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AN ARTIFICIAL NEURAL NETWORKS APPROACH TO PRODUCT COST ESTIMATION. THE CASE STUDY FOR ELECTRIC MOTOR

SZTUCZNE SIECI NEURONOWE W PROGNOZOWANIU KOSZTÓW PRODUKTU. STUDIUM PRZYPADKU DLA SILNIKA ELEKTRYCZNEGO

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Summary: The aim of this paper is to present, in theoretical and application terms, artificial neural networks (ANNs) as a method of estimating the product cost. The first part of the article reviews the methods used to estimate the product cost. The basic approaches to the problem of product cost estimation, presented by various authors, were described. In the second part an empirical study using artificial neural networks was conducted. Two research methods were used in this paper: literature analysis and empirical research carried out in the form of an extensive case study. The test object is a new generation induction motor. The main research problem of the article is the modelling of artificial neural networks for the estimation process of product costs with advanced production technology. The test procedures focus on the application aspects. The conclusions discuss the usefulness and advantages of using ANN models in estimating the costs of products.

Keywords: cost estimation model, artificial neural networks, product cost.

Streszczenie: Celem artykułu jest zaprezentowanie, w aspekcie teoretycznym i aplikacyjnym, sztucznych sieci neuronowych (ANN) jako metody prognozowania kosztu produktu. W pierwszej części artykułu dokonano przeglądu metod prognozowania kosztu produktu. Przedstawiono podstawowe podejścia do problemu prognozowania kosztu produktu prezentowane przez różnych autorów. W drugiej części artykułu przeprowadzono badanie empiryczne z wykorzystaniem sztucznych sieci neuronowych. W artykule zastosowano dwie metod badawcze: analizę literatury oraz badania empiryczne zrealizowane w formie rozbudowanego studium przypadku. Obiektem badań jest silnik indukcyjny nowej generacji. Zasadniczy problem badawczy artykułu to modelowanie sztucznych sieci neuronowych dla procesu prognozowania kosztu produktów o zaawansowanej technologii produkcji. Punkt ciężkości procedur badawczych koncentruje się na aspektach aplikacyjnych. We wnioskach omówiono użyteczność i zalety stosowania modeli ANN w prognozowaniu kosztów produktów.

Słowa kluczowe: prognozowanie kosztów, sztuczne sieci neuronowe, koszt produktu.

1. Introduction

One of the main areas of cost engineering is the estimation of production costs. Product cost estimation (PCE) is a fundamental determinant of the cost of technical and business decisions made by engineers when designing a new product. Too high level of product cost estimation may indicate refraining from implementing a new product because the enterprise will not achieve the desired profit in the future. On the other hand, too low a level of product cost may result in the decision to be unable to produce a new product at such a cost level.

At the end of the previous century, Asiedu and Gu [1998], defined two estimation methods of the product cost: parametric and analogous. In 2003 this classification was detailed by Ben-Arieh and Qian [2003] with an intuitive and analytical method. A similar position was taken by Shehab and Abdalla [2001] on the classification of product cost estimation methods.

The research conducted by Niazi et al. [2006] resulted in a systematic and detailed classification of the methods for product cost estimation. They identified two main methods, the qualitative and the quantitative method. Within these two basic methods, they distinguished the intuitive, analogical, parametric and analytical method [Huang et al. 2012]. The described classification is presented in Figure 1.

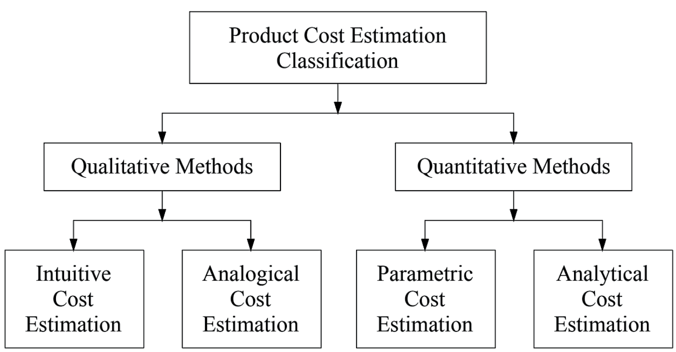

Fig. 1. The classification of product cost estimation

Source: [Niazi et al. 2006].

The basic idea of qualitative methods for product cost estimation is to determine whether a new product has any similarity to products already manufactured. The identified similarities may be used in the process of the estimation of a new product cost. The key requirements in applying these types of methods are access and historical data on the product technology, as well as its previous cost estimations. Niazi et al. [2006] assigned the qualitative methods of product cost estimation to the intuitive and analogical method.

Intuitive methods for predicting the product cost assume that similar products have similar costs [Aamodt, Plaza 1994; Roy 2003]. The design specification of a new product is adapted to the products already implemented using a knowledge base that describes the existing products. This solution enables to obtain a ready estimation of a new product cost which is subject to only minor verification. The main disadvantage of this method is that it is strongly dependent on historical data, which limits its use to new, highly innovative products.

Analogical methods for estimating the product cost are mainly regression analysis and artificial neural networks (ANNs). The effect of regression analysis carried out on the basis of collected historical data are mathematical functions which most faithfully reflect the relation between cost carriers (independent variables) and the production costs level (dependent variables). The mathematical functions used to estimate the product cost are in most cases linear. Therefore if in a new product the relations between cost drivers and product cost are non-linear, the regression analysis model is not always an adequate method to build a mathematical function of the product cost [Lewis 2000].

At the beginning of this century, manufacturing companies showed great interest in modern product cost estimation tools. The result of Wang, Stockton, Baguley [2000] study in the United States was the presentation of a new estimating model for the product cost, i.e. artificial neural networks (ANNs). In their research, Wang, Stockton, Baguley [2000] showed that artificial neural networks have the potential to overcome the drawbacks and limitations of other methods for product cost estimation. [Ikeda, Hiyama 2005] They can estimate the product cost without the need to describe mathematically the functional relations between independent variables (cost carriers) and dependent variable (costs) and the need to define assumptions on the form of cost [Heping 2010].

When estimating the product cost using quantitative methods, mathematical formulas are applied which take into account the technological parameters of the product, as well as the manufacturing and distribution processes. Quantitative methods of product cost estimation can be divided into parametric and analytical methods [Niazi et al. 2006].

Product engineers, when estimating the product cost, most often use the parametric method of estimation [Rush, Roy 2001] which is widely used in industry. Parametric estimating uses mathematical formulae that describe the linear relations between the product cost and cost carriers affecting its level [Ji et al. 2010]. The construction of the mathematical formula (function) is mainly based on technological and distribution assumptions concerning the relation between the product cost (dependent variable) and the factor affecting it (cost carrier – independent variable). Estimated product costs are a function of design, technology, distribution and marketing complexity of the new product. Technological product identifiers are the physical or functional characteristics of the new product – productivity, energy intensity, material intensity, volume, capacity, and size [Leszczyński, Jasiński 2017].

Many theorists and practitioners believe that the method of parametric product cost estimation is not commensurate with the changes taking place in the industrial and market environment (advanced technologies and modern methods of product distribution) [Mauchand et al. 2008]. Hence, companies implementing high-tech products became interested in new methods of product cost estimation, i.e. artificial neural networks.

The analytical method for product cost estimation consists in the division of the product into the elements, operations, activities to accumulate the resources used in manufacturing and distribution processes and an estimation of the costs of these components. The final estimated product cost is the sum of the estimated cost of all these components [Duverlie, Castelain 1999; Houseman et al. 2008].

The accuracy of product cost estimation using quantitative methods is higher than that with qualitative methods. However the qualitative method enables to obtain simplified cost estimation in a relatively short period of time at an early stage of product design. Therefore qualitative methods are more useful in the estimation process of product cost, when the time of preparation to estimating is limited and historical data concerning the product are available, and the requirement for accuracy of estimations is moderate [Roy et al. 2001].

The aim of this work is to present, in theoretical and application terms, artificial neural networks (ANNs) as a method of product cost estimation. The main research problem in the article is not only the essence, reliability and procedures of building the ANN model, but also the usefulness and advantages of using this model in the estimation process of product cost. The research methodology adopted in this work is a literature study on artificial intelligence, cost engineering, quantitative methods, cost management and empirical study conducted using the inductive method of an extensive case study. The case study presents the procedures of building a model of artificial neural networks for the purpose of estimating the cost of technologically advanced electric motors with various technological parameters. The authors constructed the case study based on their own research carried out in academic work and in consulting companies. The innovativeness of this article is the attempt to present artificial neural networks as a modern method of estimating the product cost in companies with advanced production technology [Kim et al. 2004].

The structure of this article is as follows. The first part reviews literature on the methods of product cost estimation. Their theoretical basis, the procedures and possibilities of application in industrial practice were discussed. The next part of the article focuses on issues related to artificial neural networks and their use in product cost estimation. In this part of the article empirical research was presented. This article ends with conclusions.

2. Basis of Artificial Neural Networks

The basic functioning principles of currently used ANNs were defined in the 1940s. McCulloch and Pitts [1943] are considered to be the creators of this artificial neuron; they presented a mathematical model of a nerve cell in 1943.

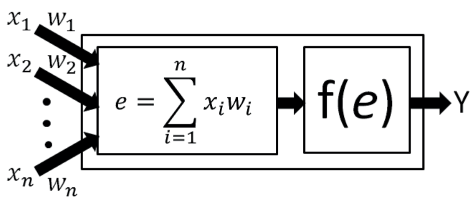

Fig. 2. Diagram of the artificial neuron

Source: own elaboration.

2.1. Construction of an artificial neuron

A diagram of a single nerve cell is presented in Figure 2. It is composed of so-called inputs, which are analogous to biological dendrites. Their task is to introduce signals into the cell interior. Each of these inputs is assigned a weight. This is the real number by which the value of signal reaching the nerve cell is multiplied. The resulting products are added together. This sum is then modified by a transformation called an activation function. Over the years, many different functions have been used in its role, ranging from the simplest ones – linear – to more complex transformations. Currently the most commonly used is the logistic functions, Gauss's hyperbolic

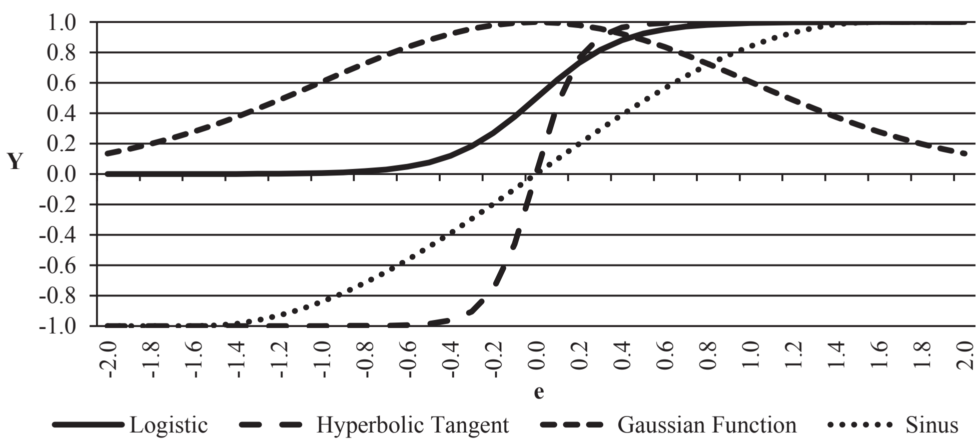

Fig. 3. Examples of the course of selected activation functions

Source: own elaboration.

tangent, modified sinus (the function defined as sinus is in fact a transformation taking the values: –1 for signals lower than –π/2, 1 for signals higher than +π/2, and sinus for signals lower than [–π/2, +π/2]). An example of the sequence of these functions is shown in Figure 3.

2.2. Construction of an artificial neuron

The term ANN covers many types of networks which differ, among others, in the direction of the signal flow inside the network, number of neurons, their grouping into so-called layers, activation functions, and used training algorithms. One of the most popular models is the so-called Multilayer Perceptron. This is an example of a unidirectional network (signals flowing from input to output, there is no feedback) in which the nerve cells are grouped into three types of layers. The first one (input) is the structure responsible for collecting signals from outside the network and then their propagation among the neurons of the next layer. This is the so-called hidden layer. The MLP may contain several such layers. In practice, they rarely reach three. Commonly used ANNs usually have one or two hidden layers. The last layer is the output layer. Its neurons also take an active part in the training process. One of its main functions is to lead the ANN response signal out of the model. A diagram of MLP construction is presented in Figure 4.

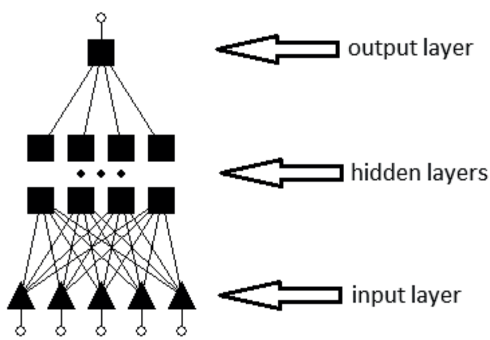

Fig. 4. Diagram of MLP construction

Source: own elaboration.

Another type of unidirectional network with a construction derived from MLP is the radial basis network (RBF). They always contain three layers: input, hidden and output. The hidden layer neurons are equipped with a radial activation function, i.e. a bell function. They include: Gauss, multiquadratic, thin-plate spline, radial cubic B-spline, radially quadratic B-spline (more in [Wu et al. 2012]). The advantage of the RBF network is the short time (compared to MLP) needed to select the optimal network structure. A diagram of an RBF network construction is presented in Figure 5.

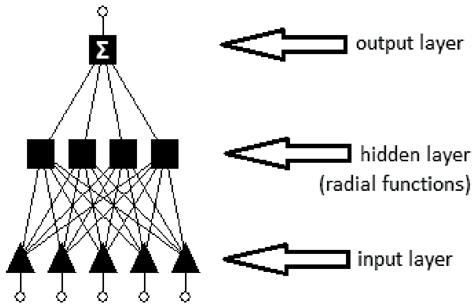

Fig. 5. Diagram of RBF network construction

Source: own elaboration.

2.3. ANN learning process

ANNs can acquire knowledge through the so-called self-learning or supervised learning mechanisms. The former does not require knowledge of the baseline standard, only the network input data is needed. During learning, there was a tendency to increase the value of weights at the neurons input, which in turn resulted in some kind of feedback, because the increasing weight causes a greater activity of neurons. When a pattern is stimulated, some neurons, or groups of neurons that cooperate with each other, are activated. In self-organizing networks, there is both a competition effect within groups of neurons and among their groups, as well as cooperation between neurons. The process of network teaching would not be possible without the redundancy of the teaching data. Repeated presentation of the network of similar data enables, by way of associations, to draw conclusions [Osowski 2000]. As this method was not used in empirical studies, its more detailed description will not be made in this paper.

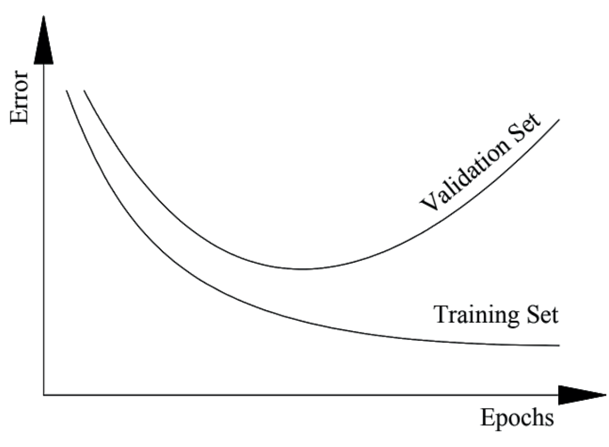

Fig. 6. Typical sequence of values of the error functions in training process

Source: own elaboration.

In the second of the above mentioned methods of ANN learning there is a subprogram called the teacher, whose task is to modify the neuron weights of the learning layers to make the network better respond to output signals. This requires knowledge of the network reference output signals. This process is based on multiple network presentations of the same input data and a comparison of the ANN response with the standard for making corrections of recalled weighting. This requires the preparation of training data set that covers already known cases. As the learning process progresses, the reply by network becomes closer to the reference values so that the model error starts approaching asymptotically to zero, and it is necessary to determine the moment at which the ANN training process should be stopped. For this purpose, a part of the data from the teaching set has been distinguished, creating a validation set. After each ANN learning with data from the learning set, the data from the validation set was presented in order to only determine the network error. In the case of observing an increase in value of the error function and to avoid the so-called ANN overtraining, the training process was stopped. A diagram of the relation between the values of the error function and the number of data presentations from the set (the so-called epoch) is presented in Figure 6.

In order to maintain the highest possible degree of objectivity in the evaluation of the results, a third set of data – a test set – is distinguished. As it is not directly involved in the learning process it can be used for ANN evaluation. Typically, the values of error measures obtained for data from the training set are noticeably lower than those calculated for the test data, and their use for network evaluation purposes should be considered as unacceptable.

3. Artificial neural networks in the product cost estimation

Empirical research included the estimation of the costs of electric motors on the basis of selected technical data. The authors of the study obtained data for 90 different types of engines, including the actual costs of products, which were the explanatory variable of model. The set of explanatory variables included six types of variables: rated power (kW), rated current (A), rotational speed (rpm), number of poles, net weight (kg) and shaft diameter (mm). The data were randomly grouped into three sets: training (54 samples), validation (10 elements) and test (26 cases). Such a division was related to the amount of available data and constituted a compromise between the desired high number of teaching resources (giving the possibility of more effective training) and the required number of cases in test resources (giving the possibility of a reliable evaluation of the model's operation).

Two groups of ANNs were tested: MLP and RBF. More than 10,000 different models were tested in each case. Only a selection of the best ANNs was presented in the study. Studies have shown that MLP-type networks generate a significantly better cost estimation for electric motors than RBF networks. MAPE for the best MLP was 9.02% and for the most precise RBF network it was 17.30%. Figure 7 shows a construction scheme of the successful MLP model (architecture: 6-3-1, activations functions: hidden layer – logistic, output layer – exponential). Figure 8 presents the estimation errors for data from the test set. Table 1 presents the test set data with example values of the estimated product costs. A similar overview for the best RBF model (architecture: 6-13-1) is presented in Figures 9 and 10.

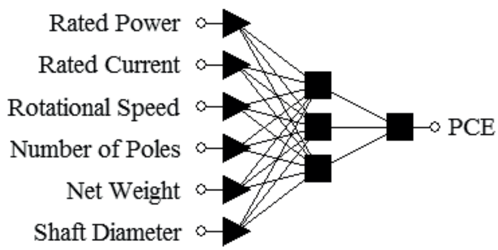

Fig. 7. Architecture of the best MLP

Source: own elaboration.

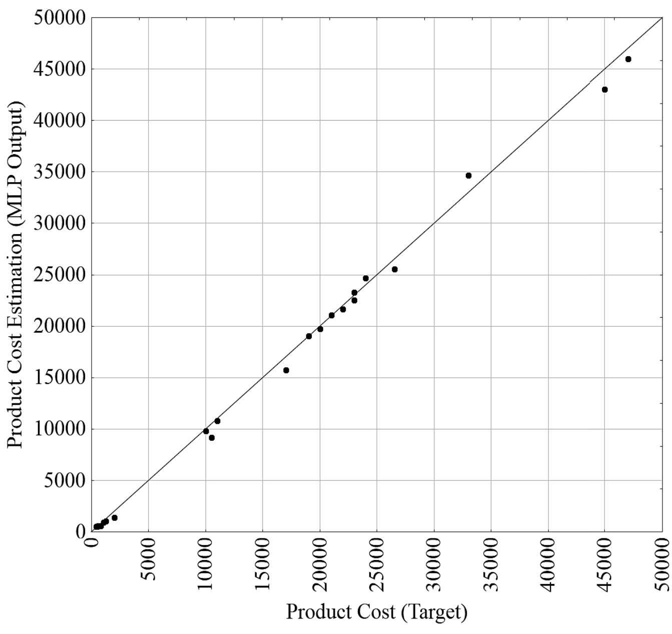

Fig. 8. Scatter diagram for the best MLP

Source: own elaboration.

For both types of ANN, there is a noticeable increase in the estimation error for the lower cost engines. The sources of this state of affairs can be seen in the fact that there is too little data on low cost engines in the teaching set. This may be suggested

Table 1. The test set data structure with example values of the estimated product costs

No.	Rated power (kW)	Rated current (A)	Rotational speed (rpm)	No. of poles	Net weight (kg)	Shaft diameter (mm)	Product cost (PLN)	Estimated product cost (PLN)
21	75	128.00	2955	2	570	65	10 500	9 199
22	90	152.00	2960	2	660	65	11 000	10 786
25	150	251.00	2980	2	1100	65	21 000	21 070

Source: own elaboration.

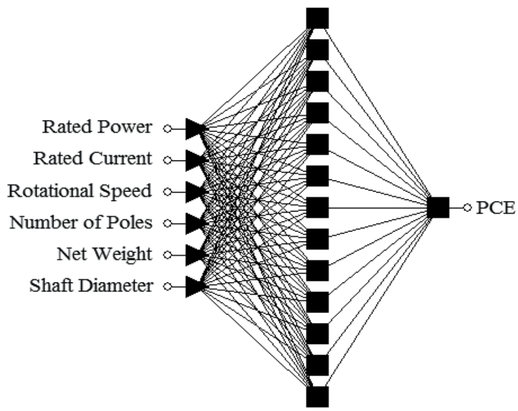

Fig. 9. Architecture of the best RBF network

Source: own elaboration.

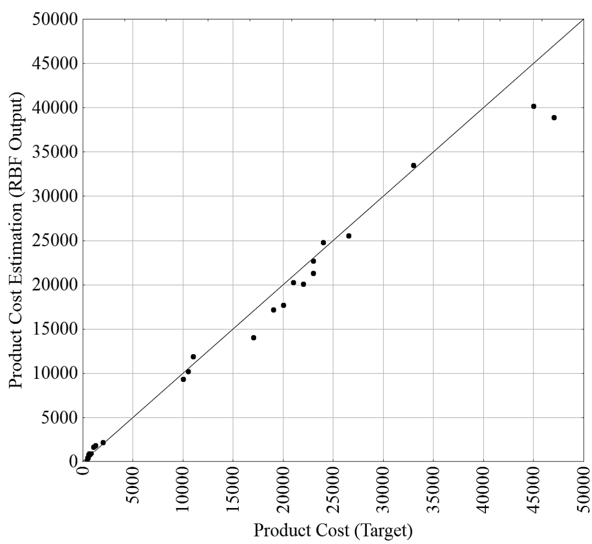

Fig. 10. Scatter diagram for the best RBF network

Source: own elaboration.

by the appearance of increased risk to obtain an unacceptable error of estimation for products deviating from the average cost.

In the case of MLP, its extension by additional hidden layers did not translate into an increase in the quality of estimations. This is confirmed by the necessity of keeping the model as simple as possible, which is often postulated in the subject literature. Empirical studies have confirmed that the complexity of the model should be selected to the given issue without any tendency to its excessive expansion.

In order to improve the quality of the ANN operation, it would be appropriate to extend the training set by data for further models of electric motors. Unfortunately, the size of the set is closely related to the actual data available in the company. This means that the poorer the company's production experience, the more difficult it is to carry out the right ANN training.

4. Conclusions

Artificial neural networks do not eliminate all the difficulties in applying other methods for product cost estimation. They are a cost-effective alternative to traditional regression analysis, parametric estimation, especially in situations where the nature of technological and production dependencies is poorly recognized, as well as the distribution between costs and their carriers. Artificial neural networks are particularly useful in the situation of the recognition of non-linear, multidimensional (several dozen of cost carriers) relations between variables (cost and its carriers), which is characteristic for products with very advanced technology. This important advantage of neural networks reduces the need for technological and production analyses and for deep technological knowledge on the part of the product cost planners. From a practical point of view, artificial neural networks enable to analyze a far greater number of potential cost carriers (even several dozen) than regression analysis. The ANN model can estimate the product cost without the need to describe mathematically the functional relation between independent variables (cost carriers) and dependent variable (product cost) [Heping 2010].

In contrast to regression analysis, the computer support for artificial neural networks is not easy and requires specific IT knowledge. The disadvantage of artificial neural networks is the significant risk in the building process of the ANN model with a small number of data sets. As the results of both literature studies [Bode 2000] and empirical studies conducted by the authors of this article indicate, the number of data samples is one of the basic elements affecting the quality of estimation. The theoretical and empirical analysis conducted in the article fully justifies the statement that ANN models are the most innovative tool for product cost estimations in an industrial environment with advanced technology and digitization of production [NASA 2002; Ruiza et al. 2011]. The concept and procedures of ANN model construction presented in the article are a reference point for further theoretical and practical research.

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