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RESEARCH ARTICLE

Modeling and optimising alternatives suitable to advance the product development process

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Abstract

In the rapidly changing technical-economical environment time has an increasingly important role in the product development besides creativity, cost, quality criteria. In this paper we aim to reveal methods that can decrease the cost and time spent on the product development increasing the efficiency of the process. This publication presents an insight of optimising with the use of design structure matrix, genetic algorithms, and neural network. Provides the opportunity of using the methods in different areas, so it may result a profitable industrial innovation, and is suitable for creating new ideas on the field of automobile engineering projects.

Keywords

product development · design structure matrix · genetic algorithms · neural

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1 Introduction

The product development applications have been many and varied and have led to a deeper understanding of how to gather and use information about the customer in the design, testing, launch, and management of new products [1].

For the time and resource perspective planning of the construction design process a Design Structure Matrix (DSM) based modelling optimization procedure was worked out applying genetic algorithms. The application of such methods gives opportunity to determinate the minimal lead time required for design activity sequence.

The intense international competition, the accelerating technical development and the increasing customer requirements resulted new and more market compatible product nnovation to be essential for companies. At these products not only the search of technical solutions but the product development and design process, the resources, capacity, costs, information flow and management are also emphasized along with a conscious quality assurance and risks that inherent in innovation management [2].

2 Product development principles

Product development is the process between defining a market opportunity based on the actual and predicted customer's needs and the beginning of the production [3]. According to Baldwin and Clark [4, page 149–165] product development is a search for something unknown, and the result is a description of a thing to be made, including instructions about how to make it.

The management of product development demands systematic methods that account for the special characteristics of the projects. Most important of the challenging factors are *extreme complexity* - today's products include tens of thousands components. *High uncertainty* - the precise functions, attributes and components of the product are unknown at the outset of a product development project. *Dynamic project context* - the customer's needs, the competitors' products and the available technologies change during the lifetime of product development project. *Iterative processes* - engineering work is creative and innovative. Product development processes are iterative, not repetitive like manufacturing or business processes. As a consequence the changes are natural part of product development projects that have to be considered during the planning and control of such projects. Fig. 1 shows the core competence of the integrated product development process.

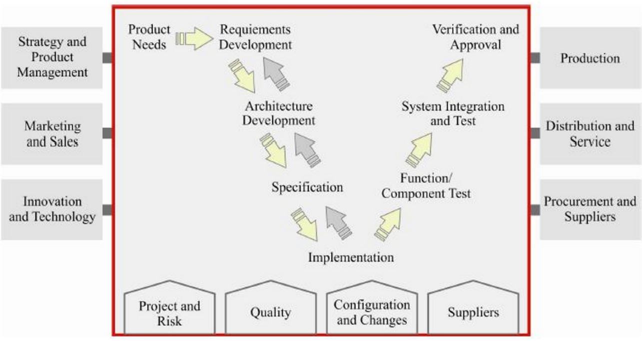

Fig. 1. Management of Product Development

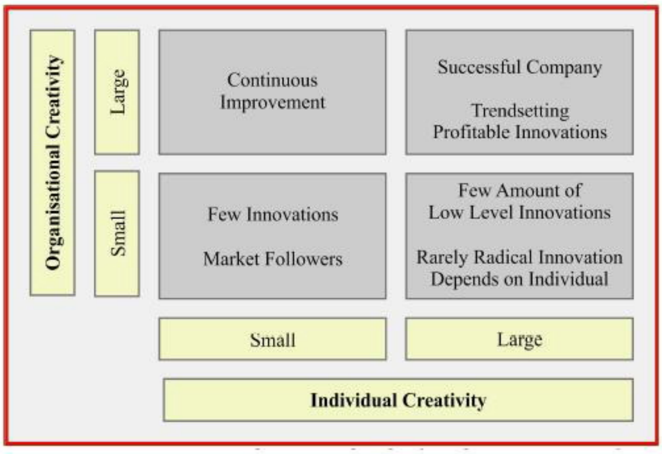

Fig. 2. Effects of innovation according to individual and organizational creativity [9]

The main goal is the increasing success to accomplish "profitable" innovation. With the use of optimisation techniques sustainable improvement in time to market, total cost, product maturity, process quality and consumer satisfaction can be reached. The integration of conceptual expertise and practicability leads to strategic alignment in product development. Efficient and mature product development processes and methods combined with a marketoriented product portfolio eventuates in a superior product development strategy.

3 Enhancing creativity and motivation at the field of organizational innovation

In terms of the innovation process the idea generating has a high level importance, which cannot be reached without appropriate motivation [5]. However, if you manage to achieve the required level of motivation, it might turn into the company's most valuable strategic advantage [6].

To enhance creativity in business, three components were needed, expertise (technical, procedural and intellectual knowledge), creative thinking skills (how flexibly and imaginatively people approach problems), and motivation (especially intrinsic motivation, comes from inside an individual, satisfaction, enjoyment of work etc) [7].

Social scientists consider creativity as an integrative and cumulative process which recombines the existing knowledge in a new way. Creativity can be observed from the aspect of an organisation or an individual. Main drives of the organisational creativity are creative and democratic leadership, opened organisational communication, diversity of the company and feedback. The influence of personal creativity is more divergent: personal competencies also take part besides the qualification of the individual [8]. Fig. 2 describes the effects of innovation according to individual and organizational creativity.

4 Modeling and optimising of development process

The challenge in this scheme is the management of a large number and variety of components, as it is the case in typical mechatronic systems. Recording the components one by one, identifying the interactions between the components, and distinguishing the relational groupings is most of the time beyond the capability of a single engineer and even of a group [10].

4.1 Design structure matrix representations

The majority of the traditional project management tools (Gantt-diagram, CPNM-PERTIDEF-methods) alone are not suitable to solve the problems derived from the complexity of the project planning. However, the Design Structure Matrix (DSM) method gives the possibility to the project and planning programme managers of modeling the sequential and overlapping activities as well as describing relationships of interdepentdent tasks; integrates the network planning, – and where applicable – the elements of cost planning [11].

For the time and resource oriented planning of the construction design process, a DSM (Design Structure Matrix) based modelling and genetic algorithm using optimization procedure was developed. By procedures using heuristic methods, it is possible – with given resources – to define the sequence of design activities requiring the minimal turnaround time.

The discrete methods can give accurate results to the resource-allocation problems with small tasks, but as the tasks grow, they become unmanageable with discrete methods, so it is advisable to use heuristic methods. According to the comparison, the decision heuristics combined with genetic algorithms achieved the best results [12].

DSM is first introduced by Steward (1981) to manage the parameter dependencies in the design of a complex system. It is widely used for managing the complexity of components and interfacing in design. A DSM is a relational matrix that constitutes a framework for documenting and evaluation of the interface architecture. The DSM is usually created following the functional decomposition of the system [13].

DSM can in fact be used in any domain where entities are related with each other on a varying relational basis. For example, it can be used for analyzing the dependencies between marketing, operations management, and engineering decisions for product development [14].

	E1	E2	E3	E4	E5	E6
E1	x	1		1		
E2		x				
E3			x			1
E4	0,5			x		
E5					x	
E6			1	1		x

(a)

	E5	E4	E1	E2	E3	E6
E5	x					
E4		x	0,5			
E1		1	x	1		1
E2				x		
E3					x	1
E6		0,5			1	x

(b)

Fig. 3. A sample DSM (a) and its diagonalized form (b)

Fig. 3a shows a sample documenting the relation between six entitis. Entity one ($E1$) provides inputs to $E2$ and $E4$, and gets input from $E4$. $E4$ gets inputs from $E1$ and $E6$. The diagonal of the matrix is redundant. The weight of the entries signifies the degree of the relation between two entities. Usually a larger value signifies higher degree of relation. Accordingly, the input relation from $E6$ to $E3$ is higher valued compared to the input relation from E6 to E4.

For modularizaztion it is usually the case that the relational matrix is "diagonalized" in the sense of bringing the larger weighted relations close to the diagonal. Diagonalization corresponds to finding the optimal permutation of the components that minimizes a cost function. This cost function decreases when the larger weighted relations are placed close to the diagonal. For example the DSM in fig. 3a can be diagonalized as in fig. 3b. Finding the optimum permutation is an NP-hard problem. A complete enumeration of the possible solutions gets computationally too costly for large number of entities.

Therefore, some heuristic search methods (genetic algorithms, simulated annealing) are used to find near-optimal solutions.

Diagonalization is obtained by minimizing a cost function which delineates the distance of the entries from the diagonal. Once the diagonalization is performed the engineer can visually determine the modules identifying the groupings in the DSM along the diagonal. In Fig. 3b the elements $\{E4, E1, E2\}$, $\{E3, E6\}$, and $\{E5\}$ constitute three groups that can be named as modules. However, when the size of the matrix is large and the grouping is not clear, visual determination of the modules is difficult and tedious [15].

4.2 Genetic algorithms and strategy development

The planning of design steps' sequence and optimization of the constructional design processes, genetic algorithm was used with integer coding.

Genetic Algorithms (GAs) are currently an accepted method for searching large multimodal domains that have inexpensive fitness function calls. The requirement regarding the execution time for the fitness function is needed as GAs often require several hundred thousand function calls to converge onto a solution. The method used in GAs, to model the solution space, is to maintain a population of candidate solutions. The biologically inspired operations of reproduction, crossover and mutation are performed on these solutions to improve their utility over successive iterations.

Input-variable dependencies, for a solution space, would provide information on how inputs might be separated into difierent sub-problems. This dependency information is modeled indirectly by GAs. The chromosome representation for GAs and the most common implementations of the crossover operator assume that coupled variables will appear near each other on the candidate string. This bias for the crossover operation, will be shown through the examples of this section.

The application of crossover within GA is an attempt to separate out a sub-solution to a component sub-problem from one parent and combine it with a sub-solution from a second parent. The child, so created, would therefore have the incorporated solutions developed from each parent. GAs do not compute the explicit relationships between input variables to determine where the best crossover points should be. They randomly select crossovers that are often not beneficial towards separating the problem into sub-problems without the aid of many repeated attemptsIn practice, expert knowledge is sometimes pulled upon to place related inputs next to each other on the candidate chromosome string; increasing the chances that a single crossover operation will carry forward discovered sub-solutions. While this approach is reasonable, it assumes access to expert knowledge for the domain at hand and presupposes that the relationships for this domain will fall within previously observed behaviors [16].

4.3 Neural networks for problem decompostion

Interesting recent work by Khare in 2006. [16] has sought to automatically decompose several problems by evolving neural networks for each sub-problem component.

As shown in Fig. 4, the method used to select among these modules is to start with a general population of modules with each module accepting a random number of the input variables. Composite system models are created from these modules and each system model trains a combining network based off of training data, Fig. 4.

The success of each system model, in predicting a validation set, provides a fitness measure for the model. The presence of modules in high performing system models provide a fitness

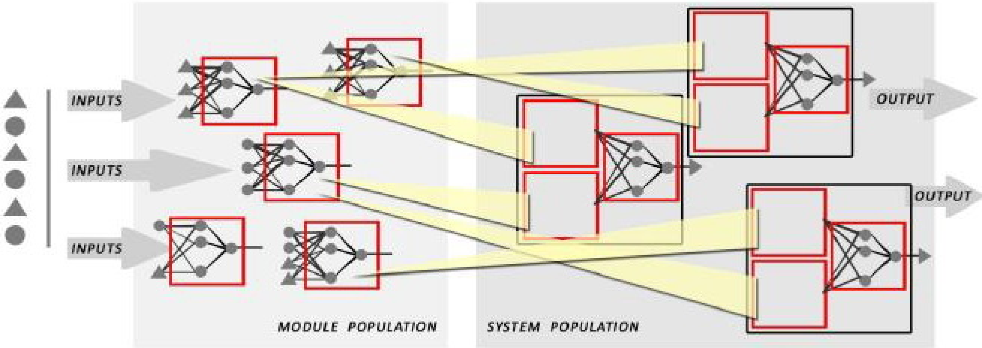

Fig. 4. Two Populations Maintained to Generate Co-evolutionary Module [17].

measure for the module population. The presence of modules in high performing system models provide a fitness measure for the module population.

Neutral Networks take a networked form inspired by the structure of neurons within the brain. They have great expressive ability for modeling non-linear functions and have been used widely within control systems and as a non-linear replacement for RSEs. There are a large number of excellent introductions to topic of neural networks [18].

Regarding the expressive power of neural networks, there are proofs that show that there exists a network of two hidden layers that can approximate any arbitrary function. A network with a single hidden layer and a suficient (possibly very large) number of nodes can represent any continuous function and all boolean functions [19].

One would use a neural network when there are a large number of varied examples for the behavior one wants to learn. The set of data may contain errors as the training is robust to noise within the training set. After a network is trained, the runtime evaluation of the regression is very rapid when compared to nearest neighbor type methods [20].

The large training set and high number of weights cause long training times. The neural networks is also not able to explain its response to human examination. The network acts as a black box. Cases of medical diagnosis, for example, require an explained set of humanreadable reasoning that is not available through a neural networks . There is also an extremely high probability that the training set will be overfit by the network during training. When a network overfits a set of data, both the information and noise from a set of data is fit by the model.

If a validation data set is used to trim links from a network, an additional validation set should be used to serve as an unbiased judge of the networks future performance. These additional data sets increase the already large sample data requirements for the network [21].

5 Conclusion

This working paper describes several promising ideas to maximize desired benefits while minimizing negative aspects of product development could be utilized to advance profitable innovation.

Approach to identifying a set of design alternatives and selecting the best candidate from within that set, engineering optimization was developed as a means of helping engineers to design systems that are both more efficient and less expensive and to develop new ways of improving the performance of existing systems.

Optimization techniques can now be used to find creative solutions to larger, more complex problems than ever before. As a consequence, optimization is now viewed as an indispensable tool of the trade for engineers working in many different industries, especially the aerospace, automotive, chemical, electrical, and manufacturing industries.

This study provides an application-oriented presentation of the full array of classical and newly developed optimization techniques now being used by engineers in a wide range of industries.

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