formulation in terms of a CSP. A method of estimating cost and searching for possible variants of NPD project performance is shown in Section 3. An illustrative example of the proposed approach is presented in Section 4. Finally, conclusion is presented in Section 5.

2. PROBLEM FORMULATION

A project prototyping problem refers to the identification of the possibilities to perform an NPD project in an alternative way, within constraints that can be related to new product features, project budget, human resources, machines, etc. This study is concerned with searching for variants of project performance by the trade-off between the desirable level of the cost related to prototype tests, production and warranty.

The proposed approach allows the decision maker to identify prerequisites, by which an NPD project can obtain the trade-off between costs related to prototype tests, production and after-sales stage. The number of possible variants of project performance depends on constraints, domains related to variables, and their granularity. Relationships between variables can be identified using previous experiences related to the similar completed projects. The identified relationships are used twofold to cost estimation and verification of the existence of such changes, by which the target cost could be reached.

The application of the proposed approach requires the specification of variables, their domains, and constraints that can be formulated in terms of a CSP as follows:

$$((V, D), C) \tag{1}$$

where:

V is a finite set of n variables $\{v_1, v_2, \ldots, v_n\}$,

D is finite and discrete domains $\{d_1, d_2, \ldots, d_n\}$ of variables V,

C is a finite set of constraints $\{c_1, c_2, \ldots, c_m\}$.

Constraints can link variables and restrict their values. The solution of a CSP is a set related to the value of each variable that satisfies all constraints C. Generally, constraints may be specified in analytical and/or logical formulas.

Modelling a project prototyping problem as a CSP includes the selection of variables and constraints regarding an NPD project and company resources. This selection is performed in an arbitrary way, taking into account the impact of a specific variable on the cost of prototyping, production, and warranty. These variables should also be controllable to change NPD project performance through their usage. The specification of a project prototyping problem in terms of a CSP enables the identification of a set of values for decision variables, if any. The problem solution is related to possible changes in NPD project performance that satisfy all specified constraints, including the desirable level of costs.

There are the following variables regarding cost estimation of a new product:

V_1 – the cost of prototype tests of a new product,

V_2 – the number of faulty products in manufacturing,

V_3 – the warranty cost,

V_4 – the cost of faulty products in manufacturing,

V_5 – the number of product components,

V_6 – the number of new components in a product,

V_7 – the number of prototype tests,

V_8 – the number of employees involved in NPD,

V_9 – the amount of materials used to produce a unit of a new product (in kilograms),

V_{10} – the number of components in a product for assembling,

V_{11} – the number of components in a product for processing.

The set of constraints is as follows:

C_1 – the budget of prototype tests of a new product,

C_2 – the maximal cost of faulty products in manufacturing,

C_3 – the maximal warranty cost,

C_4 – the minimal number of product components,

C_5 – the minimal number of prototype tests,

C_6 – the total number of employees who may be involved in NPD,

C_7 – the maximal amount of materials needed to produce a unit of a new product.

The model specification in terms of a CSP integrates technical parameters of a new product, parameters regarding the NPD project performance, estimated costs of a new product, and available resources in a company. The solution of the above-described problem can be referred to the answers to the following questions:

- what is the cost related to prototype tests, production and warranty?

- what values should have the variables related to prototype tests to reach the desirable level of total costs of a new product?

The answer to the second question refers especially to the problem formulation in terms of a CSP and its declarative programming paradigm. Using this paradigm all possible solutions are identified, if any. This often requires the verification of a large space of solutions, especially if there are many decision variables and highly differentiated domains. Consequently, there is a need to use the effective techniques of space search reduction, such as constraint programming.

3. A METHOD OF ESTIMATING COST AND SEARCHING FOR POSSIBLE VARIANTS OF PROJECT PERFORMANCE

The method consists of the following steps: 1) collecting data from existing products that are similar to a new product, 2) identifying relationships between input and output variables, 3) estimating costs related to a new product, and 4) searching for possible variants to obtain the desirable level of costs. Figure 1 illustrates a framework for the proposed decision support system that uses a parametric modelling to identify relationships and estimate costs, and constraint programming to reduce the search space and verify the possibility of reaching the desirable level of costs.

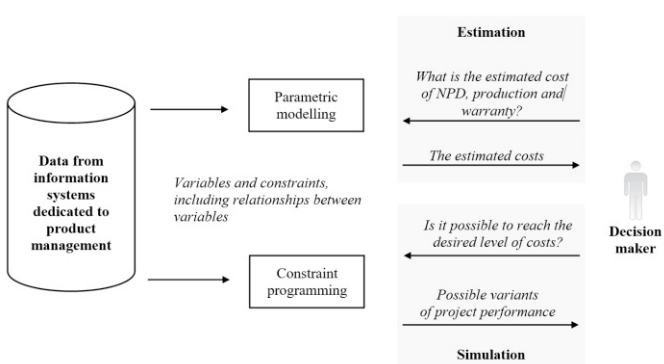

Fig. 1. A framework of the proposed decision support system.

The data is collected from enterprise databases stored in information systems that support product data management in a company. These information systems can include systems related to enterprise resource planning (ERP), customer relations management (CRM), computer-aided design (CAD), computer-aided engineering (CAE), or computer-aided manufacturing (CAM). The data stored in these systems is used in product lifecycle management.

Information of product lifecycle is acquired from specifications of past or existing products that are in the same product line as a new product. The most similar products to a new product are retrieved from the database using the similarity function and similarity value that is calculated as the arithmetic average of similarity functions for all variables. The similarity function is calculated as follows:

$$sim\left(f_i^P, f_i^R\right) = 1 - \frac{\left|f_i^P - f_i^R\right|}{\max(f_i)} \qquad (2)$$

where:
$sim\left(f_i^P, f_i^R\right)$ – the similarity function of the i-th variable between the value of the new product f_i^P and the value of the retrieved product f_i^R; it ranges from 0 to 1.

The costs of a new product can be estimated using analogical and parametric methods. Analogical methods estimate the cost using similarity to previous products. The comparison between the new and existing products can refer to cost reduction in different areas, for example, product design (Harlalka et al. 2016) and maintenance management (Adu-Amankwa et al. 2019). In turn, parametric methods estimate the cost from parameters that significantly affect the cost.

The proposed method uses cause-and-effect relationships to cost estimation within prototype tests of a new product, faulty products in manufacturing, and return of goods in the after-sales stage. Product reliability affects the number of faulty products and return of goods, increasing the total cost of production and after-sales service. Product reliability can be measured by the number of product usage to the first failure that directly depends on the number of prototype tests.

The variables to cost estimation are selected taking into account their impact on the specific cost and their controllability. For example, a company can manage the number of prototype tests, project team members, and product components. A set of variables, their domains, and constraints constitutes a CSP that is a framework for obtaining answers to the questions about the value of the cost, and if it is non-acceptable, about the values of variables that enable the desirable level of the specific cost.

The proposed method is based on parametric estimation models that include an analytical function of a set of variables. These variables are usually related to some features of a new product (e.g. the number of components, dimensions, materials used) and an NPD project (e.g. the number of prototype tests, project duration, project team members) that are supposed to have a significant impact on NPD project performance and the cost of a new product. The review of decision variables used to cost estimation at the product design stage is presented in (Ilhami et al. 2020). Parametric estimation techniques often base on regression analysis (Liu et al. 2009; Nielsen et al. 2014; Nilakantan et al. 2017), artificial neural networks (Wang 2007; Relich 2016) or hybrid systems (e.g. neuro-fuzzy and genetic fuzzy systems).

The last step of the proposed method refers to the search for possible solutions to reach the desirable cost of prototyping, production and warranty. The search space depends on the number of variables chosen to the analysis, their domains, and constraints that can link variables and limit possible solutions. An exhaustive search always find a solution if it exists but its performance is proportional to the number of admissible solutions. Therefore, an exhaustive search tends to grow very quickly as the size of the problem increases, what limits its usage in many practical problems. Consequently, there is a need to develop more effective methods for searching the space and finding possible solutions. This study proposes CP techniques to solve a CSP in an efficient way.

Constraint propagation applies constraints to prune the search space. Propagation techniques aim to reach a certain level of consistency, and accelerate the search procedures to reduce the size of the search tree (Banaszak et al. 2009). The values of variables that are excluded by constraints, are removed from their domains. As CP uses the specific search methods and constraint propagation algorithms, it enables a significant reduction of the search space. Consequently, CP is suitable to model and solve complex problems (Apt 2003).

4. AN EXAMPLE OF THE PROPOSED APPROACH

4.1. Collecting data

The similarity between the previous products and a new product is measured for products from the same product line. A set of variables for evaluating the similarity includes product size, weight, and amount of materials used. Table 1 presents the similarity function (*SF*) and similarity value (*SV*) for the most similar past product and new product.

Table 1. Similarity function and value

Variable	f^P	f^R	*SF*
Product size	0.95	0.93	97.9%
Product weight	0.89	0.85	95.5%
Amount of materials used	0.92	0.92	100%
SV = (97.9%+95.5%+100%)/3 = 97.8%			

The set of similar products to a new product includes previous products with the similarity value above 80%. There are 21 similar past products that are further considered in the analyses.

4.2. Identifying relationships between variables

The identified relationships refer to the impact of the number of prototype tests on product reliability and corresponding cost of prototyping (3), faulty products in manufacturing (4), and warranty cost in the after-sales stage (5).

$$V_1 = f(V_5, V_6, V_7, V_8, V_9) \tag{3}$$

$$V_2 = f(V_5, V_7, V_9, V_{10}, V_{11}) \tag{4}$$

$$V_3 = f(V_2, V_5, V_7, V_9) \tag{5}$$

The relationships between input and output variables have been identified using an artificial neural network (ANN) and linear regression (LR). A multilayer feedforward neural network is trained according to a gradient descent algorithm with momentum and adaptive learning rate backpropagation. The results of the ANN and LR model are compared with the average of output variables to illustrate to what extent these models outperform the arithmetic average. The dataset for analysis includes 21 completed projects that belong to the same product line as a new product. The data has been divided into training set (17 cases) and testing set (4 cases) to evaluate the quality of an estimation model. The experiments were performed using 5-fold cross validation, and the results were calculated as the average of these folds.

The optimal number of hidden neurons was selected using the trial and error approach, taking into account the mean absolute percentage square error (MAPE). The MAPE is calculated as the average of 20 simulations for each structure of an ANN with a number to the extent of 20 hidden neurons. Table 2 presents the MAPE in the training set (TR) and testing set (TE) for the cost of prototype tests (V_1), the number of faulty products in manufacturing (V_2), and the warranty cost related to the return of goods in the after-sales stage (V_3). The results indicate that the use of neural networks provides the least error among the data used.

Table 2. Comparison of estimation models

Variable	Model	MAPE for TR in (%)	MAPE for TE in (%)
V_1	ANN	1.67	2.34
	LR	2.04	2.66
	Average	9.17	10.94
V_2	ANN	2.35	5.09
	LR	2.93	5.37
	Average	14.54	16.03
V_3	ANN	2.72	3.34
	LR	3.23	3.61
	Average	14.33	16.46

4.3. Estimating costs related to a new product

The results obtained using the ANN and LR model significantly outperform the arithmetic average. As the ANN generated in the testing set smaller MAPE than the LR model, it has been used to cost estimation.

The cost of prototype test (V_1) has been estimated at 194.3 thousand €, taking into account the following values of input variables: $V_5 = 40$, $V_6 = 8$, $V_7 = 300$, $V_8 = 4$, $V_9 = 0.65$. The number of faulty products in manufacturing (V_2) has been predicted at 3 units per 1,000 products. This was calculated according to input variables such as: $V_5 = 40$, $V_7 = 300$, $V_9 = 0.65$, $V_{10} = 35$, $V_{11} = 15$. The cost of faulty products in manufacturing (V_4) reaches 212.2 € per 1,000 products. In turn, the warranty cost (V_3) has been estimated at 272.1 € per 1,000 sold products, taking into account the following input variables: $V_2 = 3$, $V_5 = 40$, $V_7 = 300$, $V_9 = 0.65$.

The budget of prototyping a new product reaches 220 thousand €, so this constraint is fulfilled. In turn, the cost related to faulty products and warranty is too high for senior managers, and they decided that these costs should be reduced to 200 € and 240 € for each 1,000 sold products, respectively. In the next step, the possibility of fulfilling these expectations is sought.

4.4. Searching for possible variants of cost reduction

The solution of the above-described problem is sought using constraint programming that requires the specification of decision variables, their domains, and constraints, including relationships between variables. Domains for considered variables are as follows: $D_7 = \{300, \ldots, 400\}$, $D_8 = \{4, 5, 6\}$, $D_9 = \{0.60, \ldots, 0.70\}$. The constraints are as follows:

- the cost of prototype tests of a new product (in thousand €):

$V_1 \leq 220$

- the warranty cost (in € per 1,000 products):

$V_3 \leq 240$

- the cost of faulty products in manufacturing (in € per 1,000 products):

$V_4 \leq 200$

- the number of product components:

$V_5 \geq 35$

- the number of prototype tests:

$V_7 \geq 300$

- the number of NPD project team members:

$V_8 \leq 6$

- the amount of materials used to produce a unit of a new product (in kilograms):

$V_9 \leq 0.7$

The criterion for selecting the best variant (*SC*) is the total cost of faulty products and warranty:

$$\min SC = V_3 + V_4 \tag{6}$$

Table 3 presents a few possible solutions for the specified variables, their domains, and constraints. The increment of prototype tests results in increasing the NPD cost but at the same time it reduces the production and warranty cost.

Table 3. An example of possible solutions

Values of variables	V_3	V_4	SC
$V_7 = 399$, $V_8 = 4$, $V_9 = 0.65$	240.0	199.8	439.8
$V_7 = 400$, $V_8 = 4$, $V_9 = 0.65$	239.7	199.8	439.5
$V_7 = 389$, $V_8 = 4$, $V_9 = 0.60$	240.0	198.3	438.3
…	…		…
$V_7 = 400$, $V_8 = 4$, $V_9 = 0.60$	237.2	197.3	434.5
$V_7 = 375$, $V_8 = 5$, $V_9 = 0.60$	240.0	199.7	439.7
…	…		…
$V_7 = 400$, $V_8 = 5$, $V_9 = 0.60$	238.9	198.8	437.7

Table 3 illustrates an example of changes in three variables. The increasing number of NPD project team members enlarges the cost of prototype tests but also can increase the quality of a new product, and consequently, reduce the cost of production and warranty. Moreover, this kind of analysis can be an advice for the decision maker about directions of changes that can lead to reach the trade-off between the prototyping, production and warranty cost.

The application of CP techniques reduces computational time compared to an exhaustive search, what is especially useful in the case of a vast space of possible solutions. Constraint programming techniques enables the use of strategies related to constraint propagation and variable distribution, significantly reducing a set of admissible solutions and the average computational time, what improves interactive properties of a decision support system.

5. CONCLUSION

The presented approach supports the decision makers in searching for alternative variants of NPD project performance, taking into account the company's resources and target costs. This approach is especially useful in the case of limited resources (e.g. project team members) to verify the possibility of project performance within the constraints (e.g. the project budget). The limited resources require more effort and attention to manage the NPD projects. Consequently, there is a need to develop a decision support system for searching variants to complete an NPD project in an alternative way. The proposed model encompasses the product specification and company's resources. This model can be formulated in terms of a CSP that includes the sets of decision variables, their domains, and constraints. The project prototyping problem is solved twofold: 1) cost estimation related to prototype tests, faulty products and warranty, and 2) identification of values of input variables that ensure the desirable level of the specific cost.

This study presents the use of computational intelligence to identify the relationships for estimating the cost of a new product. Moreover, the identified relationships can be used to generate variants of an alternative project performance. If planned project performance is unacceptable for the decision makers, then the identified variants can support them in identifying the impact of input variables on an output variable within the specified constraints. Drawbacks of the proposed approach can be seen from the perspective of collecting enough amounts of data of the existing similar products, and specifying several parameters to build and learn an artificial neural network. Future research directions include identification of the impact of the number of decision variables (including granularity of their domains) and constraints on the time needed to obtain solutions, and the effectiveness of using constraint programming techniques.

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