A predictive data-driven approach for supply chain quality risks in the automotive sector

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Abstract: Nowadays, modern supply chains are exposed to an increasing number of risks. Among different risks, supplier quality risks consist of non-compliant delivery of supplier products, which on the one hand, can affect the inventory and, on the other hand, can lead to an increased workload due to the time spent to manage quality issues. In supply chain risk management, artificial intelligence, machine learning and deep learning have been identified as valuable tools for predicting incumbent risk. However, a lack of data-driven approaches for predicting the extra amount of time required to manage supply chain quality risk has been identified in the literature. The aim of this paper is thus to present a deep learning model for predicting supplier quality risk and to investigate its predictive capabilities. The potential of the proposed approach has been tested on a real case study of an Italian automotive company and its performance has been compared with other predictive models when considering forecasts made at different levels of aggregation and with different forecasting lengths.

Keywords: Supply chain resilience, Artificial intelligence, data-driven methods, quality risks

I. INTRODUCTION

Supply chains are nowadays more prone than ever to disruptions. Indeed, extreme natural events, pandemics, and geopolitical instability have repeatedly mined their stability. In this context, building supply chain resilience (SCRES), defined as the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function [1], has thus become fundamental.

From this perspective, researchers have thus started to investigate how technologies introduced by the Industry 4.0 paradigm to gain efficiency can also be adopted in the new Industry 5.0 paradigm to gain resilience [2],[3]. In [4], Industry 4.0 technologies have been classified based on their support to SCRES antecedents and SCRES phases. Among the various technologies, artificial intelligence has shown great potential to enhance the supply chain understanding and provide vital support in the readiness phase. In particular, under the broad umbrella of artificial intelligence, supervised machine learning and deep learning tools have shown the capabilities to proactively deal with supply chain risk [5].

According to the classification proposed in [6], supply chain risks can be classified as operational and disruption risks. Operational risks can be further classified, according to [7], into quality risks, capacity/inventory risks, supply risks, demand risks, information flow risks, transportation risks, commodity price fluctuation risks, exchange rate risks, credit risks, environmental risks, and reputation risks.

In particular, the necessity of good management of quality risk has been highlighted in several works [8]. Formally quality risk is associated with variability in quality, reliability, and execution/control related to poor supplier quality and quality of products produced by the firm. As emerged from the definition, quality risk can be thus seen from two different perspectives: an internal-to-firm perspective and a supply chain-related perspective.

However, two major gaps can be noticed by revising the literature on both predictive models for operational and quality risks. On the one hand, predictive models for operational risks focused primarily on demand and supply risk. On the other hand, literature specifically focus on predictive approaches for quality risk, focused almost totally on internal to firm predictive models, neglecting the supply perspective of quality risk. Aimed by the evidence of the necessity to produce knowledge about how to design predictive approaches for managing quality risk, the main contributions of this paper are thus the following:

- A deep learning predictive approach specifically tailored for predicting supply quality risk is proposed for the first time.
- The predictive capability of the proposed approach is tested on a real case study of an automotive company.
- An experimental comparison of the proposed approach against other traditional predictive models is executed considering different forecasting horizons and levels of aggregation.

The rest of the paper is organized as follows: Section 2 reviews the literature. Section 3 presents the new proposed approach, the procedure adopted for testing the performance of the proposed approach, and the data related to the case study on which it has been tested. Section 4 presents the result of the application of the proposed approach to the case study. Lastly, Section 5 discusses the results, the implication of this work, its limits, and future research directions.

II. Related works

A. Predictive approach for operational risks

Among supply chain operational risks, supply risk, defined as the risk from upstream operations associated with suppliers and their supply network, has been the object of several predictive approaches. In [9] authors proposed a predictive approach to support cost estimation for purchasing decisions. The authors investigate the applicability and efficiency of the proposed approach in a case study of a German automotive original equipment manufacturer. Data related to the historical price of 856 cast aluminum parts and information on the raw materials and production process adopted for their production have been used to train different machine learning models. Results suggested that the best accuracy reached in the case study by the predictive approach results in a mean average percentage error of 20%. Furthermore, the same authors proposed a predictive approach for forecasting supplier delivery reliability [10]. 21'942 historical observations collected over four years have been used to train and test the capability of the predictive model to predict if the purchasing activity will respect a given performance level. Results suggest the capability of the proposed approach to reach an accuracy higher than 85%.

In the same way, demand risk, defined as risk from downstream operations associated with inaccurate demand forecasts, has attracted attention. In [11] a predictive approach based on KNN is proposed to forecast the demand for sporadic components. A case study involving 24 consecutive monthly demand observations for 3000 components in the automotive sector has been used to test the approach. According to the authors, traditional methods for intermittent demand should be preferred to the proposed approach if there is no definite knowledge that some components' demand patterns repeat themselves over time. A multivariate approach for multi-step demand forecasting has been proposed by [12] instead. Experiments have been conducted on 459 weekly demand observations for three different components identified as critical items in the logistics department of Bosch Automotive Electronics Portugal. Results highlight the superior performance of the multivariate approach compared to a univariate one. Furthermore, the traditional ARIMAX model has shown better performance than advanced machine learning models for predicting demand signals at the beginning of the life cycle. In [12] a two-fold approach for predicting demand occurrence and demand size of lumpy and Intermittent demand has been tested over three years of daily observation for 516 different components. Here authors found that global machine learning is the best choice for predicting demand occurrence. On the contrary, simple exponential smoothing forecast results better for predicting demand sizes. Lastly, a similar approach has been proposed in [13]. Two years of weekly observation for 3089 different components have been used for the tests. Experiments revealed the superior performance of the proposed approach over traditional methods.

Predictive approach for credit risk, defined as the risk that parties to whom a firm has extended credit fail to fulfill their obligations, has been proposed in [14]. The proposed approach, which aims at predicting the probability that an actor will default on its financial obligations, has been tested on a supply chain finance network of 500 organizations, reporting a maximum accuracy of 75.75%.

Lastly, predictive approaches for inventory and commodity price fluctuation risks, respectively defined as the risks associated with holding excess capacity and the risk of uncertainty of the cost of goods or energy required for production, have been proposed in [15] and [16].

B. Predictive approaches for quality risks

Multiple researches have been conducted on predictive models for forecasting the quality of products manufactured by a firm. In [17] a data-driven approach was proposed for predicting and autonomously managing quality issues in manufacturing facilities. Furthermore, in [18] authors presented a machine-learning approach for predicting the quality of weld joints in the automotive sector, whose effectiveness has been tested by collecting historical data from a welding plant every 15 minutes for three months. Another predictive approach for predicting the quality of the wholes of automotive bumpers is presented in [19]. Three years of data reporting 1255 quality measurements have been adopted to investigate the approach's feasibility. Results suggest that the quality of different holes cannot always be predicted accurately. In conclusion, the only work which proposed a predictive approach for quality risk from the supply chain perspective is that of [20]. In the work, the authors propose a Markov chain model to predict the quality level of batches of products delivered by suppliers. The model was tested using quality control data recorded over 189 days.

C. Research gap

According to Table 1, which summarizes the revised literature, an evident lack of data-driven approaches tailored explicitly for predicting supply chain quality risk can be noticed. The only paper proposing a predictive approach for quality risk is that of [20]. However, in [20] the authors aims to predict the quality level of incoming batches. No approaches to predict the extra amount of time required to solve supply chain quality issues have been thus proposed up to now. To cover this gap, this paper thus proposes a deep learning model where the traditional machine learning workflow described in [21] is explicitly tailored for this purpose.

TABLE I
LITERATURE SUMMARY (QL: QUALITY LEVEL, EW: EXTRA WORK)

PAPER	OTHER RISKS	PROCESS QUALITY RISK	SUPPLY QUALITY RISKS	
			QL	EW
[9]	x			
[10]	x			
[11]	x			
[12]	x			
[13]	x			
[14]	x			
[15]	x			
[16]	x			
[17]		x		
[18]		x		
[19]		x		
[20]			x	
Proposed approach				**x**

III. MATERIALS AND METHODS

This section presents the proposed data-driven approach to predict the extra amount of time required to solve supply chain quality issues. Afterward, the case study and the experimental comparison performed to test the proposed approach are illustrated.

A. Proposed approach

The proposed approach tailor the traditional machine learning workflow described in [21] to specifically predict the extra amount of time due to supply chain quality issues. In particular, the proposed approach frames the problem as a time series regression problem and, according to this formulation, tailor a coherent data management step and model learning step.

The proposed data management step consists of a data collection step and a data preprocessing step. The data collection step aims to generate a historical supply chain quality issues database. The proposed data collection step thus consists of generating a historical record every time a quality issue is reported. The proposed information to store is the day the quality issue is discovered, the supplier in charge of the non-compliant delivery, the components that resulted in non-compliance, and the extra time required by the manufacturing company to solve the quality issue. Once the data collection step is concluded, the preprocessing step is executed. Here, the generated database is first queried to extract from raw data time series data about the historical evolution of the overall time required to solve the quality issues at a specific level of aggregation. Subsequentially, time series data are scaled between the range [0,1] by performing a min-max normalization [22] procedure.

Once the data management step is executed, a long short-term memory model (LSTM) [23] is proposed for the model learning stage due to its capability to deal with time series data and two different strategies are proposed to tune its hyperparameters. On the one hand, a grid search procedure [24] is proposed to tune the number of layers, neurons per layer and learning rate. On the other hand, an early stopping procedure is adopted to tune the number of epochs.

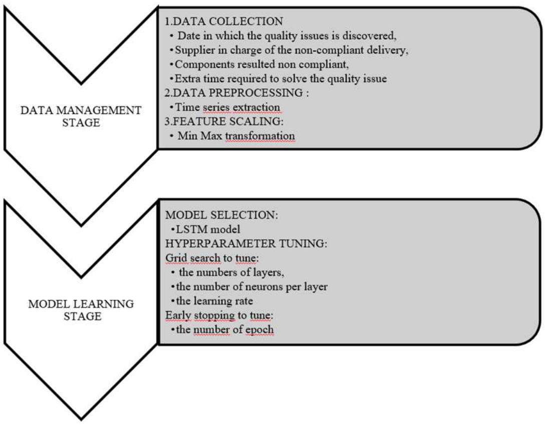

Fig. 1. Machine learning workflow specifically tailored for predicting supply chain quality risks.

B. Experimental setup

To test the effectiveness of the proposed approach a real case study involving an Italian automotive company has been adopted. The database resulting from applying the proposed data collection to the case study for 616 days resulted in quality issues data captured for 24 suppliers and 53 different components.

Starting from the original database, three different levels of aggregation for the preprocessing step have been identified: the manufacturing company level, the supplier level and the component level. As a result, 78 different time series have been extracted:

1. 1 time series containing the recorded overall extra amount of time required to manage all the quality issues experienced every day by the manufacturing company.
2. 24 time series containing the recorded extra amount of time required to manage all the quality issues related to each supplier every day.
3. 53 time series containing the recorded extra amount of time required to manage all the quality issues related to each component every day.

Once the time series have been generated, each time series has been split into three different temporal consecutive subsets, according to three commonly adopted percentages (60%-20%-20%) to obtain the so-called "training set," the "validation set," and the "test set".

For each time series, first, an LSTM model has been trained on the training set and the hyperparameters tuning has been performed, selecting the hyperparameters configuration reporting the lowest mean squared error on the validation set. Afterward, once the best hyperparameters have been selected, the LSTM model has been retrained on both the training and validation set considering the previously identified best value for the hyperparameters

C. Experimental comparison

The test set has been used to conduct experiments about the effectiveness of adopting an LSTM model in the proposed approach. In particular, the accuracy reported by the LSTM model in this set has been compared with that resulting from adopting two other widely used time series forecasting methods: a Naïve forecasting model assuming the future predicted value to be equal to the value reported the previous day and an ARIMA(p,d,q) model [25]. To effectively identify the best value of the hyperparameters p, d and q of the ARIMA model, which respectively represent the order of the autoregressive part, the level of integration and the order of the moving average part, the same setup described for the LSTM model in Section III.B has been followed. Once also the hyperparameters of the ARIMA model has been defined, for each of the three aggregation level identified in Section III.B, the predictive performance of the proposed LSTM model have been compared with that of the two other models also considering different forecasting horizon: 1 day ahead, 7 days ahead and 31 days ahead.

D. Experimental evaluation

Depending on the level of aggregation, different performance metrics have been adopted to compare the predictive performance of the proposed model against the models identified in Section III.C on the test set. In particular, for the time serie resulting from querying the original database at the manufacturing company aggregation level, the adjusted mean absolute percentage error (AMAPE), computed as the ratio between the mean absolute error (MAE) and the mean value over the test set has been used for the evaluation. In contrast, for the time series aggregated at the supplier and component levels, the percentage of times a specific model outperforms the others in terms of AMAPE has been measured. Moreover, for the supplier and components level, the distribution of the error reported every time by the model with the lowest AMAPE has been registered.

IV. RESULTS

Figure 2 compares the AMAPE reported by the proposed approach against those resulting from adopting the ARIMA or the Naïve model when applied for predictions aggregated at the manufacturing company level. According to the chart, the proposed LSTM model can reach an AMAPE of 92% when the forecast is computed one or seven days ahead, while an AMAPE of 101% is reported when the forecast is performed 31 days ahead. Moreover, the proposed approach reports the best performance compared to the other benchmark models.

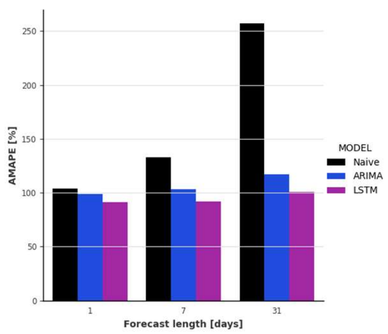

Fig. 2. AMAPE obtained for different forecast lengths for the prediction aggregated at the manufacturing company level.

The comparison results conducted at the supplier aggregation and at the component level are reported in Figures 3 and 4. According to Figure 3, the model which performs best in terms of AMAPE is the naïve forecasting method. At the supplier aggregation, the proposed LSTM outperforms the others only 18 % of times for the one-day ahead forecasting and only 3 % for the seven and 31-days ahead forecasting.

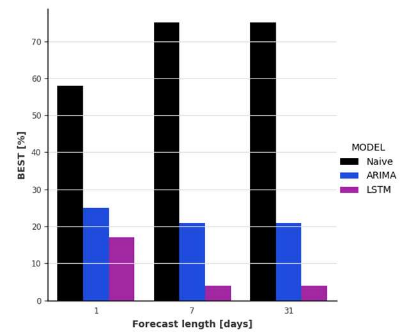

Fig. 3. Percentage of times a model overperform the others for different forecast length for predictions aggregated at the supplier level.

A slightly better performance is reported at the components level where the proposed LSTM model outperforms the other models 12 % of the time for the one-day ahead forecasting, 10% for the seven-day ahead forecasting, and 8% for the 31-day ahead forecasting. However, also for the components aggregation level, the best results are reported by the Naïve model.

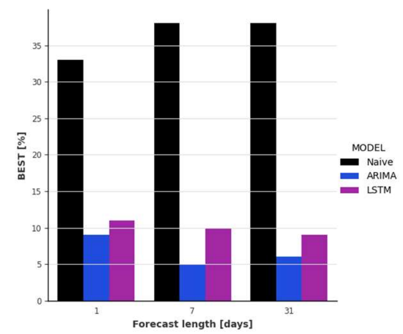

Fig. 4. Percentage of times a model overperform others for different forecast length for predictions aggregated at the components level.

Lastly, in Figure 5 and Figure 6, the distribution of the AMAPE reported by the best models when considering the forecast at the supplier and components levels, respectively, are reported. According to both charts, significantly higher errors than those reported for forecast computed at the manufacturing company aggregation level can be noticed for a certain percentage of components and suppliers.

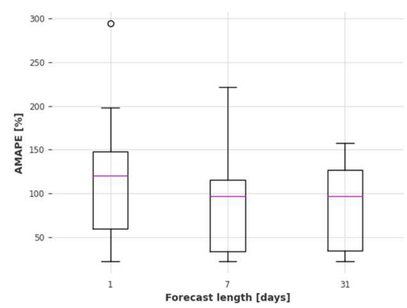

Fig. 5 Adjusted mean absolute percentage error obtained for different forecast lengths for predictions aggregated at the supplier level

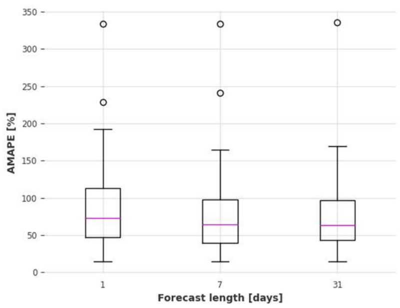

Fig. 6. Adjusted mean absolute percentage error obtained for different forecast lengths for predictions aggregated at the components level.

V. Discussions and Conclusions

Developing predictive models for proactively managing supply chain risk has become fundamental to building resilient supply chains. Quality risk, in particular, is defined as the risks related to poor supplier quality and quality of products produced by the firm that can seriously affect firm performance. Although several predictive approaches have been found in the literature to predict operational supply chain risks and the quality of products produced by firms, a lack of data-driven approaches has been identified to predict the extra amount of time required to manage supply quality risks. To cover this gap, a data-driven approach that tailor the typical machine learning workflow described in [21] is proposed to address this purpose.

Data from a real case study of an Italian Automotive company has been adopted to test the predictive capability of the proposed data-driven approach based on the use of an LSTM model. In particular, the proposed approach has been compared with prediction based on the ARIMA model and from a Naïve forecasting method when considering different forecasting horizons and aggregation levels with which the extra amount of time required to manage quality issues can be predicted.

Results have highlighted the better performance of the proposed LSTM model against the benchmark for all the forecast horizons when predictions about the extra amount of time required to manage quality issues are executed at the manufacturing company aggregation level. On the contrary, the LSTM model adopted in the proposed approach doesn't perform better than the others when forecasts are performed at the supplier or components level and significantly higher errors are reported at this aggregation level.

Discussing results, a similar outcome can be found in [26], where authors have found that deep learning models don't ensure better performance when more granular forecasts are required. However, even if some paper seems to support the obtained results, this study is still subject to some limitations. In particular, only one case study has been adopted to test the approach. Furthermore, only two years of data have been used to train the models. Lastly, the grid search procedure adopted to tune the hyperparameters of the LSTM models, as it is a heuristic procedure, could have led to sub-optimal configurations of it.

Although subject to limitations, the result obtained by applying and comparing the proposed approach with other methods can provide useful insight for practitioners. Predictive models are nowadays fundamental input for planning activities. However, the choice about which value to predict and, thus, which planning activity to support needs to be done considering where predictive models perform better. Referring specifically to supply chain quality risks, predictions in this field can be of help for inventory planning or workforce planning. However, while for inventory planning predictions at the component level are necessary, predictions aggregated at the manufacturing system level are enough for workforce planning activities. In this perspective, the proposed approach thus suggests how to build predictive models for supply chain quality risk. According to the results, tailoring a typical machine learning workflow to provide prediction useful for workforce planning activities allows in fact to use machine learning models where they perform better (i.e. at the highest aggregation level)

Concluding, an interesting future research direction to improve the proposed approach can be that of considering other data as input for the model learning stage to increase the predictive performance of the proposed approach.

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