Risk and Disruption in the Supply Chain: Detection Using an Intelligent Decision Support System with System Dynamics Modeling and Deep Learning

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Abstract Detecting and identifying anomalies that cause significant deviations from expected supply chain operations is important for maintaining efficiency and preventing major disruptions in the flow of materials and products. The identification and addressing of these anomalies allows companies to ensure smooth operations, minimize delays, reduce costs, and improve supply chain performance. Thus, effective anomaly detection helps to mitigate risks and maintain the reliability of supply chain processes. This chapter focuses on anomaly detection in the context of smart manufacturing through the use of an Intelligent Decision Support System. The proposed system consists of a prediction subsystem that, in turn, feeds a system dynamics model that simulates the states of the industrial plant. Additionally, it uses a deep learning-based network with an attention mechanism to detect disruptions. In simulation studies, the network is compared against other methods, demonstrating superior performance in the task of disruption detection. Thus our approach not only enhances the accuracy of anomaly detection but also could improve the efficiency and resilience of the supply chain management process.

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1 Introduction

Supply chain management is an important component for the success of any company that relies on the production and distribution of goods. In this context, identifying anomalies, which are significant deviations from the expected, is essential to maintain efficiency and avoid significant problems that can disrupt the flow of materials and products [9]. With technological advancements, intelligent decision support systems (IDSS) have been developed that use advanced techniques to detect these anomalies and better manage the supply chain, especially in disruptive situations [29]. Similarly, disruptions can also be considered anomalies, as they are unexpected events that can alter the normal functioning of the supply chain. Examples include natural disasters, labor conflicts, production failures, logistical problems, etc. These disruptions have significant negative impacts, such as delays in product delivery, increased logistical costs, and overall customer dissatisfaction. Therefore, it is imperative to have systems capable of anticipating and reacting to these events [27]. According to Tarei et al. [42, 43], supply chain risks have repercussions in the form of low production, lost sales, and delayed deliveries. Ivanov [17], on the other hand, focuses on preventing supply chain risks using simulation models that show the impact on order delivery. In Industry 4.0, intelligent devices that process information in real time are integrated into the supply chain to identify potential risks between demand and suppliers through the implementation of a decision support system (DSS) that helps managers to have better coordination by predicting demand with real-time data, as well as the maximum inventory level.

Predicting supply chain disruptions helps managers determine the maximum inventory level to deal with transportation and production delays. Conversely, the cost of not anticipating a disruption, specially a major outbreak like COVID-19, had significant economic impacts, including the immediate and widespread disruption of the global supply chain as revealed in the study by [32]. As noted by Wang et al [48], supply chain disruptions are caused mainly by uncertainty in demand, suppliers, and deliveries. Another study presented in [38], suggests that supplier disruption can also result from decreased capacity or bankruptcy, while Yin et al. [52] mentions that transportation disruption affects the flow of both finished products and materials in the supply chain. Thus, using a DSS that analyses these factors in a disruptive supply chain could be an efficient tool for risk analysis, as argued in Ali et al. [2]. In [33] it is proposed a DSS for dynamic risk analysis. Tsiamas et al. [47] propose a simulation model with DSS to improve decision-making and respond to anticipated supply chain disruption, relying on a historical database available. Andry et al. [3] developed a DSS to improve supply chain processes. Teniwut and Hasym [45] proposed a DSS that helps to increase efficiency, profitability and customer satisfaction in the supply chain of components. The implementation of the DSS in the supply chain requires the entry of orders, sales, transactions and safety stock. Please, note that in this work, the terms "anomaly" and "disruption" will be used interchangeably.

Based on the previous literature review, this chapter describes a proposal to use a IDSS focused primarily on anomaly/disruption detection in the context of smart manufacturing. It utilizes prediction modules and system dynamics modeling, as well as a deep learning-based architecture for disruption detection. The purpose is to enhance the efficiency, reliability, and responsiveness of supply chains. The main contributions of this work are:

- A DSS that utilizes a prediction system to feed a system dynamics model, predicting future states of the industrial plant and the subsequent detection of disruptions through artificial neural networks.
- The design of a system dynamics model specifically tailored for the metalworking industry, focusing on a supplier manufacturing membranes for automobiles.
- The development of a new deep learning architecture that employs a layer for sequential data processing using convolutional networks, GRU, and an attention mechanism for disruption detection.

2 Background

This section provides an overview of smart manufacturing and the disruptions affecting supply chains. It also discusses the use of anomaly detection in Decision Support Systems.

2.1 Supply chain management conceptualization

The supply chain is a concept that involves coordinating activities related to the production and delivery of products and services from suppliers to the final customer [31], facilitated through information flows and transactions across the entire logistics network. Some authors describe it as an internal network within an organization that facilitates the delivery of finished products or services to customers through various processes, starting with the purchase of materials and continuing with design, planning, production, and logistics management to ensure they reach their destination. This requires the flow of information, goods, products, money, and transactions from suppliers to consumers [35]. It is a complex network involving the flow of goods, services, information, and customers. Its main characteristics include material specifications, organizational structure, and regulatory frameworks, all of which influence supply chain traceability. Understanding these characteristics is key to achieving transparency, sustainability, and accountability [40].

The supply chain enables value creation, logistics management, synchronization with demand, and performance evaluation [26]. Supply chain management refers to the coordination of activities in the production and distribution of goods and services from suppliers to customers. This is achieved through the collaboration of various entities to ensure the efficient movement of products, overcoming demand variability and the risk of product obsolescence, as seen in the automotive sector [1].

2.1.1 Importance and relationship of supply chain with smart manufacturing

Today, addressing the supply chain alongside smart manufacturing is increasingly common due to their interconnection. On one hand, the former deals with aspects of Industry 4.0, which involves elements like machines, products, and people in supply chain and manufacturing processes [25]. On the other hand, the latter focuses on logistical operations from suppliers to final customers, utilizing technologies such as IoT, cloud computing, intelligent management theories, system automation, and interconnected work across all collaborating companies [50].

The integration of technologies into the supply chain has allowed companies to improve agility, customization, and responsiveness to changes and disruptions [14]. Convergence is achieved when digital twins and collaborative models for smart manufacturing, such as product development or lifecycle analysis, are applied [41, 20]. Additionally, there is greater confidence in the management of goods and products, as well as enhanced traceability and transparency throughout the entire supply chain [12].

Supply chain and smart manufacturing are closely related when approached from the perspective of Industry 4.0. For example, smart manufacturing refers to the incorporation of technologies to digitize processes within a company through extensive real-time data collection and analysis. This requires connectivity for information monitoring via IoT, cloud computing, and technologies like blockchain. This leads to the concept of an intelligent supply chain, given its positive impact on improving agility, efficiency, and quality throughout the supply chain. By adopting the principles of Industry 4.0 and smart supply chain management, companies can maintain their competitiveness in a dynamic business environment. Therefore, it is important to leverage cutting-edge technologies to enhance efficiency and transparency in production processes while adhering to the contemporary industrial approach [23].

2.2 Disruption in the supply chain

Next, we will review some studies that analyze and suggest solutions to reduce the impact of disruptions and their associated effects. The work of [51] evaluated the impact of transportation disruption on the second link of the supply chain, which impacts the service level. In [7] system dynamics is used to analyze the effects of terrorist acts on the performance of the supply chain at a global level and highlight the increase in inventory by 600% due to the increase in security measures on the border with Mexico. In [36] it is proposed a system dynamics model to analyze the probability of machine failure due to a shortage of spare parts inventory, which impacts the delivery of finished products. The study in [46] evaluates supplier disruption considering backorders using system dynamics. In [5] system dynamics and genetic algorithms are integrated to reduce the bullwhip effect in the supply chain and optimize inventory and demand forecasting values, as well as inventory costs, backorder costs. The work of [24] analyze the domino effect in the supply chain using system dynamics considering inventory level, backorders, and demand. In the study of [30] it is developed a model to quantify the domino effect in the supply chain with a proactive approach using system dynamics that impacts service level, costs, profitability, and inventory levels. In [10] it is analyzed the impact of COVID-19 on the disruption of material flow using system dynamics, which influences changes in inventory level. The study of [13] visualizes the domino effect in the supply chain, characterized by severe disruptions due to risks in demand, suppliers, and logistics using system dynamics. The work of [21] considered the impact on service level. In [18] it is proposed that to mitigate supply chain disruption, suppliers must increase their production capacity and safety stock, and also consider supplier delays due to material shortages and changes in demand. Finally in [6] it is analyzed the domino effect in the supply chain to maximize post-pandemic customer satisfaction using system dynamics.

2.3 Anomaly detection and DSS

In the supply chain, anomalies could originate from the disruption in the supply of raw material shared and transferred among supply chain members, whether related to orders, products, or other factors. This leads to misleading decisions within companies regarding production or inventory levels [11]. Other studies attribute anomalies to equity levels in the supply chain, specifically when dominant companies gain more profit compared to subordinate companies, affecting internal decisions [49].

Anomalies also arise due to the complexity of supply chains, involving multiple customers, suppliers, and consumers. This complexity leads to disruptions in logistical operations, inaccuracies in inventory, and demand fluctuations [4]. For example, the bullwhip effect amplifies variations and is a common anomaly with negative impacts on inventory management. In [22] it is noted that supply chain anomalies can also result from delays at ports or airports, inflation, or material shortages due to the complexity and global involvement in current supply chains.

When anomalies occur in the supply chain, they increase costs, cause product delivery delays, and decrease operational efficiency and performance. Detecting anomalies in supply chain management is important for preventing problems and optimizing efficiency. In [27] it is highlighted the importance of identifying these instances on time, which can improve the response of the managers to make decisions that improve the scenario in the face of disruption.

Due to the problems caused by anomalies and disruptions in the supply chain, several studies have proposed using DSS to anticipate and improve responses to these events. For example in [34], a knowledge-based IDSS is proposed for managing operational risks in global supply chains. Their system predicts supply chain performance by employing artificial neural networks alongside particle swarm optimization. It also identifies risk sources using principal component analysis and assesses risk mitigation options using a digraph-matrix approach combined with principal component analysis. In the work of [16] it is proposed a fusion IDSS which employs data envelopment analysis and rough set theory to make an analysis of the risks in the supply chain. The study in [37] proposed the use of ontology for the design of a IDSS to improve supply chain resilience against disruptions. They used semantics and ontology to develop a basic knowledge base of the supply chain network. Their knowledge base uses the semantic web rules language to encode properties types and classes and sub-classes in the supply chain. Additionally they used mixed integer linear programming to optimize a quantified resilience objective function. To solve the problem they employ a hybrid particle swarm optimization with differential evolution. In [44] it is developed a DSS to assist in the selection of strategies for risk management. Their system uses a rule-based fuzzy inference system to model the decision variables in the DSS.

3 Methodological design

The objective of this research is to address anomaly detection in the supply chain using a DSS that integrates system dynamics modeling and machine learning algorithms to predict abnormal behaviors. This approach aims to enable early detection, allowing for timely correction of errors. The Fig. 1 shows the general outline of the proposed IDSS.

3.1 IDSS for disruption detection

In this chapter, an IDSS has been chosen due to its ability to handle large volumes of data and improve decision-making accuracy. The increasing complexity of modern supply chains and the frequency of disruptions necessitate advanced tools for effective management. The proposed system will primarily focus on disruption detection, but it will also offer other key process indicators. This section provides a detailed description of the IDSS shown in Fig. 1, including its components and functionality.

3.1.1 Information Sources Module

The first component of the IDSS is the information sources. In this case, various sources have been selected such as historical data, real time data, and external and trend data. Historical data is important for analysis and strategic decision-making, as it helps identify patterns, trends, and areas for improvement, as well as to predict future behaviors and plan more efficiently. Historical data consists of detailed records collected over time on various activities and operations within the industry. These data can include production and sales volumes per period, order and delivery history, inventory levels of raw materials, work-in-progress, and finished products, purchase history of raw materials and components, shipping and delivery history, among others. In this IDSS, particular emphasis will be placed on the shipping and delivery history by monitoring shipping rates and receiving delays. In addition to historical data, real-time monitoring of the company's daily operations will also be conducted. Additionally, external and trend data are analyzed since these data provides information about market conditions, competitor activities, and economic trends. This helps businesses understand their competitive landscape and identify opportunities and threats. We also consider trend data in order to help to identify long-term shifts in consumer behavior, technological advancements, and industry standards. By processing these trends, the IDSS can adapt their strategies and scenarios for better decision support.

3.1.2 Risk Analysis Module

This module contains the system's prediction models, which include a time series prediction model and a system dynamics model. The prediction model takes time series data from the Information Sources Module as input. The module can predict future time series data over a specified prediction horizon, providing possible future scenarios. Additionally, the prediction output can feed into the system dynamics

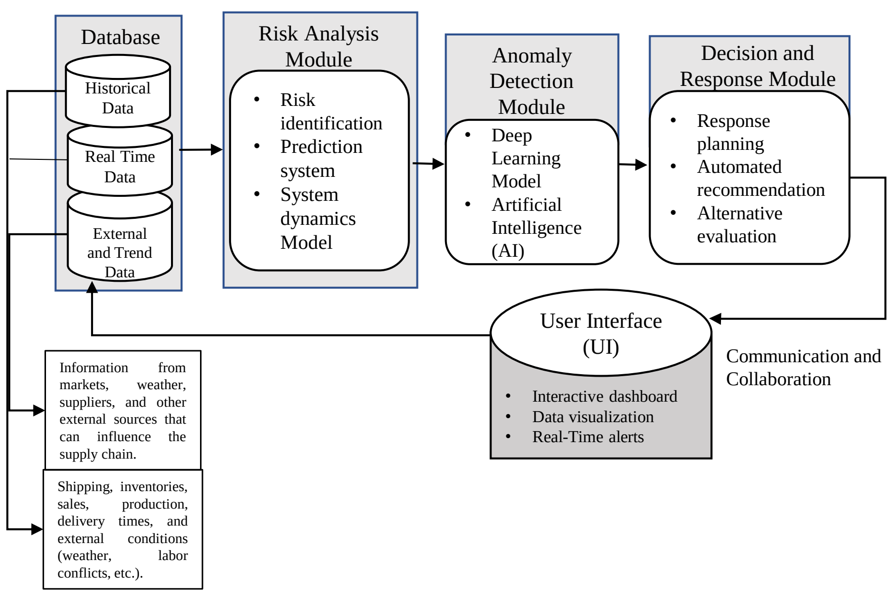

Fig. 1 Proposed IDSS for anomaly detection in the supply chain.
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model, which can simulate the behavior of other industrial plant processes based on the prediction horizon.

The prediction system is not implemented in this chapter as there are already well-established techniques in the literature, from classical methods like exponential smoothing and Autoregressive Integrated Moving Average (ARIMA) to modern techniques based on Deep Learning, such as Facebook's Prophet [28, 39]. Since we are particularly interested in disruption detection, the prediction system will take receiving delays and receiving rates as input, and use system dynamics modeling to simulate future shipping rates. This simulation will then be used by the proposed Deep Learning network for disruption detection. A block diagram of the operation of this module is shown in Fig. 2.

3.1.3 System dynamics model

In this section is presented the design of the system dynamics model. The model is tailored to the metalworking industry, specifically a supplier manufacturing membranes for automobiles.

Fig. 3 shows the causal diagram of the disruptive model used to describe potential causes and effects through dynamic hypotheses that help determine the system's behavior over time. It establishes a feedback loop between two or more variables that are related either positively or negatively. Arrows indicate a positive relationship when an increase in one variable leads to an increase in the other, represented by a positive feedback loop (R). Conversely, a negative relationship is indicated when an increase in one variable leads to a decrease in the other, represented by a negative feedback loop (B). The causal model is constructed to determine the relationship between the variables of interest: Buying Rate, Membrane Orders, Receiving Rate, Membrane Inventory, Shipping Rate, and Reorder Point.

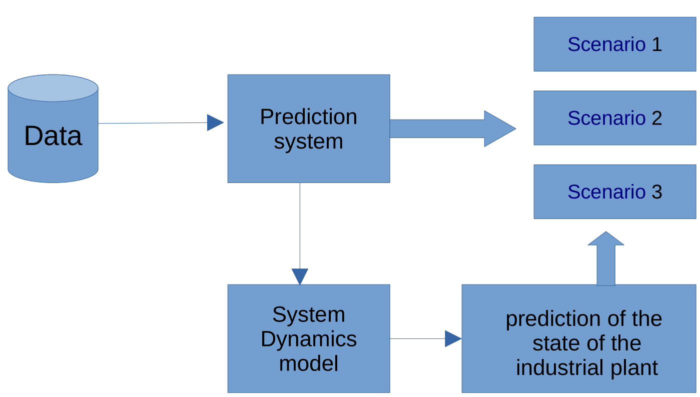

Fig. 2 Block diagram for the module using the predictor and the system dynamics model
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- B1: Shipping Rate: If the shipping rate increases, the membrane inventory level decreases. If the membrane inventory level increases, the shipping rate decreases.
- B2: Receiving Rate: If the receiving rate from the supplier increases, the number of membrane orders placed with the supplier decreases.
- B3: Membrane Inventory Level: If the buying rate decreases, the number of orders placed with the supplier increases. Consequently, the receiving rate of orders in the raw materials warehouse increases, leading to an increase in membrane inventory levels.
- R1: Buying Rate: If the buying rate increases, the reorder point increases under a continuous review policy. If the reorder point increases, the buying rate from the membrane supplier also increases.

Fig. 4 illustrates the simulation model using a system dynamics approach. The model includes two stock variables: ”Membrane Orders” and ”Membrane automotive Inventory.” It assumes a requested quantity of 100,000 membranes from the supplier, with an initial membrane inventory set to zero. The flow variables are:

- Buyer’s Order Rate: This is the difference between the reorder point and the membrane inventory, adjusted for a two-month delay due to the global steel shortage. The reorder point is the minimum inventory level at which a new order is placed with the supplier. The demand follows a normal distribution with a monthly average of 100,000 membranes and a standard deviation of 4,000 membranes. The supplier takes two weeks (0.5 months) to deliver an order, with

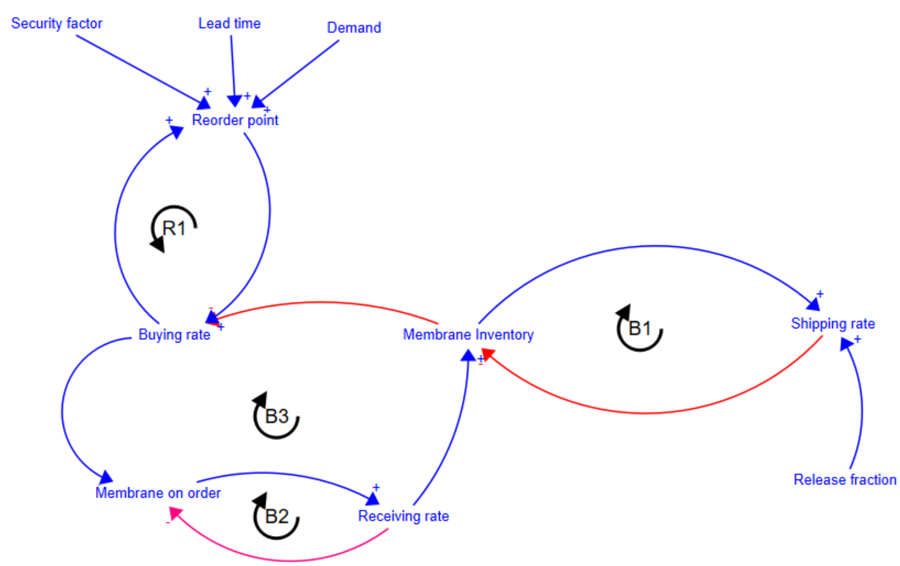

Fig. 3 Causal diagram of the proposed system dynamics model

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a 95% safety factor to meet the customer's demand. The safety stock level is set at 1,200 membranes.

- Receiving Rate: This represents the rate at which materials enter the raw material warehouse. It is calculated as the number of membranes ordered from the supplier divided by the delay in receiving materials due to transportation delays from the supplier to the company.
- Shipping Rate: This indicates the rate at which prepared membranes are shipped to the customer. It is determined by dividing the membrane inventory level by the proportion of membranes released by the customer, which ranges from 0.05 to 0.125.

The flow variables are represented by arrows, while parameters such as delivery time, delay adjustments, and the membrane release rate by the customer are represented by circles.

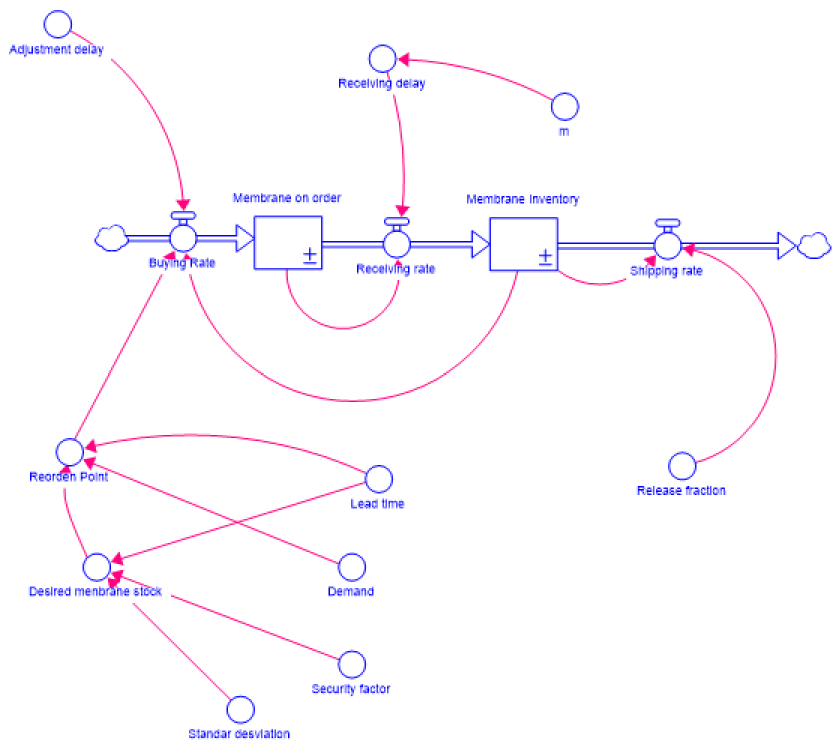

Fig. 4 Proposed system dynamics model

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3.1.4 Anomaly detection Module

In this module, a neural network architecture is proposed for the detection of disruptions. To do this, the shipping rate will be evaluated in search of any pattern that may indicate the beginning of a disruption.

Let $X = \{x_n\}_{n=0}^{N}$ be the time variation in the shipping rate, the task of the proposed network architecture is to detect a disruption from samples x_n from X. In terms of machine learning a sample x_n will be classified as part of a disruption o not. In order to provide context for x_n the input to the network is a subsequence, X_n of X, where $X_n = \{x_{n-L-1}, ..., x_{n-2}, x_{n-1}, , x_n\}$ and L is the size of the subsequence. Fig. 5 illustrate this process.

For the construction of the network architecture it is selected as input layer a convolutional element. The convolutional layer is capable of obtain rich features from the input. This layer convolved the input subsequence X_n, with several kernels or filters with learnable parameters. The output tensor consist of a series of feature maps that help in the process of classification of the following layers in the network. For the case of the proposed network architecture we used a one dimensional convolutional layer with five filters o kernels, each of size two, also we fix the length of the input subsequence to $L = 14$. Once that the input sequence is transformed into a sequence of features found by the convolutional layer, it is processed by a Gated Recurrent Unit (GRU) layer [8]. The GRU processes the input data allowing information contained in the sequence to be selectively remembered or forgotten over time. Thus, allowing to handle long-term dependencies in sequential data by selectively remembering and forgetting previous inputs. Here we used a GRU with 24 units, the output of the GRU is passed to an attention layer, these layer are know to selectively focusing on important elements of the input tensor emphasizing relevant information for the next layer to improve the classification performance. The output of the attention layer is concatenated with the output of the previous convolutional layer to obtain a richer feature tensor. This tensor is passed to dense network consisting of four layers of 80, 20, and 5 neurons respectively, all with ReLU activation functions, and finally the final classification is done by a neuron with sigmoid activation function, which

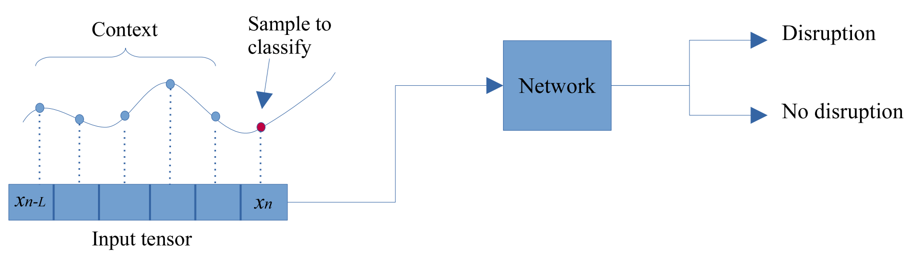


Fig. 5 Construction of the input tensor from the sample to classify and its context

classifies the input in disruption or not disruption. The complete architecture is show in Fig. 6.

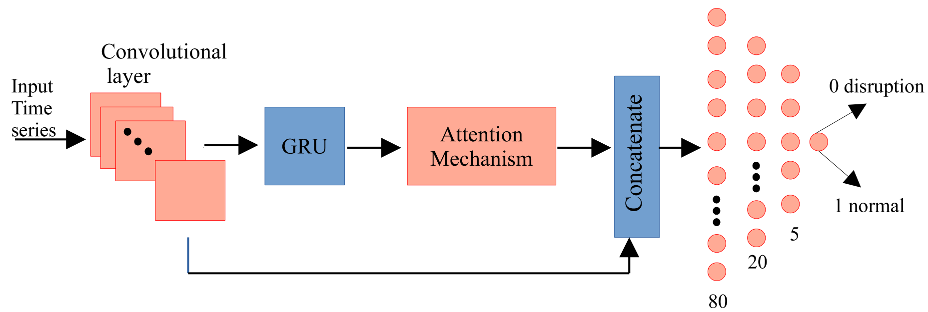


Fig. 6 Proposed deep learning architecture. From a time series input, it is able to detect whether or not there are disruptions

3.1.5 Decision and response module

The decision and response module is designed to aid decision-makers in identifying optimal actions and responses based on analyzed data and predicted scenarios. This module plays an important role in translating insights from data analysis into actionable decisions and is attached directly to the dashboard.

3.2 Metrics for disruption detection

To evaluate the performance of algorithms for abnormality/disruption detection, the following metrics are generally used.

Sensitivity

This metric evaluates how good a given model is at identifying disruptions as a percentage of all disruptions days in the data. It evaluates the proportion of disruption days that the method is able to correctly identify. This metrics is also called recall and is calculated as follows

$$Sensitivity = \frac{TP}{P} \tag{1}$$

Where TP are the true positives, in this context, these are the days classified as disruption days by the detector that are indeed disruption days, and P are the total of disruption days.

Specificity

This metric evaluates the detector's ability to identify days of no disruption as a percent of all of the observations without disruptions. This metric is calculated as

$$Specificity = \frac{TN}{N} \tag{2}$$

Where TN are the true negatives, in this case the days detected as non disruption days, and N are the number of days without disruption.

Miss rate

Also known as false negative rate and is an estimate of the probability that a true disruption day will be missed by the test. It is calculated as

$$MissRate = \frac{FN}{P} \tag{3}$$

Where FN are the false negatives.

Fall-out

Also called false positive rate or probability of false alarm. This metric measures the proportion of non-disruption days that were incorrectly identified as disruption that is false alarms. The fall-out is given by

$$Fall - out = \frac{FP}{P} \tag{4}$$

Where FP are false positives, that is false disruption days.

4 Results

In this section, we validate the Deep Learning architecture for disruption detection. We generated data by simulating disruptions in the supply chain using the system dynamics model. Specifically, we simulated a total of 1,200 days and introduced six disruptions in the receiving delay. These disruptions are modeled using ramp func-

Table 1 Detail of the disruptions

Disruptions	Begining	Days	Slope
Disruption 1	200	20	0.7
Disruption 2	350	20	0.55
Disruption 3	500	40	0.85
Disruption 4	650	20	0.35
Disruption 5	1000	15	0.55
Disruption 6	1100	15	0.75

tions with varying slopes and number of days. Table 1 provides detailed descriptions of each disruption, and Fig. 7 illustrates a segment of the simulated data depicting one of these disruptions. This will be the input to the system dynamics model, from which in turn the shipping rate will be taken as input to the neural network. Note that in this way the network can work with data that is not directly measured or with data with which it was not trained. This allows the network to be reused with different data.

The proposed algorithm for disruption detection was compared with two other methods: one based on support vector machines (SVM), commonly used in detection literature [15], and another using autoencoders based on LSTM (LSTM AC) [19]. For the SVM, a regularization parameter of one and a radial basis function (RBF) kernel were used. No optimization was done to adjust further the hyperparameters. The LSTM-based network used two LSTM layers with 104 units each; the first was in sequence-to-sequence mode, and the second returned only the last output. The decoder had the same configuration, but at the end, a dense network with four layers

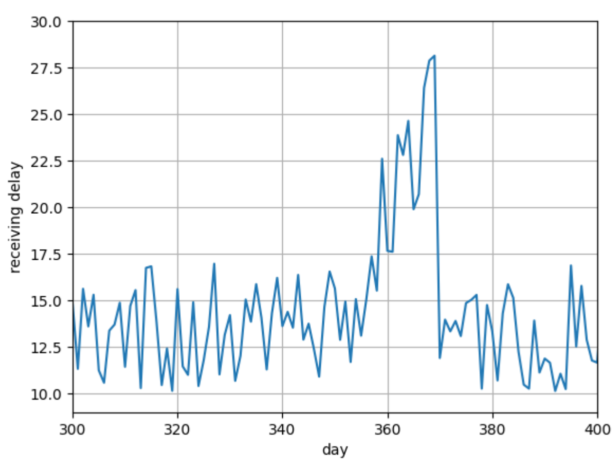
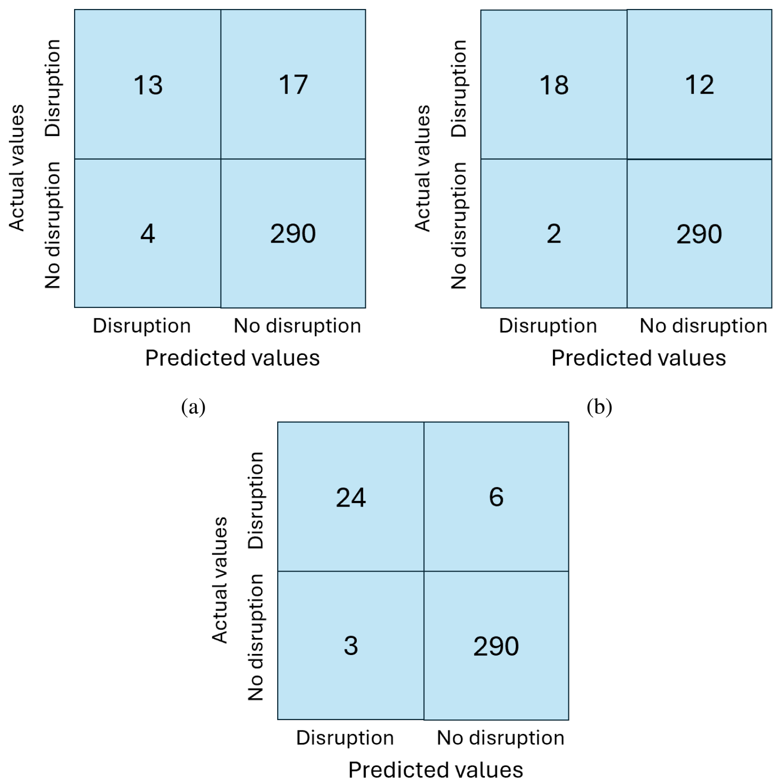


Fig. 7 Simulation data, a disruption is observed that begins on day 350 with an approximate duration of 20 days.

consisting of 150, 50, 10, and 1 neuron was used. All layers had ReLU activation, except for the last one, which used a sigmoid activation function. To build the training and test sets, the data from the systems dynamics model were divided into subsequences of 14 samples. If a subsequence contained days within the disruption, it was labeled as a disruption; if the subsequence contained no days from the disruption, it was labeled as non-disruption. Note that, in this way, there may be more subsequences labeled as disruptions than the number of simulated disruptions. For training all methods, 70% of the simulated data was used, while the remaining 30% was reserved for testing.

Fig. 8, shows the confusion matrices obtained by the different methods. The test data contained two disruptions of 15 days each, while the rest of the days contain not disruptions. The proposed method is the one that correctly detected the most days of disruption, while the SVM method is the one that correctly detects the least number of days of disruption, only 13 of the 30 days with disruptions.



(a) (b) (c)

Fig. 8 Confusion matrices of the different methods: (a) SVM, (b) LSTM AC, and (c) proposed

Table 2 Metrics of the different methods

Detector	Sensitivity	Specificity	Miss rate	Fall-out
SVM	0.43	0.98	0.56	0.013
LSTM AC	0.6	0.99	0.4	0.006
Proposed	0.8	0.98	0.2	0.010

Table 2 presents metrics summarizing the performance of each method. Our proposed method achieved the highest sensitivity at 0.8, indicating its superior ability to identify disruption days. The LSTM AC method followed with a sensitivity of 0.6, which is lower than our proposed method. For the specificity metric, all methods performed well, with LSTM AC achieving the highest score of 0.99, closely followed by SVM and our proposed method at 0.98. The proposed method also showed the lowest Miss rate at 0.2, meaning it detected most disruption days correctly. In comparison, LSTM and SVM had higher Miss rates of 0.4 and 0.56, respectively. All methods exhibited low fall-out rates (probability of false alarm), with LSTM achieving the lowest.

5 Conclusions

In this chapter was presented an approach to anomaly detection in smart manufacturing using an Intelligent Decision Support System. The proposed IDSS uses a prediction system to feed a system dynamics model, predicting future states of the industrial plant and the subsequent detection of disruptions through artificial neural networks. The integration of system dynamics modeling and deep learning algorithms allows for a more comprehensive understanding of the complex interactions within the supply chain, facilitating better decision for planning. The proposed deep learning-based network that incorporated an attention mechanism, has proven to be effective in identifying disruptions within the supply chain. In comparisons it was demonstrated that the proposed approach outperforms the other methods for the task of disruption detection. The designed model using system dynamics was tailored for the metalworking industry, specifically for a supplier manufacturing membranes for automobiles, however, underscores the practical applicability of this research, and the model can be adapted and applied to other industries or manufacturing contexts. The work presented in this chapter could contribute to the advancement of smart manufacturing by providing a new tool that enhances the efficiency, reliability, and responsiveness of supply chains, by proactively detecting and addressing anomalies.

Based on the results obtained in this research on anomaly detection in smart manufacturing using an IDSS, several directions for future work can be explored. One possibility is the expansion of the system to other industries, focusing on the adaptation and validation of the system dynamics model and deep learning architecture for different sectors. Additionally, improving deep learning algorithms could involve investigating hybrid architectures that combine various sequential data processing techniques, such as Transformers and LSTM. Finally, the integration of real-time data sources, such as IoT sensors and enterprise information systems, could enhance the IDSS's ability to detect and respond to anomalies.

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