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Declarative Modelling Approach for New Product Development

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Abstract: The paper is concerned with using constraint programming for simulating an alternative project completion of new product development (NPD). All possible variants of project completion are sought within the company's resources and requirements for an NPD project. A company and its projects can be considered in terms of variables and constraints that constitute the systems approach for a project prototyping problem. This problem is described in the form of a constraint satisfaction problem and implemented with the use of constraint programming techniques. The paper also presents a method for estimating the NPD cost and unit production cost, and simulating variants that ensure the desirable level of costs, including the impact of granularity on the number of solutions. An example shows the applicability of the proposed approach in the context of NPD projects.

Keywords: project management, systems approach, constraint satisfaction problem, modelling and decision making, information processing and decision support.

1. INTRODUCTION

Shorter product life cycles and strong competition cause that the new products development process is one of the most important activities in contemporary companies. Moreover, shorter time for NPD together with the limited resources requires more effort and attention to manage the NPD projects. Increasing competition and customers' requirements impose more frequent product introductions on the market within the research and development budget, target time and production cost. Introducing a new product before competitors and customer satisfaction are prerequisites for the product success. If the company's resources (e.g. financial, human) are not sufficient to develop an NPD project according to schedule, then the decision makers can be interested in obtaining information of alternative variants for project completion. Also, the NPD cost may have unacceptable level for the decision makers, and cause a need to verify the possibility of project performance towards preferable costs. A search for project performance variants requires the selection of variables that can be used to cost estimation. This study uses parametric estimation models to identification of relationships between variables. These relationships are used to cost estimation and verification of the possibility to complete an NPD project in an alternative way, within the specified constraints.

The identification of possible variants of project completion requires the specification of variables, their domains and constraints, including the mentioned relationships between variables. The specification of the considered problem can be formulated in terms of a constraint satisfaction problem (CSP). A CSP that generally belongs to combinatorial problems may be solved using the constraint programming (CP) techniques (Fruhwirth and Abdennadher 2003; 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 (Baptiste et al. 2001; Liu and Wang 2011; Bocewicz et al. 2016), planning (Do and Kambhampati 2001; Nielsen et al. 2019), manufacturing (Banaszak 2006; Soto et al. 2012, Sitek and Wikarek 2018), and resource allocation (Modi et al. 2001). In the context of NPD, the CSP paradigm has been mainly applied to product design (Puget and Van Hentenryck 1998; Yang and Dong 2012). The use of CP to search for variants of NPD project completion is neglected in the literature. General foundations of a project prototyping problem in terms of a CSP have been presented in (Relich 2017). This study develops previous research in the context of using a declarative modelling approach to NPD project completion, taking into account the NPD cost and production cost. Moreover, this research uses CP techniques to a time-effective reduction of the space search toward finding admissible variants of NPD project completion.

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

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2. PROBLEM FORMULATION

A project prototyping problem refers to the search for the possibilities to complete an NPD project in an alternative way, taking into account the fulfilment of the assumed constraints. This study is concerned with searching for variants of project completion by the desirable level of the NPD cost and unit production cost. If the specific cost is unacceptable for the decision maker, then according to a traditional approach to project evaluation, the project is rejected. However, if the project is important from a strategic point of view, the decision maker can be interested in obtaining the prerequisites that can enable the desirable level of costs. The proposed approach refers to the identification all possibilities (variants) to perform a project within constraints that can be related to project objectives, project budget, human resources, machines, etc. Figure 1 presents the traditional approach for project evaluation (a) and the proposed approach for searching variants within the target project performance (b). The traditional approach may be considered as a project prototyping problem stated in the forward form, whereas the proposed approach – the problem stated in the inverse form.

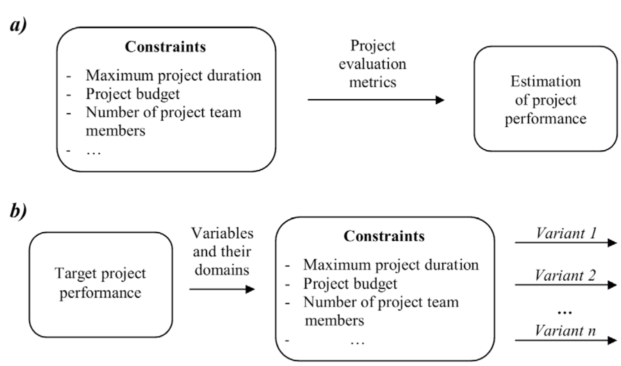

Fig. 1. A project prototyping problem stated in the forward form (a) and inverse form (b).

The proposed approach allows the decision maker to identify prerequisites, for which a project can obtain the target project performance within specified constraints, variables, and relationships between these variables. 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 and presented in the form of *if-then* rules. Then, the identified relationships are used in two fields: to estimate the cost of NPD and unit production (the traditional approach), and to verify the existence of such changes that could reach the target project performance (the proposed approach).

The use of the proposed approach requires the specification of variables, their domains, and constraints. This specification enables the identification of all available solutions, if there are any solutions. This approach may be effortlessly formulated in terms of a CSP as follows (Banaszak et al., 2009):

$$((V, D), C) \quad (1)$$

where:

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

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

C is a finite set of constraints $\{c_1, c_2, \ldots, c_m\}$ that restrict values of variables and link them.

Each constraint is treated as a predicate that may be seen as an n-ary relation defined by a Cartesian product $d_1 \times d_2 \times \ldots \times d_n$. The solution of a CSP is a vector $(d_{1i}, d_{2k}, \ldots, d_{nj})$ that is related to the assessment of a value of each variable that satisfies all constraints C. Generally, constraints may be specified in analytical and/or logical formulas.

Modeling a project prototyping problem as a CSP includes the selection of variables and constraints regarding an NPD project and enterprise capacity. This selection is conducted in an arbitrary way, taking into account the impact of a specific variable on the NPD cost and unit production cost, and the appropriateness of using this variable to the changes in the NPD process. The specification of a project prototyping problem in terms of a CSP enables the identification of a set of values related to decision variables, if any. This set of solutions can be considered as possible changes in the NPD process that satisfy all assumed constraints, including the desirable level of costs. A variable domain can have different granularity depending on variable features, e.g. a variable referring to the time can be denoted by days, weeks, months, etc. As a result, the CSP model can be specified in different resolution. Figure 2 presents an example of a set of variables affected the cost of NPD and production, and related to an NPD project and company resources.

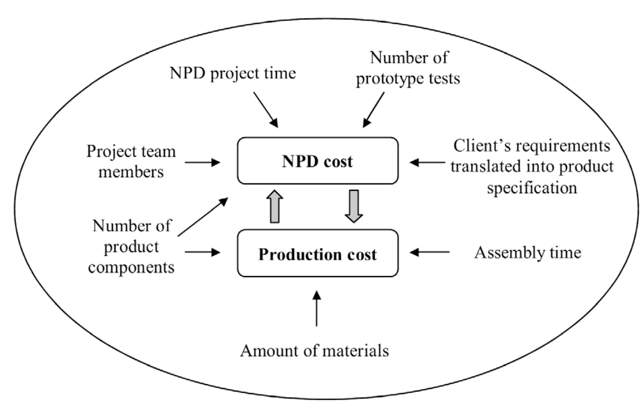

Fig. 2. Variables related to an NPD project and enterprise capacity.

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

V_1 – the NPD cost,

V_2 – the unit production cost,

V_3 – the number of project team members involved in NPD,

V_4 – the NPD project time,

V_5 – the rate of the clients' requirements translated into product specification,

V_6 – the number of prototype tests,

V_7 – the number of product components,

V_8 – the amount of materials needed to produce a unit of a new product,

V_9 – the assembly time.

The set of constraints is as follows:

C_1 – the project budget,

C_2 – the maximal cost of manufacturing a unit product,

C_3 – the total number of project team members who may be involved in an NPD project,

C_4 – the deadline for introducing a new product into the market,

C_5 – the minimal rate of fulfilling the clients' requirements,

C_6 – the minimal number of prototype tests,

C_7 – the minimal number of product parts,

C_8 – the maximal amount of materials needed to produce a unit of a new product,

C_9 – the maximal time limit for product assembly.

The model formulation in terms of a CSP integrates technical parameters of a new product, parameters regarding planned project performance, and available resources. The problem solution refers to the search for answers to the following questions:

- what is the NPD cost and unit production cost?

- what values should have the variables to reach the desirable level of costs related to NPD and unit production?

A project prototyping problem can be formulated in terms of a CSP that in turn can be solved with the use of the specific techniques such as constraint propagation and variable distribution. 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. A CSP may be effectively solved with the use of constraint programming (CP) techniques. The declarative nature of a CP is particularly useful for applications where it is enough to state *what* has to be solved without saying *how* to solve it (Banaszak et al., 2009). 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).

3. A METHOD OF IDENTIFYING RELATIONSHIPS AND SEARCHING VARIANTS OF PROJECT COMPLETION

The proposed method consists of the following steps: (1) collecting data from previous projects that are similar to a new project, (2) identifying relationships between variables, (3) estimating the NPD cost and unit production cost, and (4) searching variants for obtaining the desired level of the specific cost. Figure 3 illustrates a framework for the proposed decision support system that uses a neuro-fuzzy system to identify rules and constraint programming to reduce the search space and verify the possibility of reaching the desired level of costs.

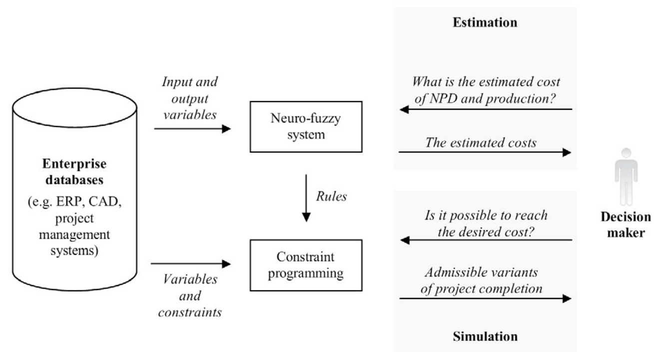

Fig. 3. A decision support system for estimating costs and searching variants of project completion.

The data is collected from databases related to information systems that support the NPD process in a company. Enterprise databases can include project management systems, enterprise resource planning (ERP) systems, computer-aided design (CAD) systems, etc. This requires the use of some project management standards, including project performance planning and executing, for example, an enterprise should use a primary schedule for monitoring performance in NPD projects.

The proposed method is based on the identification of cause-and-effect relationships that are used to cost estimation of product development and its production, and search for the desired level of these costs. There are considered variables that impact the cost and that a company may control such as the number of project team members, product components, and prototype tests. 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 desired 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. its duration, project team members) that are supposed to have a significant impact on NPD project performance. Parametric estimation techniques can be based on, for example, regression analysis (Liu et al. 2009), artificial neural networks (Seo et al. 2002; Relich 2016), fuzzy logic (Gola and Klosowski 2017; Grzybowska and Kovács 2017) or hybrid systems such as neuro-fuzzy systems (Relich and Bzdyra 2015; Relich and Pawlewski 2015).

The last part of the proposed method refers to the search of possible solutions to achieve the desired cost of NPD and unit production cost. The search space depends on the number of variables chosen to the analysis, a range of domains of variables (including their granularity), 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.

The proposed approach of solving the above-described problem also includes the aspect of granularity related to domains of variables. If there are an enormous number of possible solutions, then the decision maker can be interested in reducing this number through increasing granularity of a variable domain. For example, the number of prototype tests can be specified in hundreds instead units. This aspect is also used to illustrate the advantage of CP techniques compared to an exhaustive search.

4. AN EXAMPLE OF THE PROPOSED APPROACH

4.1. Cost estimation

The relationships between input and output have been identified with the use of an adaptive neuro-fuzzy inference system (ANFIS), and compared with linear regression (LR). The ANFIS combines the advantages of the artificial neural networks (ability to learning and identifying the complex relationships) and fuzzy logic (ability to incorporating expert knowledge and specifying the identified relationships in the form of *if-then* rules). The results of the ANFIS and LR model are compared with the average of output variables to illustrate to what extent these models outperform the simple arithmetic average. The dataset for analysis includes 27 completed projects that belong to the same product line as the considered NPD project. The data has been divided into training set (21 cases) and testing set (6 cases) to evaluate the quality of an estimating model. The experiments were performed using 5-fold cross validation, and the results were calculated as the average of these folds. The following relationships between input and output variables are sought:

$$V_1 = f(V_3, V_4, V_5, V_6, V_7) \quad (2)$$

$$V_2 = f(V_7, V_8, V_9) \quad (3)$$

Equation (2) is related to the NPD cost, whereas (3) to the production cost. The learning method and relevant parameters of the ANFIS have been adjusted in an experimental way comparing estimation errors in the testing set for methods such as grid partition and subtractive clustering that are implemented in the Matlab® environment. The results of experiments have indicated that the subtractive clustering method generated smaller errors in the testing set than grid partition method and linear regression. The subtractive clustering method has been used with the following parameters: squash factor – 1.25, accept ratio – 0.5, reject ratio – 0.15. The results of experiments have indicated that the smallest errors have been generated by the parameter of the range of influence equals 0.8 (for estimating the NPD cost) and 0.6 (for estimating the production cost). Table 1 presents the number of rules, and the root mean square error (RMSE) in the training set (TR) and the testing set (TE) for the NPD cost (V_1) and unit production cost (V_2).

Table 1. RMSE and number of rules for estimating costs

Output variable	Model	RMSE in TR	RMSE in TE	Number of rules
V_1	ANFIS	1.235	2.114	4
	LR	2.423	3.685	1
	Average	5.434	6.127	1
V_2	ANFIS	1.653	3.634	6
	LR	1.824	4.763	1
	Average	4.965	6.742	1

The results provided by the ANFIS and LR model significantly outperform the arithmetic average. The ANFIS has generated in the testing set smaller RMSE than the LR model. Therefore, rules identified by the ANFIS have been used to cost estimation. After inputting the values of input variables ($V_3 = 5$, $V_4 = 7$, $V_5 = 0.85$, $V_6 = 8$, $V_7 = 35$), the NDP cost is estimated at 154 thousand €. In turn, the unit production cost is estimated at 27 € (for the following input variables: $V_7 = 35$, $V_8 = 0.25$, $V_9 = 50$).

Let us assume that the estimated cost does not satisfy the decision maker's expectations. To check the possibility of fulfilling these expectations, the problem is reformulated into the inverse form, i.e. there is sought project performance that ensures the desired NPD cost and unit production cost.

4.2. Searching for possible variants of project completion

Let us assume that the decision maker is interested in decreasing the NPD cost to 150 thousand € (C_1) and unit production cost to 25 € (C_2). As a result, the considered problem is reformulated to the inverse form in order to verify the possibility of existing solutions. The solution of the problem stated in the inverse form is sought using constraint programming, and it requires the specification of decision variables, their domains, and constraints, among which are relationships between variables. Domains for considered variables are as follows: $D_3 = \{4, 5\}$, $D_4 = \{6, 7, 8\}$, $D_5 = \{0.80, \ldots, 0.89\}$, $D_6 = \{8, 9\}$, and $D_7 = \{32, \ldots, 40\}$, $D_8 = \{0.2, 0.3\}$, $D_9 = \{45, \ldots, 50\}$.

There are the following requirements regarding the variables:

- the desirable NDP cost (in thousand €)

$V_1 \leq 150$

- the desirable unit production cost (in €)

$V_2 \leq 25$

- the number of project team members

$V_3 \leq 5$

- the duration of NPD (in months)

$V_4 \leq 8$

- the minimal rate of fulfilling the clients' requirements

$V_5 \geq 0.8$

- the number of prototype tests (in hundreds)

$V_6 \geq 8$

- the number of product parts

$V_7 \geq 32$

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

$V_8 \leq 0.3$

- the assembly time (in seconds)

$V_9 \leq 50$

There are two criteria regarding the selection of the best variant: the NPD cost and unit production cost. Consequently, the selection criterion (*SC*) is as follows:

$$\min SC = (V_1/C_1 + V_2/C_2) / 2 \quad (4)$$

The problem stated in the inverse form has been implemented in Mozart/Oz software that is a multiparadigm programming language, including object-oriented, concurrent, constraint, and distributed programming.

Table 2 presents 12 possible solutions (variants of project completion) within the specified constraints and variables. According selection criterion (4), the most profitable variants are cases 3 and 4.

Table 2. A set of possible solutions

Case	Values of variables	V_1	V_2	*SC*
1	$V_3 = 4$, $V_4 = 8$, $V_5 = 0.80$, $V_6 = 8$, $V_7 = 32$, $V_8 = 0.3$, $V_9 = 50$	149.7	24.8	0.995
2	$V_3 = 4$, $V_4 = 8$, $V_5 = 0.81$, $V_6 = 8$, $V_7 = 32$, $V_8 = 0.3$, $V_9 = 50$	149.9	24.8	0.996
3	$V_3 = 4$, $V_4 = 8$, $V_5 = 0.80$, $V_6 = 8$, $V_7 = 32$, $V_8 = 0.3$, $V_9 = 49$	149.5	24.6	0.990
4	$V_3 = 4$, $V_4 = 8$, $V_5 = 0.81$, $V_6 = 8$, $V_7 = 32$, $V_8 = 0.3$, $V_9 = 49$	149.5	24.6	0.990
5	$V_3 = 4$, $V_4 = 8$, $V_5 = 0.82$, $V_6 = 8$, $V_7 = 32$, $V_8 = 0.3$, $V_9 = 49$	149.6	24.6	0.991
6	$V_3 = 4$, $V_4 = 8$, $V_5 = 0.83$, $V_6 = 8$, $V_7 = 32$, $V_8 = 0.3$, $V_9 = 49$	149.6	24.6	0.991
7	$V_3 = 4$, $V_4 = 8$, $V_5 = 0.84$, $V_6 = 8$, $V_7 = 32$, $V_8 = 0.3$, $V_9 = 49$	149.7	24.6	0.991
8	$V_3 = 4$, $V_4 = 8$, $V_5 = 0.85$, $V_6 = 8$, $V_7 = 32$, $V_8 = 0.3$, $V_9 = 49$	149.7	24.6	0.991
9	$V_3 = 4$, $V_4 = 8$, $V_5 = 0.86$, $V_6 = 8$, $V_7 = 32$, $V_8 = 0.3$, $V_9 = 49$	149.8	24.6	0.991
10	$V_3 = 4$, $V_4 = 8$, $V_5 = 0.87$, $V_6 = 8$, $V_7 = 32$, $V_8 = 0.3$, $V_9 = 49$	149.8	24.6	0.991
11	$V_3 = 4$, $V_4 = 8$, $V_5 = 0.88$, $V_6 = 8$, $V_7 = 32$, $V_8 = 0.3$, $V_9 = 49$	149.9	24.6	0.992
12	$V_3 = 4$, $V_4 = 8$, $V_5 = 0.89$, $V_6 = 8$, $V_7 = 32$, $V_8 = 0.3$, $V_9 = 49$	149.9	24.6	0.992

The changes presented in Table 2 refer to two variables V_5 and V_9. This may be information for the decision maker about the field of changes that may lead to project completion at the desired level of NPD and unit production cost.

The number of solutions (variants for project completion) depends on the number of variables, their domains, constraints, and the assumed granularity of variables. For example, the granularity of V_6 (the number of prototype tests) is in hundreds, whereas the granularity of V_8 (the amount of materials needed to produce a unit of a new product) in kilograms. The decrease of granularity for these variables (units for V_6 and decagrams for V_8) will result in a larger search space to find possible solutions. Table 3 presents the results of searching for admissible solutions for three cases and different strategies of variable distribution. First case refers to the basic variant (12 solutions presented in Table 2), the second case is related to an extension of the domain for variable V_6 {800, …, 900}, and the third case refers to an extension of two domains: for variable V_6 and V_8 {20, …, 30}. Different strategies of variable distribution in constraint programming with exhaustive search (ES) are compared in the context of the number of nodes checked, depth and time needed to find solutions. The calculations have been tested on an IntelCore(tm) i5-8300H 2.3-4GHz, RAM 8 GB platform.

Table 3. The comparison of strategies for different variable granularity and variable distribution strategies

Case	Distribution strategy	Number of nodes checked	Depth	Time [sec]
1	ES	12959	67	1.82
	CP Naïve	4253	54	1.27
	CP First-fail	4253	54	1.18
	CP Split	4253	54	1.12
2	ES	654479	84	6.41
	CP Naïve	110124	67	3.01
	CP First-fail	110124	67	2.76
	CP Split	110124	67	2.61
3	ES	3599639	92	11.15
	CP Naïve	285717	78	4.86
	CP First-fail	285717	78	4.02
	CP Split	285717	78	3.94

The results show that the application of CP techniques reduces computational time, what is especially important in the case of the larger number of possible solutions. The user can obtain the entire set of solutions or optimal solution according to (4). 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 project completion within available resources. This approach is especially useful in the case of limited resources (e.g. the project budget) to check the possibility of project completion within the specified constraints. 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 alternatively way. The proposed model encompasses the fields related to a product and company's resources. These fields may be described in terms of a CSP that includes the sets of decision variables, their domains, and constraints that link and limit the variables. The project prototyping problem refers to the search of answers to queries about the estimated values of an output variable (e.g. the NPD cost and unit production cost), and about the values of input variables that ensure the desired values of an output variable.

The results show that the application of the CP environment improves search efficiency of solving the considered problem, especially for a larger number of admissible solutions. Moreover, this study presents the use of a neuro-fuzzy system to identify the relationships for estimating the cost of an NPD project and unit production cost. The identified relationships are specified in the form of *if-then* rules and used to generate variants of an alternative project completion. If project performance according to original specification 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 past similar NPD projects, and specifying several parameters to build and learn a neuro-fuzzy system. Future research directions include a more comprehensive analysis of the complexity scaling regarding the CSP, and an analysis of the uncertainty in the model parameters that affect the NPD simulation.

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