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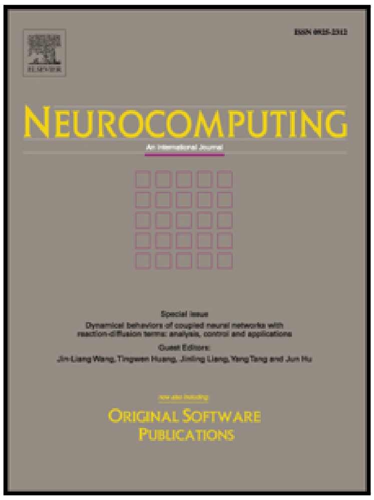

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A case-based reasoning approach to cost estimation of new product development

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Abstract

New product development (NPD) is a crucial process in maintaining a company's competitive position and succeeding in dynamic markets. One of contemporary trends in the global economy is mass customisation that bases on modifications of existing products instead of designing everything anew. The advancement of information technology helps today's enterprises in managing business processes and collecting data in enterprise systems that can be a potential source of information. Specifications of previous products deliver information of design, cost and time of past NPD projects that can be the basis for developing new products. A promising methodology for assisting conceptual product design and monitoring a NPD project is case-based reasoning. This paper is concerned with developing a case-based reasoning approach towards using neural networks to estimate the cost of NPD in one-of-a-kind production companies.

Keywords:
Artificial neural network, Case-based reasoning, Decision support tool, New product development, Cost estimation

1. Introduction

A turbulent environment imposes organisations to be smart, agile, and responsive to fast changes of business needs. In order to survive and maintain

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development, organisations have to improve their new product development process and product quality, adjust their products to customer's requirements, accelerate the process of commercialisation, and be ahead of their competitors [1]. A successful launch of products on the market seems to be critical activity in drifting a company towards a favourable competitive position.

The new product development process includes the stages of identifying customer needs, generating concepts, selecting a concept (or a set of concepts), designing a product, testing prototypes of a new product, and launching [2, 3]. As the stage of concept selection precedes the more expensive and long-term development of the selected products, it is the critical stage of the NPD process and one of the most important decisions that impact business success. The selection of product concepts usually bases on the metrics such as the cost and time of a NPD project or the potential profit from a new product.

This study is addressed to one-of-a-kind product development, in which customer requirements are increasingly involved. One-of-a-kind production companies largely depend on their ability to develop newer, more qualitative and innovative products within a short period of time [4]. It is widely accepted in many one-of-a-kind production companies that design process relies significantly on past design experience and knowledge, instead of designing a product from scratch [4, 5, 6]. A promising methodology for assisting conceptual product design is case-based reasoning (CBR).

CBR is a process for solving a new problem case by referring to the solutions of similar past cases [7]. CBR simulates the human problem-processing model and can have the self-learning function by constant accumulation of past experience [8]. A CBR system usually consists of three modules: a case representation scheme, a similarity metric, and a case retrieval mechanism. In recent years, computational intelligence techniques such as neural networks, fuzzy logic, genetic algorithms, and multi-agent systems have also been integrated with CBR to construct the retrieval mechanism [9, 10, 11].

CBR provides methodology for supporting product design by adapting previously successful solutions to current problems. The use of the customised product design increases product variety and results in updating a case base related to past product specifications. The case base can derive from an enterprise information system that can embrace software packages dedicated to enterprise resource planning, customer relationship management, and computer aided design. This system registers and stores specifications of previous products, design parameters and workflow, NPD project planning and implementation, as well as customer complaints, comments and requirements.

The aim of this study is the development of a CBR approach through the use of artificial neural networks (ANN) to adjust attribute weights and improve case retrieval that is used to cost estimation of a NPD project. The proposed approach supports the R&D department with reference to how similar past problems have been solved and which product concepts should be selected for development.

The remaining sections of this paper are organised as follows: Section 2 presents the literature review referring to the new product development process and cost estimation of a NPD project. A methodology for developing the proposed CBR approach towards using ANN is described in Section 3. Case study for illustrating the application of the proposed approach is presented in Section 4. Finally, some concluding remarks are contained in Section 5.

2. Literature review

2.1. New product development process

The new product development literature emphasises the impact of introducing new products on employment, economic growth, technological progress, high standards of living, and on continuing business success [3, 12, 13]. As new product development helps firms to survive and succeed in dynamic markets, it is a crucial process in maintaining a company's competitive position [14]. However, market competition and product technology advancement is often intense [15], what causes NPD to be a relatively risky activity [16]. Consequently, companies try to meet customer requirements by improving product attributes and the NPD process.

The NPD process consists of the stages such as identifying customer needs, establishing target specification, generating product concepts, evaluating and selecting the most promising concepts, designing and testing prototypes of new products, and finally launching new products on the market [17]. The concept selection aims to determine the most promising portfolio of new products for development through evaluating concepts with the use of relevant performance metrics, e.g. the cost and time of a NPD project or the potential profit from a product.

The effective management of NPD projects is a challenging goal, due to factors such as intensive research and development investment, long and uncertain development times, low probability of technical success, uncertain market impact and competition [18]. Moreover, companies usually develop several new products simultaneously, what increases complexity of the NDP process and requires a task-oriented tool to support the decision-makers in evaluating criteria that are used to select a portfolio of the most promising NPD projects and identifying successful past solutions to current problems appearing in the NPD process [19].

2.2. Cost estimation of new product development

According to [20], the product cost estimation techniques can be classified into four groups: intuitive, analogical, parametric, and analytical techniques. Intuitive techniques include case-based reasoning and decision support techniques including rule-based, fuzzy logic, and expert system. Analogical techniques refer to models of regression analysis and back-propagation neural network. Parametric models are based on the statistical methodologies and express the cost as a function of its constituent variables. In turn, analytical techniques include operation-based approach, break-down approach, tolerance-based cost models, feature-based cost estimation, and activity-based cost estimation.

Case-based reasoning uses the information related to previous products by adapting a past design stored in the case base that closely matches attributes of designing a new product. CBR enables cost estimation of a new product through combining the past results of existing products with modifications referring to the newly designed components and/or assemblies of a new product. This approach can significantly reduce the need to design a new product from scratch, and consequently, the cost and time of completing a NPD project. The use of a CBR approach is particularly advantageous in mass customisation where slight modifications of existing products are developed [8].

Many studies have been concerned with combining a CBR approach with various methods in order to improve the quality of cost estimation. In searching optimal weights of attributes and retrieving the most similar case to a new case, there are used methods such as feature counting [21, 22], analytic hierarchy process [21, 23], multiple regression analysis [22, 24], decision trees [25], genetic algorithms [26, 27], and artificial neural networks [28, 29, 30]. Regression analysis models and artificial neural networks use the data of historical cost to determine a relationship between the cost of developed products and the selected variables that are related to product attributes (e.g the number of components in a product).

3. The proposed case-based reasoning approach

The aim of using the proposed CBR approach is the selection of the most similar past NPD projects to new projects that are considered for the development. A set of similar cases is selected among the case base according to a similarity criterion that requires the specification of weights corresponding to attributes. The proposed approach uses ANN to calculate attribute weights and the optimal value of k nearest neighbour (k-NN). The selection of the most similar past projects to new projects allows the project manager to identify potential obstacles in the NPD process, for example, the average number of prototypes and testing cycles, additional suppliers and changes in product specification, as well as the cost of product design and production. The proposed approach also uses ANN to estimate the cost of a potential NDP project. In turn, cost estimators and identified potential problems of a NDP project are used to select the most promising portfolio of NPD projects. Fig. 1 illustrates a framework for the proposed CBR approach that involves the use of ANN.

The case-based reasoning approach begins with collecting the data of a new product that can regard customer requirements for a new product and/or trends in the market. The sales and marketing department analyses the market and customer response about existing products, and specifies attributes that refer to a new product, e.g. its application, complexity, and shape. In the next step, attributes are selected and weights are assigned to these attributes according to their impact on the cost of NPD.

The assessment of case similarity involves the comparison of attribute values of a new case and past cases that are stored in the case base. The retrieved cases are ranked according to their similarity to attributes of a new product. In this study, the nearest neighbour method is applied to calculate the similarity function (Eq. (1)) and the total similarity (TS_i) of a potentially useful case (Eq. (2)).

$$sim(f_i^P, f_i^R) = 1 - \left|f_i^P - f_i^R\right| \Big/ max(f_i) \tag{1}$$

$$TS_i = \Big(\sum_{i=1}^{n} w_i \times sim(f_i^P, f_i^R)\Big) \Big/ \sum_{i=1}^{n} w_i \tag{2}$$

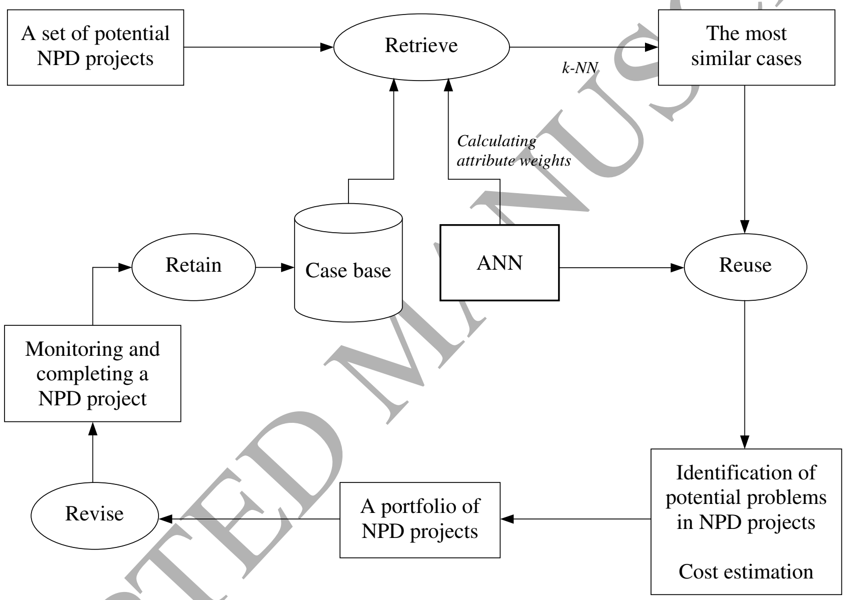

Figure 1: Framework for the proposed CBR approach

where:
w_i - the weight of the i-th attribute,
$sim(f_i^P, f_i^R)$ - the function of similarity of the i-th attribute between the value of new case f_i^P and the value of retrieved case f_i^R.

As mentioned, artificial neural networks can be used to calculate attribute weights. In this research, feedforward networks have been proposed to calculate the error between the retrieved case (X_n) and tested case (T_n). In the case base for each $\langle X_n, T_n \rangle$ are selected k-nearest neighbours, K_n of X_n. In the next step, the neural network is updated according to the following algorithm:

1. input X_n to the network and compute the output y_k of every output neuron and the output y_j of every hidden neuron
2. for each m-th case X_m in K_n compute

$$\Delta w_{kjm} = p\eta(x_{kn} - x_{km})^2 y_k(1 - y_k)y_j \tag{3}$$

$$\Delta w_{jim} = p\eta \sum_{k=1}^{M} (x_{kn} - x_{km})^2 y_k(1 - y_k) w_{kj} y_j (1 - y_j) x_{im} \tag{4}$$

where:

$$p = \begin{cases} -1 & \text{for } T_m = T_n \\ 1 & \text{for } T_m \neq T_n \end{cases} \tag{5}$$

3. update weights

$$\begin{array}{l} w_{kj} \leftarrow w_{kj} + \sum_m \Delta w_{kjm} \\ w_{ji} \leftarrow w_{ji} + \sum_m \Delta w_{jim} \end{array} \tag{6}$$

where:
w_{kj} - the weight between the k-th output neuron and the j-th hidden neuron,
w_{ji} - the weight between the j-th hidden neuron and the i-th input neuron,
y_k - the output of the k-th output neuron,
y_j - the output of the j-th hidden neuron,
x_{im} - the i-th input attribute value of X_m,
η - the learning rate.

The basic principle of the presented algorithm is the reduction of the distance between cases in the same cluster and the increase of the distance between cases in different clusters. The distance metric applied in the presented algorithm is illustrated in Eq. (7).

$$\Delta(X_n, X_m) = \sum_{k=1}^{M} y_k (x_{kn} - x_{km})^2 \quad (7)$$

The number of inputs of a neural network is the same as the number of attributes, and the structure of a neural network consists of three layers, with the sigmoid activation function for the hidden layer.

In this study, the cost of a NPD project is estimated with the use of ANN and compared with the performance of multiple regression analysis (MRA) that calculates attribute weights with the use of standardised and unstandardised coefficients. The general multiple regression model is presented in Eq. (8).

$$Y = B_0 + B_1 X_1 + ... + B_n X_n \quad (8)$$

where:
Y - dependent variable,
X_n - independent variables,
B_0 - constant,
B_n - unstandardised coefficients.

In the presented regression model, the change of an independent variable at 1 unit results in the change of the dependent variable at the unstandardised coefficient of the changed independent variable. The performance of ANN and MRA is evaluated by the mean absolute percentage error (MAPE) presented in Eq. (9).

$$MAPE = \Big(\sum_{i=1}^{n} |(C_{Ai} - C_{Ei})/C_{Ai}| \times 100\% \Big) \Big/ n \quad (9)$$

where:
C_{Ai} - the actual cost of the i-th NPD project,
C_{Ei} - the estimated cost of the i-th NPD project,
n - the number of NPD projects.

The proposed CBR approach identifies the most similar cases of past NPD projects that are further used to specify potential problems in the NPD process and estimate the cost of developing a new product. Information about the cost of a NDP project is useful in selecting a NDP portfolio and monitoring project performance. Moreover, the CBR approach allows the

R&D personnel to obtain information about specification of past products that can be used in the design and production of a new product, e.g. the amount and type of required materials, technological process, assembly and processing time.

4. Case study

Case study illustrates the use of the presented ANN algorithm in two aspects. The first aspect refers to case retrieval and comparison with a CBR approach that assigns equal weights to attributes. The second aspect is concerned with the use of the presented approach to estimate the cost of NPD projects.

In this study, the NPD process is specified according to the following attributes:

- the number of modifications proposed by customers (X_1),
- the number of customer requirements translated into product specification (X_2),
- the number of components in a new product (X_3),
- the number of new components in a new product (X_4),
- the number of project team members (X_5).

These attributes are used to select the most similar case(s) from the case base in order to identify potential problems in NPD projects and estimate the NPD cost. The proposed approach has been verified by means of a case study for company that designs lighting solutions according to client requirements. The case base of past NPD projects referring to industrial luminaires contains 61 cases. The sample of 61 past NDP projects was divided randomly into training set (49 cases) and testing set (12 cases). The tests were performed with using 10-fold cross validation according to the procedure presented in [31].

4.1. Case retrieval

In this study, two approaches have been used to case retrieval in CBR: equal weights (EW) assigned to attributes and weights adjusted according to the presented algorithm (ANN PA). The prediction error is measured as the

Table 1: Prediction errors of EW for different k

k	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
1	**9.19**	**8.17**	8.98	9.19	9.82	8.53	5.48	7.18	9.12	10.04
2	10.13	9.04	7.73	8.81	9.39	7.39	**4.78**	7.46	7.99	7.50
3	10.10	9.79	7.69	9.00	9.20	7.57	4.80	**6.19**	6.18	**5.94**
4	10.25	9.85	7.68	8.10	9.08	7.24	5.06	6.60	6.17	6.21
5	9.91	9.29	7.67	7.81	8.84	6.35	5.63	6.47	6.31	6.30
6	10.08	8.77	7.16	**7.66**	8.41	6.05	5.62	6.81	5.89	6.46
7	10.06	9.73	7.21	7.79	**8.29**	5.99	5.60	7.47	6.16	6.23
8	10.72	9.02	**7.15**	7.75	8.64	**5.94**	6.29	8.02	6.53	6.21
9	10.73	9.24	7.31	7.71	8.72	6.42	6.17	7.07	6.39	5.97
10	10.48	9.16	7.29	7.76	8.78	6.59	6.26	7.17	**5.87**	6.34

Table 2: Prediction errors of ANN PA for different k

k	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
1	4.31	4.84	**6.53**	**5.72**	6.02	**6.91**	6.23	5.73	6.08	7.15
2	4.72	5.01	6.67	5.83	**5.81**	6.97	6.30	5.81	6.19	**7.07**
3	**4.25**	5.05	7.15	5.87	6.16	6.97	6.33	**5.61**	6.25	7.33
4	4.61	**4.72**	7.31	5.98	6.22	7.26	6.11	5.97	**5.47**	7.46
5	4.28	5.27	7.42	5.80	6.06	7.12	**5.64**	6.27	6.14	7.46
6	4.76	5.49	6.93	5.87	6.37	7.51	5.78	6.04	6.28	7.59
7	4.91	5.24	6.93	6.01	6.44	7.36	6.03	6.21	6.08	7.41
8	5.41	5.56	7.03	6.29	6.48	7.42	6.14	6.51	5.75	7.52
9	5.02	5.89	7.11	6.13	6.63	7.42	6.48	6.63	6.17	7.68
10	5.23	6.14	7.23	6.13	6.76	7.61	6.39	6.42	6.28	7.35

mean absolute percentage error illustrated in Eq. (9). Table 1 and 2 present the MAPE obtained with the use of EW and ANN PA for k from 1 to 10 in 10-fold cross validation (F1, ..., F10). The highest accuracies are marked in bold for each fold. The ANN PA enables weight adaptation according to attribute importance what usually results in smaller values of the MAPE for the less number of k in comparison with equal weight assigned to attributes. The less number of k is of great importance in practical applications, since the project manager has to consider fewer cases (past NPD projects) to solve a problem (e.g. specify the number of prototype tests, estimate the cost of NPD projects).

Table 3: Prediction errors for 10-fold cross validation

Model	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Average
EW	9.19	8.17	8.98	9.19	9.82	8.53	5.48	7.18	9.12	10.04	8.57
MRA UC	9.77	8.70	8.14	7.99	8.60	8.13	5.69	6.46	6.65	6.49	7.66
MRA SC	10.53	8.45	7.39	7.85	8.68	6.90	5.60	6.84	6.11	6.27	7.46
ANN GD	6.14	4.73	5.67	5.88	8.70	7.18	5.60	7.97	4.37	6.79	6.30
ANN PA	4.31	4.84	6.53	5.72	6.02	6.91	6.23	5.73	6.08	7.15	5.95

4.2. Case reuse to cost estimation of NPD

The tests were performed with 10-fold cross validation for different methods. The presented algorithm has been compared with approach where equal weights are assigned to attributes, and approaches that are able to identify weights according to the impact of an attribute on the cost of NPD projects. These approaches include multiple regression analysis with standardised coefficients (MRA SC) and unstandardised coefficients (MRA UC), and a neural network trained with the use of the gradient descent with an adaptive learning rate algorithm (ANN GD).

Table 3 presents the MAPE for 10-fold cross validation in the testing set. The results indicate that ANN trained according to the proposed algorithm generates the least error among the considered models. Table 3 presents the MAPE of ANN that was obtained for the optimal number of hidden neurons that equals 9 and 3 for ANN trained according to the GD algorithm and the proposed algorithm, respectively. The MAPE for the different number of hidden neurons in ANN are presented in Figs. 2 and 3.

The least MAPE in the learning and testing set was obtained with the use of ANN PA that was trained according to the presented algorithm. Figs. 2 and 3 illustrate the tendency of increasing the MAPE in testing set for more than 10 hidden neurons in ANN. The discrepancy between the MAPE in training and testing set is greater for ANN trained according to the presented algorithm than with the use of ANN GD.

To illustrate the impact of learning coefficients on the performance of a neural network trained according to a gradient descent algorithm, simulations used various values of a learning rate (0.01, 0.05, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9) and momentum constant between 0.1 and 0.9 (in steps of 0.1). Fig. 4 presents the MAPE calculated for the selected range of a learning rate and momentum constant in ANN. The least MAPE was obtained for a learning rate of 0.1 and momentum constant of 0.9. This trend was confirmed by experiments carried out with various numbers of hidden neurons in ANN.

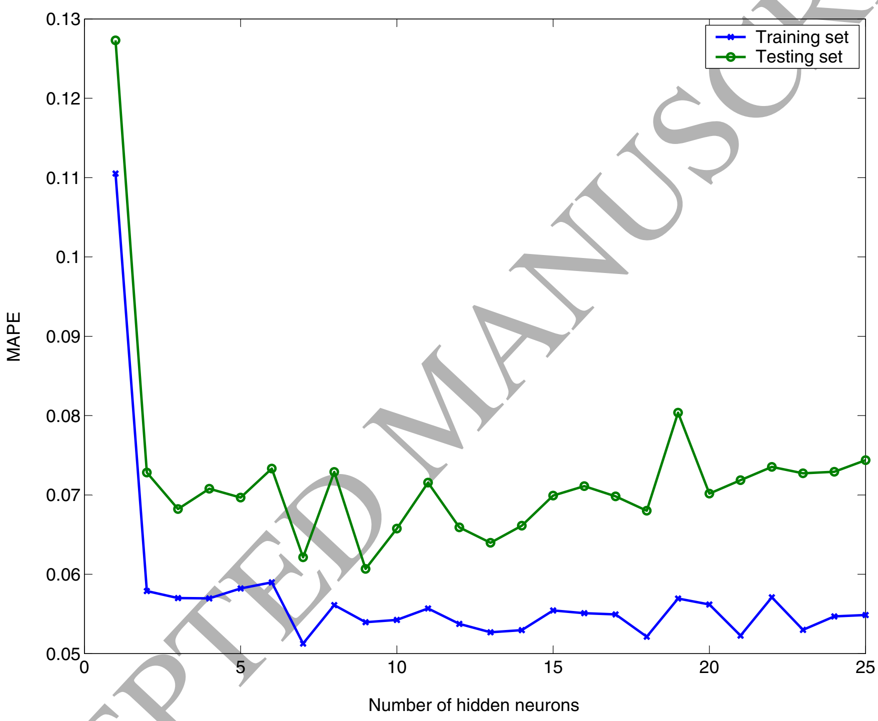

Figure 2: The MAPE for different number of hidden neurons in ANN GD

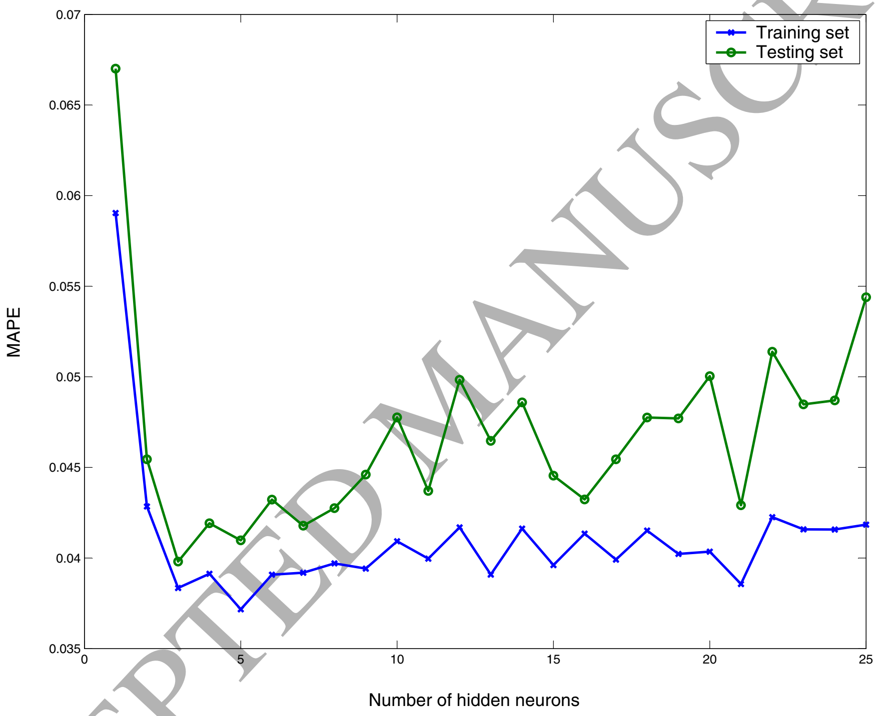

Figure 3: The MAPE for different number of hidden neurons in ANN PA

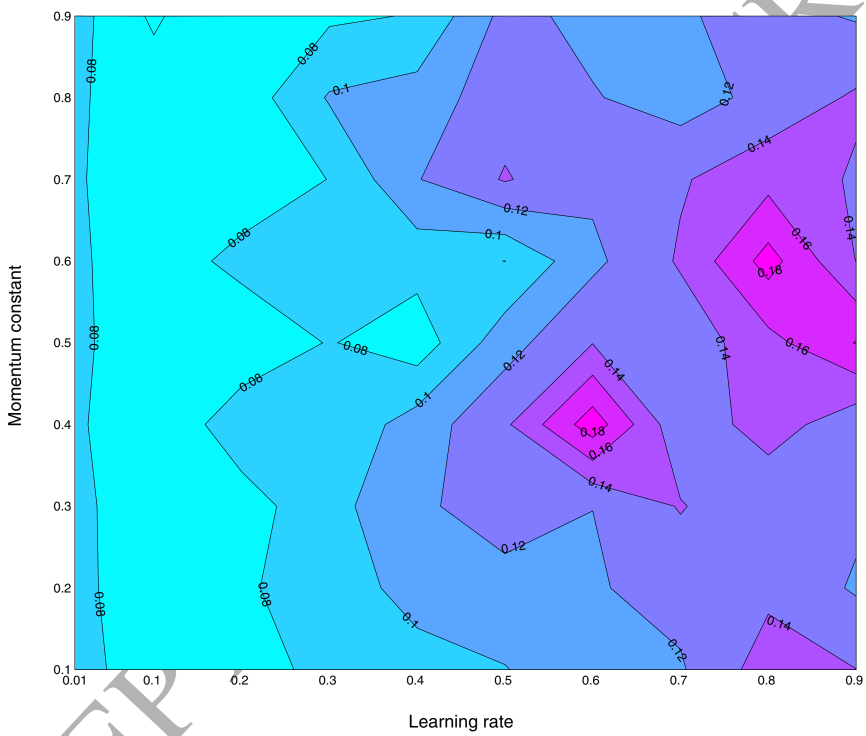

Figure 4: The impact of a learning rate and momentum on the MAPE

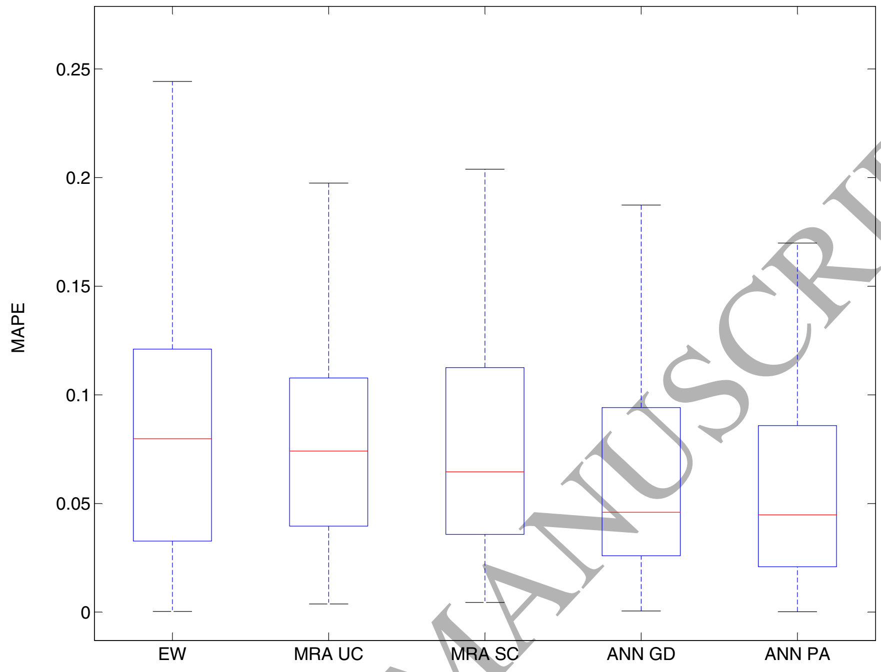

Figure 5: Box plot for the distribution of prediction errors

Fig. 5 illustrates the distribution of the MAPE for 120 cases (12 cases in the testing set for 10-fold cross validation). The differences between the considered models were verified with the use of a t-test at the 0.05 significance level.

Table 4 presents the p-values between the considered models. The results indicate the rejection of the null hypothesis, which verifies if two data vectors are from populations with equal means at the 0.05 significance level, for the MAPE of ANN PA and the MAPE of models based on equal weights for attributes and multiple regression analysis. Finally, more precise cost estimation obtained by ANN PA improves the selection of the most promising NPD portfolio and monitoring the performance of ongoing projects.

Table 4: The p-values between the considered models

Model	EW	MRA UC	MRA SC	ANN GD	ANN PA
EW	1				
MRA UC	0.1959	1			
MRA SC	0.1244	0.7470	1		
ANN GD	0.0220	0.0326	0.0765	1	
ANN PA	0.0004	0.0066	0.0198	0.5940	1

5. Conclusion

The simultaneous development of several products, long duration of product development, and usually limited amount of resources cause that the effective management of NPD projects is a challenging goal. CBR provides methodology for supporting product design by adapting previously solutions to new problems during the NPD process. This study presents the use of ANN to calculate attribute weights in a case-based reasoning approach in the context of case retrieval and reuse to cost estimation of NPD projects. In turn, cost estimation is used to select the most promising portfolio of NPD projects and then in the revision phase of CBR for monitoring the NPD process. The presented approach is able to specify a smaller number of k-NN with less prediction errors than an approach based on equal weights for attributes. Conducted experiments also illustrate that the use of the presented algorithm for calculating attribute weights improves the accuracy of cost estimation in comparison with MRA models and ANN trained according to the gradient descent with an adaptive learning rate algorithm. Consequently, more precise estimation of the new product cost helps the project manager select the most promising portfolio of NPD projects. Moreover, the retrieved cases are used to obtain additional information about developing a new product, for example, required materials and technological process, which the R&D department can use to revise requirements related to designing and testing a new product. The presented CBR approach allows the project manager during product design to refer existing problems to solutions that occurred in similar past NPD projects. Drawbacks of using the proposed approach can be considered in the perspective of collecting a sufficient number of similar NPD projects.

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