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A new support vector model-based imperialist competitive algorithm for time estimation in new product development projects

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ABSTRACT

Time estimation in new product development (NPD) projects is often a complex problem due to its nonlinearity and the small quantity of data patterns. Support vector regression (SVR) based on statistical learning theory is introduced as a new neural network technique with maximum generalization ability. The SVR has been utilized to solve nonlinear regression problems successfully. However, the applicability of the SVR is highly affected due to the difficulty of selecting the SVR parameters appropriately. The imperialist competitive algorithm (ICA) as a socio-politically inspired optimization strategy is employed to solve the real world engineering problems. This optimization algorithm is inspired by competition mechanism among imperialists and colonies, in contrast to evolutionary algorithms. This paper presents a new model integrating the SVR and the ICA for time estimation in NPD projects, in which ICA is used to tune the parameters of the SVR. A real data set from a case study of an NPD project in a manufacturing industry is presented to demonstrate the performance of the proposed model. In addition, the comparison is provided between the proposed model and conventional techniques, namely nonlinear regression, back-propagation neural networks (BPNN), pure SVR and general regression neural networks (GRNN). The experimental results indicate that the presented model achieves high estimation accuracy and leads to effective prediction.

1. Introduction

New product development (NPD) is an important activity that contributes to company growth and profits substantially in a manufacturing industry. Many companies attempt to introduce new products in major markets. The NPD project is the driving force for the companies heavily invested in their R&D department [1,2]. In competing markets, companies are facing remarkable pressure to rapidly introduce new products because product life cycles are becoming noticeably shorter. In fact, managing NPD projects is essential and there is a strong incentive to be first to major markets. NPD projects are regarded as the engine of company sales, market share, and profits. Key characteristics of these projects are as follows [3]:

- Technological novelty
- Product visibility
- Speed
- Changeability
- Risk involvement

These characteristics lead to a set of critical success factors that affect not only the process performance (e.g., speed and productivity) but also financial performance (e.g., profits, revenues, and market share) in NPD projects [3].

Estimating the project completion time is highly important for the success of project managers in modern companies. Consequently, project management activities (e.g., project planning and resource allocation) are deeply affected. The NPD project time has a tendency to increase with uncertainty and complexity in terms of tasks, resources, participants and design features [4,5]. Therefore, accurate and reliable time estimation of NPD projects should be considered during the early stages of industrial research.

In the last two decades, researchers have focused on time management and estimation in NPD projects. Karagozoglu and Brown [6] considered a problem of compressing NPD projects by focusing on stages of the innovation process based on time management in high-technology companies. Rosenthal and Tatikonda [7] reported findings from seven case studies on the management of the time dimension in NPD projects. LaBahn et al. [8] examined the influence of outcome-based performance evaluation and non-technical outside assistance on NPD cycle time in small manufacturing companies. Clift and Vandenbosch [9] applied a pattern-matching methodology, and selected 20

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NPD projects for detailed study on the complexity and efforts in order to reduce their cycle time.

Griffin [10] evaluated data to quantify average cycle times for four different types of NPD projects by business-to-business (B2B) firms. Swink [11] focused on the effect of accelerated time goals on the execution and completion of NPD projects. In fact, relations among project content, project leadership, and aspects of design integration are studied. Chen et al. [4] proposed a framework for the NPD project scheduling and rescheduling based on DSM in large-scale projects. Dragut and Bertrand [12] extended a simple queuing model including four factors to estimate the solving-time distribution for a finite set of design tasks in NPD projects. Langerak and Hultink [13] studied the impact of nine NPD acceleration approaches on the development speed. This research illustrates that firms developing different types of new products should utilize different NPD acceleration approaches. Wang and Lin [14] developed an overlapping process model to capture the uncertain nature and complex interactions of NPD process. Their model is presented to forecast the impacts of process structure on the development lead-time. Reboreda et al. [15] used the SVR for estimation of time in injection modeling production in automotive industries. They applied RBF kernels in their approach and obtained results in automatic time estimation of the task execution. However, they did not consider the optimization of the SVR parameters.

The review of the previous work shows that there are a few studies to implement artificial intelligence (AI) models within the time estimation and prediction in NPD projects. On the other hand, having a reliable approach to estimate the time of NPD projects is a major concern of top managers in an NPD environment. Traditionally, to handle the prediction problems, simple and multiple regressions have been applied, which had some limitations and poor performances. For this purpose, AI models can be regarded as a powerful and effective approach to solving NPD project problems. In addition, this paper combines two new approaches in order to utilize advantages of the AI and evolutionary algorithms, and improve the performance of prediction dramatically in complex and nonlinear systems.

Support vector regression (SVR) introduced by Vapnik [16] has been used in a wide range of applications with considerable results. SVR is based on statistical learning theory and employed to solve various regression problems. Also, SVR is regarded as a new neural network and supervised learning technique, and is a learning approach. It overcomes weaknesses of conventional prediction techniques, such as artificial neural networks (ANNs) and fuzzy systems, in real-world applications because of their excellent performance in generalization and their capacity for self-learning [17]. In fact, SVR is a regression technique which belongs to both statistical and AI techniques. SVR has recently been successfully utilized in numerous industrial fields. For instance, cost estimation of the wing-box structural design [18], prediction of the dissolved gases content [19], forecasting tourism demand [20] and prediction of bankruptcy [21]. In SVR, the solution of a nonlinear problem in the original lower dimensional input space can find its linear solution in the higher dimensional feature space [16]. In addition, this technique can find the optimal solution by using convex quadratic programming.

Currently, the commonly used optimization tool, namely genetic algorithm (GA), is widely considered for searching optimally by some researchers [21,22]. This algorithm has a few weaknesses that can lead to problems. Although it may obtain the optimal or near-optimal solution, the operation of GA is difficult and often time-consuming [21]. Different types and rates of genetic operators, such as crossover and mutation, need to be set for different optimization problems [19]. In addition, conventional evolutionary algorithms, such as GA and ant colony optimization (ACO), have been used as the searching strategy to reduce the computational time. Foregoing algorithms are inspired by natural behaviors. To address the above-mentioned problems, this paper utilizes a new global optimizing algorithm, namely imperialist competitive algorithm (ICA), which is inspired by an imperialistic competition mechanism. The ICA was first introduced by Atashpaz-Gargari and Lucas [23] and Atashpaz-Gargari et al. [24] in order to solve continuous optimization problems. This algorithm not only is easy to implement, powerful and computationally efficient but also has a few parameters to adjust.

This paper aims to improve the performance of time estimation in NPD projects by introducing an integrated support vector model. The selection of parameters in the SVR model is optimized by using the ICA simultaneously. This proposed model is validated by using a real data set collected from a case study for NPD projects in a manufacturing industry. By using the proposed model, top managers can recognize and control the potential problems, which have negative impacts on the project success, in an NPD environment and consequently dynamically monitor time management through the project life cycle. Comparisons are also made among the performance of the proposed model and conventional techniques, including nonlinear regression, back-propagation neural network (BPNN), pure SVR and general regression neural network (GRNN).

The rest of this paper is organized as follows. In Sections 2 and 3, some basic concepts on the SVR and the ICA are briefly introduced, respectively. In Section 4, the proposed SVR model-based ICA is described for estimating the project time in an NPD environment. Section 5 provides the background information for the case study problem in order to illustrate their potential applications in NPD projects, and obtains the estimation results. In Section 6, comparative evaluations are made to contrast the performances of four conventional techniques and discussions. Finally, conclusion remarks are drawn in Section 7.

2. Support vector regression

The support vector machine (SVM) was first introduced by Vapnik in late 1960s based on the foundation of statistical learning theory. However, since the middle of 1990s, the algorithms used for SVMs started emerging with the greater availability of computing power, paving the way for numerous practical applications [16,18,25–28]. The basic SVM deals with two-class problems in which the data are separated by a hyper plane defined by a number of support vectors. For detailed descriptions, readers are referred to the tutorials on SVMs [25,26].

The SVR is a new training technique based on the SVM; however, it requires only the solution of a set of linear equations instead of the long and computationally hard quadratic programming problem involved in the standard SVM [28]. In the following, a brief introduction to the SVR is given [25,26].

First, to better explain the SVR, linear regression is briefly addressed. Consider a given training set $(x_i,d_i)_{i=1}^{N}$, where $x_i \in R^P$ represents a p-dimensional input vector and $d_i \in R$ is a scalar measured output, which represents the model output. The objective is to construct a linear function $f(x)$ which estimates the dependence of the output d_i on the input x_i. We define the form of this function as

$$f(x) = w^T.x + b, \tag{1}$$

where w is the weighting vector and b is the bias term. This paper constructs this function to predict the time of NPD projects. The regression model (1) can be constructed by using a nonlinear