

A Study of Solution of Combinatorial of New Product Problem Using Constraint Programming Planning and Simulation

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Abstract – Currently used decision support solutions allow decision-makers to estimate and compare the cost to the target costs of developing a new product, its manufacturing and promotion. These solutions are however insufficient to support simulation of conditions for identifying the specific costs. The proposed approach provides a framework to look for potential variants to achieve the target cost of production. This paper deals with the product development prototyping problem described in terms of the problem of limited satisfaction. The proposed method uses parametric estimates to identify relationships between different variables and restrictive programming to find variants to complete the project within the resources and project requirement of the company. Experiment results show that restrictive programming provides effective search strategies to find acceptable solutions. The proposed approach therefore provides decision makers with the option of obtaining alternative scenarios within production process limits. This exceeds current methods dedicated to the assessment of a new product's total costs. This paper uses the declarative approach to shape cost of production, but can be expanded easily to other aspects of product development (e.g., product reliability).

Key Words – Constraint Programming; Constraint Satisfaction Problem; Cost Estimation; Decision Support Systems; Multicriteria Optimization; Production Planning; Project Management.

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INTRODUCTION

In contemporary companies which compete in a saturated market with short product life cycles, the process for new product development (NPD) belongs to key processes. The successful delivery of NPD projects affects the profitability and survival of the company. Regrettably, many NPD projects fail totally, miss the deadline, or surpass the budget. According to a study by the Project Management Institute (PMI), changes in priorities within the company and limited resources are some of the main causes of project failure. A number of reasons are given to exceed project duration and cost[1,2]: use of static and uncompromising approaches, use of low-end software solutions that are deprived of all the NPD process-related features, failure to harmonize the goals and strategies for the company, poor management support and poor communication. The last three reasons depend on organizational problems, while the second two concern technical support for improving the performance of the project. The purpose of this study was to devise a method for decision makers to look for alternative scenarios for project completion.

Currently used project planning software solutions provide information on project estimates[3]. If the company does not provide enough resources (e.g., financial, human), the decision-maker may be interested in obtaining information on the alternative project variants, depending on the time schedule, to develop an NPD project. Furthermore, the estimated NPD costs may be unacceptable to them. However, current software solutions cannot support project managers in reviewing project performance opportunities so that, given their company resources and project requirements, the preferred NPD costs are achieved. The approach proposed fills this gap and aims to lay down the foundations for the development of a decision support system for project prototyping solutions. The aim of this paper is to develop an approach that includes research and development (R&D), production and sales promotion factors for the planning and exercise of the NPD project. Since the cost of production is usually most of the overall cost of the product placement in the market, the focus of this study is primarily on the production field. In order to select the most promising NEP project, the proposed approach seeks to identify the costs of R&D and

production and support in the early phase of the NPD project.

The current methods of project planning represent the procedural approach where an NPD model is built for a specific problem and where the structure of the model is sufficient to solve this problem the process of modelling ends. In contrast, a single NPD model is created in the declarative approach to formulate various decision-making problems relating to NPDs. A NPD model declaratory representation enables effective techniques to be used to reduce the search area for the eligible solutions. This is particularly important when selecting for simulations many decision variables with big domains. There are declarative modelling methods for simulated models that can be used to make alternative NPD project performance variants more efficient. A decision maker can carry out simulations for a whole range of admissible alternatives using a declaratory representation of an NPD model. The decision maker therefore obtains more alternative scenarios for the NPD projects than a traditional scenario analysis that incorporates the basic, optimistic and pessimistic variants. In addition, the decision maker can achieve NPD project performance variations which they will never come up with. In multi-project environments, where resources are shared, this is particularly important.

REPRESENTATION COMBINING LEARNING AND SEARCHING

The NP-Hard COPs remain a challenge to solve due to a state-space explosion. In this paper we propose to solve COPs which can be modeled with DP a generic and complete solver based on DRL and CP. This section describes the entire framework architecture. Figure 1 shows a high-level image of the architecture. The study phase, the resolution and the unification of the representation function as a bridge between the two steps, is divided into three parts. There are multiple components in each part. The original contributions of this work, green blocks and arrows, and blue blocks are the known algorithms that we adapted.

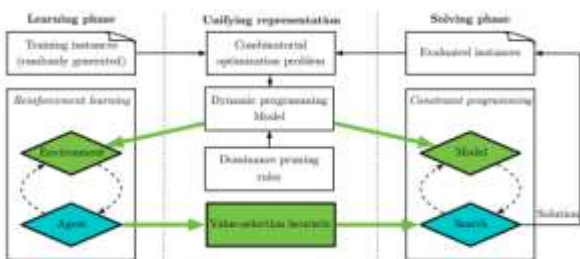


Figure 1: Overview of our framework for solving COPs.

1. Dynamic Programming Model

Dynamic programming (DP)[7] is a technique that combines math and computer modeling to resolve

complex optimisation issues such as NP-hard problems. In its simplest form, a problem is broken into sub-problems and linked by a recursive wording. Then the initial problem is remedied and, by tracking the already-calculated data, successively the optimal values of the decision variables are recovered. Let us consider a general COP $Q : \{\max f(x) : x \in X \subseteq Z^n\}$, where x_i with $i \in n$ are n discrete variables that must be assigned in order to maximize a function $f(x)$. In the DP terminology, the decision variables of Q are referred to as the controls (x_i). They take value from their domain $D(x_i)$, and enforce a transition ($T : S \times X \rightarrow S$) from a state (s_i) to another one (s_{i+1}) where S is the set of states. The initial state (s_1) is known and a transition is done at each stage ($i \in \{1, \dots, n\}$) until all the variables have been assigned. Besides, a reward ($R : S \times X \rightarrow R$) is induced after each transition. Finally, a DP model can also contain validity conditions ($V : S \times X \rightarrow \{0, 1\}$) and dominance rules ($P : S \times X \rightarrow \{0, 1\}$) that restrict the set of feasible actions. The difference between both is that validity conditions are mandatory to ensure the correctness of the DP model ($V(s, x) = 0 \Leftrightarrow T(s, x) = \perp$) whereas the dominance rules are only used for efficiency purposes ($P(s, x) = 0 \Rightarrow T(s, x) = \perp$), where \Leftrightarrow , \Rightarrow , and \perp represent the equivalence, the implication, and the unfeasible state, respectively. A DP model for a COP can then be modelled as a tuple $\langle S, X, T, R, V, P_i \rangle$. The problem can be solved recursively using Bellman Equation, where $g_i : X \rightarrow R$ is a state-value function representing the optimal reward of being at state s_i at stage i :

$$g_i(s_i) = \max \left\{ R(s_i, x_i) + g_{i+1}(T(s_i, x_i)) \right\} \quad \forall i \in \{1..n\} \text{ s.t. } T(s_i, x_i) \neq \perp$$

2. RL Encoding

An introduction to reinforcement learning is proposed in Appendix A. Note that all the sets used to define an RL environment are written using a larger size font. Encoding the DP formulation into a RL environment requires to define, adequately, the set of states, the set of actions, the transition function, and the reward function, as the tuple $\langle S, A, T, R_i \rangle$ from the DP model $\langle S, X, T, R, V, P_i \rangle$ and a specific instance Q_p of the COP that we are considering. The initial state of the RL environment corresponds to the first stage of the DP model, where no variable has been assigned yet.

3. Learning Algorithm

We have implemented two different agents: one based on the DQN method and the other based on the policy gradient (PPO). In both cases, the weight vector (w) of a neural network is parameterized, which gives the Q-values (DQN) or policy probabilities (PPO). The training takes place with randomly generated instances sampled from a distribution similar to those that we want to resolve. It is important to point out that this learning procedure assumes that we have a generator that

can create the same distribution that we want to tackle, or enough similar instances of past data, to create random instances (Qp). In the vast majority of works that tackle NP-hard issues this assumption is common.

4. Neural Network Architecture

In order to ensure the genericity and effectiveness of the framework the design of the neural network architecture is necessary to two things: (1) being able to deal with instances of the same COPs but with a number of variables (i.e. being capable of operating on non-fixed dimension vectors) and (2) being invariant in the process of input permutations. That is to say, x_1 , x_2 and x_3 encode variables should be equivalent to the x_3 , x_1 , and x_2 encoding forecast. The first option is to integrate the variables into a set transformer architecture that ensures both. In addition, numerous COPs also have a naturally occurring graph structure. For this reason, we also looked at another integration based on a graphical attention network (GAT). The insertion can then be used as input for a feed forward network to obtain a prediction, either using the GAT or set transformer. Case studies show both architectures practical application. For the DQN network, the dimensions of the last output layer are the total number of COP actions and the Q values for each of these measures are calculated. In order to eliminate unfeasible actions, the output is masked. In the PPO, the actor and the critics have established separate networks. Only one value is given in the last layer of critics. For the actor it is similar to the case DQN, but after the last layer a soft max selection is used to get the probability of selecting each action.

NEW PRODUCT DEVELOPMENT

New product development starts with market needs identification and ends with market introduction. The literature distinguishes between the intermediate phases of the NPD process. [5] proposed to plan, develop concepts, design systems, details, tests and refinement, and increase production phases in the NPD process. The NPD process is based on the following phases: The NDP model was then developed by [6], which identified the identification and selection of opportunities, concept generation, concept assessment, product development, and launch. Once a product has been placed onto the market, sales and activities related to production and promotion are the next phase of the product life cycle. If a new product has been launched successfully on the market, most of the cost of the entire product life cycle is incurred in the production stage. Custom cash flows (sales, costs, and related profit and losses) are illustrated in Figure 2.

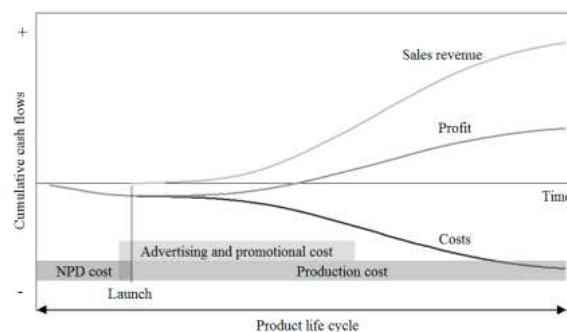


Figure 2. Product development cash flow

A comparison of the predicted cash inflows with outflows can measure the potential of a new product within a given duration. Sales and costs of product development, production and promotion must therefore be predicted. Projections for sales and cost estimates rely on the available data for previous similar NPD projects. Analogic models can be used to estimate costs if the new product belongs to the existing product line. In turn, analytical models are better suited for the assessment of sales or costs of a new product if a company is developing a completely new product. The cost of product development, production, and promotion are included in the cumulative costs. Before a new product is released on the market, NPD costs occur. The cost of producing a new product appears in the NPD period and lasts until the end of the cycle of production life. In turn, before launching a new product, advertising and advertising cost can begin and usually occur in the first sales phase. When comparing alternative new products, product life, sales and costs must be predicted. The assessment of the potential for new products can also include the discount rate (as in NPV) to reflect the investment period's opportunity cost of capital and inflation.

Cost Estimation Techniques

Empirical studies indicate that the size and budget of a project team are key structural variables that affect the quality and success of the NPD process [7]. Research of new product forecasts for industrial enterprises shows that customer/market research, look-like analysis, trend line analysis, average move, scenario analysis and multi-attribute model research are among the most popular techniques [8,9]. To a lesser extent, companies use nonlinear regression, expert systems, neural, and neuro-fuzzy networks for their forecasting techniques [8,10]. Techniques of cost estimation may be divided into intuitive, analogous, parametric and analytical groups [11,12]. Intuitive methods use an estimator's past experience. Similar to previous products, analogical methods calculate the costs of new products. The cost of a new product is calculated by parameters that have a significant impact on the costs. By decomposing product development into

basic tasks at known cost, analytical methods estimate the cost of a product. The techniques for the parametrical estimation of regression can be based [13,14], artificial neural networks [15, 16], furious logic systems, or hybrid systems, such as neurofuzzy systems and genetic fuzzy systems. A detailed analysis of the product characteristics and the production process are the basis for engineering approaches. For instance, in this approach, the cost of a new product is calculated as the sum of resources used to design and produce each product component (e.g., raw materials, labor, and equipment). In the final phases of product development, the engineering approach is best used, which defines the product and process well.

Constraint Programming Techniques

A CSP can be formulated to create a project prototyping problem by setting limitations and variables. The use of restricted programming solves CSPs that are combinatory problems (CP). CP includes consistency techniques and systematic search strategies which are crucial in the resolution of CSPs in order to improve search efficiency. Therefore, CP provides an adequate framework to develop decision-making software to support the identification of alternatives for project completion. Two phases of constraint programming are defined: first, in terms of constraints, the problems are specified, then resolved. The problem specification with restrictions is very flexible because restrictions can be added, removed or changed. Instead of general methods, CP's aim is to develop efficient domain-specific approaches. You can develop more efficient restriction solvers, propagation constraints and search algorithms. CP is therefore a strong paradigm for the resolution of joint search issues, whereby the user declaratively states the restrictions on viable solutions for a set of decision variables. The advantages of using CP include declarative problem modelling, spreading decision-making effects through efficient algorithms and the quest for optimum solutions. The particular search processes and limit propagation algorithms used in CP reduce search space considerably. CP is therefore appropriate for the modelling of complex planning, production, resource allocation, supply chain problems, and so forth. The CP paradigm was used for the NPD project in fields like design and product configuration, planning of projects and prototyping of projects. While CP is widely discussed in the literature on the selection and planning of projects, the problem of the prototyping of NPD project has not so far been examined.

Problem Formulation

The project prototyping problem is a problem where alternative NPD scenarios for project completion are sought in view of the restrictions adopted. The aim of this study is to identify variants that fulfill the desired NPD cost for projects. When the decision-maker

finds a certain cost unacceptable, the project is rejected in the traditional project assessment approach. If the project is strategically important, however, the decision maker is interested in the preconditions that need to be fulfilled to achieve the desired cost limit. The approach proposed is to identify all possible project (variant) scenarios that meet project objectives, project budget, human resources, machinery etc. The traditional project evaluation approach (Figure 3a) is compared to the proposed approach in which variants in the objective project performance are searched (Figure 3b). The traditional approach can be regarded as a problem with prototyping of projects stated in a forward version, whilst a similar type of problem in an inverse version can be viewed in this study.

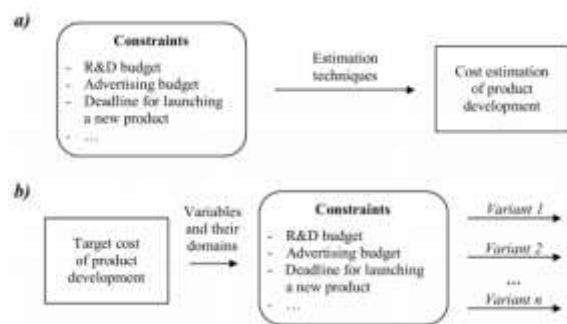


Figure 3. The project prototyping problem stated in a forward (a) and inverse form (b)

In light of the specific limitations, variables and connections between these variables, the proposed approach enables decision-makers to identify the prerequisites that must be fulfilled to achieve the desired performance levels. The number of possible project variants depends on what limitations and variable domains are taken into consideration and on the granularity of variables in decision. Based on previous experiences with similar projects and as a rule, relations between variables can be identified and presented. They can then be used to predict a project's potential (the traditional approach) or to test whether alternate project completion scenarios can provide the project's desired output (the proposed approach). Using CSP to formulate the prototyping problem of the project offers considerable flexibility in the approach proposed. A simultaneous recalculation and a new set of possible solutions is caused by the addition and removal of variables or constraints from/to CSP. The current prototyping approach for the project needs variables, fields and constraints to be specified. This enables all available solutions to be identified, if they exist. The prototyping problem can be easily expressed as a CSP which can be described in the following form:

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

There are the following constraints regarding the available quantity of resources in a company and

technical parameters of a new product: NPD project budget (PB, in thousand €), total number of R&D employees involved in an NPD project (TE), deadline for launching the new product into the market (LD, in months), time needed to manufacture a unit of a new product (MT), and advertising and promotional budget (AB, in thousand €). The set of constraints and relationships is as follows:

$$V_1 \leq PB \quad (2)$$

$$V_4 + V_5 \leq TE \quad (3)$$

$$V_6 + V_7 \leq LD \quad (4)$$

$$V_{12} + V_{13} \leq MT \quad (5)$$

$$V_3 \leq AB \quad (6)$$

$$V_2 \cdot V_{17} = V_{18} \quad (7)$$

$$V_2 + V_{19} \leq V_{20} \quad (8)$$

$$V_1 + V_3 + V_{18} \leq V_{21} \quad (9)$$

The model formulated as a CSP incorporates the technical parameters of the new product that refer to the planned project performance and the available resources.

The Proposed Method for Planning and Simulation of Production Cost

The proposed method consists of the following phases: (1) collecting data from previous projects that are similar to the new project, (2) identifying relationships between variables, (3) estimating the production cost, and, if needed, (4) searching for variants that allow to obtain the desired cost. Figure 4 shows a framework for the proposed decision support system that uses parametric estimation techniques to identify relationships and constraint programming to reduce the search space and test the possibility of reaching the desired production cost.

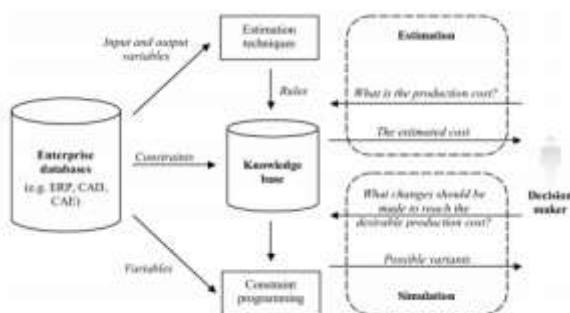


Figure 4. A framework for the proposed decision support system

In the first phase, the data is collected from enterprise databases, for example related to information systems such as enterprise resource planning (ERP), computer-aided design (CAD), and computer-aided engineering (CAE). This requires the

use of some project management standards, including project performance planning, monitoring, control, and appropriate project planning and execution techniques. The use of the proposed approach requires the access to the sufficient amount of data related to the past NPD projects that can be outdated, which causes the need to consider the delay aspect. The applicability of the proposed method depends on whether or not the following data management procedures are used: the enterprise adjusts the common project management standards to its needs, distinguishes phases in the NPD process, uses standards for specifying tasks in an NPD project and for project portfolio management, measures the success of new products on corporate financial performance, uses the results of a financial performance analysis to improve the effectiveness of NPD projects, registers performance and metrics of NPD projects, uses a primary schedule for monitoring performance in NPD projects, and uses the defined procedure to allocate employees to NPD projects. In the second phase of the proposed method, cause-and-effect relationships are identified and then used to estimate the cost of product development, and search for a desirable outcome of an NPD project. The input variables should impact the cost and be controlled by a company, such as the number of project team members, product components, and prototype tests. A set of variables, their domains, and constraints constitute a CSP, which provides a framework for finding the value of the NPD, production and promotional cost (the third phase), and, if that is unacceptable, the values of variables at which the desired cost of a new product can be achieved (the fourth phase).

In the third phase, the cost is estimated using the parametric models based on linear regression and artificial neural networks. The quality of the obtained results is compared using the root mean square errors. The data set is divided into learning and testing sets to verify the quality of the learned neural network. The small errors in the testing set exhibit good predictive abilities of the learned network.

The fourth phase of the proposed method refers to the search for possible solutions to achieve the desired cost. The size of the search space depends on the number of variables analyzed, the range of decision variable domains, and the constraints that link the variables and limit the set of possible solutions. An exhaustive search always finds a solution if one 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, which limits its usage in solving many practical problems. Consequently, more effective methods for searching the space and finding possible solutions are needed. This study proposes a CP that can be used to efficiently solve a project prototyping problem

modelled as a CSP. Figure 5 shows a framework for solving this problem in the inverse form.

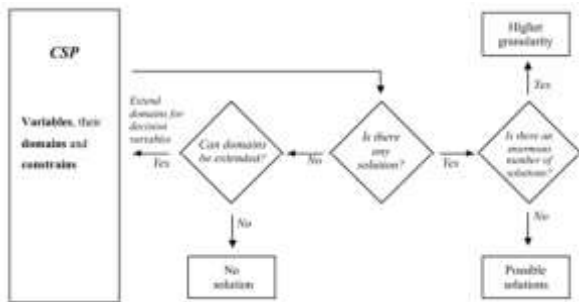


Figure 5. A framework for solving the inverse form of the project prototyping problem

Three stop/go conditions are included in the approach proposed. Due to the specified input and output variable, their domains and constraints, the first stop/go condition checks whether there exists a solution for a set of decision variables. When such a solution is available, a number of solutions will be checked for user acceptability or not. Otherwise, the solution's granularity is increased. In addition, granular changes have to do with scaling domains and affect the efficiency of the CP application in a significant way (e.g., the production cost specified in 1000 euros provides a smaller number of solutions than when specified in single euros). If a solution exists, the possibility is tested to extend the domains relating to the selected decision variables. In addition, the last stop condition will lead to the empty solution set if the fields of the selected decision variables cannot be changed.

CONCLUSION

The declarative approach proposed in this paper is an alternative to current methods that estimate only the cost of NPD, production and promotion. NPD prototyping is a declarative approach. All possible scenarios for completing the project, if any, are sought in the proposed prototyping method. These variants inform the decision maker whether an NPD project can be carried out on the basis of resources and project requirements of the company. Limited-resource companies need to make further efforts to manage NPD projects. This approach is particularly useful for such firms (e.g., with a limited project budget), as it enables them to verify whether a project can be carried out under the specified limits (e.g., the desired level of the unit production cost). Therefore, a decision-making support system must be developed to look for possible variants of cost reduction. The model proposed includes areas relating to a product and the resources of a company. This is a CSP which includes a set of decisions variables, areas and constraints. These areas have been described. The problem of the project prototyping is the answer to questions on the estimated cost and input variables that ensure the desired cost. The results of this study not only

include the possibility of checking to achieve the desired cost level, but also to identify potential variants of project completion. The presented process can be used to check whether an NPD project can be completed at the target time and specify the necessary resources for reducing project duration. This is one of the main issues in connection with the new product development process. The problem in this paper is a prototyping issue which is stated in the reverse and which aims at ensuring the desired cost of production in the possible variants. However, in other areas, for example project scheduling, product configuration, resource allocation and supply chain issues, it is also possible to use the proposed approach. The results show that the application of a CP improves search efficiency, especially when a larger number of solutions are acceptable, in the context of project prototyping problems. In addition, this survey identifies the relationships for cost estimation within a product life cycle through the use of artificial neural networks. The relationships identified are stored in a knowledge base and used to create different variants for the production of a new product. If decision makers find that the cost of product development are unacceptable, they can use the variants identified to support the identification of the influence of input variables on an output variable under the specified restrictions (e.g. unit cost of production). The disadvantage of the proposed approach is the need to collect sufficient data on similar past NPD projects and to specify a number of parameters to build and train an artificial neural network. In addition, the restriction on the present study is the selection of input variables which have a significant impact on new product costs and are controllable by a company, and the time required by the decision maker to analyze every solution. For a large number of admissible options the domain granularity can be increased, or in the calculations the minimum and maximum domain values can be considered. In our further work we would like to check the approach proposed in the different business sectors of project-oriented companies. We also intend to extend the implementation of the approach presented by including the guarantee costs in the overall development costs of the product.

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