Journal of Theoretical and Applied Information Technology
15th December 2025. Vol.103. No.23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AN EFFICIENT REINFORCEMENT LEARNING-BASED SUPPLIER SELECTION FRAMEWORK THROUGH RISK PREDICTION PROCEDURES

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ABSTRACT

Supply networks have needed structural modifications to react to both positive and negative occurrences such as Industry 4.0 and natural disasters. Both negative and positive things can disrupt corporate business operations and have an impact on their continuation. Selected suppliers can support the organizations against disruptions. To check uninterrupted materials across flow of the Supply Chain Management (SCM) supplier selection and other distribution must be reorganized in light of the dynamics of disaster Industry 4.0 occurrences. SCM is directly impacted by different decision-making processes like supplier evaluation and selection. Several approaches have been used to evaluate suppliers' performance and choose the top suppliers more effectively, enhancing the overall performance at diverse conditions. Yet, the conventional approaches are not sufficient for managing with large volumes of training datasets within a restricted period, minimizing the convergence speed. Also, it is not capable for generating optimal solution in the validation phase and it requires most efficient performance measures. Therefore, this research is also exploring a new supplier selection strategy incorporating heuristic-driven deep learning. In the initial stage, the industrial data are gathered and forwarded to the data cleaning phase to increase the data quality. Then, the data transformation is conducted to enhance the efficiency of information flow without unnecessary complexity. The next stage is the optimal weighted feature selection, where the weights and optimal features are optimized using a new hybrid optimizer termed Position Updated-Archimedes and Fruit Fly Optimization (PU-AFFO) technique. Finally, the selected weighted features are given to the risk prediction performance, where the outcomes related to the risk is acquired using the Adaptive Transformer Bidirectional Long Short-Term Memory with Weighted Bayesian Learning (ATransLSTM-WBL). Here, the parameters of every network are tuned using the same PU-AFFO technique. Finally, based on the predicted risk, Reinforcement Learning is performed for the final supplier selection. At last, to check the developed system performance, various statistical analyses are utilized and the outcomes given statistically powerful GEP model. Here, the designed framework has attained a lower error rate of 1.01, 0.01, 3.27, 1.12, and 5.88 in terms of MEP, SMAPE, MASE, MAE and RMSE measures, which demonstrate the overall efficiency of the designed technique than the conventional methods.

Keywords: *Risk Prediction-based Supplier Selection Model; Position Updated-Archimedes and Fruit Fly Optimization; Transformer Bidirectional Long Short-Term Memory; Weighted Bayesian Learning; Weighted Feature Selection*

1. INTRODUCTION

SCM is one of the top priorities for any manufacturing organization and also it increases success [1]. The industrial community mostly used an SCM because it is an emerging field. It entails all actions taken in connection with the flow of goods, transformation and SCM related services [2], as well as the accompanying data flow in the material sources to the final consumers [3]. The advantages include lower supply chain and production risk, increased revenue, enhanced customer service, maintaining an optimal boosting profitability and inventory level and satisfaction of customer [4]. Supplier selection technology is still necessary to consolidate paradigms such as

Industry 4.0. It is a recent trend of automation methods in the production of sector. The decision-making process for selecting technology is influenced by a number of factors [5]. The basic supply chain is said to be Supplier selection and the issue that has been studied extensively over a long time by industrial researchers and academic area using various techniques and approaches [6]. A decision making problem combines qualitative and quantitative criteria [7].

The suppliers availability to deliver a specific category of machine with the appropriate papers at the specific rates must be taken during the technology selection process [8]. It is important to consider supply chain issues and supplier concerns while choosing the best manufacturing technology [9]. However, supplier selection with technology relies on specific processes, sectors, and companies. The selection of suppliers is crucial to the production company [10]. By lowering the supply chain upstream expenses, choosing the best supplier can significantly increase supply quality and reliability while lowering procurement costs for an organization. It can also contribute to raising consumer satisfaction. Quality, service, delivery and pricing are the basic factors [11]. A group of experts from inside the organization often decides on the set of sub-criteria and methods, while it is also possible to choose among the many studies [12].

As a result, numerous hybrid and solo techniques for supplier selection and evaluation have been developed [13]. Individual techniques like analysis, decision making, hierarchy process and Artificial Intelligence (AI) are developed [14]. The algorithms like Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and fuzzy were investigated [15]. The main drawback of AI-related techniques is that they contain a black box, meaning they do not present a clear relationship to compute the outcome [16]. The AI techniques like ANN and Support Vector Machines (SVM) have been utilized in supplier selection and evaluation. In other words, the conventional methods cannot offer a clear mathematical model for suppliers. As a result, this research suggested a risk prediction novel based on a deep learning-aided supplier selection strategy using the machine learning method [17].

Motivation:

The supplier selection is one of the crucial tasks for reducing the purchasing cost of a product in supply chain management system. The conventional Gradient Boosting Machine (GBM) approach [37] is not sufficient for determining the normal and expected flow of components due to the presence of glitches, disruptions and unplanned events, enhancing more lead-times, which can significantly affect the overall performance. It is not capable of effectively managing and ensuring a smooth flow of products through the supply chain, enhancing more computational cost rates. Also, it is not sufficient for managing and mitigating the attacks and risks in supplier selection phase to enhance more vanishing gradient complexities. The conventional a hybrid Artificial Neural Network-Recurrent Neural Network (RNN-ANN) model with Gradient Boosting (GB) approach [38] is not sufficient for handling imbalanced and background noise data in the training phase to make overfitting complexities, which can significantly impact the supply chain. It is not suitable for maintaining the competitiveness and resilience of organizations also; it does not accurately predict the supply chain risks in an earlier stage, facilitating overfitting issues while handling large dimensional datasets, enhancing decision-making performance [39]. In the iterative phase, it generates more error value to impact the adaptability and it does not analyze and identify the level and dimension of each risk, causing substantial losses. Considering the existing [40] approach, it fails for qualitatively analyzing the occurrence and potentially impact of risks. Further, the information about demand forecasting and price prediction is does not automatically extracted from the input data, enhancing operational inefficiency. In order to minimize these complexities, a novel deep learning based framework is designed in this study, which helps to automatically select the superior supplier based on the risk prediction performance.

The deep learning-based developed supplier selection model objectives are mentioned below.

- To implement a deep learning-based supplier selection model for effectively selecting the suppliers to help the companies reduce the wastage of costs. It decreases the purchase risk and makes a long time relationships with buyers and suppliers.
- To develop a PU-AFFO algorithm to tune the parameters like an activation function, batch size, epoch, and optimizer from TransBiLSTM to increase the performance of the developed system. Parameter optimization is used to maximize precision and accuracy.
- To optimize the features and weights from the transformed data for selecting the most prominent features to maximize the

correlation coefficient using the developed PU-AFFO algorithm that increase the performance of the risk prediction.
- To develop an effective ATransLSTM-WBL-based risk prediction system with parameter optimization using the PU-AFFO algorithm to predict the bidding price per unit risks that is helpful for selecting suppliers.
- To implement Reinforcement learning is used to effectively select the suppliers in the final stage for reducing the wastage of costs in the companies.
- To estimate the effectiveness of the proposed Reinforcement learning-based supplier selection approach than other conventional frameworks with some performance measures.

The summarization of the deep learning-based supplier selection model is presented in the remaining sections. Phase II explains the advantages and disadvantages of the deep learning-based supplier selection model. The dataset explanation, the suggested approach, and the preprocessed method explanations are described in phase III. The description of the data transformation technique and implemented strategy details are given in the phase IV section. The risk prediction methods explanations are summarized in phase V. Phase VI describes the experimental analysis and findings of the developed model. The designed system conclusion is mentioned in phase VII.

2. LITERATURE SURVEY

2.1 Related Works

In 2021, Kaur *et al.* [18] have developed a multi-stage hybrid supplier segmentation and selection method for predicting risks and interruptions into account. The suppliers were assessed using advanced techniques in accordance with a set of criteria that might be appropriate for the Industry 4.0 environment, and they were further prioritized using the new technique. The research suggested an advanced technique to optimize the multi-item, multi-period, distribution to suppliers in order to concurrently reduce overall costs and disruption risk. The developed risk prediction model achieved high performance than other traditional models.

In 2020, Wilson *et al.* [19] have offered a random forest-related machine-learning technique for identifying the top 20 suppliers' performance. Every provider was assessed based on sub-criteria and different criteria. The criteria utilized in that work were previously employed by numerous manufacturing industry specialists and used up in research studies. The experts employed different methods to determine that weightage. In that article, they had ranked based on the supplier's rank.

In 2021, Li *et al.* [20] have presented a new fuzzy comprehensive evaluation system that chose the best supplier to carry out the supply mission and fulfilled the tasks of lowering procurement costs and enhancing reliability and quality. Objective weights and subjective of criteria were established for selection of supplier. To creatively accomplish the difficult conversion process, the two-phase fuzzy deep learning approach was used. Additionally, the benefits of the objective weighting and subjective methods were combined to determine the comprehensive weight using game theory. Therefore, the developed model was given high extensibility and rationality outcomes in the selection of supplier process.

In 2021, Zhao *et al.* [21] have offered a machine learning method to determine an expert's reliability based on historical data, which was then transformed into weights in the evaluation process. They first classified the experts historical information and determined the credibility of the expert's evaluations using the deep learning classifier. Next, they determined the evaluation experts weights. At last, they put together the optimally evaluated outcomes and obtained a effectiveness order for suppliers selection.

In 2021, Carvalho *et al.* [22] have developed a system that taken hazards into account while choosing suppliers using the deep learning. With a useful application in the Brazilian oil sector, they specifically sought to evaluate the application of the fuzzy approach in selection of supplier and to investigate the help of the developed model to selection of supplier considering risks. The experienced managers from the target organization selected and evaluated compared to the primary alternatives, sub-criteria and criteria for selecting the suppliers. The each item priority weights were determined using the fuzzy computational technique. The supply chain's competitiveness was enhanced in the training phase that could minimize the duration and maximize the effectiveness of the developed system to effectively reducing the supply risks.

In 2021, Mondragon *et al.* [23] have implemented a new novel for technology and selection of supplier based on 12 parameters influencing supply chain-related manufacturing technology. Technology selection was still difficult and complex in many manufacturing companies, particularly when deciding between competing technologies with comparable performance levels. Two competing technologies such as complete lamination and solvent-free lamination were used. The identification of numerous variables influencing the supply chain's selection of manufacturing technology, the application of function approaches in the senior management sites with the of a the high textiles sector came next.

In 2021, Kannan *et al.* [24] have developed a metaheuristic method for incorporating heterogeneous information into the new paradigm. The suggested method combined the models that are heterogeneous data and a weighted operator for preventing the data loss rather than transforming it into a single form. Based on the deviation degree, the consensus between the group and individual was calculated. One of the algorithms, Jaya was used to maximizing these weights. The supplier selection issue was picked in order for validating the suggested system and contrast it with various models of a same nature. The outcomes showed that the suggested method could not only prevent information loss but also successfully integrate heterogeneous information in the heterogeneous environment.

In 2017, Fallahpour *et al*. [25] have suggested a new robust genetic-based intelligent approach to enhance supply chain supplier selection and addressed the shortcomings of existing intelligent approaches in that domain. An example from the textile manufacturing sector demonstrated the applicability of that strategy. Comparisons with four intelligent techniques demonstrated the effectiveness of the genetic system of mathematical representation. Using a dataset gathered from a textile mill, the outcomes of the intelligent approaches were contrasted. Other statistical analysis were also employed to confirm the validity of the constructed system and the findings demonstrated the model's statistical strength.

2.2 Problem Statement

There is a need to examine the various factors in supplier selection in manufacturing industries, which are environmental impacts, training or hiring of staff with new skills, level of real-time service or deliveries to customers, effectiveness of supply chain, return-based investment, low-cost manufacturing, minimization of supply chain cycle time, higher volumes and capacity sizing in manufacturing, faster prototyping or manufacturing, automation, the technology utilized by the customers, and technology utilized by the suppliers. These constraints also require suitable solutions in getting the supplier selection phase in the SCM strategy. Some of the supplier selection strategies in the SCM process are listed in Table 1.

- The conventional MIP [18] approach can optimally enhances the overall risk of disruption and it is not applicable for extending the logistics, warehousing, and production strategies. Also, it does not determine the optimal suppliers for the industry and enhance the time of processing. Moreover, it is not suitable for dealing with imbalanced and noisy data to enhance the inaccurate prediction outcomes. In this research work, the preprocessing performance is utilized in the training process to ultimately identify and clean the noisy data for enhancing the quality of data.
- The existing TFN [20] approach can gradually minimize the reliability and quality of suppliers and it does not efficiently handle vast amount of training data. Further, it generates more inaccurate solution in evaluation phase to impact the supplier selection performance. It does not estimate the efficiency of supplier selection for manufacturing industries. AHP and Fuzzy AHP [23] minimize the efficiency regarding solvent or dot lamination free and solvent or full lamination type, achieving lower functionality for the textiles industry. It suffers from overfitting issues. Here, the proposed approach is highly sufficient for handling vast amount of training data in the evaluation phase to minimize the overfitting and underfitting complexities. It has the ability to potentially generate a accurate outcomes while dealing with imbalanced datasets.
- The traditional TOPSIS [24] approach is not efficiently incorporates a heterogeneous environment with heterogeneous information and enhance the loss of information and minimize the decision-making with the similarity values. Also, it does not perfectly tune the prescribed parameters in the optimization phase to minimize the training speed and maximize the vanishing gradient issues. In this research work, the presence of PU-AFFO algorithm can ultimately tune the weight and feature parameter in the optimization phase to ensure the training

speed by minimizing the inaccurate outcomes.

- GEP [25] shows the performance evaluation regarding accuracy along with statistical tests and provides the intelligent-aided mathematical system for managing the supplier selection performance. It does not estimate the fuzzy numbers of gathering data. Thus, this research recommends a new deep learning-aided supplier selection strategy based on predicted risks using machine learning techniques. Here, the A TransLSTM-WBL-based rick prediction approach consumes minimal training and inference duration to check and rectify the inconsistency and data quality issues without any interference. It has the ability to automatically handle and capture long-term dependencies from a large quantity of datasets, ensuring better generalization ability. Also, it can ultimately provide better positive outcomes to minimize the supplier selection performance complexities.

Table 1. Advantages and disadvantages of traditional supplier selection strategies in Industries

Author [citation]	Methodology	Advantages	Disadvantages
Kaur and Prakash [18]	MIP	It minimizes the overall risk of disruption and cost. It is more useful in handling disasters that occur by disruptions, inclusive of supply shortages and demand fluctuations.	It is not applicable to extending the logistics, warehousing, and production strategies.
Wilson *et al.* [19]	Fuzzy AHP	It determines the optimal suppliers for an industry. It reduces the time of processing.	It does not process real-time data from the industry.
Li *et al.* [20]	TFN	It increases the reliability and quality of suppliers. It handles every weight proportion issue and also has higher extensibility.	The analysis process and subjective evaluation of suppliers are not explored.
Zhao *et al.*[21]	SVM	It increases the scientificity and fairness of supplier selection and maximizes the credibility of estimation outcomes.	The performance of SVM is lacking.
Carvalho*et al.* [22]	Fuzzy AHP	It promotes the performance of supply chain competitive ness, the overall assessment of supply risks and reduces purchasing costs.	It does not estimate the efficiency of supplier selection for real-time manufacturing industries.
Mondragon *et al.* [23]	AHP and Fuzzy AHP	It increases the efficiency regarding solvent or dot lamination free and solvent or full lamination type. It achieves higher functionality for the textiles industry.	It suffers from the overfitting issue.
Kannan *et al.* [24]	TOPSIS	The decision-making with the right solutions is presented by taking the degree of similarity values.	It is not explored in Election Predictor Systems, Health Care and Education Systems.
Fallahpour *et al.* [25]	GEP	It shows the performance evaluation regarding accuracy along with	It does not estimate the fuzzy numbers of gathering data.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

		statistical tests. It provides an intelligent-aided mathematical system for managing supplier selection performance.	

3. A NOVEL SUPPLIER SELECTION STRATEGY BASED ON PREDICTED RISKS USING REINFORCEMENT LEARNING STRATEGY

3.1 Proposed Reinforcement Learning-based Supplier Selection Model

The conventional supplier selection model contains several contradictory characteristics, such as low quality and high cost. One of the difficult responsibilities is choosing the right suppliers. Decoupling economic growth from the corresponding environmental degradation is one of the challenges organizations and their supply chains must overcome. This is because of some pressures, including the ever-tighter environmental regulatory mandates, the rise of consumer awareness, and the resulting shift in attitudes toward product purchases. Organizations need to focus on both intra-organizational and inter-organizational components of their supply chains to effectively manage the surroundings costs of their supply chains. This means that they must look outside of their own walls and into the performance of their suppliers. AI techniques are also used in supplier selection and evaluation models. As a result, the AI methods are unable to offer a clear mathematical model of a supplier's performance based on several criteria. The diagrammatic representation of designed deep learning-based supplier selection model is given in Fig. 1.

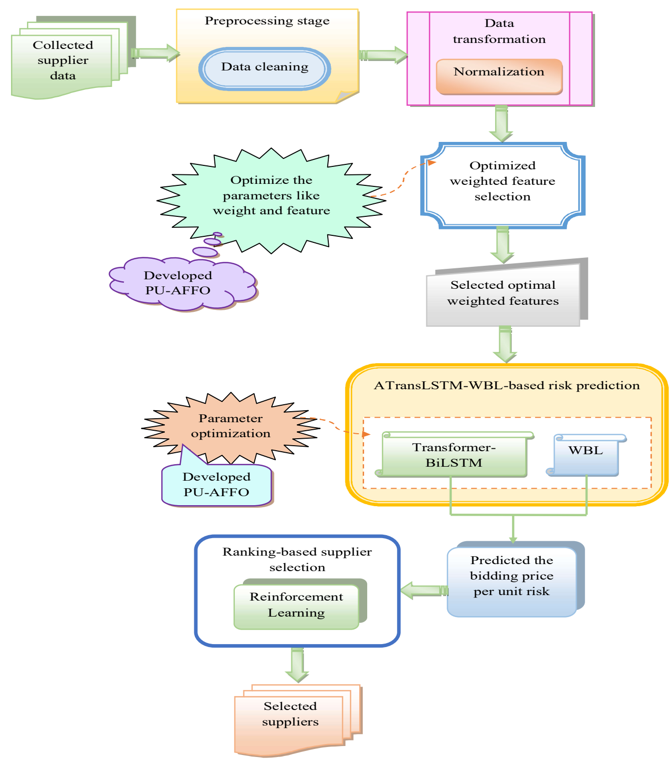

Fig 1. Structural illustration of implemented deep learning-based supplier selection model

A new deep learning-based supplier selection model based on predicting risk is designed to effectively select the suppliers. Also, it gives financial and business stability. In companies, the supplier selection model is used to reduce wasteful costs. The data is gathered manually by researchers. The gathered information is provided to the section of preprocessing performance. The data cleaning method is performed in the preprocessing stage to increase data quality. Then, the preprocessed data is passed through the data transformation section. Here, the normalization approach is utilized to decrease the complexity and increase efficiency. Then, the normalized data is fed into the weighted feature selection section. Here, the developed PU-AFFO model is adopted to tune the parameters like features and weight in the optimization phase for enhancing the correlation coefficient. Then, the weights and features are optimized and concatenated. The selected optimized weighted features are given to the ATransLSTM-WBL-based risk prediction section. The BiLSTM and WBL networks are integrated into the ATransLSTM-WBL-based risk prediction section. Here, the bidding price per unit is effectively predicted. The implemented PU-AFFO algorithm is utilized to parameter optimization for maximizing the precision and accuracy with the optimized parameters. The parameters such as epochs, batch size, optimizer and activation functions like linear, relu, tanh, sigmoid are optimized. The effectiveness of the designed risk prediction-based supplier selection model is compared to several traditional risk prediction models with different performance metrics to show its greater performance.

3.2 Data Collection

Dataset (Experts data): It is contained 100 supplier details and it is collected manually. It contained 17 ranking attributes. That is supplier, financial viability supplier, experience in the industry, organization structure adequacy, the competence of staff, proposed plan and approach, project management practices, quality, bidding price per unit, prompt delivery, service, support, completeness, risk, overall responsiveness and overall professionalism. Amongst all the attributes, the bidding price per unit is considered as the target. Other than this feature, all other attributes are given as input for prediction system, where the supplier selection takes place.

Hence, the number of total supplier data is denoted by d. The supplier data is indicated by N_d^{SD}, where $d = 1,2,\cdots,D$.

3.3 Data Cleaning

The gathered data N_d^{SD} is fed into the preprocessing section. Data preprocessing is the phase of changing raw data through data preprocessing into valuable information fed into the training performance for accurate prediction. The preprocessing step of the data cleaning procedure is used to improve the data quality. In order to make data ready for analysis, information must be removed or changed if it is incomplete, erroneous, redundant, missing, or presented improperly. It entails the process of rectifying grammatical and syntax faults, standardizing data sets, fixing errors like empty fields, and locating duplicate data points. After the data cleaning, the preprocessed data is indicated by N_d^{YP}.

4. OPTIMAL WEIGHTED FEATURE SELECTION STRATEGY FOR RISK PREDICTION USING HYBRIDIZED ARCHIMEDES AND FRUIT FLY OPTIMIZATION

4.1 Data Transformation

The process of changing information from one type to another type is called data transformation. Making wiser decisions is aided by it. This is one of the methods that you increase the quality of your data through data transformation. Predictions are incorrect if your dataset has missing values or is not clean. So, data transformation is used to solve these issues. The preprocessed data is given to the normalization method and it is represented by N_d^{YP}.

Normalization [26]: The Normalization method is one of the data transformation methods. It entails the database's data is organized. It is used to get rid of undesired traits, including insertion, update, and deletion anomalies and minimize repetition from a relation or collection of relations. By removing redundancy, complexity, and inconsistent dependency, it also serves to secure data and increase database flexibility. When the gradient descent step is stabilized, we can employ higher learning rates or models converge more quickly for a given learning rate. At last, the normalized data is noted by N_d^{Nor}.

4.2 Weight Optimized Feature Selection

The normalized data is given to the feature selection stage and it is indicated by N_d^{Nor}. Feature Selection is the method of reducing irrelevant data. It is used to reduce the input variable by using only relevant data. Also, it is used to remove the unwanted information. It is the procedure of automatically selecting pertinent model attributes. The developed PU-AFFO algorithm is adopted for optimizing the values, such as weight and features, to maximize the correlation coefficient. Here, the 7 are features optimized from 16 attributes and it is taken in the range of $[0.7]$. Finally, the features and weights are optimized and concatenated to get selected features. The weight is optimized in the range of $[0.01.0.99]$. The term Ob_1 is the objective function of the optimized weighted feature selection and it is given in Eq. (1).

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$Ob_1 = \underset{\{RO_{ATT}^{Feature}, KY_{ATT}^{weight}\}}{\arg\min} \left(\frac{1}{corr}\right) \quad (1)$$

Here, the term $RO_{ATT}^{Feature}$ is the optimized feature from 16 attributes and it is selected in the range of$[0.7]$. The optimization of weight is denoted by KY_{ATT}^{weight} and it is chosen in the range of$[0.01.0.99]$. The formula of correlation coefficient is given in Eq. (2).

$$Corr = \frac{u\sum gh - \sum g \sum h}{u\sum g^2 - (\sum g)^2) - (u\sum h^2 - (\sum h)^2)} \quad (2)$$

Here, the term u indicates the join pairs of g and h, respectively. Then, the optimized features and weights are concatenated and it is given in Eq. (3).

$$HP_B^{OFu} = KY_{ATT}^{weight} * RO_{ATT}^{Feature} \quad (3)$$

Here, the term HP_B^{OFu} is the selected optimized weighted features.

4.3 Proposed PU-AFFO

The newly implemented PU-AFFO model is used to improve the efficiency of the investigated risk prediction-based supplier selection system. The optimized weight is used to maximize the correlation coefficient for enhancing performance. Also, the suggested PU-AFFO model is used to choose the features optimally in the feature selection section. The suggested PU-AFFO algorithm is helpful for parameter and weight optimization. The optimized values like epoch, batch size, optimizers like SGD, rmsprop, adagrad, adadelba, adam, and the activation function like sigmoid, linear, tanh and relu to maximize the precision and accuracy from BiLSTM. The AOA provides efficient exploration while the division and multiplication operator's potent capacity to produce values with the high distribution. However, it has significant drawbacks, including a slow convergence rate, early convergence, and ease of fail with the optimal local parameter. And also, the AOA is susceptible to falling into local optimum. The FFO algorithm gives faster speed in the execution. On the other hand, swarms of many fruit flies will benefit from a steady search path and a faster convergence rate. But, the disadvantage is struggled to execute large datasets. Hence, the developed PU-AFFO algorithm is helped to overcome these issues and provide higher performance. The developed PU-AFFO is related to the recent fitness function. The term pos is the random position. In the AOA algorithm, the position is denoted by cee_{best} and Y_j, respectively. In the designed PU-AFFO, the term pos is the updated position and it is calculated on the basis of the obtained position of AOA and FFO. The newly adaptive concept is updated using the parameter pos and it is provided in Eq. (4).

$$pos = mean(Y_j, cee_{best}) + std(Y_j, cee_{best}) \quad (4)$$

Here, the term cee_{best} is the position of the AOA model and the term Y_j is the position of the FFO algorithm. The position is noted by pos. The updated value helped to increase the effectiveness of the system.

AOA [27]: The population-based algorithm known as AOA. Individuals in the population serve as the immersed objects in the suggested approach. The AOA is a global optimization in the solution space since it takes both the exploration and exploitation phases. The object-initialized process is given in Eq. (5).

$$Q_k = nd_k + rond \times (wd_k - nd_k) \quad (5)$$

Here, the term Q_k is the population of the items. The term nd_k is the lower bound and the term wd_k is the upper bound. The calculation of the search density Fgp_k is given in Eq. (6).

$$Fgp_k = rond \quad (6)$$

The random parameter is represented by $rond$ and it is selected in the range of$[0,1]$. The search volume xqn_k is measured by Eq. (7).

$$xqn_k = rond \quad (7)$$

The acceleration value cee_k is validated using Eq. (8).

$$cee_k = nd_k + rond \times (wd_k - nd_k) \quad (8)$$

The updated volume is denoted by fgp_k^{v+1} and the term xqn_k^{v+1} denoted as the updated density. The terms fgp_k^{v+1} and xqn_k^{v+1} are calculated using Eq. (9).

$$fgp_k^{v+1} = efgp_k^v + rond \times (fgp_{best} - efgp_k^v)$$
$$xqn_k^{v+1} = xqn_k^v + rond \times (xqn_{best} - xqn_k^v) \quad (9)$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Here, the object's best density is noted by fgp_{best} and the object's best volume is denoted by xqn_{best}. The transfer operation is denoted by VH is and it is calculated by Eq. (10).

$$VH = \exp\left(\frac{v - v_{\max}}{v_{\max}}\right) \tag{10}$$

The VH transfer function reduces the time while in the searching space. The decreased factor is indicated by f and it is measured by Eq. (11).

$$f^{v+1} = \exp\left(\frac{v - v_{\max}}{v_{\max}}\right) - \left(\frac{v}{v_{\max}}\right) \tag{11}$$

It quickly locates the promising area with the aid of decreasing factors throughout time. Here, the random value is denoted by ot. The object's updated acceleration with $v+1$ iteration is measured by Eq. (12).

$$cee_k^{v+1} = \frac{fgp_{ot} + xqn_{ot} \times cee_{ot}}{fgp_k^{v+1} \times xqn_k^{v+1}} \tag{12}$$

The object's density and volume are denoted by cee_k and xqn_k^{v+1}, respectively. The term fgp_k is the object's acceleration. The behavior parameter for exploration and exploitation is 0.5. The best position is noted by cee_{best}. The random values of the object's density and volume are represented by cee_{ot} and xqn_{ot}^{v+1}, respectively. The behavior of the acceleration updating process is given in Eq. (13).

$$cee_k^{v+1} = \frac{fgp_{best} + xqn_{best} \times cee_{best}}{fgp_k^{v+1} \times xqn_k^{v+1}} \tag{13}$$

Here, the term cee_{best} is the object's best acceleration. The best chosen acceleration is then normalized using the normalization process. The normalization process is used to calculate the percentage and it is given in Eq. (14).

$$cee_{k-Nor}^{v+1} = w \times \frac{cee_k^{v+1} - \min(cee)}{\max(cee) - \min(cee)} + n \tag{14}$$

In the normalization process, the terms n and w is chosen in the range of $[0.9, 0.1]$. The term cee_{k-Nor}^{v+1} represents the normalized value. Therefore, the best position is effectively determined.

FFO [28]: It is a new technique for determining global optimization based on how fruit flies obtain food. The coordinates of a fruit fly individual are represented in a plane, and uniform mutation is generated around the historically optimal solution, also known as the present population position. The current location is given in Eq. (15).

$$Y_j = Y\_axis \pm \beta \times rn(),$$
$$Z_j = Z\_axis \pm \beta \times rn(), \tag{15}$$

Here, the uniform mutation is denoted by β. The term rn is the rand parameter. The present coordinate sets are noted by Y_j and Z_j, respectively. The present individual is denoted by y_j. The Euclidean distance is validated using Eq. (16).

$$y_j = \frac{1}{\sqrt{Y_j^2 + Z_j^2}} \tag{16}$$

The fruit fly's location is calculated by Eq. (17).

$$y_j = Y_j,$$
$$v = Y\_axis \tag{17}$$

The new linear methodology is measured using Eq. (18).

$$\lambda = \lambda_0 \times \beta^{itr},$$
$$y_j = v \pm \lambda \times [m + (v - m) \times rn()], \tag{18}$$

Here, the term λ denotes the weight. The starting weight is indicated by λ_0 and the weight coefficient is indicated by β. The recent generation is noted by itr. The uniform mutation of the single-gene mode is given in Eq. (19).

$$\vartheta \leftarrow \vartheta_{\max} \times \exp\left(\log\left(\frac{\vartheta_{\min}}{\vartheta_{\max}}\right) \times \frac{itr}{itr_{\max}}\right) \tag{19}$$

Here, the maximum radius is indicated by $\vartheta_{\max}$ and the term $\vartheta_{\min}$ is the minimum radius. As a result, the convergence rate for solving high-dimensional functions has been low. The developed PU-AFFO pseudo-code is shown in Algorithm 1. The flow diagram of the proposed PU-AFFO model is provided in Fig. 2

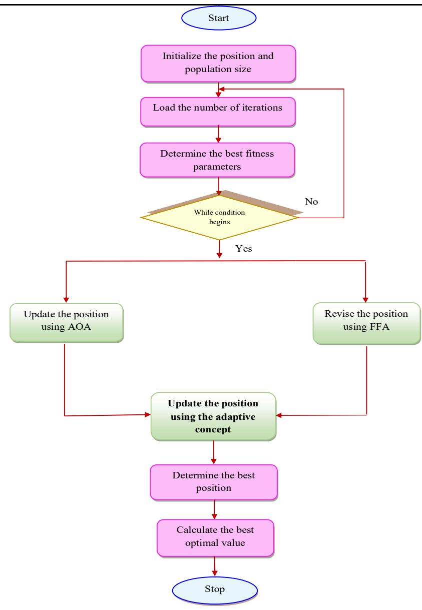

Fig 2. A flowchart of the designed PU-AFFO model

5. PREDICTION OF RISK USING HEURISTIC AIDED ADVANCED DEEP LEARNING AND SUPPLIER SELECTION USING REINFORCEMENT LEARNING

5.1 Basic TransBi-LSTM

The BiLSTM is used to predict the target risk of the developed model. The feed-forward network and self-attention build up the transformer-BiSTM. A personal attention layer is created to take the grammatical and semantic relationships to the many words in particular sentence. In the meantime, numerous layers of self-attention are created in a multi-head mechanism to increase capacity. The self-attention layer's multi-head mechanism-related output will be processed using the Residual Connection and Normalization Layer. Transformer-BLSTM comprises four parts: an input gate and associated weight matrices, a forget gate and weight measures, an final gate and associated weight measures, and the present state of that cell. The input gate is calculated using Eq. (20).

$$j_u = \beta\left(X_{yj} + X_{ij} i_{u-1} + X_{dj} D_{u-1} + c_j\right) \tag{20}$$

Here, the terms X_{yj} and $X_{ij} i_{u-1}$ are the initialization of the input layer. The output gate is calculated by Eq. (21).

$$g_u = \beta\left(X_{yg} y_u + X_{ig} i_{u-1} + X_{dg} D_{u-1} + c_g\right) \tag{21}$$

The terms $X_{yg} y_u$ and $X_{ig} i_{u-1}$ are the initialization of the output layer. The forget gate is measured using Eq. (22).

$$h_u = \tanh\left(X_{yh} y_u + X_{ih} i_{u-1} + X_{dh} D_{u-1} + c_h\right) \tag{22}$$

The weight matrices are indicated by D_u and p_u, respectively. The terms D_u and p_u are calculated by Eq. (23) and Eq. (24), respectively.

$$D_u = j_u * h_u + g_u D_{u-1} \tag{23}$$

$$p_u = \beta\left(X_{yp} y_u + X_{ip} i_{u-1} + X_{dp} D_{u-1} + c_p\right) \tag{24}$$

$$i_u = p_u * \tanh\left(D_u\right) \tag{25}$$

The same output layer is shared by the two networks. In other words, the output layer contains all of the contextual data for every point in the initial sequence. The basic diagram of Transformer BILSTM is given in Fig. 3.

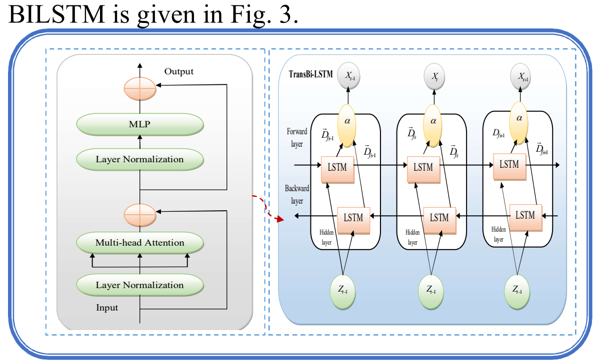

Fig 3. A basic diagram of Transformer BILSTM

5.2 Basic WBL

The WBL is used to predict the risk of the developed model. It offers a natural and ethical method for integrating facts and prior knowledge into a strong decision theory framework. The WBL is used to improve the system's effectiveness for predicting supplier risk. The WBL remains quick because of the WBL method's usage of sensible weights for attributes depending on their relevance to prediction, which also lessens the effect of impute self conditional assumption on the effectiveness of predictions. The term $q\left(D_k \mid Y\right)$ is calculated using Eq. (26).

$$q\left(D_k \mid Y\right) = \arg\max_{D_k} q\left(D_k\right) \prod_{j=1}^{o} q\left(B_j \mid D_k\right)^{xj} \tag{26}$$

Here, the weight parameter is denoted by x_j. The specific instance value is indicated by Y. The correlation value is noted by $q(B_j \mid sfm)$ and it is measured by Eq. (27).

$$q(B_j \mid sfm) = \frac{count(B_j = b_l \wedge D_k)}{count(B_j = b_l)} \quad (27)$$

The irrelevant measure is represented by $q(B_j \mid irr)$ and it is calculated by Eq. (28).

$$q(B_j \mid irr) = 1 - q(B_j \mid sfm) \quad (28)$$

The weight parameter is calculated using Eq. (29).

$$x(B_j, b_l, k) = \frac{q(B_j \mid sfm)}{q(B_j \mid irr)} \quad (29)$$

The prediction of the WBL formula is measured using Eq. (28). At last, it is based on the specific parameter of each feature and the weight value of the likelihood associated with the current category label is selected for computation, and the result parameter of each category is compared. The highest category in the prediction corresponds to the highest value. The diagrammatic illustration of Weighted Bayesian Learning is provided in Fig. 4.

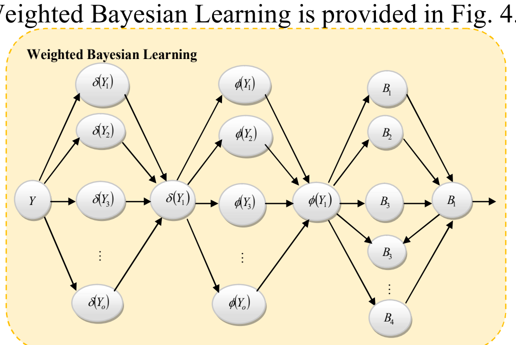

Fig 4. A basic diagram of Weighted Bayesian Learning

5.3 Bidding Price Per Unit Prediction using ATransLSTM-WBL

The selected optimized weighted feature HP_B^{OFu} is given to the risk prediction section. The bidding price per unit risk is effectively predicted in the risk prediction section. The developed PU-AFFO optimization for parameter optimization. It is optimized the batch size, activation functions like linear, relu, tanh, sigmoid, optimizer and epochs for increasing the precision and accuracy from BiLSTM. Here, the TransBiLSTM and WBL are combined to form the network. Using technology and methodologies to derive insights, by applying tools and procedures to gather knowledge, estimate plausible scenarios, and forecast future events, risk prediction can be managed more effectively. Ensuring that risks are managed successfully requires a plan for a risk prediction model. In the BiLSTM, the black box aspect of the system, the increased computational load, and the likelihood of overfitting problems are drawbacks. In order to rectify these complexities, a developed ATransLSTM-WBL-based risk prediction approach is designed. The objective function is calculated using Eq. (30).

$$Ob_2 = \underset{\{HV_{BiLSTM}^{Act}, FT_{BiLSTM}^{epoch}, CH_{BiLSTM}^{optiz}, XS_{BiLSTM}^{batch}\}}{\arg\min} \left(\frac{1}{acc} + \frac{1}{pr} \right) \quad (30)$$

Here, the optimized batch size is noted by XS_{BiLSTM}^{batch} and it is chosen in the interval of $[4, 512]$. the term FT_{BiLSTM}^{epoch} is the optimized epoch in the BiLSTM and it is taken in the interval of $[50, 100]$. The term CH_{BiLSTM}^{optiz} is the optimized optimizer in the BiLSTM and it is taken in the interval of $[0, 4]$. In the BiLSTM, the activation function is optimized and it is noted by HV_{BiLSTM}^{Act} in the interval of $[0, 3]$. Accuracy is the degree of closeness between a measurement and its true value. The accuracy formula is given in Eq. (31).

$$acc = \frac{(NH_q + MT_g)}{(NH_q + MT_g + NH_g + MT_q)} \quad (31)$$

Here, the term NH_q indicates a true positive parameter and the term NH_g is the true negative. The term MT_g is false positive and the term MT_q is the negative parameter. Precision is defined as the consistency or repeatability of values. The precision parameter is measured by Eq. (32).

$$pr = \frac{MT_g}{MT_q + NH_g} \quad (32)$$

The structural representation of the suggested ATraansLSTM-WBL-based supplier selection framework is displayed in Fig. 5.

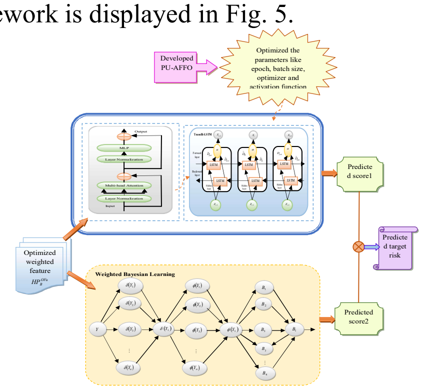

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Fig 5. Structural representation of suggested ATransLSTM-WBL-based risk prediction model

5.4 Supplier Selection using Reinforcement Learning

The risk predicted outcome is given to the reinforcement learning-based supplier selection section. Learning is a crucial aspect of our existence and has played a significant role in AI research. Using perceptions for both acting and enhancing an agent's capacity to act in the future is the aim of learning. Three stages of AI learning exist are reinforcement learning, unsupervised and supervised. In essence, supervised learning involves learning a function from its inputs and outputs, whereas unsupervised learning focuses on identifying input patterns when there is no corresponding output data. An agent is how to act to maximize a numerical reward signal, and reinforcement learning is considered a more general situation where this is expected to happen. Some of the points are representing the process of reinforcement learning [29], listed as below.

- Term $t \in T$ is the possible states (supplier information) of the environment in learning method.
- Term $p \in P$ is the possible actions (risk value) that can be obtained by the risk prediction network.
- Finally, $r \in R$ is the reward (predicted outcome) attained by the agent performs action with state.

The quality of the selected action at a certain step is defined by the reward, which is a feedback value. An agent in a real-world problem interacts with the problem environment by doing actions, and changing states of reward values. The previous stage and the agent's exploited action determine both the prize and the subsequent step. In the context of this research, reinforcement learning will be used to simulate how a provider gains knowledge from his prior behavior and behaves optimally going forward. Although reinforcement learning is thought to be a strong tool, it has two significant flaws. Supplier selection is the procedure used by businesses to find, assess, and work with suppliers. In most cases, choosing the finest supplier is crucial to the existence and successful operation of the business. A supplier ranking system assures that all vendors are evaluated on a consistent basis and treated equitably. The structural representation of developed supplier selection using the reinforcement learning model is displayed in Fig. 6.

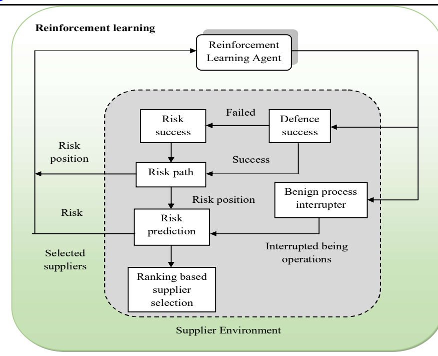

Fig 6. A diagrammatic representation of developed supplier selection using reinforcement learning

6. RESULTS AND DISCUSSIONS

6.1 Experimental setup

The investigated PU-AFFO-ATransLSTM-WBL-based supplier selection model was executed and implemented using Python software. The iteration was set to 10, the population was set to 10, and the chromosome length was set to 4. Several heuristic algorithms and risk prediction methodologies were used to perform the experimental analysis with performance metrics. The methods like CNN [28], GRU [29], RNN [30], LSTM [31] and BiLSTM [32] and the heuristic algorithms such as Coati Optimization Algorithm (COA) [33], Harris Hawks Optimization (HHO) [34], AOA [27] and FFO [28] were utilized for the experimental analysis.

6.2 Evaluation measures

Several efficiency measures utilized for the proposed supplier selection model are explained below:

(a) Mean: $Q_{d_k} = \dfrac{\Sigma Q_{d_k}}{O}$

(b) Median: $Of = m + \dfrac{\left(\dfrac{N}{2} - o\right)}{f} \times e$

(c) ONE-NORM: $N_1 = \sum_k |N_k|$

(d) RMSE: $RM = \sqrt{\dfrac{\sum_{k=1}^{k} \left(cx_{k2} - hx_{k1}\right)^2}{k}}$

(e) TWO-NORM: $N_2 = \left(\sum_{k=1}^{k} N_k^2\right)$

(f) MEP: $M = \dfrac{100\%}{L} \sum_{k=1}^{k} \dfrac{cx - hx}{cx}$

(g) MASE: $MA = Mean\left(\frac{|hx|}{\frac{1}{l=1}\sum_{k=1}^{L}|cx_k - hx_{k-1}|}\right)$

(h) MAE: $ME = \frac{\sum_{k=1}^{l}|hx_k - cx_k|}{l}$

(i) Infinity-Norm: $N_{jog} = \underset{1 \le k \le l}{Max}|N_k|$

6.3 Performance evaluation over various risk prediction-based supplier selection methods

The performance of the suggested PU-AFFO-ATransLSTM-WBL-based supplier selection model was compared to the traditional risk detection approaches and it is shown in Fig. 7. A hyper parameter called learning rate determines how much to alter the model each time the estimated error is received. It easily compares the values. The suggested PU-AFFO-ATransLSTM-WBL-based supplier selection model outcomes demonstrated that MAE of 40% than CNN, 37.6% than GRU, 40.2% than RNN, 29% than LSTM and 48% than BiLSTM over the learning percentage parameter of 45. The developed risk prediction with supplier selection model outperformed than recently used supplier selection methods.

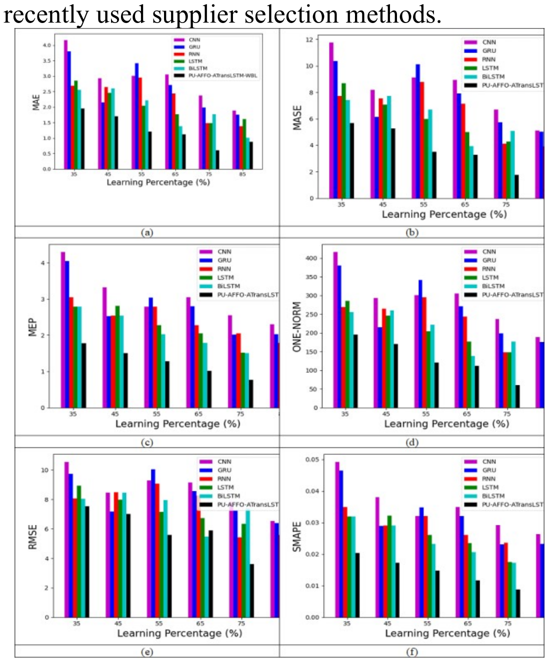

Fig 7. Performance validation on suggested supplier selection system using deep learning with several conventional techniques in terms of (a) MAE (b) MASE (c) MEP (d) ONE-NORM (e) RMSE (f) SMAPE (g) TWO-NORM (h) INFINITY-NORM

6.4 Performance evaluation over various risk prediction-based supplier selection heuristic algorithms

For comparing the performance of the designed PU-AFFO-ATransLSTM-WBL-based supplier selection model to various heuristic models and it is provided in Fig. 8. The developed PU-AFFO-ATransLSTM-WBL-based supplier selection model demonstrated a low MAE of 35% than COA-ATransLSTM-WBL, 43.4% than HHO-ATransLSTM-WBL, 50% than AOA-ATransLSTM-WBL, and 55% than FFO-ATransLSTM-WBL in the learning percentage of 55. The "learning rate" refers to how frequently the weights are updated during training. The developed risk prediction-based supplier selection model achieved greater performance than conventional heuristic models in terms of MAE.

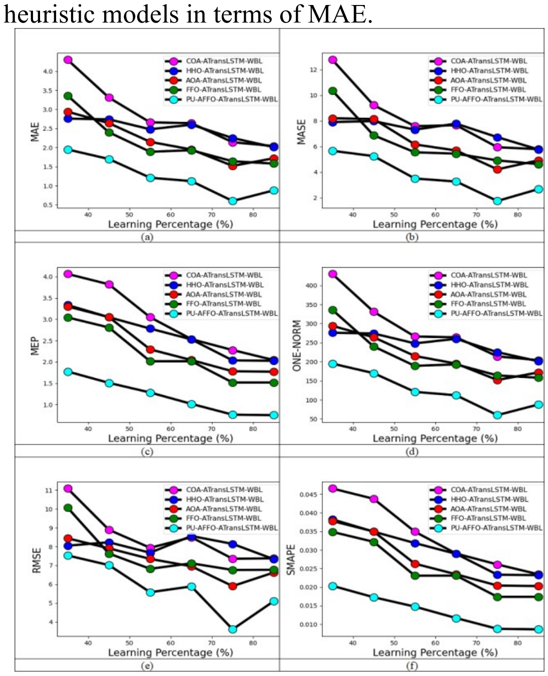

Fig 8. Performance analysis on investigated supplier selection system using deep learning over different algorithms with respect to (a) MAE (b) MASE (c) MEP (d) ONE-NORM (e) RMSE (f) SMAPE (g) TWO-NORM (h) INFINITY-NORM

6.5 Overall evaluation of the developed risk prediction-based supplier selection framework

The effectiveness of the implemented PU-AFFO-ATransLSTM-WBL-based supplier selection approach is validated using traditional methodologies and algorithms and it is shown in Table 2 and Table 3. The suggested PU-AFFO-

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ATransLSTM-WBL-based supplier selection model showed high efficiency with less MEP of 50.2% than COA-ATransLSTM-WBL, 50.9% than HHO-ATransLSTM-WBL, 60% than AOA-ATransLSTM-WBL, and 60.4% than FFO-ATransLSTM-WBL. In comparison to existing risk prediction models, the developed supplier selection model offered superior effectiveness.

Table 2. Performance validation of the implemented risk prediction-based supplier selection model over heuristic algorithms

Terms	COA [33]	HHO [34]	AOA [27]	FFO [28]	PU-AFFO-ATransLSTM-WBL
MEP	2.534937	2.529241	2.044835	2.018103	1.017494
SMAPE	0.029029	0.028954	0.023445	0.023094	0.011658
MASE	7.671265	7.792916	5.696371	5.446693	3.275628
MAE	2.64	2.6	1.95	1.93	1.12
RMSE	8.498235	8.563878	6.953416	7.112665	5.883876
ONE-NORM	264	260	195	193	112
TWO-NORM	84.98235	85.63878	69.53416	71.12665	58.83876
INFINITY-NORM	32	35	31	37	37

Table 3. Performance validation of the implemented risk prediction-based supplier selection system over existing methods

Terms	CNN [28]	GRU [29]	RNN [30]	LSTM [31]	BiLSTM [32]	PU-AFFO-ATransLSTM-WBL
MEP	3.049193	2.799777	2.277423	2.047461	1.794791	1.017494
SMAPE	0.034931	0.032081	0.026073	0.02348	0.020588	0.011658
MASE	8.92551	7.911825	7.134342	5.005141	3.938311	3.275628
MAE	3.05	2.71	2.43	1.77	1.38	1.12
RMSE	9.138381	8.555115	8.272243	6.714909	5.471746	5.883876
ONE-NORM	305	271	243	177	138	112
TWO-NORM	91.38381	85.55115	82.72243	67.14909	54.71746	58.83876
INFINITY-NORM	36	37	37	37	29	37

6.6 Score and rank table of the developed risk prediction-based supplier selection model

The score and rank obtained from the designed PU-AFFO-ATransLSTM-WBL-based supplier selection approach are given in Table 4. The 1 to 20 supplier ranks are presented in the table. The actual rank and predicted rank are also presented in the table. The reward analysis of the implemented PU-AFFO-ATransLSTM-WBL-based supplier selection model with windows size variations like 10, 20, 30, 40 and 50 are given in Fig. 9. The windows size is the parameter of the reinforcement learning. Using the windows size variations like 10, 20, 30, 40 and 50 the reward of the implemented PU-AFFO-ATransLSTM-WBL-based supplier selection model is effectively analysis.

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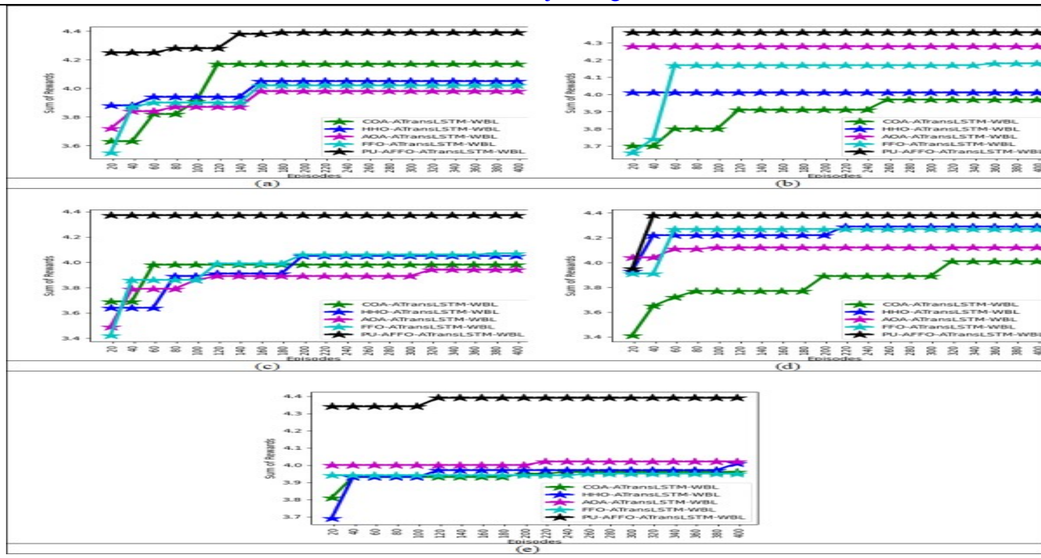

Fig 9. Performance validation on investigated supplier selection system using deep learning over different algorithms with respect to (a) 10 (b) 20 (c) 30 (d) 40 (e) 50

Table 4. Score And Rank Table Of The Developed Risk Prediction-Based Supplier Selection Model

Supplier	Score	Actual_Rank	Predict_Rank
S1	0.728	1	1
S2	0.644	15	14
S3	0.825	11	11
S4	0.643	7	7
S5	0.954	2	2
S6	0.565	12	12
S7	0.745	17	16
S8	0.697	3	3
S9	0.698	8	8
S10	0.732	16	17
S11	0.874	20	20
S12	0.823	4	4
S13	0.845	13	13
S14	0.899	9	10
S15	0.749	19	19
S16	0.687	5	5
S17	0.778	14	15
S18	0.712	18	18
S19	0.79	10	9
S20	0.7109	6	6

6.7 Achievement of the proposed approach difference from prior works

Table 6 shows the achievement of the proposed approach difference from prior works.

Table 6. Achievement of the proposed approach difference from prior works

Prior works challenges	Proposed method
The conventional Fuzzy AHP [19] approach needs more high-quality industrial data in the training process and it is not capable of managing large quantity of input data to maximize the overfitting issues. Also, the traditional TFN [20] framework does not easily recognize and clean the irrelevant informative contents from the input data for minimizing the generalization and decision-making performance. Further, the SVM [21] framework needs more computational time to efficiently select the supplier based on risk prediction, thus it optimally provide inaccurate outcomes. The TOPSIS [24] mechanism does not successfully tune the relevant parameters in the optimization phase to impact the convergence speed. The existing GEP [25] approach requires more performance metrics in the estimation phase, leading to larger mis-predicted and negative outcomes for affecting the timely intervention. Here, the GEP approach has attained higher MSE error value of 20.054.	The developed ATransLSTM-WBL approach is capable of ultimately managing low quality large quantity of industrial data and it learns the underlying patterns and relationships among data for reducing the overfitting complexities. The normalization and data cleaning phases are utilized to ultimately clean the irrelevant and background information from the supplier data to enhance the data quality. Also, it takes lower training period to predict the relevant supplier to enhance the decision-making and generalization ability. The PU-AFFO algorithm is used in the training process to tune the parameters within a restricted time for enhancing accurate results. In the evaluation phase, various performance metrics are utilized in this framework to predict the subtle variations. Here, the designed framework has attained lower MSAE error value of 3.27 to prove its superior performance.

6.8 Problems and open research issues of the designed framework

The designed technique is highly professional for generating better solution yet, it does not utilize the real-time industrial data in the validation phase to absolutely enhance the generalization ability. In the training phase, the proposed approach does not utilize the feature extraction phase to optimally recognize and extract the relevant informative features for maximizing the overfitting complexities. An ensemble light weight mechanism is does not incorporate to the preprocessing performance to quickly clean the background noises from the input data, ensuring data quality.

Future work: In future, the proposed approach will be integrated to the anomaly detection approach for determining customer preferences and economic situations to ensure the scalability and computing efficiency, which is highly useful for the automobile sector. In future, the input data will be gathered from social media and IoT devices to enhance the precision rate of supplier selection process, especially in dynamic network scenarios. The proposed approach will be integrated to the feature extraction process to automatically differentiate the informative features from the gathered data. Also, the external and real-time datasets will be utilized to validate the prediction performance, thus it can improve the generalization capability under various environmental situations and input variations.

7. DISCUSSION

In order to optimally improve the entire performance of the proposed approach, various performance metrics are utilized to potentially validate the supplier section process. In Fig. 7, the traditional CNN framework attains a higher MAE error rate of 4.5 at 35th learning percentage, which is not sufficient for managing large quantity of datasets within a restricted duration. Also, it does not have the ability to potentially extract the meaningful features in the collected input data, thus it maximizes the overfitting complexities in the validation phase. However, the designed approach attained a lower MAE error rate 1.7 at 35th learning percentage. It has the ability to reliably estimate the entire process while handling vast amount of training datasets also, it can effectively minimize the inaccurate outcomes to enhance the generalization ability. The MEP error value of the proposed approach has minimized than 58% COA-ATransLSTM-WBL, 46% than HHO-ATransLSTM-WBL, 46% than AOA-ATransLSTM-WBL, and 41% than FFO-ATransLSTM-WBL in the learning percentage of 40. Here, the designed approach attains a minimal MEP value than the conventional methods, which can optimally enhance the gathered data quality by minimizing the disruptions from faulty goods, leading to reliable supplier relationships via consistency performance. It can significantly tune the parameters in the optimization phase for ensuring the convergence speed. In table 2 analysis, the proposed approach attains a better ONE-NORM value 112% to absolutely minimize the missed prediction performance, enhancing better decision-making and supply chain resilience. It can enhance the overall quality and stability of the supply base to ensure robust intervention. In Fig. 9 (a), the conventional AOA-ATransLSTM-WBL model has a minimal sum of rewards value of 3.9 at 160th episodes that can potentially difficult for balancing cost with quality and reliability, enhancing poor performance. Yet, the designed framework has a better sum of rewards value of 4.4 at 160th episodes than the conventional methods to ultimately minimize the operational disruptions and ensure a better resilient supply chain. Thus, it proved that the proposed approach's superior task prediction based supplier selection performance.

8. CONCLUSION

In this research work, a novel deep learning-based supplier selection approach has been proposed for effectively selecting the suppliers with the help of risk prediction performance. Initially, the prescribed data was collected from the benchmark sources and the data was fed into the preprocessing stage. Here, the data were preprocessed using the data cleaning method and it increased the quality of the data. Then, the preprocessed information was fed to the data transformation. Here, the normalization technique was used to reduce the complexity. Then, the normalized data was fed into the feature selection phase. The developed PU-AFFO algorithm optimized the parameters like weight and features for enhancing the accurate solution. The optimized parameters such as activation functions like linear, relu, tanh, sigmoid, optimizer, epochs and batch size. The selected optimized weighted features were given to the ATransLSTM-WBL-based risk prediction. Here, the bidding price per unit was effectively predicted. The developed deep learning-based supplier selection model was shown with an improved mean of 7.61% than COA-ATransLSTM-WBL, 17.7% than HHO-ATransLSTM-WBL, 16.4% than AOA-ATransLSTM-WBL, and 42% than FFO-ATransLSTM-WBL. The effectiveness of the designed risk prediction-based supplier selection model was compared to several existing risk prediction models. It achieved higher performance in terms of high precision and accuracy and it can quickly choose the appropriate suppliers for enhancing the system performance without any interference.

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