Journal of Trade Science

ISSN 1859-3666
E-ISSN 2815-5726

Volume 11 Number 1 March 2023

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Journal of Trade Science 11:1 (2023) 64 - 73
ISSN 1859-3666
E-ISSN 2815-5726

PREDICTING RISKS FOR SUPPLY CHAIN MANAGEMENT NETWORKS WITH MACHINE LEARNING ALGORITHM

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Received:*10th August 2022* ***Revised***: *26th Setember 2022* ***Accepted***: *18th October 2022*

Predicting risk in supply chain management networks has been interested by many researchers because supply chain management can be seen as a core factor of businesses activities. Using machine learning algorithm, especially with Bayesian networks, to predict risk in supply chain management network can help to control and monitor the supply chain process in particular in the second step of identification. If the supply chain risk is effectively evaluated, it can support supply chain partners to assess, identify, monitor, and mitigate risks in order to increase robustness and resilience, reduce supply chain vulnerabilities, ensuring continuity and profitability. The Bayesian network have advantage of optimization in explosion dataset based on treating the weights and outputs which find their marginal distributions that best fit the data. The contribution of the paper focuses on summarize the applying of machine learning algorithms in predicting in supply chain management field, proposing supply chain management risk framework in which machine learning algorithms are applied, and demonstrate the case study to show the advantage of using machine learning algorithm in particular of Bayesian networks in risk prediction. The experimental case study shows the good results with the risk model. This implicates the performance of using machine learning in predicting risk in support supply chain management networks.

Keywords:*Supply chain management networks; Risks; Machine learning algorithm; Bayesian neural network.*

JEL Classifications: *C11*

DOI: *10.54404/JTS.2023.11.01.06*

1. Introduction

A Supply Chain Management Network can be seen as a system including many partners such as enterprise of businesses, retailers, suppliers, and others. Therefore, supply chains here are defined as a set of sequential, vertically organized transactions representing successive stages of value creation (Sergio et al, 2001). Other constituent processes of the supply chain include raw material purchasing, warehousing, production, inventory, outbound, transportation and distribution (Rahmani et al., 2020; Hasani et al., 2021).

The vertical interdependencies require a systemic knowledge of resource allocation and information interact between firms engaged in sequential stages of production (Christopher, 1998;

ISSN 1859-3666
E-ISSN 2815-5726

Simchi-Levi et al., 2000). Supply Chain Management (SCM) is a process of planning, implementing and controlling all supply chain activities in an efficient way.

Supply chain is also understood as a chain of products and services that are closely linked together. According to Christopher (Christopher M, 1998) the supply chain management as a network of organizations that have interrelated, through linkage from small to large size, and productive activities that create value for the end consumer's products and services.

Risk in SCM is the probability of a damage or loss or occurrence of any negative events. To reduce the negative effects of risks some actions should be applied consist of identifying risks, assessing and prioritizing them, monitoring and controlling the risks. According to Chopra and Sodhi (2004), the different groups of risks are associated with SCM including delay, inaccuracy in forecasts, or failures in procurement, etc. Any of the mentioned risks threat the overall performance of SCM systems and companies' profitability. As a result, supply chains management systems should be capable in predicting the risks and they have the ability to deal with risks. Therefore, manage the risk is an important issue in SCM.

It is not denying of data role in predicting risks of many systems such as SCM. In addition, based on numerous decisions, uncertainty or information asymmetry also affects supply chain management. Early detection of various supply chain is essential for giving well-timed countermeasures to prevent supply chain disruptions. Minimizing financial losses and processing failures throughout the supply chain are two main purposes of supply chain management based on forecasting potential causes of these process disruptions and analyzing previous interruptions. Machine learning (ML) algorithms can aid in the early detection of risks (Schroeder & Lodemann, 2021). Applying machine learning algorithms to the SCM system can be seen as the process of visualization, automation, and intelligent management of all links in the supply chain. This can effectively help enterprises reduce operating costs and improve their ability to respond to market demands, thereby increasing overall operational efficiency (Haifeng et al, 2022). The accurate collection and reception of information in each link and the rapid and efficient implementation of manager decisions have become crucial to the supply chain management networks.

In this paper, machine learning algorithm is applied with time series data in order to attain requirements for managers' making decisions. The Bayesian network is applied in order to predict the supply chain risk. The advantage of using Bayesian instead of other machine learning algorithms is that Bayesian network can maintain the model's parameters as well as suitable function values in order to optimize the data domain in risk prediction.

The paper has been organized as follows: general introduction about risk assessment in supply chain as well as machine learning in supply chain area is shown in section 1. Section 2 shows the related works. Framework of using machine learning in supply chain management is shown in section 3. In here, the definition of how to calculate the risk indexes for supplier, distributor, retailer, etc. also is introduced. An experimental case study with data is shown in section 4. Implications and conclusion of using machine learning, in particular Bayesian network is introduced in the last section.

2. Related work

Machine learning algorithms can be used to price, adjust storage capacity, change transportation plans by predicting the weather, and timely adjusting business decisions using external data (Ghorashi et al., 2020; Gholizadeh et al., 2020). Machine learning algorithms can be divided to several types such as supervised, unsupervised and reinforcement learning. The supervised learning algorithm is a process in which coding program is trained with historical data. The learning process aims is to find a connection in the form of rules between input data and output data in order to apply the learned rules to the new data. The popular tasks in supervised learning algorithms are classifications and regressions.

Otherwise, unsupervised learning algorithms describe a system in a way to discover knowledge. The output is not defined from starting process. The answers only can be found at the end of applying algorithms. For example, alternative group customers are defined after clustering from potential customers' dataset.

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E-ISSN 2815-5726

With reinforcement learning algorithms, the process tries to find out the optimal solution. Therefore, the learning process must be determined iteratively. In this process, there is a reward or punishment for a solution depending on the output results.

Machine learning algorithms have become a topic of our mainstream and everyday. The potential of machine learning to enhance day-to-day business operations and strategies has not only captured the interest of people and organizations globally, but has already begun to roll out rapidly.

In SCM models, there are three main tasks such as supply chain design, supply chain planning, and supply chain execution (Kuhn and Hellingrath, 2002).

The first task deals with long term planning related to make-or-buy decisions, supply relationships etc. For example, in this field, the challenge is remaining to find suitable business partners to exploit new opportunities. This is especially valid regarding the globalization and the fast development of technology. The machine learning algorithm can help to find new plausible business partners based on company profiles and transaction relationships (Mori et al, 2010). In this publication, a machine learning algorithm of Support Vector Machine (SVM) was applied to find the relationships of the interlinkage of firms such as customers and suppliers as well as number of employees and capital. The accuracy of the SVM algorithm was 85%. The alternative machine learning algorithms also applied in supplier selection processes such as Radial Basis Function (RBF) and SVM neural networks (Kong and Xue, 2013), decision tree and logistic regression (Zhang et al, 2017). For further detail can be seen in Hana et al (2019).

The machine learning algorithms also can be applied in predicting future demand for enterprise (second task). For example, one of Germany's largest drugstore companies (DM) used machine learning algorithms to predict demands for 3,350 store worldwide to ensure the availability of goods via alternative distribution centers. Planning well in advance is accompanied by long-term orders, resulting in high storage costs and tied up capital. Machine learning algorithms are used to create weekly demand forecasts based on 2.5 years of distribution center dataset. As a result, the demand forecasts became so precise in about period of six months and a significant improvement in forecast quality could be achieved and industrial partners are now able to plan much earlier (JDA Software, 2019). The predicting demand also can be seen in publication of Sarhani and El Afia (2014); Gamasaee, Zarandi and Turksen (2015); and dynamic forecasting problem of the supply of goods in the event of a catastrophe (Xue et al, 2018). Machine learning algorithm of SVM was used in all of these publications.

The third task can be seen in the use of RFID identification supporting the shipment of goods and the automatic inventory adjustment issue. In order to differentiate between the moving and static pallets, METRO Group Cash & Carry applied machine learning algorithms which are based on the recorded attributes by each pallet to monitor the pallets in inventory. The used algorithm could correctly classify more than 95.5% of the data. Thus the pallets can be quickly identified and false-positive pallets can be captured directly. This minimized faulty inventory adjustments and deliveries (Keller et al., 2010).

There are some publications related to other supply chain execution such as order management, supply chain event management, and inventory. For example, the manufacturing priority of an order is determined by using RBF neural network (Zhu, Ma and Zhang, 2014). The publication of Arumugam, Umashankar and Narendra (2018) shown an intelligent logistics solution that negotiates contracts, and includes logistics planning and condition monitoring of the facilities. Inprasit and Tanachutiwat (2018) used advantage of neural networks to optimize safety stocks and reorder points for products. The decision tree algorithm was used to solve the obsolete spare parts in the warehouse (Priore et al, 2018).

Risk evaluation in supply chain network is considered as one of vital tasks mentioning to the coordinated and collaborative efforts of all supply chain stakeholders to assess, identify, monitor, and mitigate risks in order to increase robustness and resilience, reduce supply chain vulnerabilities, ☞

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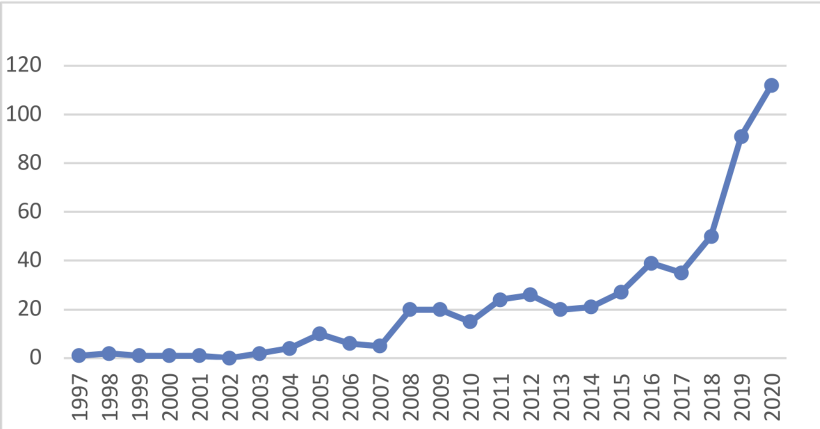
E-ISSN 2815-5726

ensuring continuity and profitability. Using machine learning to assess the risk in supply chain network has been attracted many research and become potential approaches. Especially, applying neural networks in supply chain risk management tend to increase dramatically (see in Figure 1).



Source: Schroeder & Lodemann, 2021

Figure 1: *Historical series of published papers on machine learning in Supply chain risk management.*

For other areas of using machine learning algorithms dealing with big data, the purpose is extracting automatically the patterns inside data from multi-dimensional resource. For more detail, the publications can be seen in (Baryannis et al., 2019; Schroeder & Lodemann, 2021). Banerjee et al (2020) proposed Pareto Optimization based on a genetic approach to estimate uncertainty of the model and compare the results with serveral state-of-art machine learning techniques such as LSTM, CNN, RNN.

Schroeder & Lodemann (2021) proposed a framework to identify the risks in supply chain management practical use cases based on machine learning, including procurement, production, transportation and sales. His results showed that applicable examples are mainly related to early risks' detection in production, transportation and supply in order to quickly resolve potential supply chain issues.

Although many studies have shown some limitation of these approaches such as not offering any real-world examples, machine learning has positive effect on supply chain risk management. So, applying machine learning can become a bright future in supply chain management (Ni et al., 2020; Wang & Zhang, 2020). The model applying machine learning in SCRM can:

Identify, predict, assess, monitor, and mitigate risks

Increase robustness and resilience of the supply chain

Ensure profitability and continuity.

3. Predicting Risk in supply chain management network using machine learning algorithm

3.1. *Risk predicting framework*

Supply chain network risk management is a long-term strategy, to develop a complete risk management plan, businesses often rely on 4 basic steps (Hanah et al, 2019) such as: Identify, Evaluate and analysis, Handle and Monitor risks. Detail each step in supply chain network risk management can be done as follows:

Step 1: Identify risks: Although risks come from many different causes, even from things that businesses cannot anticipate. However, much of the risk comes from avoidable causes. Therefore, risk identification is the first and indispensable step of a supply chain risk management strategy. This is a step that needs to be followed closely and continuously updated to ensure that risks are addressed in a timely manner. At this step, businesses need to establish a list of possible risks for the current situation of the supply chain. Then it is to classify them

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E-ISSN 2815-5726

into their respective risk groups to provide appropriate risk approaches and solutions. There are many ways to classify risks such as: classification by level of impact, classification by risk nature, or risk classification in each function in the supply chain, etc. To create a comprehensive risk portfolio, managers need to capture information from all parts of the supply chain. In other words, collecting opinions, evaluations and reports from personnel or departments responsible for operating a specific function in the chain such as demand forecasting, purchasing, production, logistics, transportation, etc. From the information of the parties involved, businesses can identify a list of issues that can affect activities in the supply chain.

Step 2: Analyze and Evaluate risks: After listing and classifying, the next step is to make an assessment for each risk group in order to establish an appropriate solution. The goal of the risk assessment is to show which activities in the supply chain are the most at risk of problems. By assessing risks, businesses can know the nature and causes of risks as well as the frequency of risks and their potential impacts on the supply chain. Thereby the business can give priority order and reasonable resource allocation in approaching and dealing with risks. Risk assessment is usually based on two main factors: the magnitude of the impact of the risk on the supply chain and the probability of its occurrence. The magnitude of the impact of risk can be determined by simulating possible events and measuring their consequences for groups such as the financial model of the business. In contrast, the frequency of risks is a more difficult factor to determine unless the business has enough historical data to calculate the frequency of the risks that may occur.

Step 3: Handle risks: Risk treatment can be performed in some following solutions

Avoid the risk: The activities in this step are to avoid potential risks to the supply chain. For example: If it is found that a product does not bring benefits in terms of profit, on the contrary, it is likely to bring risks to the enterprise in the production process, the enterprise may choose to stop producing that product. Or when the company realizes that a supplier may not be able to guarantee the source of raw materials for the supply chain, the company can completely replace with another supplier. These are actions that help businesses avoid future risks to their supply chains.

Prevent the risk: Preventing includes efforts to limit the likelihood that a risk will materialize, or reduce the supply chain impact. Businesses will apply this option to risks that have occurred to the supply chain. For the risks that have never appeared, this method seems to be difficult or impossible as if the risks are very hard to predict or prevent. One of the ways to prevent risks is to build a contingency plan. For example, to guard against supply risks, businesses can cooperate with many suppliers to reduce the risk of shortages, since the probability of all suppliers being interrupted at the same time is very low.

Share the risk: Risk sharing is understood as the business will transfer a part of the risk to stakeholders outside the supply chain. Sharing the cost of product development or insurance for goods is one of the methods of risk sharing. Companies can establish a policy with suppliers to clearly define responsibility when there is a risk, for example: During transportation, if the goods are damaged, the responsibility will be on the supplier. Or businesses can buy insurance for some types of risks that may occur in the supply chain such as risks of natural disasters, epidemics, etc.

Accept the risks: In some cases, the perceived risk does not have a significant impact on the supply chain. The cost of addressing risk outweighs the impact of causing, or there is no solution existing to reduce and share risks. In this case, in the short term, accepting to live with risk will be the most feasible decision.

Step 4: Monitor risks: The supply chain is constantly changing, and the risks also become more complex and unpredictable. Therefore, in addition to planning for risk management and settlement, businesses must continuously monitor risks. The risk management plan also is constantly updated all situations such as changes in the organization, society, environment, etc. in order to make judgments and guess about possible risks as well as how they affect the supply chain.

Risk management is an integral part of supply chain operations, and should be done step by step, depending on the model of each business. There are

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E-ISSN 2815-5726

4 basic steps of a supply chain risk management process including: Identification, Evaluation and Analysis, Handling, and Monitoring risk. Companies always have to put risks in many different situations to ensure maximum control of possible risks and adjust as well as offer appropriate solutions in the shortest time. In these steps, the evaluation and analysis can be performed effectively with the help of machine learning. This help the managers to define clearly risks as well as an order list of risks for next steps. The framework of using machine learning in supply chain management network can be seen in Figure 2, it can be used with the advantage of machine learning in the risk management process. To represent the framework of using machine learning algorithm, an experimental case study has been used in the next section.

Sub-step 2.2. Dividing dataset as training and testing: In this step, the data is divided into two datasets. In this paper, the training set contains 80% of data whereas the remaining is for testing set.

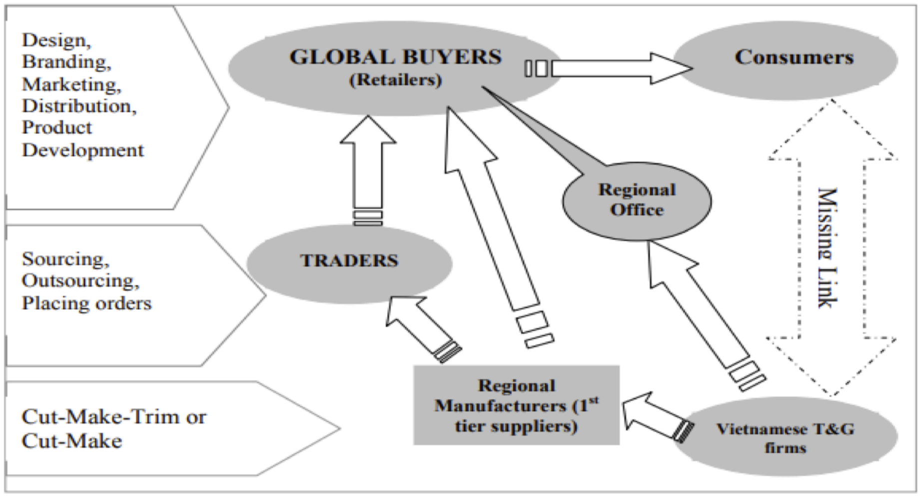
Sub-step 2.3. Use machine learning techniques: alternative machine learning techniques can be used here to predict or classify the risk. Based on the inputs, the supply chain risk outputs are divided on 5 risk classes such as "Very High"; "High"; "Medium"; "Low" and "Very Low".

Sub-step 2.4. Report: In this step, a report of supply chain risk is produced to sent to the users in step 2.

3.2. ***Experimental Case Study***

3.2.1. Data

The dataset is derived from Banerjee et al. (2020). This dataset is generated to evaluate Risk Index and Total supply chain cost by using MATLAB Simulink



Source: Authors re-describe based on Hanah et al, 2019.

Figure 2: *Framework of using machine learning algorithms in predicting Risk in supply chain management network*

In Figure 2, the sub-steps of machine learning are used to predict supply chain risks. Theses sub-steps will be used in step 2 to support users in analyzing and evaluating supply chain network risks. Detail of sub-steps can be seen as:

Sub-step 2.1. Input dataset (RI,TC): After step 1, alternative risks are identified. Before loading to database, the supply chain indexed risk and total cost are calculated basing on reliability theory (see detail on the next section). These results are organized in database as the input of machine learning process.

with probabilistic risk assessment model and a Linear Programming models. The generated dataset is used to deal with classification problems related to Supply Chain Risk Management (SCRM) such as Non-linear Autoregressive and Deep Neural Networks. The dataset includes two files of time series data. The training set has 649999 samples whereas the test set has about 150000 ones. The training data is generated in different time from 2016 to August 2018 whereas the test data is from 2016 to 2017. The outputs for data are classified into 5 categories according to the

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objective function of Z as: Z= w_1 TC_n + w_2 TRI_n, where TC_n is normalized total cost and TRI_n is normalized total Risk Index, and w_1, w_2 are the weights and $w_1 + w_2 = 1$. The output classification is ordered like lilkert scale of "very low risk"; "low risk", "medium risk", "high risk" and "very high risk" according to the labels of 0, 1, 2, 3, 4 respectively. This classification is the same as ones shown in Robert et al (Baryannis et al., 2019).

Before going to perform the experiment, the data has been cleaned by filling the missing values in the dataset. (detail of missing can be seen in Table 1, Table 2 and Table 3).

Output: Y = (Y_{t+N+1}, Y_{t+N+2}, …, Y_{t+2N}) is the predicted values.

For example, we use the Risk Assessment in Supply Chain Networks of five previous months to predict the future, so N = 5. At the first time, t = 1, we have X = (X_1, X_2, …, X_5) corresponding to five months from January to May, then the output Y = (Y_6, Y_7, …, Y_{10}) corresponding to five months from June to October.

The detailed proposal algorithm as following:

Step 1: Build the hyper-parameters and architecture of the model

Step 2: Apply LSTM model

Table 1: *Statistics for training dataset*

		RI_Supplier1	RI_Distributor1	RI_Manufacturer1	RI_Retailer1	Total_Cost	SCMstability_category
N	Valid	649971	616624	649817	649841	614518	649999
	Missing	28	33375	182	158	35481	0
Mean		1.703540	2.437000	2.636818	2.404150	87.171639	1.71
Std. Deviation		.0435194	.6863271	1.1423024	.2444397	76.0997320	1.026
Minimum		.0000	.0000	1.2511	1.0000	-23.9400	0
Maximum		2.0368	6.3716	4.7253	3.4288	200.0000	4

Table 2: *Statistics for testing dataset*

		RI_Supplier1	RI_Distributor1	RI_Manufacturer1	RI_Retailer1	Total_Cost	SCMstability_category
N	Valid	149989	139000	149967	149965	149994	150001
	Missing	12	11001	34	36	7	0
Mean		1.707075	2.325443	2.679723	2.378669	88.752551	1.52
Std. Deviation		.0477037	.7706969	1.1474319	.2718705	78.1396634	1.071
Minimum		.9338	.0000	1.2759	1.7127	-18.4000	0
Maximum		7.5664	6.3392	4.7263	3.4256	189.1000	4

Table 3: *SCMstability_category training set*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	86411	13.3	13.3	13.3
	1	176381	27.1	27.1	40.4
	2	250802	38.6	38.6	79.0
	3	109880	16.9	16.9	95.9
	4	26525	4.1	4.1	100.0
	Total	649999	100.0	100.0	

3.2.2. Algorithm

In ML algorithms (see in Figure 2), we denote X and Y are the input and output of the framework.

Input: X = (X_t, X_{t+1}, …, X_{t+N}) where X_t is the observed sample at time t with N is the number of samples.

Step 3: Use the Bayesian optimization

If the result is good, next to step 4

Else Back to the Step 1

Step 4: Predict the values

Step 5: Evaluate the model

3.2.3. Evaluation metric

The predictive performance (sharpness in statistics) can be assessed by treating the estimator as the prediction. To evaluate the performance of the model's prediction, we use MSE to measure the mean square of errors in the prediction and is calculated as average squared of the difference between predicted value and actual value, called prediction error. MSE is a risk function, corresponding to the expected value of the squared error loss and is defined as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (9)$$

where $\hat{y}_i$ and y_i are the observed and predicted values at time step i, n is the length of the sample data.

3.2.4. Result

The model was trained for 10 epochs to minimize the mean absolute error loss function with a batch size of 128. We used the Adam optimization algorithm, with $\alpha = 1 \times 10^{-4}$ for epochs 1 to 10. L_2 regularization with $\lambda = 1 \times 10^{-5}$ was used in all convolutional layers to decrease overfitting. These hyper parameters were determined heuristically iteratively. Only one hyper parameter was changed at a time, while the others remained constant. Because the training, validation, and test sets were recorded during separate sessions, they were not drawn at random from the entire dataset. Figure 3 depicts the minimization of the loss function during the training process.

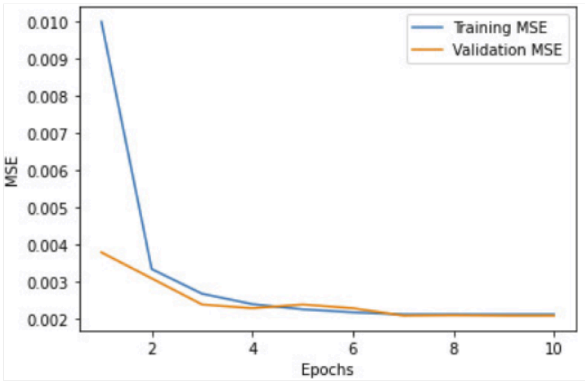
When applying Bayesian in deep learning model, we obtained the results on MSE value, 0.0025. This shows the accuracy for classification is nearly 100% (see Figure 3)

4. Conclusions

The predicting risk in supply chain management networks is performed after creating a base of potential suppliers. By using machine learning algorithms, the risk is determined which is calculated via inputs of RIs and TC as well as their weights. Therefore, in the supply chain risk management process, the defining risks are very important. The more well-defined risks, the more effective the following steps will be.

Machine learning algorithms have been proved by many publications in supply chain management networks. The reinforcement approach in machine learning algorithms in specifically of Bayesian networks can reduce the uncertainty during learning process. It predicts the next emotion based on the utility function finding proper stimuli for target emotion from domain knowledge. Hence, the Bayesian networks maintain a distribution such as model's parameters, function value, etc. so that domain knowledge is encoded in prior distribution, and optimize the exploration of data in predicting process. From there, the risk can be found easily from data patterns.

To sum up, the enterprises can remain profitable and improve the assets if they have a good decision in choosing the right supply chain networks. The



Source: Experimental result from Authors

Figure 3: *MSE results for training and validation dataset*

ISSN 1859-3666
E-ISSN 2815-5726

predicting risk methods might affect to management making decision such as improving the identification of cost-effective and reducing the risk with respect to suppliers and customers. The goal of quality management philosophies is cultivating the strong relationship between suppliers, customers and the enterprise. Understanding the supply chain management risks can help enterprise' managers can determine how many suppliers and customers would be needed within the supply chain. Moreover, this can support to define supplier selection criteria for long-term enterprise's strategy relationship.◆

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Summary

Dự báo rủi ro trong mạng lưới quản lý chuỗi cung ứng đã nhận được nhiều mối quan tâm của các nhà nghiên cứu bởi quản lý chuỗi cung ứng có thể được coi là yếu tố cốt lõi trong hoạt động của doanh nghiệp. Sử dụng thuật toán học máy, đặc biệt là với việc sử dụng mạng Bayesian, để dự báo rủi ro trong mạng lưới quản lý chuỗi cung ứng có thể giúp kiểm soát và giám sát quy trình chuỗi cung ứng và cụ thể là ở bước thứ hai trong việc nhận dạng rủi ro. Nếu rủi ro chuỗi cung ứng được đánh giá hiệu quả, nó có thể hỗ trợ tốt các đối tác tham gia trong chuỗi cung ứng trong việc đánh giá, xác định, giám sát và giảm thiểu rủi ro để đảm bảo tính liên tục của mạng lưới và mang lại lợi nhuận. Mạng Bayesian có lợi thế là tối ưu hóa sự bùng nổ của dữ liệu chuỗi dựa trên xây dựng các trọng số và xử lý đầu ra để tìm phân phối cận biên sao cho chúng phù hợp với dữ liệu chuỗi ban đầu. Đóng góp của bài báo tập trung vào tổng kết việc ứng dụng thuật toán học máy trong dự báo trong lĩnh vực quản lý chuỗi cung ứng, đề xuất khung rủi ro quản trị chuỗi cung ứng áp dụng thuật toán của học máy và minh họa nghiên cứu trường hợp để chỉ ra ưu điểm của việc sử dụng thuật toán học máy và đặc biệt là sử dụng mạng Bayesian trong dự báo rủi ro. Nghiên cứu trường hợp thử nghiệm cho thấy có kết quả tốt với mô hình rủi ro. Điều này cho thấy hiệu quả của việc sử dụng học máy trong việc dự đoán rủi ro trong việc hỗ trợ mạng lưới quản lý chuỗi cung ứng.