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Research Article

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An artificial intelligence model based on LS-SVM for third-party logistics provider selection

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Abstract

The use of third-party logistics (3PL) providers is regarded as new strategy in logistics management. The relationships by considering 3PL are sometimes more complicated than any classical logistics supplier relationships. These relationships have taken into account as a well-known way to highlight organizations' flexibilities to regard rapidly uncertain market conditions, follow core competencies, and provide long-term growth strategies. Choosing service providers has been considered as a notable research area in the last two decades. The review of the literature represents that neural networks have proposed better performance than traditional methods in this area. Therefore, in this paper, a new enhanced artificial intelligence (AI) approach is taken into consideration to assist the decision making for the logistics management which can be successfully presented in cosmetics industry for long-term prediction of the real performance data. The presented AI approach is based on modern hybrid neural networks to improve the decision making for the 3PL selection. The model can predict the overall performance of the 3PL according to least squares support vector machine and cross validation technique. In addition, the proposed AI approach is given for the 3PL selection in a real case study for the cosmetics industry. The computational results indicate that the proposed AI approach provides high performance and accuracy through the real-life situations prediction along with comparing two other two well-known AI methods.

Keywords : Artificial Intelligence (AI); Least squares support vector machine (LS-SVM); Cross validation; Third-party logistics (3PL) provider selection problem.

1 Introduction

Considering intense global competition, logistics has now being taken into account as a significant field where various industries for enhancing customer service and selecting appropriate inventory levels along with increased competitiveness. New trend is outsourcing logistics activities to show the core competence, and improve the quality of services. Third-party logistics (3PL) providers let many organizations to increase logistics levels and functions which have been regarded as operational ways for them [1]. The key merits of logistics alliances are to highlight the outsourcing organizations by focusing on the core competence, increasing the efficiency and service along with decreasing the transportation and operational costs [2, 3]. Within outsourcing of logistics tasks, shippers have been followed to appraise and choose the best suitable 3PL provider [4, 5]. The related literature has represented the application of different multi-criteria analysis tools in this context. Efendigil

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et al. [6] introduced a tool for evaluating suitable third-party vendors by regarding the subjective requirements of the organization. The presented tool has provided the development of a conceptual framework by hybridizing fuzzy logic and artificial neural networks (ANNs) while focusing on the environmental attributes or factors in the selection process of the reverse logistics provider.

Cakir et al. [7] noted logistics service provider selection with decision support system based on the fuzzy analytic hierarchy process (FAHP) method. Kannan et al. [8] found a fuzzy based multi-criteria group decision-making tool to provide the suitable selection process of best 3PRLP. The assessment was according to interpretive structural modeling (ISM) and fuzzy technique for order preference by similarity to ideal solution (TOPSIS). Liu and Wang [9] described a fuzzy tool for the evaluation and appraisement of 3PL providers. Singh Bhatti et al. [10] showed the intangible variables into 3PL choice and appraisement by 4PL players. They applied a risk-based index to denote the risks according to any particular choice performed by the 4PL. Ding and Chou [11] represented a fuzzy multi-criteria analysis model to appraise middle managers for 3PLs. Govindan and Murugesan [12] concentrated on a decision tool for selection of third-party reverse logistics provider by fuzzy assessment. Zhang et al. [13] provided an innovative information granulation entropy method to appraise3PL providers. A fuzzy appraisement matrix, an information granulation entropy tool according to information science theory and data mining approach, was given to obtain the weights of factors or criteria. Finally, TOPSIS closeness rating tool was considered to give the priorities of candidates or alternatives.

The review of the related literature indicates that there existed several papers for the appraisement of providers in the 3PL problem. Taking artificial intelligence (AI) models into account for the 3PL provider selection problem can be presented and regarded as new approaches with suitable results in this field of research. In fact, AI models have been employed to several industries for appraising the alternatives, suppliers, or providers [14, 15, 16, 17].This study is a first attempt to illustrate a new AI-based approach in the 3PL selection problem regarding the time series prediction. Key merit of the AI models is that the complicated process of the decision making is not applied under multiple appraisement criteria or factors. In the AI approaches, the user or expert follows available information according to current situation. It means that the overall performance of alternatives or providers can be taken into account versus the appraisement criteria or factors, based on the approach's learning from the decision makers or cases in the past [15].

The available statistical methods, such as multiple linear regression and general exponential smoothing, could predict the linear time series; however, they cannot taken the nonlinear character of time series into account because of the inflexibility in their structures along with the inherent limitations [18, 19, 20]. The ANN approaches could learn a non-linear mapping between the input and output of a process in logistics management, and then to approximate non-linear functions properly without considering any assumptions taken by the statistical tools. Therefore, some recent studies in different industries have proposed the ANNs instead of statistical regression [16]. Also, the new ANN approach, i.e., LS-SVM, can theoretically provide the global optimum, rather than local optima, as there is a common-phenomenon in the traditional AI models [21]. Moreover, in the related literature regarding time series forecasting, there are useful applications of the LS-SVM in the recent years (e.g., supplier selection [15]; tourism demand forecasting [21], structural design cost estimation [18], pipe image interpretation [22].

This paper introduces a hybrid AI approach for appraising and selecting 3PL providers in the logistics management. Then, a computationally efficient approach that is based on the least squares support vector machine (LS-SVM) and cross validation is proposed to predict the overall performance of 3PL providers for the logistics management. The LS-SVM provides the global optimization solution given by a convex quadratic programming, and then takes the structural risk minimization principle into account by minimizing an upper bound on the generalization error [18]. In fact, cross validation technique trains the proposed AI approach to avoid over fitting and create the reliable results. This approach can handle the learning regarding the available data by utilizing the concepts of ANNs and holdout tools. The AI approach is implemented for the logistics management in a real case study in the cosmetics industry to appraise and select the providers. Further, to highlight the high performance of the presented AI approach, two well-known intelligent tools, including back propagation neural network (BPNN) and radial basis function (RBF) neural network are followed and the comparative analysis is given in detail.

The rest of this paper is organized as follows. In Section 2, assessment criteria or factors are considered and hierarchical structure is provided for the 3PL selection problem. The proposed hybrid AI model is given in Section 3. In Section 4, the comparisons among three AI models are conducted in the case study for the cosmetics industry. Finally, conclusion remarks are shown in Section 5.

2 Assessment factors for 3PL selection problem

In this section, the appraisement attributes or factors and the hieratical structure are taken into account for the complex 3PL selection problem. The goal of hierarchy model is the appraisement of the 3PL providers for logistics management that is denoted in the first level. These attributes or factors are represented according to the help of literature survey [6, 23] and the discussion with the experts in logistics management. Hence, sixteen appraisement attributes or factors are listed as follows. The hierarchical structure is indicated in Figure 1 to show the aforementioned attributes or factors.

- On time delivery ratio (C_1)
- Confirmed fill rate (C_2)
- Service quality level (C_3)
- Unit operation cost (C_4)
- Capacity usage ratio (C_5)
- Total order cycle time (C_6)
- System flexibility index (C_7)
- Integration level index (C_8)
- Increment in market share (C_9)
- Research and development ratio (C_{10})
- Environmental expenditures (C_{11})
- Customer satisfaction index (C_{12})
- Communication systems (C_{13})
- Enterprise alliance (C_{14})
- Location (C_{15})
- Experience (C_{16})

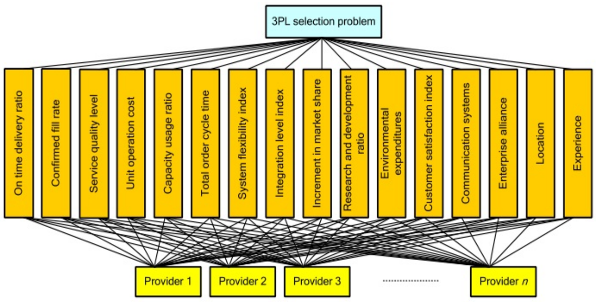

Figure 1: Hierarchical structure of the 3PL provider selection problem [24].

3 Proposed artificiel intelligence approach

Real-life applications in 3PL selection problem are not amenable to linear prediction tools. Indeed, 3PL selection problem are complex in logistics management and often nonlinear in nature. Therefore, conventional linear prediction tools are not applicable; presenting advanced AI-based approaches for forecasting the performance of 3PL providers is necessary in this field. To overcome the disadvantages of the commonly-used tools, this paper focuses on the selection of these 3PL providers by developing a new hybrid AI approach according to two powerful tools given as follows.

3.1 Support vector machine

Support vector machines (SVMs) were first presented by Vapnik in the late 1960s regarding to the foundation of statistical learning theory. There are numerous real-life applications of this method with considerable results [18, 19, 20]. The basic SVM regards two-class problems in which the data are separated by a hyper plane, given by a number of support vectors as represented in Figure 2, [25, 26, 27]. LS-SVM is a new version of the training technique based on the SVM; however, only the solution of a set of linear equations should be provided instead of the computationally hard quadratic programming problem available in the standard SVM. In fact, the LS-SVM could handle a least squares cost function [27].

Classification: The main aim of the SVM is to consider a separate function that training instances from distinct groups are regarded in terms of their class labels with major applications to solve complex problems in classification and re-

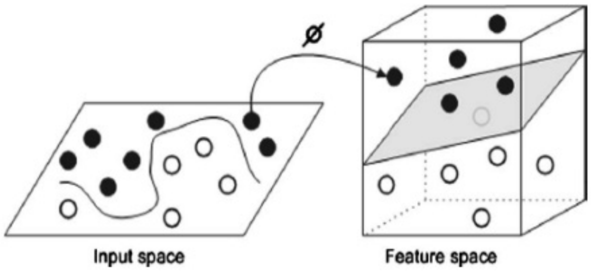

Figure 2: Nonlinear suppor vector machine.

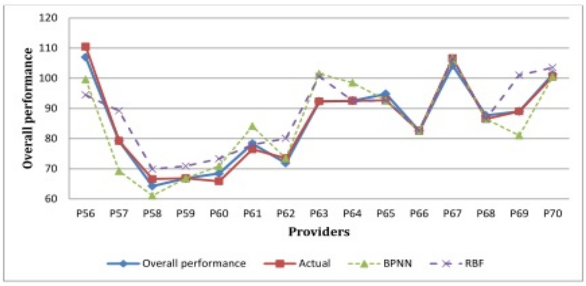

Figure 3: Comparative analysis according to actual overall performance ratings, BPNN, RBF and proposed AI-based approach for test records.

gression [28]. By mapping input vectors x into a high-dimensional feature space, SVM models given in the new space can represent a linear or nonlinear decision boundary in the original space. In the new space, an optimal separation is determined between instances of distinct classes according to the hyper plane which has the maximal distance to the nearest training instances. Therefore, the SVM is regarded as a new AI approach that focuses on the maximum margin hyper plane to supply the maximum separation between distinct classes. The maximum margin hyper plane for available learning problem is uniquely demonstrated regarding the instances that are closest to it, and these instances are taken as support vectors. In addition, the separate function for this approach could be linear or nonlinear [28].

For the linearly separable case, let S a given set with n labeled training instances $\{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$. Each training instance $x_i \in R^k$, for $i = 1, 2, ..., n$, regards either of the two classes versus its label $y_i \in \{-1, +1\}$, where k is the input dimension. The maximum margin hyper plane could be supplied by the following equation:

$$y = b + \Sigma w_i y_i x(i)x, \tag{3.1}$$

where denotes the dot product; the vector x expresses a test example and the vectors $x(i)$s are regarded as the support vectors. In this equation, b and w_i are regarded as parameters, in which the hyper plane could be learned by the SVM. To create an optimal hyper plane, the following quadratic programming problem can be solved:

$$Minimize\ \frac{1}{2}\|w\|^2$$
$$Subject\ to\ y_i(wx_i + b) \geq 1, \tag{3.2}$$
$$i = 1, 2, \ldots, n. \tag{3.3}$$

where the function $K(x(i), x)$ is regarded as the kernel function. There are several kernels for building SVMs regarding the different types of nonlinear decision surfaces in the input space. The commonly-used kernel functions include the polynomial kernel $K(x, y) = (xy + 1)^d$, and the Gaussian radial basis function $K(x, y) = \exp(\frac{-1}{\delta^2(x-y)^2})$, where d is regarded as the degree of the polynomial kernel, and δ^2 is regarded as the bandwidth of the Gaussian radial basis function.

Regression: The concept of a maximum margin hyper plane that are described above is only considered for the classification. However, the SVM has been extended for general prediction and forecasting problems that include LS-SVM as a version of the SVM for regression. The objective of the LS-SVM is to obtain a function, approximating the training instances well regarding the minimization of the prediction error. When minimizing the error, the risk of over-fitting is reduced by taken the maximization of the flatness for the function [25, 26, 27]. By solving the following quadratic programming problem, an optimal hyper plane could be determined:

$$Minimize\ \ \tfrac{1}{2}\|w\|^2$$

$$Subject\ to\ y_i(wx_i + b) \leq \varepsilon, \quad i = 1, 2, ..., n. \tag{3.4}$$

where ε regarded as the bound for the prediction error.

In cases where $f < w, x > +b$ exists and approximates all pairs (x_i, y_i) with ε precision, the above convex optimization problem could be feasible. To taken some errors in the exchange for the flexibility of this tool, we present slack variables ξ_i, ξ_i^* to tackle otherwise infeasible constraints of the following optimization problem:

$$Minimize \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*)$$

$$Subject\ to \tag{3.5}$$

$$\begin{cases} y_i - < w, x_i > -b \leq \varepsilon + \xi_i \\ < w, x_i > +b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases}$$

The constant C computes the trade-off between the flatness of f and the amount up to which deviations larger than ε are tolerated. By constructing the Lagrangian function, this optimization problem can be provided as a dual problem:

$$\begin{aligned} L =& \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \\ & - \sum_{i=1}^{l}\lambda_i \left(\begin{array}{l} \varepsilon + \xi_i - y_i + < w, x_i > \\ +b \end{array} \right) \\ & - \sum_{i=1}^{l}\lambda_i^*(\varepsilon + \xi_i^* + y_i - < w, x_i > -b) \\ & - \sum_{i=1}^{l}\lambda_i(\eta_i\xi_i + \eta_i^*\xi_i^*), \\ & and\ \lambda_i, \lambda_i^*, \eta_i, \eta_i^* \geq 0. \end{aligned} \tag{3.6}$$

By solving the Lagrangian, we provide the optimal solutions w^* and b^*:

$$\begin{aligned} & w^* = \sum_{i=1}^{l}(\lambda_i - \lambda_i^*)x_i, \\ & b^* = y_i - < w^*, x_i > -\varepsilon, \\ & 0 \leq \lambda_i \leq C, \quad i = 1, 2, \ldots, l, \\ & b^* = y_i - < w^*, x_i > +\varepsilon, \\ & 0 \leq \lambda_i \leq C, \quad i = 1, 2, \ldots, l, \end{aligned} \tag{3.7}$$

Similar to classification, the inner products could be regarded as proper kernels in nonlinear problems. Controlling the tradeoff between minimizing the prediction error and maximizing the flatness of the regression function can be performed by taking the upper limit C on the absolute value of the coefficients $w_i s$. Restricting the upper limit influences off the support vectors on the shape of the regression function and taking a parameter that the user or decision maker could consider beside ε . The larger C is, the more closely the function may fit the data. In the degenerate case where $\varepsilon = 0$, the method simply conducts least-absolute-error regression under the coefficient size constraint, and all training instances could be support vectors. Conversely, if ε is large enough, the error models zero, and the presented method outputs the flattest that includes the data irrespective of C [28, 29, 30].

3.2 Cross validation technique

A well-known tool namely cross validation is taken for the prediction of generalization error [31, 32].This paper utilizes K-fold among several types of the cross validation to enhance the hold-out technique. For this purpose the dataset is separated K subsets, and the presented technique is repeated K times. Each time, one of the K subsets can be proposed as the test set and the other $K-1$ subsets are denoted as a training set. Then, the average error is obtained across all K trials. The key merit of this presented method is that separating the data is not vital. It means that every data point can be regarded in a test set exactly once, and taken as a training set $K-1$ times. In the related literature, 3-fold, 5-fold and 10-fold as commonly-used cross validation approaches were introduced to apply in the real-life applications [29, 30, 31, 32].

3.3 Steps of the proposed approach

The presented hybrid AI approach takes two powerful techniques into account, namely LS-SVM and cross validation. In the presented approach, the LS-SVM is taken as a supervised learning methodology to consider input-output mapping and regard characteristics of 3PL selection data in the logistics management, and the K-fold cross validation is taken to train the LS-SVM tool in order to create a more realistic evaluation of the accuracy by dividing the training dataset into several training and test sets (K subsets), and to recommend suitable results. The presented AI approach can be a computationally efficient combination and can be reliable in the logistics management for the data prediction for performances of 3PLproviders. The main steps of the presented approach are described as follows:

Step 1. Dividing all data into the training dataset and test dataset: To create the LS-SVM, the training data are taken, and the test data are utilized to appraise the LS-SVM model performance.

Step 2. Training data: Training data is applied as sequential data. In this step, the sequential data follows the identified factor or criteria, and the training data can be normalized into the same range $(0, 1)$ by the following relation (3.8):

$$x_{sca} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{3.8}$$

Step 3. Training the LS-SVM: In this step, LS-SVM is deployed to handle input-output mapping. The Gaussian radial basis function kernel is applied as a reasonable choice. By using the K-fold cross validation technique on the training dataset, the LS-SVM training is performed to obtain the prediction model. In fact, for training set, K-fold cross validation is conducted on the training set, and the average cross validation accuracy (i.e.,$\min \mathrm{MAPE}_{\mathrm{CV}}$) is calculated based on the combination of the LS-SVM parameters (i.e., C and δ).

Fitness definition: The K-fold cross validation technique is taken into account in this step. In fact, K subsets randomly are taken after dividing the training dataset, and by considering a set of parameters (C, δ) with $K-1$ subsets as the training set the regression function is given; where $C \in (0, 10^{17})$, $\delta \in (0, 300)$. The last subset is taken as the validation. The above approach can be repeated K times. Consequently, the fitness function, namely $MAPE_{CV}$, is provided for the K-fold cross validation on the training dataset:

$$Fitness\ value = \min \ MAPE_{CV} \tag{3.9}$$

$$MAPE_{cv} = \frac{1}{l} \sum_{j=1}^{l} \mid \frac{y_j - \tilde{y}_j}{y_j} \mid \times 100\% \tag{3.10}$$

where y_J is denoted as the actual value; $\tilde{Y}_J$ is regarded as the predicted value and l is considered as the number of subsets. The solution with a smaller $MAPE_{CV}$ of the training dataset can be donated as a smaller fitness value.

Step 4.Determining parameters: The parameters of LS-SVM in this step are created to predict. Step 5. Adopt the best parameter combination to build the LS-SVM approach: Replacing the test dataset into LS-SVM approach to take the estimation values. Considering performance factors or criteria to provide the error between actual and estimation values regarding the testing performance can give the LS-SVM's estimated capability.

4 Model validation and comparative results

Kaf company is regarded as case study in this section. It is the leading producer of cosmetic and hygienic products (oldest brand "DARUGAR") in Iran. The studied company is taken into account as pioneer of innovation in the cosmetics industry for the logistics management. The 3PL provider selection can be one of the most significant tasks of logistics management by considering the key role of providers' performances on cost, quality, delivery and service in achieving the functions of logistics management. In fact, 3PL provider selection for Kaf company is denoted as a complex decision problem, in which several conflicting factors should be considered for the appraisement and selection. In order to show the capability of the presented AI-based approach, the above company is given as our case study for the logistics management.

4.1 Dataset

To test the validity of the presented AI-based approach, we apply a real set for the overall performances of 3PL providers for the logistics management. The experimental data could be divided into the following subsets: (1) training dataset and (2) test dataset. The dataset size could be enough to produce appropriate training and test. For this case, a total of 55 training data and 15 test data are given. Hence, the real dataset in the ratio of 79: 21 is divided into training and test datasets. Notably that 16 appraisement factors are regarded as qualitative and quantitative attributes which are denoted in section 2. To provide the performance of each 3PL provider by considering qualitative factors in the dataset, Table 1 is recommended using a 9-scale that is described by the verbal judgments of managers or professional experts. Finally, the output of the presented approach is a score for the individual 3PL provider as demonstrated in Table 2.

Table 1: 9-scale for performance of 3PL providers rating versus qualitative factors

Verbal judgment	Explanation	Corresponding number
Absolutely Poor (AP)	Performance of a 3PL provider with respect to an appraisement factor is absolutely poor.	0
Very Poor (VP)	Performance of a 3PLprovider with respect to an appraisement factor is very poor.	1
Poor (P)	Performance of a 3PLprovider with respect to an appraisement factor is poor.	3
Medium Poor (MP)	Performance of a 3PLprovider with respect to an appraisement factor is medium poor.	4
Fair (F)	Performance of a 3PLprovider with respect to an appraisement factor is fair.	5
Medium Good (MG)	Performance of a 3PLprovider with respect to an appraisement factor is medium good.	6
Good (G)	Performance of a 3PLprovider with respect to an appraisement factor is good.	7
Very Good (VG)	Performance of a 3PLprovider with respect to an appraisement factor is very good.	9
Absolutely Good (AG)	Performance of a 3PLprovider with respect to an appraisement factor is absolutely good.	10

Table 2: Dataset for predicting of overall performance for 3PL providers

	Input data Appraisement factors																Output Overall
3PL providers	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	(0-120)
Score-training data																	
P_1	7	8	7	8	6	5	6	6	8	7	9	6	6	8	8	8	86.492
P_2	6	6	6	7	7	5	4	6	4	6	4	5	8	9	10	7	88.774
P_3	9	7	8	6	6	7	8	5	6	6	3	7	10	5	6	8	81.676
P_4	5	8	7	6	6	8	6	6	5	4	6	9	7	7	8	6	95.831
P_5	6	6	9	5	8	6	5	7	7	4	7	10	6	8	5	6	99.428
P_6	8	6	5	4	8	4	8	5	8	6	7	4	9	6	5	9	73.864
P_7	4	5	6	7	4	6	7	4	6	5	3	6	8	9	6	5	77.644
P_8	6	5	7	8	4	3	6	7	3	7	5	8	9	6	7	4	97.412
P_9	7	7	6	7	5	7	6	6	5	8	8	9	10	6	9	8	88.382
P_{10}	8	8	4	7	6	7	5	8	8	5	4	5	8	9	4	7	70.294
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
P_{53}	7	6	4	6	7	7	6	8	7	7	5	7	9	5	9	7	86.464
P_{54}	4	5	8	8	6	4	6	6	8	6	7	8	9	4	6	6	64.890
P_{55}	7	4	7	5	4	6	7	5	5	7	9	9	10	6	5	5	91.994
Score-Test data																	
P_{56}	6	7	9	7	6	8	6	7	7	4	8	10	5	6	9	7	106.974
P_{57}	7	9	8	6	4	5	7	6	6	7	8	9	6	8	6	4	79.234
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
P_{69}	8	6	8	4	9	7	6	5	6	5	4	7	8	7	7	10	89.044
P_{70}	5	6	9	7	7	5	9	7	9	6	9	5	8	8	10	6	101.276

4.2 Statistical metrics

Common statistical criteria or metrics, i.e., mean squared error (MSE), mean absolute percentage error (MAPE), root mean squared error (RMSE) and R-squared (R^2), are given to appraise the estimation performance of the proposed AI-based approach. Four criteria or metrics are provided as below:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(p_i - \hat{p}_i)^2 \tag{4.11}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \left| \frac{p_i - \hat{p}_i}{p_i} \times 100 \right| \tag{4.12}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_i - \hat{p}_i)^2} \tag{4.13}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(p_i - \hat{p}_i)^2}{\sum_{i=1}^{N}(p_i - \bar{p}_i)^2} \tag{4.14}$$

where, p_i and $\hat{p}_i$ denotes the actual and estimated values of the i-th data, respectively. Also, $\bar{p}$ is the average of the actual values, and N is the number of data.

4.3 Results and discussion

The parameters of two well-known AI-based approaches, i.e., BPNN and RBF, for the comparative analysis given in this case study for the logistics management are as below:

- BPNN: The number of neurons in the hidden layer is 3 and
- the function is $logsig(n) = \frac{1}{(1+\exp(-n))}$.

For the proposed AI-based approach, LS-SVM: $C = 79810$ and $\gamma = 0.096$. Also, the Gaussian radial basis function kernel is taken as a commonly-used function. In addition, 10-fold cross validation is regarded for the computational process. This paper considers $K = 10$, meaning that all data provided by the training dataset could be separated into 10 subsets, each of which could take turns at being the test dataset. The other 9 subsets take into consideration as the training dataset for finalizing the model parameters. This implementation is computed according to the Libsvm introduced by [27]. Finally, the overall comparative results for the logistics management according to the MSE, MAPE, RMSE and R^2 criteria or metrics are provided for the proposed AI-based approach in Table 3. According to Table 3, the presented hybrid AI-based is placed in the first rank. The BPNN and RBF tools are denoted as the second and third ranks, respectively. Further, the computational results for the prediction of BPNN, RBF and the proposed AI-based approach are taken and compared in Figure 3 by regarding actual overall performances of 3PL providers for test records (56-70) for the logistics management. The real dataset from Kaf company is given in terms of the qualitative and quantitative appraisement factor or criteria (i.e., evaluation factors: C_1 to C_{16}) according to the experts' judgments and available information of the logistics management for the 3PL providers' evaluation. Values of the 3PL providers versus the selected appraisement factors are the inputs of the presented AI-based approach. On the other hand, the overall performance of each 3PL provider as the output of the presented approach is calculated by the final reports of the studied company after appraising and cooperating 3PL providers according to final decisions of the line and top managers. In fact, this paper could recognize the relation between the overall performance of each 3PL provider and the set of appraisement factors to help top managers for the logistics management in order to take the overall performance of potential 3PL providers as new candidates or alternatives for the investment, and to recommend the best provider(s) more precisely than traditional and trial-and-error tools. Notably that the relationship between the appraisement criteria or factors or the past time series data and the final rating of each 3PL provider is complex and non-linear in nature for real-life applications of the logistics. This study is a first attempt to provide the overall performance of 3PL providers regarding the complex selection problem in the cosmetics industry by new AI-based approaches. The efficiency and suitability of the AI-based approach is appraised by a real dataset for the logistics management in Iran, and its accuracy is taken and compared with the two well-known tools according to common statistical criteria or metrics, resulting in attractive findings.

Table 3: Overall comparative results of three intelligent models

Intelligent models	MSE	MAPE	RMSE	R^2
BPNN	28.9652	6.3261	4.0141	0.1313
RBF	31.0786	6.4923	4.3198	0.1298
Proposed AI-based approach	27.9623	5.8707	3.6294	0.1407

5 Conclusion

The appraisement and selection of third-party logistics (3PL) providers has been taken into account many criteria or factors, resulting in complex conditions that could be identified by some conventional tools and methods. To overcome this problem in this research we provided a new hybrid artificial intelligence (AI)-based approach according to least square-support vector machine and cross validation methods. Support vector machine is taken to provide the non-linear relationship between selection, appraisement factor or criteria and performance rating of 3PL providers and has proved high overall performance of non-linear representations. To demonstrate the ability and suitability of the presented AI approach, we have applied real test data set for the logistics management in 3PL provider appraisement and selection problems. Then we have compared our AI-based approach with two well-known tools, including BPNN and MLP, for the performance rating estimation. The comparative analysis indicated that the presented AI approach has a higher generalization performance for the logistics managers and provides lower estimation error. Notably that the ability of presented AI approach for overall rating prediction is affected by input parameters. As further research, the optimization of the input parameters is suggested for the possible improvement to predictions and estimations in the logistics management.

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An artificial intelligence model based on LS-SVM for third-party logistics provider selection

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یک مدل هوش مصنوعی مبتنی بر حداقل مربعات ماشین بردار پشتیبان برای انتخاب تامین کننده لجستیکی طرف سوم

چکیده:

استفاده از تامین کننده لجستیکی طرف سوم به عنوان یک راهبرد جدید در مدیریت لجستیک در نظر گرفته می شود. ارتباطات با در نظرگرفتن این تامین کننده، گاهی از اوقات پیچیده‌تر از ارتباطات سایر تامین کنندگان لجستیکی سنتی است. این ارتباطات به عنوان یک راه مشهور به منظور پررنگ نمودن توانمندیهای سازمانی با لحاظ شدن شرایط عدم قطعیت بازار، پیروی از شایستگی های اساسی و تامین راهبردهای بلند مدت در نظر گرفته می شود. انتخاب تامین کنندگان خدماتی به عنوان یک مسیر درخشان تحقیقاتی در دو دهه اخیر مطرح شده است. مرور ادبیات موضوع بیانگر آن است که شبکه های عصبی عملکرد بالاتری نسبت به روشهای سنتی در این حوزه از خود نشان داده اند. بنابراین در این مقاله یک رویکرد هوش مصنوعی برای تصمیم گیری بهتر مدیریت لجستیک در نظر گرفته می شود که به طور قابل ملاحظه ای در صنعت آرایشی برای پیش بینی بلندمدت براساس داده های عملکرد واقعی ارائه می گردد. رویکرد ارائه شده مبتنی بر شبکه‌های عصبی ترکیبی جدید برای بهبود تصمیم گیری برای انتخاب تامین کنندگان است. این مدل می‌تواند عملکرد کلی تامین کننده را براساس حداقل مربعات ماشین بردار پشتیبان و روش کراس ولدیشن پیش بینی نماید. علاوه براین رویکرد پیشنهادی در یک مطالعه موردی واقعی در صنعت آرایشی به کار گرفته می شود. نتایج محاسباتی بیانگر این است که رویکرد پیشنهادی عملکرد و دقت بالا در شرایط واقعی پیش‌بینی در مقایسه با دو روش مشهور دیگر دارد.