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Sustainable Supplier Selection by a New Hybrid Support Vector-model based on the Cuckoo Optimization Algorithm

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ABSTRACT

For assessing and selecting sustainable suppliers, this study considers a triple-bottom-line approach, including profit, people and planet, and regards business operations, environmental effects along with social responsibilities of the suppliers. Diverse metrics are acquainted with measure execution in these three issues. This study builds up a new hybrid intelligent model, namely COA-LS-SVM, for taking performance variations of the sustainable suppliers quantified by the performance index. The presented artificial intelligent (AI) model is introduced in light of a new combination of least squares-support vector machine (LS-SVM) and cuckoo optimization algorithm (COA). The LS-SVM is used in regards to the mapping capacity amongst performance index and its causative input criteria. The COA is presented to advance LS-SVM tuning parameters. In this exploration, an illustrative database comprising of 80 historical cases is gathered to set up the presented intelligence system. In the light of experimental results, the presented COA-LS-SVM can effectively illustrate performance index's variances since it has accomplished relatively low statistical metrics. Therefore, the proposed hybrid AI framework can be a promising approach to help the supply chain decision-makers in sustainable supply chain management (SSCM).

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1. INTRODUCTION

Business associations are under genuine threat to maintain their current supply chain because of globalization, challenging market, and demand uncertainty along with economic competitiveness. The idea of sustainability has picked up unmistakable quality in recent years to follow these developing difficulties. Incorporating sustainability ideas in center business elements of supply chain empowers association to accomplish competitive position in the market, in this contemporary period of an all-around testing environment [1]. Sustainable supply chain management (SSCM) is being regarded as a coming of another time that fuses environmental performance, social performance, and economic contribution-or what has been alluded as a convergence of main spheres of sustainable development [2].

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Supplier selection assumes an imperative part, while dealing with the supply chain. During important tasks of purchasing management in supply chain and in this process, suppliers are investigated, assessed and turn into a part of the company's supply chain [3]. Number of evaluation factors or criteria expanded as environmental, social, economic and consumer loyalty concerns were added to the customary variables, for example, quality, convey, cost and some more. Notwithstanding this, a portion of the criteria are clashing in nature which requires the use of artificial intelligent (AI) techniques [4-6]. Fundamentally, sustainable supplier selection issue can be seen in two issues: identification of factors and ranking the suppliers by regarding the chose criteria [7].

AI-based models are perceived to be the suitable techniques for assessing and prioritizing the suppliers in the SSCM. AI-based decision making is conceivable considering acquiring specialists and additionally historic data. The neural network-based models, because of their benefits are generally utilized among the current

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techniques as a part of the AI approach. Not requiring the complicated process of decision-making is one of the fundamental benefits of the AI models. The innovations in light of the AI approach are utilized in spaces of sustainable-suppliers [8-10].

Amindoust et al. [11] the sustainable supplier selection factors and sub-factors were resolved and in light of those factors and sub-factors a strategy was extended onto evaluation and ranking of a given arrangement of suppliers based on fuzzy inference system (FIS). Kuo et al. [12] built up an intelligent supplier-DSS which could regard the quantitative and subjective factors concurrently based on a particle swarm optimization (PSO)-based fuzzy neural network (FNN). In Azadnia et al.'s study [7], an incorporated approach of fuzzy analytical hierarchy process (AHP) and fuzzy logic were provided with a specific end goal to tackle sustainable supplier selection problem. In Omurca's study [13], a hybridization of fuzzy c-means (FCM) and rough set theory (RST) procedures was reported as another answer for supplier selection, evaluation and development issue. Jauhar et al. [14] intended to analyze the difficulties of sustainable supplier selection and proposed a differential evolution-based approach for selecting sustainable suppliers in the pulp and paper industry. Jauhar and Pant [15] introduced the supplier contribution in the related activities of the SCM by using differential evolution (DE) to choose the effective practical supplier, giving the greatest satisfaction to the sustainable criteria decided. Bhardwaj [16] built up a model for sustainable system by using an asset-based approach and value chain investigation. Kara et al. [17] intended to investigate the sustainability issues in supplier assessment and to propose sustainable supplier assessment criteria by the related literature. Ahmadi et al. [18] provided an organized and coordinated choice model for assessing suppliers in the SSCM with regards to telecom industry by consolidating the AHP and enhanced grey relational analysis. Ağan et al. [19] introduced a comprehension of environmental supplier development (ESD), which was the improvement of suppliers to producers with the end goal of natural execution with data gathered from several Turkish manufacturing plants. Girubha et al. [20] regarded interpretative structural modelling by hybrid multi-attribute decision-making (MADM) methods to assess sustainable supplier. Luthra et al. [21] considered a structure to assess sustainable supplier selection by using an incorporated AHP and VIKOR within multi-criteria compromise solution approach with an application to automobile company in India. Ghadimi et al. [22] focused on a useful decision-making way to deal with assessing the most sustainable suppliers for an automotive industry by a fuzzy inference system.

In this paper, an endeavor is made to streamline the performance ratings of sustainable suppliers in the SSCM by presenting a novel hybrid AI model. In fact, this paper builds up a new hybrid intelligent model, namely COA-LS-SVM, for taking performance variations of the sustainable suppliers quantified by the performance index. The presented AI model is introduced in light of a new combination of least squares-support vector machine (LS-SVM) and cuckoo optimization algorithm (COA). LS-SVM is used for regarding the mapping capacity amongst performance index and its causative input criteria. The LS-SVM is a new neural network and directed learning technique to handle different network issues. Because of their fabulous execution in speculation and their ability for self-learning, the LS-SVM have defeated the potential shortcomings of ordinary expectation procedures, in particular artificial neural networks (ANNs) in real-world applications. The COA is presented to advance LS-SVM tuning parameters. In this exploration, a database comprising of 80 historical cases is gathered to set up the presented COA-LS-SVM model in the SCM. Similar investigations are likewise directed to evaluate the execution of the proposed model and conventional techniques in the related literature, including RBF, MLP neural network and LS-SVM.

The organization of the rest of this paper is provided as follows: In Section 2, the theories on the LS-SVM and COA are presented. Section 3 is devoted to the description of the COA-LS-SVM model. The background information for the SSCM problem is given in Section 4. Section 5 provides the comparative assessments. Finally, Section 6 gives some concluding remarks.

2. RESEARCH BACKGROUNDS

2. 1. Least Square-support Vector Machine (LS-SVM)

LS-SVM is an adjusted variant of support vector machine (SVM) [23, 24]. In the LS-SVM training, a least solution, cost function has been provided to get a linear set of equations in the dual space. To determine the arrangement, it is necessary to manage an arrangement of linear conditions as opposed to illuminating a nonlinear programming as standard SVM [23, 25]. The detailing of LS-SVM can be expressed as the accompanying optimization issue:

$$\begin{aligned} &Minimize\ J_p(w,e) = \frac{1}{2}\ w^T w + \gamma \frac{1}{2} \sum_{i=1}^{N} e_i^2 \\ &Subjected\ to\ y_i = w^T \phi(x_i) + b + e_i\ ,\ \ i = 1, \ldots, N \end{aligned} \tag{1}$$

where $e_i \in R$ are error variables; $\gamma > 0$ is a regularization constant.

In Equation (1), the objective function can be made out of a total of squared fitting error and a regularization term [26]. Notwithstanding, when w gets to be distinctly boundless dimensional, one could not consider this primal issue. Subsequently, it is important to set up Lagrangian and infer the double issue. The Lagrangian is reported as follows [27].

$$L(w,b,e;\alpha) = J_p(w,e) - \sum_{i=1}^{N} \alpha_i\{w^T\phi(x_i) + b + e_i - y_i\} \tag{2}$$

where α_i refers to Lagrange multipliers. The conditions are as follows.

$$\begin{cases} \frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{i=1}^{N} \alpha_i \phi(x_i) \\ \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{N} \alpha_i = 0 \\ \frac{\partial L}{\partial e_i} = 0 \rightarrow \alpha_i = \gamma e_i \ , i = 1, \dots, N \\ \frac{\partial L}{\partial a_i} = 0 \rightarrow \quad w^T\phi(x_i) + b + e_i - y_i = 0, i = 1, \dots, N \end{cases} \tag{3}$$

After elimination of *e* and *w*, the following linear model can be given by:

$$\begin{bmatrix} 0 & 1_v^T \\ 1 & \omega + I/\gamma \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{4}$$

where $y = y_1, \dots, y_N, 1_v = [1; \dots; 1]$, and $\alpha = [\alpha_1; \dots; \alpha_N]$. In addition, the kernel function is applied as follows.

$$\omega = \phi(x_i)^T \phi(x_l) = K(x_i, x_l) \tag{5}$$

The function estimation is provided by:

$$y(x) = \sum_{i=1}^{N} \alpha_i K(x_i, x_l) + b \tag{6}$$

where α_k and b can be denoted as the solution to the linear model (4). RBF kernel is presented below.

$$K(x_i, x_l) = \exp\left(\frac{\|x_i - x_l\|^2}{2\sigma^2}\right) \tag{7}$$

where, σ is the kernel function parameter.

The LS-SVM has widely been applied to engineering applications [28-30]; for instance, data fitting of small samples [31], electrical energy consumption forecasting [32], curing thermal process [33], cosmetics productions [34], river water pollution [35], pipeline critical deposition velocity prediction [36], forecasting in civil engineering [37].

2. 2. Cuckoo Search Algorithm

The cuckoo search (CS) or cuckoo optimization (CO) algorithm was initially created by Sun et al. [38]. It is gotten from the activity of cuckoos laying their eggs in the nests of other birds to regard those birds hatch eggs for them. Nonetheless, once the host bird's creatures find the cuckoo eggs, the eggs could be discarded or the host birds can surrender their homes and revamp another nest somewhere else.

In the CS calculation, every home speaks to an answer. Bouzerdoum [39] introduced in the algorithm, can help in comprehension of the CS procedure. The L'evy flight specified in the pseudo code is created by:

$$x_i^{t+1} = x_i^t + \alpha \oplus L\acute{e}vy\ (\lambda) \tag{8}$$

Determine the objective function $g(x),\ x = (x_1, x_2, \dots, x_d)^T$;
Initialize the population of N host nests $x_i\ (i = 1, 2, \dots, N)$;
WHILE (*The stop criterion has not met*)
Choose a cuckoo randomly by L´evy flights and evaluate its goodness of fit or quality G_i
Choose a nest among N (*say* j) *randomly*;
IF $(G_i > G_j)$
Replace j by the new solution;
END IF
Abandon a fraction (p_a) *of worse nests and build new ones*;
Keep the best solutions (*or nests with quality solutions*);
Rank the solutions and find the current best solution;
ENDWHILE
Post-process results;

Figure 1. Steps of the proposed COA.

where $\alpha > 0$ can be the step size. The product $\oplus$ denotes entry-wise multiplication location a Levy flight can be regarded when the step-lengths could be distributed according to the probability distribution as:

$$L\acute{e}vy \sim u = t^{-\lambda},\ 1 < \lambda \leq 3 \tag{9}$$

which has an infinite variance. Thus, the consecutive steps of a cuckoo search forms random walk process that obeys a power-law step-length distribution with a heavy tail.

3. Proposed COA-LS-SVM Model

To remedy the deficiencies on generalization ability and suitability along with predictive accuracy of the LS-SVM, a novel AI model is proposed in this paper for the sustainable supply chain. The AI model consists of two new approaches (i.e., LS-SVM and COA) in Figure 2.

The COA within the LS-SVM leads to dynamically optimize the LS-SVM parameters to boost the sustainable supply chain-prediction efficiency. The COA-LS-SVM algorithm for the sustainable supplier selection problem in the SSCM is presented in subsequent steps:

Step 1. Scale data. The input data are normalized to ensure that diverse units of estimation are evacuated and all factors or attributes are defined in the same range [0,1] by:

$$x_{sca} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{10}$$

After implementing this transformation, the effect of dimension is removed from all the variables.

Step 2. Prepare the necessary data. Training and test data sets are considered.

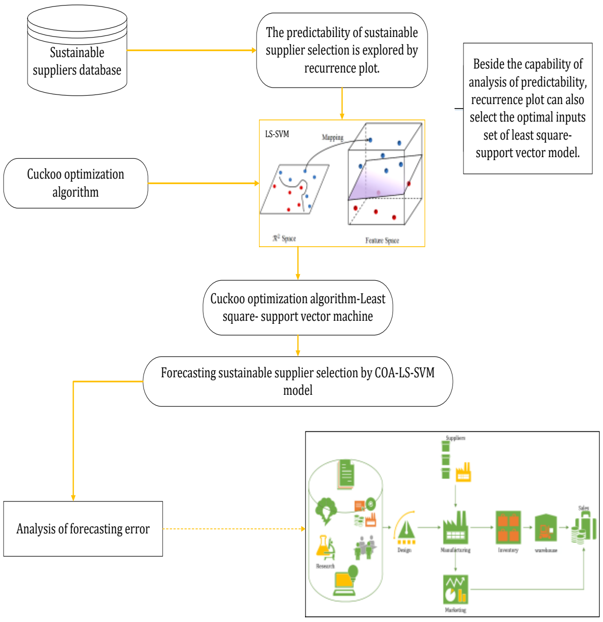

Figure 2. Framework of the proposed COA-LS-SVM

Step 3. Initialize parameters of the COA, range of kernel function and its parameters(γ, σ).

Step 4. Select randomly a kernel function. Generate a random set of γ and σ in the given valuing ranges. Selected kernel function and its parameters such as γ and σ is considered as an individual of LS-SVM.

Step 5. Deploy the selected parameters and the obtained support vectors to represent a LS-SVM model. To test estimation ability of the LS-SVMs, the testing samples are used. Applicability of the model is measured by fitness as:

$$Fitness\ function = \min_i \left(\left| p_i - \hat{p}_i \right| \right) \tag{11}$$

where, p_i and $\hat{p}_i$ denoted the actual and estimated values of the i-th data.

Step 6. If fitness is accepted, then the training procedure of LS-SVM terminates and the best SVMs are determined. Otherwise, go to step 7 and produce the new solution.

Step 7. Apportion a determined number of eggs to each cuckoo in the COA.

Step 8. Calculate egg-laying radius (ELR) for each cuckoo in the COA. An ELR can be indicated for each cuckoo as:

$$ELR = \alpha \times \frac{Number\ of current cuckoos' egg}{Total\ number\ of\ eggs} (var_{ub} - var_{lb}) \tag{12}$$

where $\alpha \in \mathbb{Z}$ is supposed to control the maximum value of ELR, var_{ub} and var_{lb} are the upper bound and lower bound for variables, respectively.

Step 9. Destroy the detected parasite eggs by host birds.

Step 10. Let other eggs which are not identified hatch and attain maturity.

Step 11. Evaluate the habitat of recently grown cuckoos.

Step 12. Limit the maximum number of cuckoo, those who live in worst habitat must die.

Step 13. Cluster cuckoos to provide the target habitat regarding immigration of cuckoos.

Step 14. Let new cuckoo population migrate toward target habitat.

Step 15. Stop condition checking: if stopping criteria (maximal running time predefined or the error accuracy of the fitness function) are met, go to step 16. Otherwise, go to the step 3.

Step 16. Terminate the training procedure, output the best solution.

In Figure 3, the flowchart of the proposed COA-LS-SVM model is illustrated. The COA is used to explore a better combination of the two parameters in the LS-SVM model. The values of two parameters are updated when a new solution of the COA is generated. Afterwards, a forecasting process is implemented and a forecasting error is computed. Finally, if the stopping criterion is satisfied, then stop the algorithm and the latest solution is a best solution. This algorithm is employed to find a better combination of the LS-SVM parameters so that a smaller fitness function is attained during estimation iteration.

4. PROPOSED MODEL APPLICATION

Sustainable supplier selection is regarded as a complicated process as it contains numerous evaluation

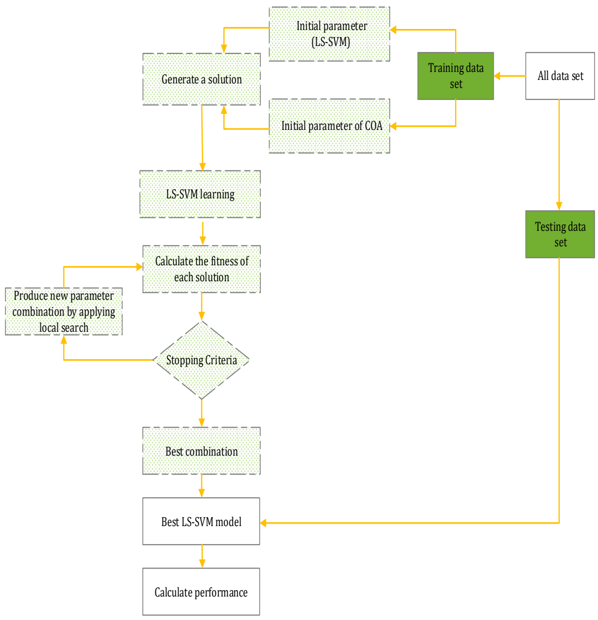

Figure 3. Flowchart of the proposed hybrid COA-LS-SVM model

factors or criteria, consideration of criteria weights and the most significant factor is that the selection of suitable factor based on all the three pillars of sustainability. For this purpose, the evaluation criteria are provided by the literature review as given in Table 1 (e.g., [20, 40, 41]).

TABLE 1. Evaluation criteria for the sustainable supplier selection problem

Sustainable supplier selection problem	
Criteria	Economics sub-criteria
C_1	Price performance value
C_2	On time delivery
C_3	Transportation cost
C_4	Compliance with sectorial price behavior
C_5	Warranties, claim policies and quality assurance
C_6	Organization commitment
C_7	Responsiveness
	Social sub-criteria
C_8	Rights of stakeholders
C_9	Work safety
C_{10}	Information disclosure
C_{11}	Respect for policy
	Environmental sub-criteria
C_{12}	Green design and Recycling
C_{13}	Green R&D
C_{14}	Environmental management system
C_{15}	Use of environment friendly technology
C_{16}	Pollution control initiatives

To test the adequacy of the proposed COA-LS-SVM model, we use a genuine arrangement of execution rating of sustainable suppliers in the SSCM. Then, issue of sustainable supplier evaluation and selection can be a standout amongst the most noteworthy errands and exercises of obtaining administration due to the key a portion of sustainable supplier's performance on cost, quality, delivery and service in achieving objectives of the sustainable supply chain. With a specific end goal to actualize the proposed COA-LS-SVM model the supposed organization is regarded as a dataset in the SSCM. A sum of 55 training data points and 25 training data points are given. Henceforth, the genuine information set is partitioned into training and test data set in the proportion of 69% to 31%. Table 2 outlined 55 input data as for each of sustainable supplier evaluation criteria which are characterized in 3 areas for the sustainable supplier selection problem and 25 approval cases.

Three common statistical metrics including (1) mean absolute percentage error (MAPE), (2) root mean squared error (RMSE), and (3) standard deviation error (SDE) are employed to appraise the estimation performance of the proposed AI model. These metrics are defined by [23, 42-45]:

TABLE 2. Patterns for performance rating of the supplier selection problem in SSCM

Input data																	
Sustainable Suppliers	Economics Criteria							Social Criteria				Environmental Criteria					Performance rating
	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}	
Score-train data																	
ss_1	53	74	76	60	52	79	72	97	93	71	54	37	61	56	58	94	71.36
ss_2	65	60	75	64	58	71	88	86	74	68	67	60	67	78	66	85	66.36
⋮																	
ss_{54}	53	71	52	58	44	63	70	93	87	82	54	40	56	59	46	91	84.20
ss_{55}	58	80	72	76	49	62	68	94	77	69	55	37	45	77	62	89	58.59
Score-test data																	
ss_{56}	55	55	53	55	48	56	82	96	98	77	48	30	46	57	56	91	58.74
ss_{57}	42	79	61	79	39	74	82	84	74	75	56	58	48	78	79	80	68.06
⋮																	
s_{79}	62	61	60	61	56	83	88	99	79	66	42	59	56	60	50	77	52.43
ss_{80}	40	65	76	71	68	69	82	88	85	82	56	32	56	66	61	70	73.41

(1) $$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{p_i - \hat{p}_i}{p_i}\right| \times 100\% \qquad (13)$$

(2) $$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(p_i - \hat{p}_i\right)^2} \qquad (14)$$

(3) $$SDE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(e_i - \bar{e}_i\right)^2}; \quad e_i = \hat{p}_i - p_i, \quad \bar{e}_i = \frac{1}{N}\sum_{i=1}^{N} e_i \qquad (15)$$

where, p_i and $\hat{p}_i$ represent the actual and estimated values of the i-th data, respectively. Three criteria or metrics were used to quantify the deviation between the actual and predicted values in the SSCM.

The first performance metric (i.e., MAPE) is viewed as a relative measure that considers errors as a rate of the real data, regarded as a viable method for judging the degree or significance of errors for the estimations. The second execution metric (i.e., RMSE) indicates the deviation between the actual and estimated values by the proposed display; consequently, smaller values of this rule are favored for various circumstances into a solitary measure of prescient one. The third performance metric (i.e., SDE) denotes the square root of the variance of error, the deviation between the actual and predicted values.

The above-mentioned criteria are regarded as commonly-used measures for differences between values in statistics in the related literature, particularly in trend estimations [23, 43-52]. The lower values of the three statical criteria (i.e., MAPE, RMSE, SDE) indicate the better performance and more accuracy in the estimations in the SSCM.

In this paper, the radial basis function is employed as the kernel function for performance prediction in the sustainable supplier selection in the SSCM. There are two independent parameters while using RBF kernels (i.e., γ and σ). Searching two parameters can be very significant for the best forecasting ability. Finally, the parameters in the proposed AI model are as follows: $\gamma = 58942$ and $\sigma = 0.104$.

The processes of determining the parameters for three conventional techniques are presented. The AI technique (i.e., MLP) is a feed forward ANN model that maps sets of input data onto a set of appropriate output [47-52]. The input layer includes three nodes. The number of output nodes can be set to 1. The number of neurons in the hidden layer can be 6. The activation functions for the hidden and output layers are regarded as the hyperbolic tangent transfer function and linear function respectively. To train the network Levenberg-Marquardt back propagation is regarded. The third conventional technique (i.e., SVM) is a machine learning based on the statistical learning theory by considering several merits over other ANN techniques. There are no general rules for setting the SVM parameters. The authors' experience and trial-and-error are employed. Finally, the values of parameters obtained by the SVM technique are: $\gamma = 546000$ and $\sigma = 0.081$. The overall comparative results based on the MAPE, RMSE, and SDE indices are illustrated for the proposed AI model in Table 3.

According to three commonly-used measures in the related literature reported in Table 3, the computational results indicate that the proposed COA-LS-SVM model has achieved the lowest prediction error and the highest forecasting ability in SSCM. The proposed AI model is compared with other intelligent techniques, including RBF, MLP and LS-SVM, for performance prediction in the sustainable supplier selection in SSCM. In fact, the proposed COA-LS-SVM has the lower values based on the first three performance criteria (i.e., MAPE, RMSE and SDE). As it can be seen from Table 3, the COA-LS-SVM model is put in the first rank, and other AI models (i.e., LS-SVM, MLP and RBF) are put in the second, third and fourth ranks, separately in the decision problem. In addition, Figure 4 contrasts the outcomes acquired and the expectation comes about because of RBF, MLP, LS-SVM and LS-COA-LS-SVM with actual performance rating of suppliers for test records (56-80) individually.

TABLE 3. Overall comparative results of the sustainable supplier selection

Intelligent techniques	MAPE	RMSE	SDE
RBF	10.840422	6.941306	0.126621
MLP	9.756181	6.147641	0.102860
LS-SVM	9.693930	6.281161	0.124358
Proposed COA-LS-SVM	9.213324	5.907949	0.110132

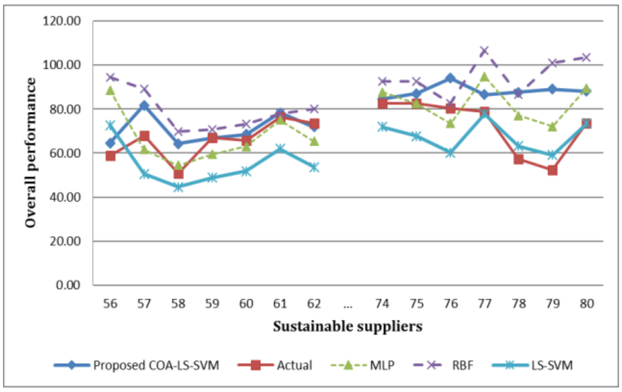

Figure 4. Comparisons among actual performance ratings of the sustainable supplier selection

Figure 4 portrays the performance ratings of the sustainable suppliers for the sustainable supplier evaluation problem in SSCM, contrasted and genuine information from the proposed COA-LS-SVM and other intelligent techniques. The general performance estimation of the suppliers from the intelligent model are close to real performance data in the SSCM. In fact, the COA-LS-SVM has been considered with the maximum generalization ability and can properly be capable to model nonlinear relationships in SSCM.

5. CONCLUSIONS

This paper has displayed a new hybrid intelligent approach (i.e., COA-LS-SVM) to facilitate managers in sustainable supplier performance estimation through improvement of the performance index modeling exactness. The COA-LS-SVM was produced by a new combination of the LS-SVM and COA. The LS-SVM was used to find the basic mapping between affecting components and the sustainable supplier performance records. The COA was proposed as the optimizer to search for LS-SVM ideal parameters. By this component, the proposed AI framework can work independently in light of the fact that it dispenses with the trial-and-error procedure in parameter setting. The LS-SVM used as a main part of this paper can deal with data with nonlinear features, and the COA technique received to improve the estimation approach, which was used to optimize the parameters in the LS-SVM model. Subsequent to being trained, COA-LS-SVM can be regarded as a causal prediction model to make induction of performance index in the SSCM at whatever point an input pattern was given. Through examinations, it was presumed that the proposed COA-LS-SVM has demonstrated a superior generalization performance and yielded a lower estimation error of the sustainable supplier selection problem. In fact, the COA-LS-SVM considered with the maximum generalization ability can properly be capable to model nonlinear relationships in SSCM. For further research directions, the proposed prediction method can be applied to other sustainable supply chain decisions for the mid and long-term planning, e.g., measurement of supply chain agility, minimizing the bullwhip effect, facility location and vehicle routing.

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Sustainable Supplier Selection by a New Hybrid Support Vector-model based on the Cuckoo Optimization Algorithm

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چکیده

به منظور ارزیابی و انتخاب تامین‌کنندگان پایدار، این تحقیق یک رویکرد سه قسمتی شامل سود، مردم و سیاره و توجه به عملیات کسب و کار، اثرات زیست محیطی همراه با مسئولیت‌های اجتماعی از تامین کنندگان را در نظر می گیرد. متریک-های متنوع با اجرای اندازه گیری، ما را از این سه مسئله مطلع می‌سازد. این مقاله یک مدل هوشمند ترکیبی جدید، به نام COA-LS-SVM، برای تعیین کمی تغییرات عملکرد تامین‌کنندگان پایدار با استفاده از شاخص عملکرد ایجاد می‌کند. مدل پیشنهاد شده هوشمند مصنوعی (AI) ترکیب جدیدی از ماشین بردار پشتیبان با حداقل مربعات (LS-SVM) و الگوریتم بهینه‌سازی فاخته (COA) معرفی می‌کند. LS-SVM برای بیان ظرفیت نگاشت در میان شاخص‌های عملکرد و معیارهای ورودی مسبب آن استفاده شده است. COA به منظور پیشبرد میزان‌سازی پارامترهای LS-SVM پیشنهاد شده است. در این جستجو، یک پایگاه داده متشکل از ۸۰ داده تاریخی برای راه اندازی سیستم هوشمند ارائه شده، جمع آوری شده است. در پرتو نتایج تجربی، از آن–جا که متریک‌های آماری نسبتا کم انجام می‌گیرد، LS-SVM–COA می‌تواند به طور موثری شاخص عملکرد واریانس را نشان دهد. بنابراین، چارچوب AI ارائه شده می‌تواند یک روش امیدبخش برای کمک به تصمیم گیرندگان زنجیره تامین، در مدیریت زنجیره تامین پایدار باشد.

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