Strategic Supplier Selection in Advanced Automotive Production: Harnessing AHP and CRNN for Optimal Decision-Making

Karim Haricha[1*], Azeddine Khiat[2], Yassine Issaoui[3], Ayoub Bahnasse[4], Hassan Ouajji[5]
Computing, Artificial Intelligence and Cyber Security (2IACS), ENSET of Mohammedia,
University Hassan II of Casablanca, Morocco[1, 2, 3, 5]
Engineering of Structures, Processes, Intelligent Systems, and Computer Science (ISPS2I), ENSAM of Casablanca, Morocco[4]

***Abstract*—This study presents a novel supplier selection methodology that integrates the Analytic Hierarchy Process (AHP) with a Convolutional Recurrent Neural Network (CRNN) to address the complexities of decision-making in dynamic industrial environments. The AHP component provides a systematic and transparent framework for evaluating many factors, ensuring consistency and minimizing subjective biases in supplier assessment. The Analytic Hierarchy Process (AHP) effectively combines expert knowledge with individual preferences, therefore embodying the human element of decision-making. The CRNN concurrently leverages its ability to process large sequential data, uncover hidden patterns, and assess supplier performance over time. This expertise enhances decision-making by transcending the limitations of traditional analytical methods in managing intricate, multidimensional data. The integration of AHP and CRNN offers a comprehensive evaluation framework, including both objective and subjective factors to enhance effective supplier selection decisions. This approach enhances the long-term sustainability of manufacturing operations by fostering reliable supplier relationships and ensuring access to high-performing suppliers. Experimental validations affirm the efficacy of the suggested approach in promoting sustainable manufacturing systems, highlighting its practical use. The findings demonstrate that the AHP-CRNN framework improves supplier selection criteria and offers prospects for future development and adaptation to address emerging challenges in complex manufacturing environments.**

Keywords*—Supplier selection; analytic hierarchy process; convolutional recurrent neural network; sustainability; decision-making

I. Introduction

Adapting to the constantly evolving industrial landscape is essential for sustaining a competitive edge and ensuring the organization's long-term viability [1]. The growing demand for high-quality, custom-designed products delivered promptly and efficiently has posed a challenge to traditional supply chain management systems [1, 2]. Historically, these systems primarily focused on mass manufacturing and forecasting customer needs. The appeal of these items has increased significantly in recent years. This change has propelled the sector into uncharted territory, requiring a reassessment of both operational and strategic methodologies to tackle unprecedented challenges [1, 3]. Given its importance, you must pay particular attention not just at the outset but throughout the whole process of selecting suppliers. Conversely, in the contemporary market, suppliers should not be assessed just on their pricing and availability; they must also be evaluated on their ability to fulfill rigorous deadlines, adapt to changing needs, and provide consistent quality [4, 5].

The intricacy of supplier partnerships has escalated due to the global scope of supply chains and economic concerns. Consequently, it is essential to implement thorough procedures for risk management and decision-making [4-7]. Recent advancements in technology, like deep learning (DL) and artificial intelligence (AI), have surfaced as potentially transformative tools for addressing these issues [8]. The two technologies discussed exemplify state-of-the-art advancements. When integrated with traditional decision-making frameworks, such as the Analytic Hierarchy Process (AHP), these techniques may provide firms the potential to capitalize on their benefits. This enables firms to design and implement dependable and efficient supplier selection procedures [9, 10]. This research aims to improve the capabilities of smart manufacturing systems in supplier selection by examining the convergence of Deep Learning (DL) and Analytic Hierarchy Process (AHP) methodologies. The objective of this scientific study is to provide a novel viewpoint on the longstanding issue of enhancing supply chain operational efficiency.

A. Problem Statement

Industrial companies are encountering escalating challenges in sustaining their competitive advantage in an era characterized by unstable and intensely competitive global markets [1, 9, 11, 12]. Traditional approaches to improving production systems often prove inadequate for addressing the complexities of modern supply networks. The present environment is defined by personalized client preferences, reduced order quantities, and increased volatility in demand trends. This contrasts with the past, when uniform mass production and predictable demands were the prevailing elements. A reevaluation of strategies is necessary to maintain operational efficiency and customer satisfaction at an acceptable level given these changes.

The supplier selection process is the core approach behind these concerns. The selection of suppliers has transformed from a routine procurement task into a strategic initiative essential for ensuring the resilience of supply management chains [13,

*Corresponding author: Karim Haricha

14, 15]. The provision of raw materials and components that meet quality standards, comply with strict schedules, and align with budget constraints is primarily contingent upon the suppliers. Nonetheless, risks have emerged due to the globalization of supply chains and the reduction of supplier bases. Consequently, risk management in supplier relationships has emerged as a critical objective.

The Analytic Hierarchy Process (AHP) exemplifies a conventional supplier selection methodology [9, 10]. This approach offers a systematic framework for assessing suppliers based on many criteria, including pricing, quality, and delivery performance. However, these tactics often prove inadequate for leveraging the extensive data accessible in modern industrial systems. Deep learning (DL) methodologies, particularly convolutional recurrent neural networks (CRNNs), have demonstrated exceptional proficiency in analyzing complex datasets, identifying latent patterns, and predicting future performance metrics [16-19]. This contrasts with conventional machine learning methods. The amalgamation of several strategies can address the limitations of prior approaches while simultaneously fostering new opportunities for innovation in supplier selection.

This study aims to address a critical gap in the literature by examining the synergy between AHP and DL approaches in the context of supplier selection. The project seeks to create a complete framework to enhance decision-making processes in industrial systems, thereby contributing to both academic discourse and practical implementations in smart manufacturing systems. This will be achieved by leveraging the advantages of both systems.

B. Research Questions

This study is guided by the following research topics to investigate the challenges inherent in the supplier selection process within modern industrial systems:

- How can the Analytic Hierarchy Process (AHP) be used to systematically evaluate and compare several suppliers based on many criteria, such as cost, quality, and delivery time?
- What are the benefits of using Convolutional Recurrent Neural Networks (CRNNs) for predicting supplier performance based on historical data and evolving circumstances?
- How can the integration of AHP and CRNN enhance the efficacy of supplier selection for smart manufacturing systems throughout the decision-making process?
- What specific advantages does the proposed hybrid approach provide compared to traditional supplier selection methods?
- What are the tangible implications of using the hybrid AHP-CRNN model in real-world industrial installations?

C. Contributions

The primary contribution of this paper is the creation of a hybrid decision-making framework that optimizes supplier selection in smart manufacturing systems by combining the Analytic Hierarchy Process (AHP) with Deep Learning (DL), specifically Convolutional Recurrent Neural Networks (CRNNs). The objective of the investigation is to:

- Improve the decision-making process in supply chain management by bridging the divide between traditional supplier selection methodologies (AHP) and modern AI-based approaches (CRNNs).
- Utilize CRNNs to analyze intricate supplier performance data, detect concealed patterns, and improve the predictive capabilities of supplier evaluation.
- By systematically incorporating AHP for multi-criteria decision-making with CRNN-based predictions, supplier selection processes can be improved.
- Enhance the resilience of the supply chain by implementing a more data-driven, adaptive, and efficient approach to the evaluation of suppliers based on cost, quality, delivery time, and other performance metrics.
- Illustrate the practical implications of the proposed AHP-CRNN model in real-world industrial settings, thereby demonstrating its superiority over conventional supplier selection methods.

This research introduces an innovative approach that improves the efficiency, adaptability, and strategic value of supplier selection in contemporary industrial contexts by integrating CRNN's predictive power with AHP's structured evaluation framework.

The remainder of the paper is organized as follows: Section II provides a literature review. Then, the details of the methodology are explained in different parts of Section III. Next, the results are presented in Section IV, along with a discussion. Finally, Section V presents the conclusion.

II. Literature Review

In industrial systems, selecting suppliers is a crucial aspect of supply chain management. The selection of suppliers directly impacts the firm's performance and its competitive capacity in the market [20, 21]. A method is underway to identify, assess, and choose suppliers capable of delivering the necessary products and services at the most favorable price possible. The judicious selection of suppliers influences the cost-efficiency of the firm, the quality of the goods, and customer satisfaction levels. Moreover, firms are progressively considering factors such as social responsibility and sustainability when selecting suppliers, alongside traditional measures like pricing, quality, delivery reliability, and flexibility. Businesses are increasingly considering these aspects.

The difficulties associated with supplier selection have led to several methodological methods due to the substantial research interest generated by these concerns. Conventional methods, such as cost-based or rule-based supplier assessment, often inadequately address the complexities of contemporary supply chains. Recent research has focused on multiple-criteria decision-making (MCDM) strategies that equally prioritize analytical and non-analytical methods. AHP, TOPSIS, and

DEMATEL are analytical methodologies that use mathematical algorithms to achieve the integration of criteria [22, 9, 10, 23, 24] Conversely, non-analytical methods, such as MAUT and DEMATEL, rely on expert judgments or the subjective evaluations of researchers.

Nair et al. [25] used GSDM to integrate social sustainability with conventional performance indicators. Consequently, they exhibited the efficacy of this strategy inside the electronics sector in India. Nair et al. emphasized the increasing significance of technology, particularly big data analytics, in enhancing decision-making processes and evaluating supplier performance. This aligns with previous discussions.

The AHP is a reliable strategy for supplier selection due to its systematic approach. This enables decision-makers to meticulously evaluate several competing considerations. In supplier selection, Mani et al. [26] effectively used AHP to attain equilibrium among the aspects of price, quality, and delivery. To improve the quality of sustainability assessments, Jessin et al. [27] integrated AHP with resilience-based metrics.

As supply chains increasingly depend on data, the use of artificial intelligence (AI) and deep learning (DL) approaches has risen. Research has shown that artificial intelligence methodologies, like Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), may predict supplier performance using historical data. Yuan et al. [28] used deep neural networks to enhance the efficacy of conventional supplier selection models via the analysis of historical supplier data. This was achieved via the use of deep neural networks.

Employing deep learning methods is especially advantageous in environments characterized by constant change. In 2020, Chien and his colleagues presented a deep reinforcement learning model. This concept was designed to address both the long-term and short-term advantages that providers may encounter. By integrating Industry 4.0 data with conventional performance indicators, Abdulla et al. [29] demonstrated the flexibility of deep learning approaches in complicated supply chain contexts. Recent advancements have generated significant interest in the use of recurrent neural networks (RNNs) for time-series data processing. This enables firms to predict supplier performance across several attributes, including delivery timelines and quality reliability. Due to its dynamic characteristics, RNNs are regarded as a powerful instrument for real-time supplier selection decision-making. This is due to the flexibility they exhibit.

Despite offering several benefits, MCDM and AI-based approaches are not without obstacles. Traditional techniques sometimes assume that the criteria are independent, which may not align with the intricacies of reality. Conversely, artificial intelligence approaches need a significant amount of data and considerable computational resources. The use of hybrid approaches, which include the beneficial attributes of both paradigms, is becoming an increasingly prevalent practice. Vazquez et al. [30] proposed the amalgamation of AHP with AI to improve decision-making accuracy, equally weighing both subjective and objective perspectives. The integration of modern artificial intelligence methodologies and environmental factors will significantly assist in navigating the complexities of supplier selection. This is due to the ongoing expansion of production systems. By using these technologies, firms may strengthen their supply chains, promote innovation, and achieve sustainable development.

III. METHODOLOGY

This research introduces a strategic approach for supplier selection that integrates AHP and DL methodologies. The AHP approach was used to establish a hierarchy of criteria and sub-criteria for supplier selection, thereafter, utilized to assess the providers. Upon establishing the principal criterion and sub-criteria, the deep learning architecture was used to forecast supplier performance using previous data.

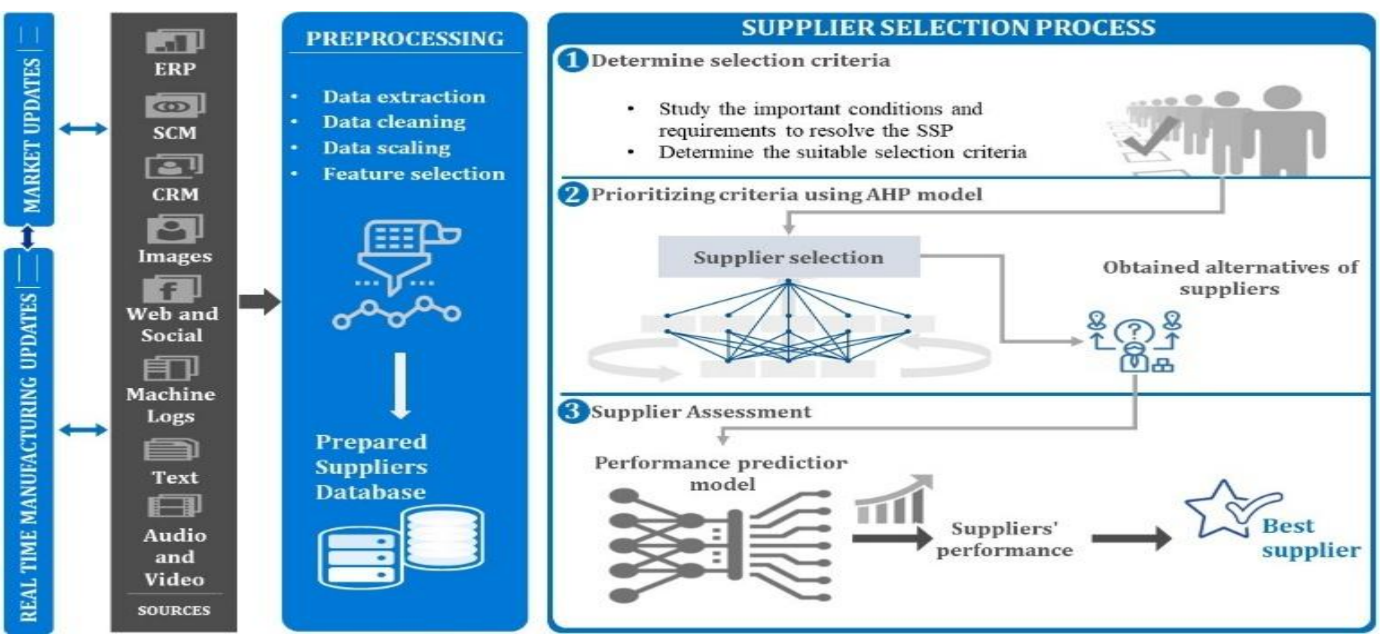

Fig. 1. Flowchart of the presented process.

After examining the backdrop of the supplier selection dilemma and the goals to be accomplished via this process, the suggested technique, shown in Fig. 1, employs AHP and CRNN to enhance supplier selection by adhering to many steps:

- Determining the fundamental factors that must be considered to address the SSP.
- Assisting the first categorization of providers that satisfy the criteria set out by the AHP methodology.
- Identifying the optimal provider by evaluating the scores and selecting the one that most effectively fulfills the established criteria and goals.

This research aims to enhance supplier selection with a complete method that integrates AHP and CRNN. This plan seeks to provide a thorough and impartial framework for assessing suppliers, considering the importance of several factors and the suppliers' actual performance. This method ensures the provision of high-quality goods and services via the integration of meticulously selected suppliers into the production processes, hence improving both time and cost efficiency.

A. Selecting Suppliers

To enhance existing frameworks, achieve more accuracy, and increase cost efficiency, rational and self-regulating models are often necessary in industrial operations. This is executed to enhance operational efficiency. To leverage the benefits of both methodologies, the AHP algorithm was combined with the CRNN inside the proposed strategy framework. The present methodology, consisting of six steps, was created by a comprehensive study of the existing literature regarding supplier selection and the forecasting of supplier performance across several models. This study was conducted to establish the current technique.

1) Defining the criteria of supplier selection: The formulation of objectives for the supplier selection process is crucial, as it serves as a framework for the selection approach and aids in prioritizing relevant factors. This step enhances the decision-making process by providing a full awareness of the expectations placed on providers. This facilitates an impartial and equitable evaluation of potential suppliers. This encourages suppliers to identify with the firm's continuing aims and values, thereby enhancing the overall efficiency of procurement and supply chain operations. Defining precise objectives is essential to improve the efficacy, efficiency, and methodical nature of the supplier selection process. In time, this will cultivate deeper relationships with the organization's suppliers, so enhancing the organization's overall performance.

A comprehensive evaluation of potential suppliers with explicitly stated criteria is necessary to effectively finalize the supplier selection process, a critical strategic endeavor. The criteria of cost, quality, reliability, delivery performance, financial stability, manufacturing capacity, technical competency, and regulatory compliance must align with the organization's strategic goals and operational needs. The specific selection factors vary among industries, market conditions, and business objectives, underscoring the need of modifying and prioritizing these criteria to achieve optimal outcomes.

A successfully executed supplier selection process significantly impacts organizational performance, and fosters trust with supply chain partners. Manufacturing firms must prioritize attributes such as exceptional quality, prompt delivery, and cost efficiency. Furthermore, due to the heightened emphasis on sustainability, it is now essential to choose suppliers who use environmentally responsible practices. Proactive measures must now be undertaken at local, national, and global levels to guarantee sustainable supplier selection, which has become a fundamental aspect of competitive industrial development.

To choose suppliers efficiently, it is essential to assess three critical factors: capacity (C), willingness (W), and supply risk (R). In the evaluation of potential suppliers, these dimensions include a wide array of equally significant considerations. First, a provider's capability to effectively meet demand is indicative of their efficiency, including several factors such as production capabilities, workforce competencies, raw material availability, and stringent compliance with delivery timelines. Critical aspects of capacity include:

- Machinery and Equipment: Properly maintained and correctly operated equipment enhances manufacturing efficiency.
- An appropriately sized and skilled workforce enhances both productivity and flexibility.
- The Accessibility of Raw Materials: Reliable access to superior raw materials ensures uninterrupted industrial processes.
- Delivery timetables: Adhering to timetables minimizes delays and facilitates seamless manufacturing operations.

Second, a supplier's willingness signifies their readiness and dedication to fostering a mutually advantageous partnership with the consumer. Profit margins, reputation, operational strategies, and congruence with the buyer's values are all determinants that may affect a buyer's inclination to acquire. Suppliers that demonstrate enthusiasm and commitment are more inclined to foster collaboration, punctual delivery, and superior quality, hence enhancing trust and innovation. Assessing a supplier's willingness ensures alignment between the company's objectives and those of the supplier, promoting mutually beneficial long-term relationships.

Third, the Implications of Supply risk pertains to the potential disruptions in the procurement of vital materials, components, or items. Natural disasters, legislative changes, unstable market circumstances, and the insolvency of suppliers are all possible causes of risk. Efficient management of supply risks include:

- Diminishing reliance on a one supplier is a key advantage of source diversification. Contingency planning involves preparing for expected disruptions.

- Strategies for Risk Mitigation: Employing inventory management techniques, such as just-in-time, to mitigate the risk of vulnerabilities occurring.
- Attributes of Innovative Dimensions and Standards for Supplier Selection
- A systematic supplier selection approach evaluates capacity, willingness, and supply risk. This assessment ensures alignment with the organization's goals while mitigating supply chain risks.

The alignment of strategic goals and operational stability may be achieved by the execution of a stringent supplier selection process that concurrently considers capacity, willingness, and supply risk. Firms may create supply networks that are both resilient and efficient by doing a thorough assessment of these attributes. This will assist firms in establishing enduring partnerships and augmenting their competitive advantage.

2) Prioritizing criteria with AHP: To rank criteria in accordance with the objectives of decision-making, the Analytic Hierarchy Process (AHP) takes into consideration both qualitative and quantitative data. Sub-criteria are given subjective weights via the use of this method, which is based on the competence of those who are responsible for making decisions. Because of this, it is possible to conduct an accurate assessment of the significance of each criterion, as well as an evaluation of the alternatives that are relevant to these criteria. First, a hierarchical structure of criteria is created, considering the significance and importance of the different criteria. Because of this framework, it is much simpler to carry out an in-depth examination of the issue of decision-making.

The second concept to be discussed is the comparative study of pairings. Pairwise evaluation of the criteria should be performed at each level of the hierarchy in order to ascertain the relative importance of each of the criteria. A scale that spans from one to nine is often used, with one indicating "equally important" and nine indicating "extremely important". This scale is commonly used since it is customary practice. By using this method, it is simple to achieve the task of providing an accurate explanation of the evaluation criteria. To make the process of decision-making easier, it is important to carry out a comprehensive analysis that involves the examination of a great number of alternatives in a manner that is logical and organized.

Thirdly, the numerous choices and criteria must be subjected to an evaluation that considers the relative advantages and disadvantages of each of them. Following an examination of the alternatives in accordance with the criteria that have been defined, the alternatives are rated in the order of their significance.

Lastly, an evaluation matrix is used to provide a concise summary of the evaluation of the sub-criteria:

$$J_M = \begin{bmatrix} Op_{11} & Op_{12} \dots & Op_{1n} \\ Op_{21} & Op_{22} \dots & Op_{2n} \\ \vdots & \vdots & \vdots \\ . & . & . \\ Op_{n1} & Op_{n2} \dots & Op_{nn} \end{bmatrix}_{n \times n} \quad (1)$$

where n represents the number of assessment sub-criteria and the relative importance of sub-criterion i and the sub-criterion j can be expressed by Op_{ij}.

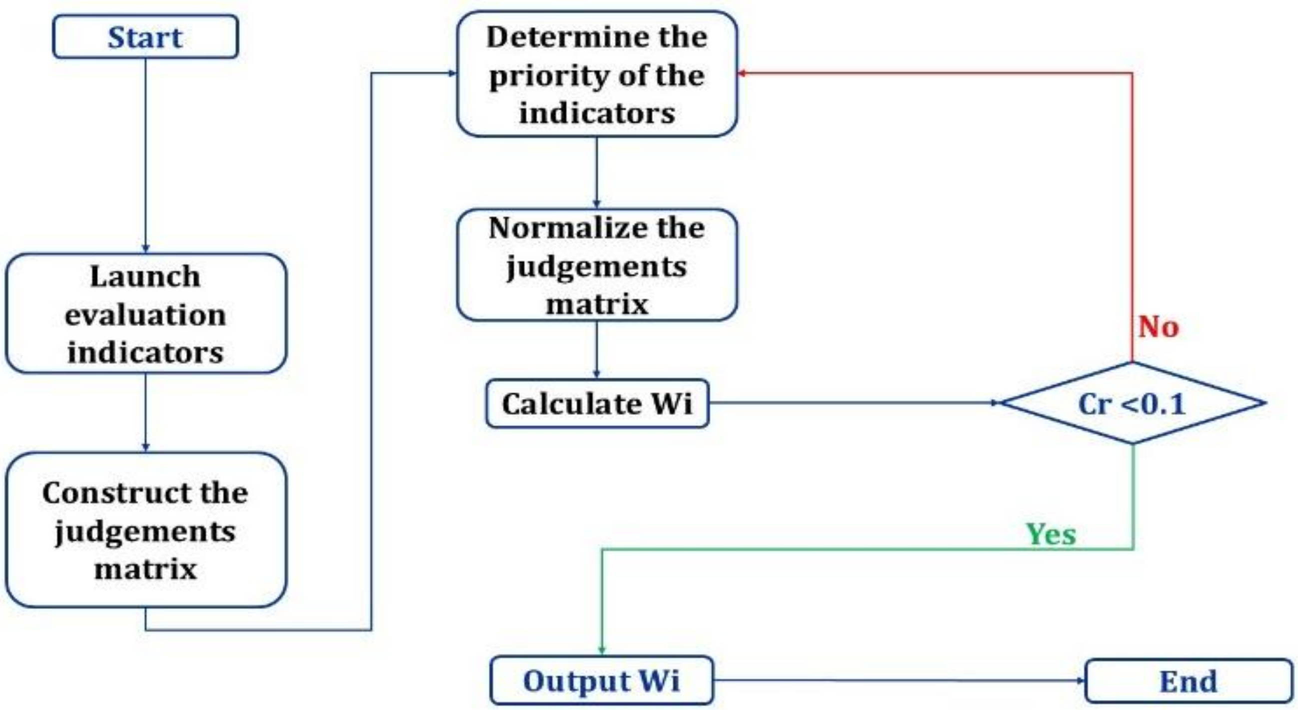

Fig. 2. Weight determination based on AHP.

Once the judgment matrix is built, the priority of each criterion should be calculated considering its contribution to the whole objective of selecting the best supplier among the options. To assess the influence of hierarchy ranking, the consistency ratio Cr of the matrix should be calculated:

$$Cr = \frac{Ci}{RI} \quad (2)$$

With:

- Ci represents the consistency index calculated by: $Ci = (root_{max} - n)P(n-1)$ with the maximum $root_{max}$ indicates the characteristic root.
- RI the random consistency index, which quantifies the size of Ci, is calculated by: $RI = \frac{Ci_1 + Ci_2 + \cdots + Ci_m}{m}$ with m being the number of items being compared for RI.

If $Cr > 0.1$, it reveals that the pairwise comparison is inconsistent. Otherwise, if the $Cr \ll is$ 0.1, the consistency is considered reasonable (as explained in Fig. 2).

Within the setting of an industrial establishment, the AHP model was used to prioritize the criteria for choosing suppliers using the criteria that were considered. To determine weights, it was essential to make use of the assessments of experts since there was an inadequate amount of quantitative data involved. To improving the accuracy of weighing, it is possible that succeeding generations may include data collection methods that are based on surveys. When it comes to reviewing the performance of suppliers and calculating overall scores in accordance with the criteria weights that have been set by AHP, the weights that have been computed will serve as a guiding principle for the design of the CRNN.

B. *Assessing Supplier Performance Through CRNN Architecture*

Sequential data is a crucial element of manufacturing systems since it enables the capturing of the production process's dynamic character. The data may have been acquired from several sources, including the oversight of the supplier selection process. Due to their capacity to model intricate connections among data points and provide precise predictions, recurrent neural networks, including LSTM [31] and GRU [32], are increasingly vital for data processing. Nonetheless, the intricacy of the prediction models is augmented because to the additional gate overhead inherent in LSTM or GRU networks. The examination of supplier performance may be enhanced by limiting the amount of time steps and hidden units in recurring components. Fig. 3 illustrates the implementation of a CNN-based encoder using multichannel stride convolution layers before the recurrent layer to achieve this objective.

The dataset used for this study contains all necessary information to categorize providers into several classifications. Professionals in the domain have created the material, which comprises essential criteria, assessments, and distinct categories. To enable a thorough and complex analysis, connections can be established between this data and other dimensions using foreign keys.

Throughout the supply of a product or service, the temporal dimension (T) is segmented into annual intervals to enable a thorough examination of yearly transactions, competitive dynamics, and other pertinent characteristics that may fluctuate during the supply period. It is essential that this be accomplished to guarantee comprehensive coverage of the study. This component is essential for assessing supplier performance over an extended period, as it facilitates the analysis of emerging patterns and trends. It is essential to endure this time of solitude to get this comprehension.

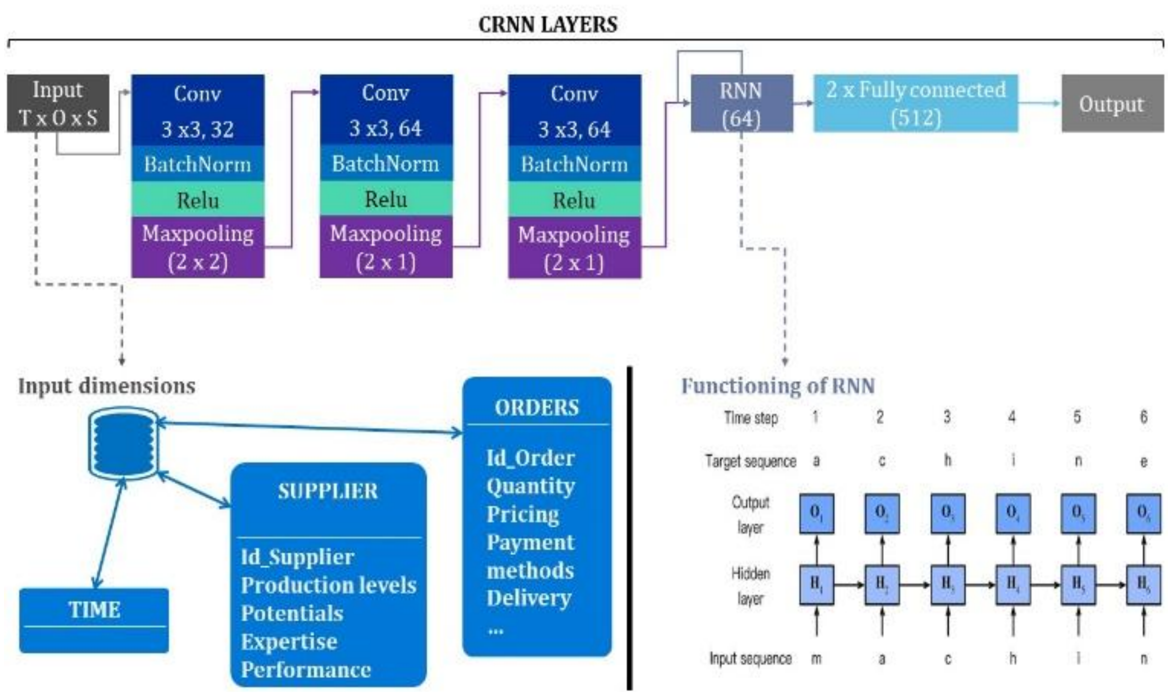

Fig. 3. Schematic diagram of the used CRNN.

The Schematic diagram of the used CRNN, illustrated in Fig. 3, which consistently generates a 2 x 512-dimensional embedding. Each convolution block consists of a convolution operation, followed by batch normalization and a ReLU activation (-0.1 slope). Following that, a 2 x 2 maximum pooling is conducted. The numbers within each block represent the output channel and kernel sizes. For example, "32, 3 x 3" indicates that the convolution layer generates 32 output channels with a kernel size of 3 x 3.

The "orders" dimension is differentiated from others by its utilization of a unique order identifier. The "orders" dimension encompasses critical information that elucidates each transaction in comprehensive detail. Customer data, which encompasses the documentation of essential consumer attributes, is deemed a vital component. Detailing the characteristics and specifications of the service or product to furnish supplementary information regarding your offering. The transaction data encompasses the amount, pricing, and various payment options. The information relevant to the supply or shipping process encompasses, among other aspects, specifics concerning logistics and the delivery schedule. All these components are encompassed in the data.

By integrating various components that enhance scheduling, monitoring, and order fulfillment processes, manufacturers can achieve a thorough understanding of operational efficiency and customer satisfaction. Manufacturers may enhance their processes because of this.

Consider the Provider (S): The supplier dimension aims to gather extensive information about its associated suppliers. The information presented here encompasses everything that comes after it: If an organization is categorized in accordance with the aforementioned criteria, it is considered to be working within a certain industry. "Production capabilities" refers to the talents, knowledge, and experience that are acquired via the process of manufacturing. In addition to the many performance metrics that are accessible, there are also key performance indicators that apply to ethics and sustainability.

Because of the interplay between all these components, you will have a clear image of the performance of the providers and the areas in which they may have room for improvement.

CRNN is used to describe a system that combines CNNs with RNNs. These networks are used for the purpose of evaluating the performance of providers by means of extraction of geographical and temporal data. Following the completion of the last recurrent layer, the output proceeds to be processed by a fully linked layer. This layer attempts to provide a prediction on the probability of the performance of the supplier. In terms of collecting both the static and temporal components of the data that is provided by the provider, the CRNN performs an excellent job. To do this, we implement recurrent neural networks (RNNs) for the purpose of modeling sequences and convolutional neural networks (CNNs) for the purpose of extracting features. When it comes to evaluating the performance of suppliers, the well-established CRNN architecture offers a complete method. It is possible to take this approach thanks to the innovative design. The capabilities of recurrent neural networks (RNNs) in temporal modeling are utilized in this approach, which makes use of the advantages that convolutional neural networks (CNNs) offer in terms of spatial information extraction. Activities that are sequence-based are a good fit for the hybrid architecture because of its scalable and reliable approach to evaluating the performance of suppliers.

IV. Results and Discussion

A. Data Description

As we propose a supplier selection approach combining criteria analysis and performance prediction, the evaluation phase requires the use of a dataset containing supplier information and supply operation history. To this end, we have chosen to use publicly available data to facilitate the evaluation of this approach, and to provide researchers with a basis for comparison using the Medicare & Medicaid Services (CMS) [33]. The website gives direct access to different data released by CMS. The datasets used for this study included information concerning durable medical Equipment and supplies with the supplier's information (payments, usage, submitted charges, beneficiary demographic…). This dataset is built on information gathered from CMS administrative during the period 2015-2020, whose dataset of each year exceeds 786040 elements.

B. Training Setups and Evaluation Metrics for CRNN

For the training of the CRNN, the Adam optimizer [34] is used, with a preliminary learning rate of 0.001. Every two epochs, this rate was reduced by a factor of 0.95, and the batch size was set to 32. The model was trained for 60 epochs in the whole experiment. We evaluated the performance of the CRNN model using the main evaluation metrics: the Mean absolute error (MAE), the mean absolute percentage error (MAPE), the Mean Squared Error (MSE), and the root mean square error (RMSE) [35]. For the CRNN modeling, we organized the training into a period sequence and feedback the sequence into the CRNN network constituted of various connected units, as explained above, to accomplish the current training model. Then, for the model optimization, the CRNN was trained to compute the values of the predicted variables at the set time.

The collected dataset has a total of 74,588 instances. These examples were randomly separated into three sets: a training set with 70% of the instances, a validation set with 20% of the instances, and a test set with 10% of the instances.

C. AHP Weightage

As stated previously, we applied AHP to calculate the weights and ranks of the various selection criteria. In the case of supplier selection, each level requires to be weighted to rate this large matrix. In this study, firstly, the weights of level 1 of each criterion are established and reviewed to determine the importance of each criterion. After that, the weight calculation steps of AHP are followed.

1) Calculate the Weight of the selection criteria: As supplier selection is paramount in manufacturing, this study presented a framework for analyzing its data, regardless of the size of the company, small, large, or medium. Manufacturing companies generate a large scale of diversified business processes. This is more convenient because they have a history of transactions in addition to more recent data, with a strong experience of experts in the sector, which can ease the implementation of this approach. The chosen list of criteria in conjunction with the sub-criteria for each dimension was identified from the literature analysis, concerning the opinions of industry experts to ensure compatibility between the theoretical study and the practical aspects of supplier selection. The used sources offer a huge amount of data to study the previous records of the suppliers, which helped to confirm the list of criteria and sub-criteria.

At the preliminary stage, the criteria used were analyzed to recognize the most applicable criteria for the supplier selection process. Initially, there were ten criteria and 30 sub-criteria. Then preliminary discussions conducted with industrial experts were intended to gain a professional opinion about the criteria list. Then all these data were arranged and examined systematically.

The ranking results demonstrate that the most significant criteria that should be well studied while selecting suppliers for a specific product or service are quality and delivery of the suppliers followed by technological advances, performance improvement, and long-term relationship, which gained priority weightage of 0,462, 0,434, 0,359, 0,281 and 0,272 respectively the ranking weights. Based on the judgments given by the expert decision-makers, these criteria remain the most significant aspects that should be respected within a supplier selection process. According to these findings, it can be concluded that information sharing, subjective risks, intangible, cost-effective, and objective risks of the supplier gained relatively low priority weightings. When analyzing the priority weights for sub-criteria price appropriateness of the supplier is the most important criterion for them.

2) Suppliers ranking: The use of AHP to prioritize vital factors in manufacturing organizations may produce different importance values given to the specific requirements of each company. Moreover, these priorities may adjust regarding internal and external aspects, which can impact manufacturing operations.

TABLE I. PERFORMANCE RESULTS OF THE COMPONENTS OF PROPOSED METHOD

Method	AHP	CRNN	Proposed AHP_CRNN
Accuracy	90, 36 %	92,07%	95,96%
MAE	0.00554	0,05048	0,0771
MAPE	0,725782	1,004297	1,386251
MSE	0,00000602	0,00293	0,00262899
RMSE	0,00245	0,01711	0,04127

Table I demonstrates the results of supplier selection. Characteristically, the selection process ends once a supplier is chosen. However, other difficulties can occur regarding its performance and dedication, so it is quite important to analyze these aspects to avoid any potential risk that could affect the smooth running of manufacturing operations. Consequently, our study offers the possibility of having an optimized list of suppliers to select the most efficient one that will meet the needs effectively and continuously, while ensuring the best gains and stability of manufacturing activities. Here best highest final values reveal that (Supplier_5), (Supplier_4), and (Supplier_2) are the most suitable suppliers for this supplier selection case, with the final values (2,031), (1,964), and (1,855) respectively.

D. Prediction of Supplier Performance

To quantify and assess the performance of the proposed method, the evaluation results of the AHP, CRNN, and the presented method. It can be noticed from the statistics in the table that the results of the three methods are all good with MAE < 0.1, MAPE < 1.5, MSE < 0.005, and RMSE rate < 0.5. The effects of using AHP and CRNN helped the proposed method to gain better results compared with traditional AHP and CRNN networks. The proposed strategic method proved higher prediction accuracy (95, 96%) with stronger generalization capability, and better operability, which shows that the AHP-CRNN proposed in this study is more appropriate for the supplier selection process in manufacturing systems.

While the first step, AHP, provided a methodological selection of the suppliers, the records of the best suppliers were captured and analyzed to reveal their performance. With all the completed preparations using AHP, the CRNN model computed iteratively the data, which contains the transaction history of the period 2015-2020 of the three suppliers, and provided the analytical results, as shown in Table II.

The anticipated values of providers exhibit significant consistency; however the projected values of some categories diverge considerably from prior assessments.

TABLE II. PREDICTION RESULTS OF THE PERFORMANCE OF SUPPLIERS REGARDING THE BEST-RANKED CRITERIA

Quality satisfaction								
	Observed						Predicted	
Year	2015	2016	2017	2018	2019	2020	2025	2030
Supplier_2	29,50 %	44,32 %	51,25 %	57,50 %	63,52 %	69,32 %	71,39 %	76,41 %
Supplier_4	41,34 %	56,16 %	63,09 %	69,34 %	75,36 %	59,48 %	65,55 %	73,57 %
Supplier_5	53,18 %	68,00 %	74,93 %	81,18 %	87,20 %	71,32 %	77,39 %	85,41 %
Delivery transactions								
	Observed						Predicted	
Year	2015	2016	2017	2018	2019	2020	2025	2030
Supplier_2	12300	15950	25071	38978	45328	53218	67309	93684
Supplier_4	13191	16841	25962	39869	46219	54109	68200	94575
Supplier_5	14082	17732	26853	40760	47110	55000	69091	95466
Technological advances								
	Observed						Predicted	
Year	2015	2016	2017	2018	2019	2020	2025	2030

Supplier_2	33,56 %	55,23 %	61,98 %	68,78 %	70,62 %	76,55 %	80,32 %	85,69 %
Supplier_4	34,51 %	56,18 %	62,93 %	69,73 %	71,57 %	77,5 %	81,27 %	86,64 %
Supplier_5	34,28 %	55,95 %	62,7 %	69,5 %	71,34 %	77,27 %	81,04 %	86,41 %
Performance improvement								
Observed							Predicted	
Year	2015	2016	2017	2018	2019 %	2020	2025	2030
Supplier_2	34,92 %	56,59 %	63,34 %	70,14 %	71,98 %	77,91 %	81,68 %	87,05 %
Supplier_4	42,84 %	64,51 %	71,26 %	78,06 %	79,9 %	85,83 %	89,6 %	94,97 %
Supplier_5	40,17 %	61,84 %	68,59 %	75,39 %	77,23 %	83,16 %	86,93 %	92,3 %
Long-term relationship								
Observed							Predicted	
Year	2015	2016	2017	2018	2019	2020	2025	2030
Supplier_2	52,17 %	63,84 %	70,59 %	77,39 %	75,23 %	81,16 %	82,93 %	88,3 %
Supplier_4	60,09 %	71,76 %	78,51 %	85,31 %	83,15 %	89,08 %	90,85 %	96,22 %
Supplier_5	61,42 %	73,09 %	79,84 %	78,64 %	80,48 %	88,41 %	89,18 %	94,55 %

The analyzed data on long-term relationships clearly indicates that although Supplier_5 exhibited the best results from 2015 to 2017, there was a decline in performance in this criterion from 2018 to 2022, resulting in Supplier_4 outperforming Supplier_5, even in projected values. Supplier_4 marginally exceeded Supplier_5 in technology advancements and performance enhancement. Furthermore, the calculated performance metrics of the lower-ranked criterion exhibited varying levels of supplier performance. Particularly after 2018, when global economic problems emerged, affecting inflation rates and fluctuations in the international market following the coronavirus health crisis in 2020. The discrepancies in supplier performance underscore the significance of all selection criteria, not alone those identified by the AHP technique, to mitigate unanticipated factors that may disrupt production processes.

TABLE III. PREDICTION RESULTS OF THE PERFORMANCE OF SUPPLIERS CONSIDERING THE SUB-CRITERIA

Dimensions	**Criteria**	**Detailed sub-criteria**	**Supplier_2**	**Supplier_4**	**Supplier_5**
Capacity (C)	Cost-effective (C1)	Reduced cost/price of a product (C11)	44,67%	52,07%	49,55%
		Financial competence (C12)	57,64%	73,45%	58,52%
	Delivery (C2)	Available production (C21)	49,16%	52,23%	63,79%
		Delivery satisfaction (C22)	58,89%	63,96%	83,42%
	Intangible (C3)	Performance history (C31)	43,29%	51,44%	73,01%
		Responsiveness and situation in the industry (C32)	38,10%	77,65%	65,83%
	Technological advances (C4)	Design (C41)	42,06%	50,48%	46,12%
		Quantity of patents applying (C42)	28,06%	56,20%	44,32%
		Relative shares (C43)	24,04%	52,19%	48,35%
		R&D expenses input intensity (C44)	21,04%	67,79%	62,57%
	Quality (C5)	Reliability of product (C51)	59,74%	76,89%	82,97%
		Specific characteristics of remaining products (C52)	49,78%	68,92%	72,86%
		Quality of products (C53)	43,06%	61,21%	59,35%
Willingness (W)	Information sharing (W1)	Honest and regular communications (W11)	-	-	-
		Relationship proximity(W12)	-	-	-
	Long-term relationship (W2)	Dedication to quality (W21)	-	-	-
		Long-term commitment (W22)	21,26%	59,14%	54,99%
		Mutual honesty and respect (W23)	69,08%	77,06%	68,99%
	Performance improvement (W3)	Commitment to permanent development in products and processes (W31)	31,15%	56,65%	61,80%
		Effort in supporting “just-in-time” standards (W32)	54,16%	57,16%	84,69%
Risk of supply (R)	Objective risks (R1)	Geographical closeness (R11)	48,09%	73,19%	76,87%
		Bankruptcy (R12)	57,78%	86,07%	83,40%
		Strikes, natural disasters, pandemics (R13)	41,19%	81,30%	67,91%

		Transportation disruptions (R14)	40,96%	62,26%	53,54%
		Fluctuations in the market price of raw materials (R15)	44,24%	50,94%	70,73%
	Subjective risks (R2)	Reputation (R21)	35,99%	71,10%	70,64%
		Organizational management (R22)	70,95%	80,94%	41,98%
		Social responsibility (R23)	59,89%	84,68%	56,99%
		Political and regulatory environment (R24)	53,92%	71,27%	64,12%
		Market conditions (R25)	40,97%	56,57%	56,09%
Global performance			46,84%	66,93%	66,03%

The list derived using the AHP approach identifies the top three suppliers: Supplier_5, Supplier_4, and Supplier_2. Nevertheless, the performance analysis of each supplier over the years indicates that Supplier_4 is a viable contender to Supplier_5. We used the AHP phase as input for the CRNN rather than the whole list of vendors. The use of AHP enabled us to generate a concise list, facilitating the CRNN's emphasis on the specifics of each supplier's performance according to the selection criteria. In the prior assessments, we only used the selection criteria from Table III, without considering the influence of the sub-criteria on supplier selection. To provide a fair comparison among the suppliers, the subsequent test involves evaluating the performance of each supplier based on the selection sub-criteria outlined in Table III. The performance prediction findings, based on the selection sub-criteria, indicated that Supplier_4 outperforms Supplier_5.

This study's findings and existing literature demonstrate that using AHP enables manufacturing businesses to make supplier selection decisions based in methodical and objective assessments of available alternatives. This may mitigate the risk of bad decision-making and assure the selection of the appropriate supplier to fulfill the organization's objectives and specifications. Generally, selecting the appropriate provider to guarantee prompt delivery of superior quality.

Choosing appropriate items or services is crucial, since picking the incorrect option may result in many complications, such delivery delays, substandard quality, or even legal ramifications. To mitigate these possible issues, it is essential to adopt a comprehensive methodology for supplier selection that encompasses all relevant criteria and sub-criteria. By evaluating the suggested selection criteria with other pertinent organizational characteristics, decision-makers may mitigate the risk of supplier-related issues and assure the selection of an appropriate partner for their requirements. We have used deep learning to analyze and forecast the performance of the selected providers in order to mitigate risks. The AHP-CRNN methodology facilitates enhanced analysis to get increased revenues via the selection of the appropriate provider.

E. Comparison with Former Methods

The AHP-CRNN model was reviewed from multiple angles in the preceding sections. To properly demonstrate the operational effectiveness of AHP-CRNN, we chose four extensively proposed and used techniques (RNN, RDNN, CRNN, and LSTM). Based on the relevant published works, we retrieved the corresponding architectures and parameters of the abovementioned methodologies for this comparative analysis. As stated in the preceding sections, the experimental setting for the comparison maintained a consistent unified strategy. This included using the same database and keeping the percentages for the training, validation, and test datasets the same.

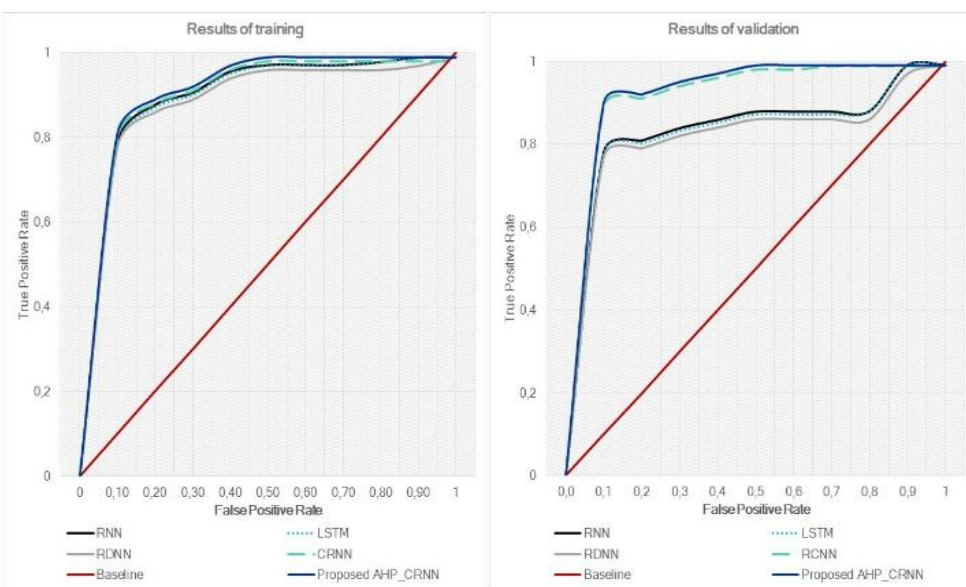

Fig. 4. The overall supplier selection assessment compared to other models in training and validation processes.

Because of the large amount of experimentation data, it is not possible to offer detailed convergence accuracy metrics for all tested approaches. As a result, in this section, we will instead provide statistical rankings. Fig. 4 depicts an overview of true positive (TP) and false positive (FP) rates for the training and validation sets, allowing for a thorough evaluation of the proposed supplier selection technique.

It allowed us to understand the model's ability to correctly identify positive examples and avoid false positives. As comparing the TP and FP rates of the training and validation sets is an important aspect of deep learning evaluation and tuning, the results show a massive improvement while using the AHP-CRNN model.

The proposed AHP-CRNN-based method for supplier selection employs a strategic process. We used the AHP phase to select a list of potential suppliers, which is used as the input of the CRNN model. The strategic AHP-CRNN-based approach strengthens the multi-objective analysis in the process of supplier selection. The CRNN employs CNN layers for feature extractions and RNN layers for the temporal dependencies assessment.

The proposed method was proven performant compared to traditional RNN [36], LSTM [31], RDNN [28], and CRNN [37]. To further compare and quantify the performance of the proposed AHP-CRNN strategy, the evaluation results of the literature models are displayed in Table IV.

TABLE IV. PERFORMANCE COMPARISON OF DIFFERENT LITERATURE MODELS

Method	Accuracy	MAE	MAPE	MSE	RMSE
RNN	89,99 %	0,00928	0,963097	0,0005007	0,0158807
LSTM	92.56 %	0,01838	0,972197	0,00072	0,0161
CRNN	92,07 %	0,05048	1,004297	0,00293	0,01711
RDNN	91,73 %	0,05998	1,013797	0,00150599	0,050047
Proposed AHP_CRNN	95,96%	0,0771	1,386251	0,00262899	0,05127

The findings show that the LSTM surpasses the traditional RNN. That can be explained by the fact that LSTM networks can store long-term dependencies better than traditional RNNs. In traditional RNNs, the information from long-term dependencies can easily be forgotten or lost as it moves through the network. However, LSTMs have an internal memory cell that can store information for a longer period, allowing them to better capture long-term dependencies. However, traditional RNNs are often computationally simpler and more efficient than LSTMs, which can be more complex and computationally demanding. Applications combining RNNs with other types of neural networks, such as CNN or DNN, showed improved model performance. As the use of RNN with other networks makes it possible to address multiple tasks simultaneously or tackle more complex manufacturing data, the proposed method is based on a CRNN to have to ability to handle structured as well as unstructured data, ensure better generalization to new data, and reduce the overfitting.

F. Discussion

Comprehending these distinctions is crucial for efficient supplier selection. By analyzing historical data, decision-makers may identify suppliers who consistently perform effectively, even under challenging circumstances. This mitigates risks and ensures supply chain continuity. Moreover, analyzing supplier performance longitudinally allows for the identification of suppliers who consistently improve their performance. This information is crucial when considering long-term partnerships and developmental potential.

The proposed method facilitates the benchmarking of suppliers, highlighting top performance and identifying those requiring development. This data-driven approach enables decision-makers to make objective and informed choices, leading to cost reductions and enhanced efficiency. Moreover, evaluating supplier performance over time enables the optimization of your supply base. Organizations may establish robust relationships with reliable suppliers by acknowledging consistent performance, leading to enhanced negotiating leverage and favorable conditions. Evaluating supplier performance over time is essential for supplier management, since it offers insights into the consistency and dependability of providers.

The study outlined in the article examines the difficulties encountered by industrial units in a competitive and worldwide market, emphasizing the need of optimizing supply chains and choosing appropriate suppliers for success. The research underscores the evolving dynamics of consumer needs, stressing the necessity for enterprises to provide superior products/services at competitive pricing more swiftly than their rivals. This requires a rigorous supplier selection procedure to ensure supply chain integrity, preserve profit margins, and meet customer satisfaction.

The AHP-CRNNstrategy in supplier selection offers several practical advantages, such as cost reduction, risk alleviation, quality enhancement, ethical procurement, and strengthened supplier relationships. Through the methodical assessment and selection of suppliers using both quantitative and qualitative criteria, firms may enhance their supply chains, secure a competitive advantage, and establish a robust and sustainable business environment.

The AHP-CRNN technique significantly influences supplier selection decisions. A primary advantage is the capacity to make well-informed supplier selection judgments. By methodically assessing prospective suppliers against several factors, including cost, quality, and delivery time, firms get an extensive understanding of their alternatives. This allows them to choose providers who fulfill urgent requirements while also aligning with long-term strategic objectives. In a more competitive business landscape, educated decision-making may profoundly influence a company's performance and competitiveness.

- Financial Implications and Efficiency: The AHP-CRNN methodology yields significant cost savings. By systematically evaluating suppliers, firms may discern those providing the most advantageous terms and pricing. This may result in substantial cost reductions, an essential element in sustaining profitability. Furthermore, choosing suppliers that can adhere to stringent delivery timelines and adjust to fluctuating circumstances improves supply chain efficiency. Minimized supply chain interruptions and enhanced delivery times may result in decreased operating expenses and heightened customer satisfaction.

Quality assurance and risk management are essential in the selection of suppliers. The AHP-CRNN methodology facilitates the identification of suppliers with a demonstrated history of providing high-quality goods or services. Consistently choosing such suppliers guarantees the preservation of high-quality standards and mitigates the likelihood of product recalls or quality-related problems. Moreover, effective supplier selection is essential for risk minimization. Companies may choose suppliers recognized for their resilience and adaptability to unanticipated obstacles, thereby mitigating supply chain risks.

The AHP-CRNN methodology fosters a culture of ongoing improvement and data-driven decision-making. Organizations may evaluate previous supplier performance data and trends to perpetually enhance their selection criteria. This iterative procedure results in improved supplier selection over time. Furthermore, the methodology cultivates a data-driven culture throughout the firm, transcending supplier selection. It advocates for decision-makers to use data and analytics for informed decision-making across diverse business functions.

V. Conclusion

The suggested method of supplier selection using the Analytic Hierarchy Process (AHP) and Convolutional Recurrent Neural Network (CRNN) has significant consequences. Initially, using AHP provides a structured framework for systematically and openly evaluating and contrasting various criteria. The suggested technique enhances the long-term sustainability of manufacturing operations by ensuring efficient supplier selection. Fostering robust connections with suppliers and achieving favorable outcomes are essential for the seamless operation of production processes. The systematic strategies obtained from the AHP-CRNN approach facilitate the enhancement of production systems, guaranteeing the sustained availability of reliable and high-performing suppliers. The applicability of the suggested technique has been shown via several experimental experiments, highlighting its efficacy in supplier selection for sustainable manufacturing systems. This illustrates its potential for practical use. The study indicates that the intelligent judgment methodology may be improved to better the selection criteria for complex manufacturing systems, suggesting that the suggested method may be expanded and modified in future research.

References

[1] Schlemitz A, Mezhuyev V. 2024. Approaches for data collection and process standardization in smart manufacturing: Systematic literature review, Journal of Industrial Information Integration, Volume 38,2024,100578, https://doi.org/10.1016/j.jii.2024.100578.

[2] J. Huang et al., "Deep Reinforcement Learning-Based Dynamic Reconfiguration Planning for Digital Twin-Driven Smart Manufacturing Systems With Reconfigurable Machine Tools," in IEEE Transactions on Industrial Informatics, vol. 20, no. 11, pp. 13135-13146, Nov. 2024, doi: 10.1109/TII.2024.3431095.

[3] Sun, L., He, H., Yue, C. et al. Unleashing Competitive Edge in the Digital Era: Exploring Information Interaction Capabilities of Emerging Smart Manufacturing Enterprises. J Knowl Econ 15, 10853–10897 (2024). https://doi.org/10.1007/s13132-023-01545-w

[4] Sahoo, S. K., Goswami, S. S., & Halder, R. (2024). Supplier Selection in the Age of Industry 4.0: A Review on MCDM Applications and Trends. Decision Making Advances, 2(1), 32–47. https://doi.org/10.31181/dma21202420

[5] Sheykhizadeh, M., Ghasemi, R., Vandchali, H.R. et al. A hybrid decision-making framework for a supplier selection problem based on lean, agile, resilience, and green criteria: a case study of a pharmaceutical industry. Environ Dev Sustain 26, 30969–30996 (2024). https://doi.org/10.1007/s10668-023-04135-7

[6] Bai, C., Zhu, Q. and Sarkis, J. (2022) 'Circular economy and circularity supplier selection: a fuzzy group decision approach', International Journal of Production Research, 62(7), pp. 2307–2330. doi: 10.1080/00207543.2022.2037779.

[7] Pamucar, D., Ulutaş, A., Topal, A., Karamaşa, Ç., & Ecer, F. (2024). Fermatean fuzzy framework based on preference selection index and combined compromise solution methods for green supplier selection in textile industry. International Journal of Systems Science: Operations & Logistics, 11(1). https://doi.org/10.1080/23302674.2024.2319786

[8] Acerbi, F., & Taisch, M. (2020). Information flows supporting circular economy adoption in the manufacturing sector. In Ed., L. B, Department of Management, Economics and Industrial Engineering pp. 703–710. Springer. Available at. https://doi.org/10.1007/978-3-030-57997-5_81

[9] Emrouznejad, A. and Marra, M. (2017), "The state of the art development of AHP (1979–2017): a literature review with a social network analysis", International Journal of Production Research, Vol. 55 No. 22, pp. 6653-6675.

[10] Liu, Y., Eckert, C.M. and Earl, C. (2020), "A review of fuzzy AHP methods for decision-making with subjective judgments", Expert Systems with Applications, Vol. 113738

[11] Belotti Pedroso, C., Tate, W. L., Lago da Silva, A., & Ribeiro Carpinetti, L. C. (2021). Supplier development adoption: A conceptual model for triple bottom line (TBL) outcomes. Journal of Cleaner Production, 314(June), 127886. Available at. https://doi.org/10.1016/j.jclepro.2021.127886

[12] Wang, C.-N., Pan, C.-F., Tinh Nguyen, V., & Tam Husain, S. (2022). Sustainable supplier selection model in supply chains during the COVID-19 pandemic. Computers, Materials and Continua, 70(2), 3005–3019. Available at. https://doi.org/10.32604/cmc.2022.020206

[13] Mei, Y., Ye, J., & Zeng, Z. (2016). Entropy-weighted ANP fuzzy comprehensive evaluation of interim product production schemes in one-of-a-kind production. Computers & Industrial Engineering, 100, 144–152. Available at. https://doi.org/10.1016/J.CIE.2016.08.016

[14] Kaur, H., Singh, S. P., Garza-Reyes, J. A., & Mishra, N. (2020). Sustainable stochastic production and procurement problem for resilient supply chain. Computers & Industrial Engineering, 139,105560. Available at. https://doi.org/10.1016/j.cie.2018.12.007

[15] Zeydan, M., Çolpan, C., & Çobanoğlu, C. (2011). A combined methodology for supplier selection and performance evaluation. Expert Systems with Applications, 38(3), 2741–2751. Available at.https://doi.org/10.1016/j.eswa.2010.08.064

[16] Shiri, I., AmirMozafari Sabet, K., Arabi, H. et al. (2021)Standard SPECT myocardial perfusion estimation from half-time acquisitions using deep convolutional residual neural networks. J. Nucl. Cardiol. 28, 2761–2779. https://doi.org/10.1007/s12350-020-02119-y

[17] Yuan, Y.; Shao, C.; Cao, Z.; He, Z.; Zhu, C.; Wang, Y.; Jang, V. (2020) Bus Dynamic Travel Time Prediction: Using a Deep Feature Extraction Framework Based on RNN and DNN. Electronics 2020, 9, 1876. https://doi.org/10.3390/electronics9111876

[18] Chien, CF. et al. (2020) Deep reinforcement learning for selecting demand forecast models to empower Industry 3.5 and an empirical study for a semiconductor component distributor, International Journal of Production Research, 58:9, 2784-2804, DOI: 10.1080/00207543.2020.1733125

[19] Bera, S., Shrivastava, VK(2020) Analysis of various optimizers on deep convolutional neural network model in the application of hyperspectral remote sensing image classification, International Journal of Remote Sensing, 41:7, 2664-2683, DOI: 10.1080/01431161.2019.1694725

[20] Acerbi, F., Rocca, R., et al. (2023) Enhancing the cosmetics industry sustainability through a renewed sustainable supplier selection model, Production & Manufacturing Research, 11:1, DOI: 10.1080/21693277.2022.2161021

[21] Chai, J., Ngai, EWT. (2020) Decision-making techniques in supplier selection: Recent accomplishments and what lies ahead. Expert Systems with Applications. Volume 140, 2020, 112903, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2019.112903

[22] Stević, Z.(2020) Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS), Computers & Industrial Engineering, Volume 140, 2020, 106231,https://doi.org/10.1016/j.cie.2019.106231.

[23] Memari, A., Dargi, A., Akbari Jokar, M. R., Ahmad, R., & Abdul Rahim, A. R. (2019). Sustainable supplier selection: A multi-criteria intuitionistic fuzzy TOPSIS method. Journal of Manufacturing Systems, 50, 9–24. Available at. https://doi.org/10.1016/j.jmsy.2018.11.002

[24] Zhang, J.; Yang, D.; Li, Q.; Lev, B.; Ma, Y. (2021) Research on Sustainable Supplier Selection Based on the Rough DEMATEL and FVIKOR Methods. Sustainability 2021, 13, 88. https://doi.org/10.3390/su13010088

[25] Nair, R.K., et al. "The impact of formal supplier selection process on supplier performance and supplier relationship," Journal of Supply Chain Management, vol. 56, no. 4, 2020.

[26] Mani, V., Agrawal, R., Sharma, V. (2014) Supplier selection using social sustainability: AHP based approach in India. International Strategic Management Review, Volume 2, Issue 2, Pages 98-112

[27] Jessin, T.A., Rajeev, A. and Rajesh, R. (2023), "Supplier selection framework to evade pseudo-resilience and to achieve sustainability in supply chains", International Journal of Emerging Markets, Vol. 18 No. 6, pp. 1425-1452. https://doi.org/10.1108/IJOEM-11-2021-1704

[28] Yuan, Y.; Shao, C.; Cao, Z.; He, Z.; Zhu, C.; Wang, Y.; Jang, V. (2020) Bus Dynamic Travel Time Prediction: Using a Deep Feature Extraction Framework Based on RNN and DNN. Electronics 2020, 9, 1876. https://doi.org/10.3390/electronics9111876

[29] Abdulla, A.; Baryannis, G.; Badi, I. Weighting the Key Features Affecting Supplier Selection using Machine Learning Techniques. Preprints 2019, 2019120154 (doi: 10.20944/preprints201912.0154.v1).

[30] Fernandez-Vazquez, S., Rosillo, R., de la Fuente, D. and Puente, J. (2022), Blockchain in sustainable supply chain management: an application of the analytical hierarchical process (AHP) methodology, Business Process Management Journal, Vol. 28 No. 5/6, pp. 1277-1300. https://doi.org/10.1108/BPMJ-11-2021-0750

[31] Cahuantzi, R., Chen, X., Güttel, S. (2021) A comparison of LSTM and GRU networks for learning symbolic sequences. https://doi.org/10.48550/arXiv.2107.02248

[32] Medicare & Medicaid Services (CMS). (2022) https://data.cms.gov/provider-data/

[33] Feng, W., Zhu, Q., Zhuang, J., et al. (2019) An expert recommendation algorithm based on Pearson correlation coefficient and FP-growth. Cluster Comput 22 (Suppl 3), 7401–7412 (2019). https://doi.org/10.1007/s10586-017-1576-y

[34] Bera, S., Shrivastava, VK(2020) Analysis of various optimizers on deep convolutional neural network model in the application of hyperspectral remote sensing image classification, International Journal of Remote Sensing, 41:7, 2664-2683, DOI: 10.1080/01431161.2019.1694725

[35] Chicco D, Warrens MJ, Jurman G. (2021) The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE, and RMSE in regression analysis evaluation. PeerJ Computer Science 7:e623 https://doi.org/10.7717/peerj-cs.623

[36] Guo, K., et al., Optimized Graph Convolution Recurrent Neural Network for Traffic Prediction, in IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 2, pp. 1138-1149, Feb. 2021, doi: 10.1109/TITS.2019.2963722.

[37] Sheng, Z., Wang, H., Chen, G. et al. Convolutional residual network to short-term load forecasting. Appl Intell 51, 2485–2499 (2021). https://doi.org/10.1007/s10489-020-01932-9