International Journal of Decision Support System Technology
Volume 14 • Issue 1

Optimal Strategy for Supplier Selection in a Global Supply Chain Using Machine Learning Technique

Itoua Wanck Eyika Gaida, Amity Institute of Information Technology, Amity University Uttar Pradesh, Noida, India

Mandeep Mittal, Department of Mathematics, Amity Institute of Applied Sciences, Amity University Uttar Pradesh, Noida, India*

https://orcid.org/0000-0002-7501-6571

Ajay Singh Yadav, Delhi NCR Campus, SRM Institute of Science and Technology, Modinagar, India

ABSTRACT

This paper proposes an optimization strategy for the best selection process of suppliers. Based on recent literature reviews, the paper assumes a selection of commonly used variables for selecting suppliers and using logistic regression algorithm technique to build a model of optimization that learns from customer requirements and supplier data and then makes predictions and recommendations for best suppliers. The supplier selection process can quickly at times turn into a complex task for decision-makers to deal with the growing number of suppliers. But logistics regression technique makes the process easier in the ability to efficiently fetch customer requirements with the entire supplier base list by predicting a list of potential suppliers meeting the actual requirements. The selected suppliers make up the recommendation list for the best suppliers for the requirements. And finally, graphical representations are given to showcase the framework analysis, variable selection, and other illustrations about the model analysis.

KEYWORDS

Artificial Intelligence, Global Supply Chain, Logistic Regression, Machine Learning

1. INTRODUCTION

Decisions making process is among the greatest challenges of our developing world. Industries and corporates are often called to make big and essential decisions at each steps varying from the manufacturing phase and all the way up to delivering at the customer's door-steps. Likewise, in the global supply chain the supplier's selection is an important key factor to consider for business reliability, as per Van Weele (2014), the selection of suppliers plays a predominant role in the procurement management, as it considerably impacts on the supply chain performance. Supplier's performance and consistency have greater consequences on the fulfillment of customer's requirements. The ability and capacity of suppliers to provide required resources is vaguely dependent on various parameters

DOI: 10.4018/IJDSST.292449 *Corresponding Author

of high interest such as, availability, time management, cost effectiveness, quality insurance, etc., and ensuring the best list of suppliers for the requirements within an extending supplier base can be trickier and challenging over time. As reported by Çebi & Otay (2016); Karsak & Dursun (2015) that, in spite of the difficulties maybe involved in the supplier selection, the process remains a necessity for its substantial influence on the organization operation and profitability. For some of the papers from Reshu & Mittal (2019), Jayaswal et al. (2019), Jaggi et al. (2011), Mittal et al. (2017), proposed supply chain models with various features. Optimization of the process of selecting suppliers is of an exceptional importance for corporates and businesses in the amplitude to enable high efficiency in the process, so by allowing time saving, cost minimization, and a considerable lead time in the delivering of services. A large number of variables, both quantitative and qualitative, can become complex for the selection of appropriate suppliers, according to Adam & Filip (2018). Supplier's selection of variables is usually dependent on industries specificities and requirements, and as per Deng et al. (2014), companies entertain different strategies and cultures which considerably impact on the variables selection; Kar (2013), also reported on the prioritization approach of selection criteria for supplier. Globally, similarities in the use of certain variables as important basis for supplier's selection can be observed from the literature survey by Adam & Filip (2018), from which a total number of 29 variables were identified. Newer opportunities are emerging in these recent years and have allowed incredible technology advancements in many areas, such as in AI (Artificial Intelligence) which Jordan & Mitchell (2015) explained the prospect in length. And Machine learning as a sub part of AI (Artificial Intelligence), helps address challenges of our modern world era with its developing techniques, that improve on problem solving, solution finding, optimization of existing process, just as Zhou et al. (2017) reported on its immense opportunities and also challenges; its applications on the optimization of supply chain by Sandhya et al. (2019). Machine learning enables decision makers to act meaningful over variations and changes in the process. For Hurwitz & Kirsch (2018), Machine learning comprises four different learning approaches such as, supervised learning, unsupervised learning, reinforcement learning and deep learning. Quite few recent articles, such by Mohammed et al. (2020), Brewer et al. (2019), Kumar (2019), David (2020), Atefeh (2018), Hayk (2020), Boyce & Mano (2018), attempted to address the similar subject of optimization but using different approaches in determining important set of variables, and as per Zhang et al. (2016), a minimum of sixteen (16) variables can be used with machine learning. Further methodological approaches can be examined for the model of optimization, and since no one solution fits all sort of problem, this paper considers a unique approach in the assumption of 18 common variables of types quantitative and qualitative for the selection of supplier, and an optimization approach based on Logistic regression machine learning technique. The model learns from historical data, and make prediction for best suppliers as to match customer's requirements. In this study, the subsequent sections include, a theorical analysis in the selection process of supplier, a definition of supplier's selection framework, a description of the model of optimization based on machine learning algorithm technique, evaluation and discussion on the optimization model, and finally concluding remarks.

2. MOTIVATION

To the extent of our current knowledge on the subject of suppliers in the global supply chain, not many of the modern solution approaches have been considered in the quest of finding an optimal model to facilitate the selection of relevant suppliers to meet customer's requirements. For Hurwitz & Kirsch (2018), Zhang et al. (2016), Adam & Filip (2018), there is no limitation as per the number of variable's selection to observe, and different methodologies and requirements can be set to achieve efficiency and get near accurate results. In today's recent techniques, such as of machine learning under the umbrella of Artificial Intelligence, various methods of optimization can be analyzed and validated as appropriate to address typical problems, and this paper takes the advantage to study a new model of optimization to improve the process of supplier's selection in the global supply chain.

3. THEORETICAL ANALYSIS

Van Weele (2014), refers to the process of selecting supplier as a set of activities required to gather the best possible suppliers. Based on the literature review by Adam & Filip (2018) and Van Weele, (2014), this paper derives and illustrates important points of consideration in the selection process.

Figure 1 illustrates the process from determining customer's requirements in order to acquire the order's specifications, and then find potential suppliers, which can be filtered from the list of suppliers. An edition of RFQ (request for quotation) is prepared and sent for acceptance to suppliers, and finally a list of accepted bids by suppliers for the fulfillment of customers requirement is retained for the procurement operation. Just as Lima junior et al. (2014) emphasizes in the supplier selection to be a progressive process, and variations over time might occur based on the supplier base volume and new changes over the order requirements or variables.

Figure 2 shows that by optimizing the selection process of potential suppliers (circled in green) as early before sending the RFQ (request for quotation), can contribute to increase the number of acceptance of bids by potential suppliers, which should only include those suitable suppliers for the specific requirements, so to minimize the number of rejection.

As per the literature survey by Adam & Filip (2018), the following table 1 below shows a list of reviewed variables used for supplier's selection in the global supply chain.

Figure 1. Supplier selection process (own illustration, based on Van Weele, 2014)

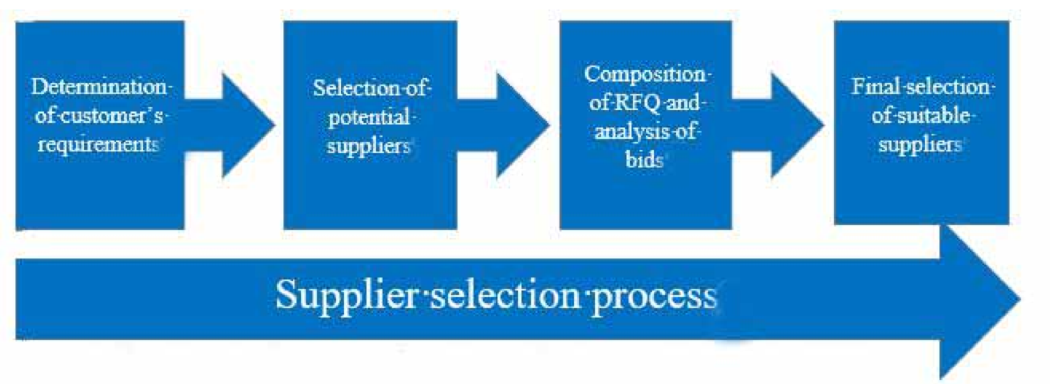


Figure 2. Supplier selection process (own illustration, based on Adam & Filip, 2018)

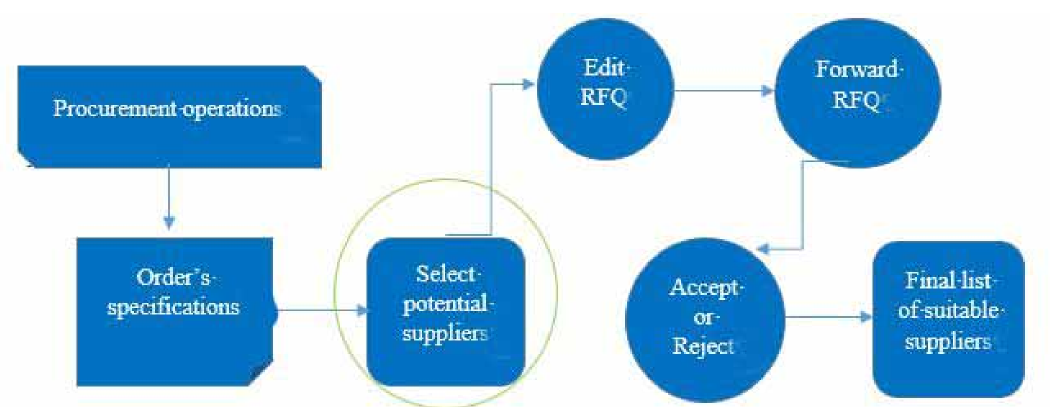


Table 1 describes 29 identified variables from the literature review by Adam & Filip (2018). In their review process of different variables involved for the selection of suppliers, twenty-two (22) variables of qualitative type and seven (7) variables of quantitative type are observed. For every variables are associated more or less research papers or review articles where which they have been referenced. Furthermore, variables have been classified by frequency of use and rank priority just as described from table 2 below.

Table 2 illustrates the variables classifications. Variables are grouped together in the context of their common reference from multiple review articles based on their frequencies of use (rate), and ranked by priority level from higher to lower (One (1) as higher) in terms of their importance in the selection process. As described in table 2, variables such as ***Product price***, ***Delivery Compliance/Performance***, ***Product Quality/Reliability***, ***Technological Capability***, ***Financial Position/Situation***, have higher number of references, which explains their exceptional consideration in the process of selecting suppliers, and constitute for about 50% percent of distinguished importance in the variables selection. The other average in the list with frequency rates between three (3) and two (2), such ***Flexibility and responsiveness***, ***Service/Relationship***, ***Conformance to specification***, ***Market reputation***, ***Total logistics management cost***, ***Reaction to demand change in time***, ***Lead-time***, ***Customer response/communication***, ***Commitment to quality***, ***Production Capability***, ***Innovation***, ***Information sharing***, ***Facility and infrastructure***, ***Geographical location***, ***Environmental factors***, represent for about 30% percent. At last, the remaining nine (9) variables with lower frequencies rates as one (1) represent the other 20% percent.

4. FRAMEWORK FOR SUPPLIER SELECTION

The framework model as described below, illustrates a sequential and consecutive phases or stages involved in the determination of a model of optimization for supplier's selection.

4.1. Identification and Selection of Relevant Variables

For their greater implications in businesses globally and applicability using machine learning, this paper considers about eighteen (18) variables for the best selection of supplier out of the 29 identified variables from the literature review by Adam and Filip (2018). A mixture of seven (7) quantitative and eleven (11) qualitative variables.

As shown from table 3, these 18 selected variables can be used for training the algorithm model. Quantitative types only deal with numbers, while qualitative types are more descriptive, just as well explained by Surbhi (2016) in the contrast between quantitative and qualitative data. The combination of both types of variables can provide a greater understanding as what is required to fulfill the requirements.

4.2. Collection, Extraction, and Normalization of Data

Preparation of data is an important phase in machine learning, as it prevents misrepresentations, errors and miscalculations by fear to alter the machine learning optimization process. Inputs need to be clean, by means of removing inconsistencies, missing values, mistypes, noise, determine whether to consider unstructured or structured form. Hurwitz & Kirsch (2018) splits data into three (3) categories: unstructured, structured, and semi-structured form. Machine learning algorithm works with numerical values especially for predictions and recommendations, and not only they are required into a numerical format, but also feature scaling can be applied to add more precision and increase the performance of machine learning algorithm. Overfitting and Underfitting are very important concepts when training the algorithm. Because of noisy inputs and some random fluctuations in it, the model may learn them as concepts and have a negative impact on the outcomes (also known as overfitting), but when the model fails to capture its underlying trend, the model can result in producing a low percentage of accuracy and not fitting well enough (also known as under fitting). Nevertheless, the availability of

Table 1. An illustration of the 29 identified variables from the literature survey by Adam and Filip (2018)

References	Variables	Quantitative	Qualitative
Kar and Pani (2014); Chang et al. (2011); Chang et al. (2008); Lima Junior et al. (2014); Şen et al. (2008); Paul (2015)	Price/Product Price (cost)	✓	
Chan et al. (2008); Lima Junior et al. (2014)	Total logistics management (cost)	✓	
Chan et al. (2008)	Tariff and taxes (cost)	✓	
Kar and Pani (2014); Chang et al. (2011); Chan et al. (2008); Lima Junior et al. (2014); Şen et al. (2008)	Product Quality/Reliability (quality)		✓
Paul (2015)	Percentage of defective items (quality)	✓	
Lima Junior et al. (2014)	After sale/Warranty (quality)		✓
Kar and Pani (2014); Chang et al. (2011); Chan et al. (2008); Lima Junior et al. (2014); Şen et al. (2008); Paul (2015)	Delivery Compliance/Performance (service performance)	✓	
Chang et al. (2011); Paul (2015)	Reaction to demand change in time (service performance)		✓
Chang et al. (2011)	Stable delivery of goods (service performance)	✓	
Chang et al. (2011); Paul (2015)	Lead-time (service performance)	✓	
Chan et al. (2008); Lima Junior et al. (2014); Paul (2015)	Flexibility and Responsiveness (service performance)		✓
Chan et al. (2008); Lima Junior et al. (2014)	Customer response/communication (service performance)		✓
Lima Junior et al. (2014); Paul (2015)	Commitment to quality (supplier profile)		✓
Kar and Pani (2014); Chang et al. (2011)	Production Capability (supplier profile)		✓
Kar and Pani (2014); Chang et al. (2011); Chan et al. (2008); Lima Junior et al. (2014); Paul (2015)	Technological Capability (supplier profile)		✓
Kar and Pani (2014); Chang (2011); Chan et al. (2008); Lima Junior (2014); Paul (2015)	Financial Position/Situation (supplier profile)		✓
Kar and Pani (2014)	E-transaction Capability (supplier profile)		✓
Lima Junior et al. (2014); Paul (2015)	Innovation (supplier profile)		✓
Chang et al. (2011); Lima Junior et al. (2014); Şen et al. (2008)	Service/Relationship (supplier profile)		✓
Chan et al. (2008); Lima Junior et al. (2014); Paul (2015)	Conformance to specification (supplier profile)		✓
Chan et al. (2008)	Quality assessment technique (supplier profile)		✓
Chan et al. (2008); Paul (2015)	Information sharing (supplier profile)		✓
Chan et al. (2008); Paul (2015)	Facility and infrastructure (supplier profile)		✓

continued on following page

Table 1. Continued

References	Variables	Quantitative	Qualitative
Chan et al. (2008); Lima Junior et al. (2014); Paul (2015)	Market reputation (supplier profile)		✓
Chan et al. (2008); Lima Junior et al. (2014)	Geographical location (supplier profile)		✓
Chan et al. (2008)	Political stability and foreign Policies (risk)		✓
Chan et al. (2008)	Exchange rates and economic Position (risk)		✓
Lima Junior et al. (2014); Paul (2015)	Environmental factors (risk)		✓
Chan et al. (2008)	Terrorism and crime rate (risk)		✓

Table 2. An illustration of classification of variables from the literature survey (Adam & Filip, 2018)

		Rank (priority)	Frequency of use (rate)
Variables	Product Price, Delivery Compliance/Performance.	1	6
	Product Quality/Reliability, Technological Capability, Financial Position/Situation.	2	5
	Flexibility and responsiveness, Service/Relationship, Conformance to specification, Market reputation.	3	3
	Total logistics management cost, Reaction to demand change in time, Lead-time, Customer response/communication, Commitment to quality, Production Capability, Innovation, Information sharing, Facility and infrastructure, Geographical location, Environmental factors.	4	2
	Tariff and taxes, Percentage of defective items, After sale/Warranty, Stable delivery of goods, E-transaction Capability, Quality assessment technique, Political stability and foreign policies, Exchange rate and economic position, Terrorism and crime rate.	5	1

Figure 3. Framework support for supplier selection (own illustration)

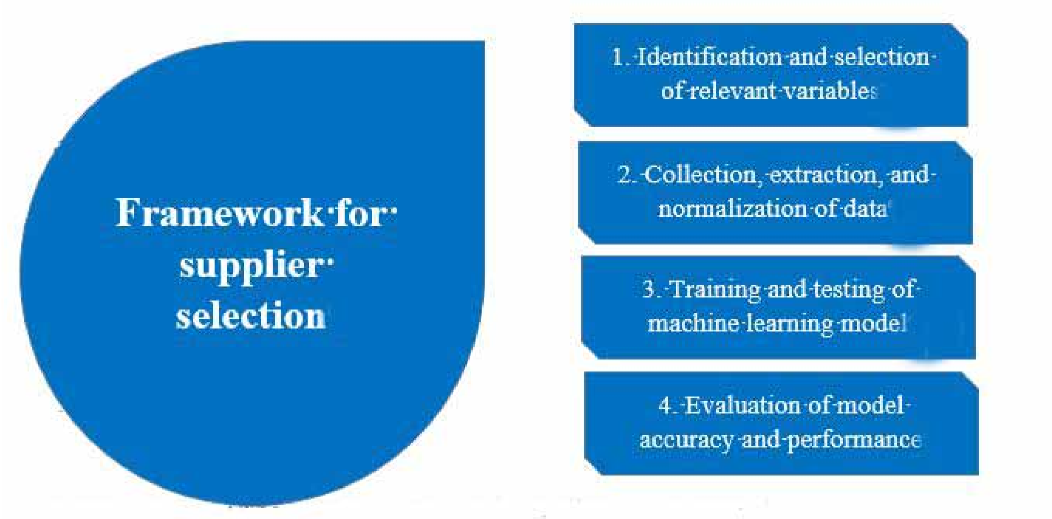


Table 3. Selection of Eighteen (18) variables both qualitative and quantitative (own illustration)

	Qualitative	Quantitative
Variables	Flexibility and responsiveness	Product Price
	Product Quality/Reliability	Stable delivery of good
	Geographical location	Delivery Compliance/Performance
	Conformance to specification	Tariff and taxes
	Commitment to quality	Lead-time
	Customer response/communication	Percentage of defective items
	Quality assessment technique	Production Capability

data is a crucial aspect that enables the ability to train the model, because the more it is accessible the better the algorithm will perform over time. The algorithm learns repeatedly from current and historical records and there can be scenarios where not enough or neither of it is yet available, which then handicaps the possibility to consider applying machine learning.

4.3 Machine Learning Algorithm

Logistic regression algorithm inclines to be suitable for this study, as to optimize the selection of supplier process by building up a classification model to filtering out unwanted suppliers and recommend the best in the list. According to Adam & Filip (2018), different learning approaches can work greater or poor depending on the type of problem and data. Logistic regression is part of the classification algorithms under supervised machine learning, used to predict binary outcomes for a given set of independent variables. The dependent variable's outcome is discrete means either 0 or 1. A threshold value has to be set and in general it is picked as 0.5, points equal or falling below the threshold are considered to be 0 and those above the threshold as 1. In our case the customer's requirements will be considered as independent variables and the supplier's performances as dependent variable.

In figure 4, the model predicts suppliers and classifies them based on their performances, whether above, equal, or below the threshold value. Suppliers with performances greater (>0.5) than the threshold value are classified above the red threshold line and are set as fit to meet customer's requirements and those whose performances are equal (=0.5) or smaller (<0.5) are classified below the red threshold line and set as not fit to meeting customer's requirements. Those Suppliers appearing above the red threshold line will make up the best recommendation list for suppliers as per the requirements.

Dataset for suppliers and customer's requirements on selected variables will first need to be normalized and prepared. Supplier's dataset is represented in the Y-axis as the dependent variable and for the X-axis, the customer's requirements as independent variables (figure 4).

4.3.1 Training and Testing of the Model

Selected variables for the supplier selection are identified as labelled data and both variables and dataset are fed to the model. The dataset will be split into two 2 parts, the training data part which is used to train the model, and during the training process on historical dataset, the model learns about the correlation between supplier's data and customer's requirements data, and by then get tested using the testing data part (new data) to predict the best selection of suppliers as per customer's requirements.

Logistic regression uses a probability function P(x) to forecast values of the dependent variable and draws a curved line between the points as opposed to a straight line in linear regression.

$$P(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$

Equation of a Sigmoid function.

β_0: Intercept of line
e: Euler's number ~ 2.71828
β_1: Slope
X: Independent variable set of values

Figure 4. Logistic regression plotting graph. (own illustration)

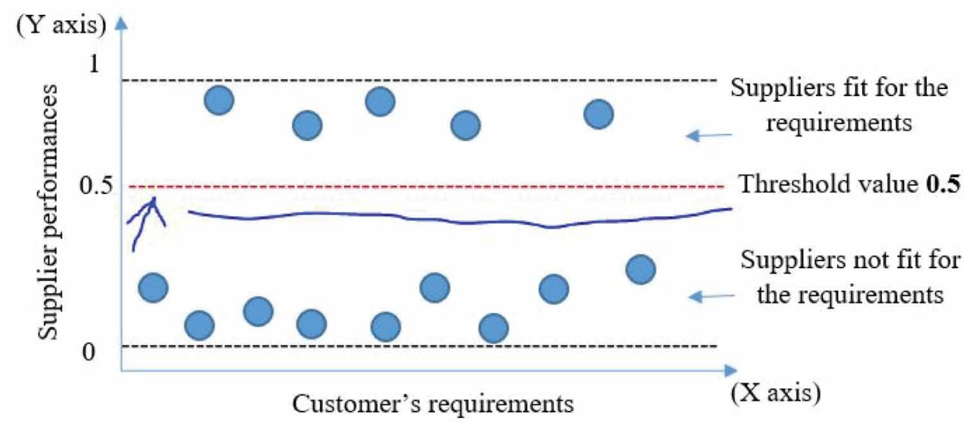
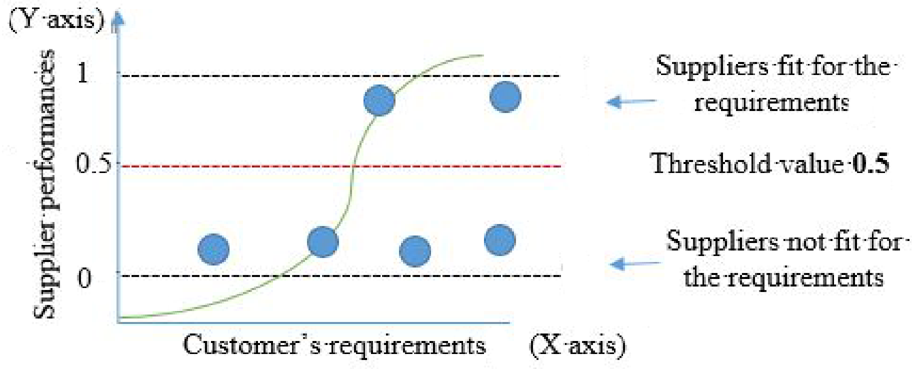


Figure 5. Logistic regression curved line between the points (own illustration)



4.3.2 Evaluation of Model Accuracy and Performance

After training the model for a consecutive number of times, the model gets tested with new data on customer's requirements and then predicts suitable suppliers for the requirements. The forecasting results objective is to obtain an accuracy level near 95% of truthfulness in the capacity of the predicted suppliers to actually meet the requirements and remaining 5% is about the factor of uncertainty. Logistic regression's accuracy level is probabilistic, the higher it can select appropriate suppliers, the better its accuracy level gets, Ghahramani (2015) just well reported on probabilistic machine learning. The performance of the algorithm increases overtime when the model learns repeatedly from more data available. And as per Hurwitz & Kirsch (2018), machine learning models can predict for regular new data.

5. RELEVANCE AND MANAGERIAL CONTRIBUTION

With many challenges that today's businesses deal with in the global supply chain, the selection of best and suitable suppliers plays a critical role in the operations involved to render an outstanding delivery and services to the customers. As customer's requirements continue to grow and as well as the number of supplier increases, it is of great benefit for businesses to maximize on cost effectiveness, time management, lead-time delivery, and at most on customer's satisfaction. In the process of fulfilling customer's order requirements, a much greater attention is required as to avoid misleads with inappropriate suppliers, and sometime human errors and mismatches may occur if done manually, which can end up in a significant time consumption. From results proven machine learning techniques, like logistics regression, businesses can profit of such exceptional opportunities that help in intelligibly and expeditiously process customer's order requirements based on supplier's records and recommend the best list of suppliers for the requirements. The objectives and expectations are to improve on businesses' profit, time saving and customer satisfaction, to deliver in a well time bounded, goods and services that correspond to customers' requirements.

6. LIMITATION

The model of optimization used for this study is an attempt to better optimize the selection process of suppliers, especially when the suppliers base continues to grow. A non-consistent technology support that assists the process can significantly become expensive for corporates or industries to handle efficiently the process and maximize profit. Ensuring a long-term efficiency requires regular and rigorous control over the supplier's performance and customer's satisfactions. Suppliers should be willing to share on regular basis their consistent information updates, as to contribute in a sustainable collaboration with their partners in the procurement businesses. Selection of best suppliers contributes only in part for an optimized operation process with other interconnected components in the chain. However, it remains a challenge to believe of an overall optimization of supply chain operations when it addresses only one specific area in the global supply chain management. Still many important sub-areas of supply chain management need to be identified and addressed.

7. CONCLUSION

Suppliers in the chain operation network represent a greater factor to ensuring reliability and effectiveness in the delivering of services. Determining the best often requires a strict control analysis and more flexibility which often comes at a cost of being subject of a continuing rigorous check on a long run, depending on the variations of requirements over time. Businesses will not have to rely always on human inconsistent decisions making power which at times are based on feeling, guts, or just a broader experience, and as per Adam & Filip (2018), humans are often liable to make mistake when it comes to the analysis and determination of variables relationships; and also according to Muhammad Babar Ramzan et al. (2019), the labor competence within the accessible work force differs from individual to individual, and which the human based system performance is totally depended on; and similarly Jayaswal et al. (2019), mention the implementation of an effective monitoring system that better analyze the worker's outcomes in view of controlling the production shortcomings; and follows, Rita Yadav et al. (2021), who illustrate an interactive approach to please both parties, merchant and consumer, in balancing between pricing effect and product quality. Support in the decision-making process with proven developing technologies can better assist the process in handling efficiently repetitive analysis tasks that can sometime be very challenging and expensive for businesses to deal with enormous volume of data and make important decisions on regular basis, and Bryan & Tom (2016), explored the application and association of computer algorithms in human decisions in their daily lives. Application of modern approaches should allow further improvements on optimized solution for the growing challenges. Logistic regression algorithm demonstrates by its classification capability to extract in an efficient way best supplier as per the requirements, and its extent to deliver accurate results rapidly can help businesses and corporates improve over time efficiency, cost effectiveness and lead-time.

8. FUTURE RESEARCH

The optimized model of supplier's selection addressed by this study is just one way of finding the best solution to improve on this area. Many newer developing technological tools are emerging promptly, and more greater techniques can be assessed to further prove efficacity and obtaining higher accuracy results and one can also consider different approaches to selecting more variables to include in the optimization of the supplier selection process. Researchers have now greater focus to put into use and practices, many advanced developing tools already underway, just as reported by Wenzel et al. (2019), that due to the recent development in ML (machine learning) and based on the abstracts, a total number of 38 relevant papers were identified. Further improvements can always guarantee an adapt solution to the growing challenges.

CONFLICT OF INTEREST

The Author(s) declare(s) that there is no conflict of interest.

REFERENCES

Allgurin & Karlsson. (2018). Linnaeus University, Sweden, degree project in logistics. In Exploring Machine Learning for Supplier Selection. Bufab Sweden AB Enterprise.

Amindoust, A. (2018). A resilient-sustainable based supplier selection model using a hybrid intelligent method. *Computers & Industrial Engineering, 126*, 122-135. 10.1016/j.cie.2018.09.031

Boyce, W. S., & Mano, H. (2018). An inquiry into the supplier selection decision from the business-to-consumer (B2C) perspective. *Journal of Business and Industrial Marketing*, *33*(8), 1221–1230. doi:10.1108/JBIM-06-2018-0183

Brewer, B., Ashenbaum, B., & Blair, C. W. (2019). Cross-Functional Influence and the Supplier Selection Decision in Competitive Environments: Who Makes the Call? *Journal of Business Logistics*, *40*(2), 105–125. doi:10.1111/jbl.12199

Çebi, F., & Otay, I. (2016). A two-stage fuzzy approach for supplier evaluation and order allocation problem with quantity discounts and lead time. *Information Sciences*, *339*, 143–157. doi:10.1016/j.ins.2015.12.032

Chan, F. T. S., Kumar, N., Tiwari, M. K., Lau, H. C. W., & Choy, K. L. (2008). Global supplier selection: A fuzzy-AHP approach. *International Journal of Production Research*, *46*(14), 3825–3857. doi:10.1080/00207540600787200

Chang, B., Chang, C.-W., & Wu, C.-H. (2011). Fuzzy DEMATEL method for developing supplier selection criteria. *Expert Systems with Applications*, *38*(3), 1850–1858. doi:10.1016/j.eswa.2010.07.114

Christian & Griffiths. (2016). *Algorithm to live by*. The Computer Science of Human Decisions.

Deng, X., Hu, Y., Deng, Y., & Mahadevan, S. (2014). Supplier selection using AHP methodology extended by D numbers. *Expert Systems with Applications*, *41*(1), 156–167. doi:10.1016/j.eswa.2013.07.018

Ghahramani, Z. (2015). Probabilistic machine learning and artificial intelligence. *Nature*, *521*(7553), 452–459. doi:10.1038/nature14541 PMID:26017444

Gligor, D. (2020). Birds of a feather: The impact of race on the supplier selection and evaluation process. *International Journal of Production Economics, 230*. 10.1016/j.ijpe.2020.107802

Hurwitz & Kirsch. (2018). *Machine Learning for Dummies*. IBM Limited Edition.

Jaggi, C. K., Khanna, A., & Mittal, M. (2011). Credit financing for deteriorating imperfect-quality items under inflationary conditions. *International Journal of Services Operations and Informatics*, *6*(4), 292–309. doi:10.1504/IJSOI.2011.045560

Jayaswal, M., Sangal, I., Mittal, M., & Malik, S. (2019). Effects of learning on retailer ordering policy for imperfect quality items with trade credit financing. *Uncertain Supply Chain Management*, *7*(1), 49–62. doi:10.5267/j.uscm.2018.5.003

Jayaswal, M. K., Sangal, I., Mittal, M., & Malik, S. (2019). Effects of learning on retailer ordering policy for imperfect quality items with trade credit financing. *Uncertain Supply Chain Management*, *7*(1), 49–62. doi:10.5267/j.uscm.2018.5.003

Jordan, M. I., & Mitchell, T. M. (2015). Machine Learning: Trends, perspectives and prospects. *Science*, *349*(6245), 255–260. doi:10.1126/science.aaa8415 PMID:26185243

Kar, A. K. (2013). An approach for prioritizing supplier selection criteria through consensus building using Analytic Hierarchy Process and Fuzzy set theory. *2013 IEEE International Conference on Signal Processing, Computing and Control (ISPCC)*. doi:10.1109/ISPCC.2013.6663456

Kar, A. K., & Pani, A. K. (2014). Exploring the importance of different supplier selection criteria. *Management Research Review*, *37*(1), 89–105. doi:10.1108/MRR-10-2012-0230

Karsak, E. E., & Dursun, M. (2015). An integrated fuzzy MCMD approach for supplier evaluation and selection. *Computers & Industrial Engineering*, *82*, 82–93. doi:10.1016/j.cie.2015.01.019

Kumar, V., Sarkar, B., Sharma, A. N., & Mittal, M. (2019). New product launching with pricing, free replacement, rework, and warranty policies via genetic algorithmic approach. *International Journal of Computational Intelligence Systems*, *12*(2), 519–529. doi:10.2991/ijcis.d.190401.001

Lima, F. R. Jr, Osiro, L., & Ribeiro Carpinetti, L. C. (2014). A comparison between Fuzzy AHP and Fuzzy TOPSIS methods to supplier selection. *Applied Soft Computing*, *21*, 194–209. doi:10.1016/j.asoc.2014.03.014

Makkar, Devi, & Solanki. (2019). Applications of machines learning techniques in supply chain optimization. *ICICCT 2019 – System Reliability, Quality Control, Safety, Maintenance and Management*.

Manucharyan, H. (2020). *Dealing with uncertainties of green supplier selection: A fuzzy approach.* Working Papers 2020-13, Faculty of Economic Sciences, University of Warsaw.

Mittal, M., Khanna, A., & Jaggi, C. K. (2017). Retailer's ordering policy for deteriorating imperfect quality items when demand and price are time-dependent under inflationary conditions and permissible delay in payments. *International Journal of Procurement Management*, *10*(4), 461–494. doi:10.1504/IJPM.2017.085037

Mohammed, A., Harris, I., Soroka, A., Naim, M., Ramjaun, T., & Yazdani, M. (2021). 2020, Gresilient supplier assessment and order allocation planning. *Annals of Operations Research*, *296*(1-2), 335–362. doi:10.1007/s10479-020-03611-x

Paul, S. K. (2015). Supplier selection for managing supply risks in supply chain: A fuzzy approach. *Int J Adv Manuf Technol Vol*, *79*(1-4), 657–664. doi:10.1007/s00170-015-6867-y

Ramzan, M. B., Qureshi, S. M., Mari, S. I., Memon, M. S., Mittal, M., & Imran, M. (2019). Effect of time-varying factors on optimal combination of quality inspectors for offline inspection station. *Mathematics*, *7*(1), 1–18.

Reshu Agarwal, G. L., & Mittal, M. (2019). Inventory classification using multilevel association rule mining. *International Journal of Decision Support System Technology*, *11*(2), 1–12. doi:10.4018/IJDSST.2019040101

Şen, S., Başligil, H., Şen, C. G., & BaraÇli, H. (2008). A framework for defining both qualitative and quantitative supplier selection criteria considering the buyer–supplier integration strategies. *International Journal of Production Research*, *46*(7), 1825–1845. doi:10.1080/00207540600988055

Surbhi, S. (2016). *Difference Between Qualitative and Quantitative Data*. https://keydifferences.com/differencebetween-qualitative-and-quantitative-data.html

Van Weele, A. J. (2014). *Purchasing and Supply Chain Management* (6th ed.). Cengage Learning EMEA.

Wenzel, H., Smit, D., & Sardesai, S. (2019). *A literature review on machine learning in supply chain management*. Hamburg University (TUHH), Institute of Business logistics and General Management.

Yadav, Pareek, Mittal, & Jayaswal. (2021). Two-level supply chain models with imperfect quality items when demand influences price and marketing promotion. *Journal of Management Analytics*. 10.1080/23270012.2021.1944350

Zhang, R., Jingfei, L., Wu, S., & Meng, D. (2016). Learning to Select Supplier Portfolios for Service Supply Chain. *PLoS One*, *11*(5), 1–19. doi:10.1371/journal.pone.0155672 PMID:27195756

Zhou, L., Pan, S., Wang, J., & Vasilakos, A. V. (2017). Machine learning on big data: Opportunities and challenges. *Neurocomputing*, *237*, 350–361. doi:10.1016/j.neucom.2017.01.026

Itoua Wanck Eyika Gaida, is a software developer and a tech enthusiast, he a Bachelor Degree in Computer sciences and Network (B.Sc.) from ESGAE (Higher Education Institute of Management and Business Administration, Congo, Brazzaville) in year 2014, and lately a Master Degree in Computer Applications (MCA) from PTU (Punjab Technical University, Jalandhar, Punjab, India), in 2018. He evolved since and took part in multiple projects realisation ranging from school projects during his studies to other personal projects, internship projects and a bit of freelancing. He is now a PhD scholar and pursuing his PhD in IT (Information Technology, 2020-2023), from AIIT (Amity Institute of Information Technology), Amity University Noida, Uttar Pradesh, India. He has written and published multiple interdisciplinary research papers in the field of Supply chain efficiency using Artificial Intelligence (AI) techniques, and he continues to sharpening his skills and seek for more knowledge and opportunity to learn and accomplish higher.

Mandeep Mittal started his carrier in the education industry in 2000 with Amity Group. Currently, he is working as a Head and Associate Professor in the Department of Mathematics, AIAS, Amity University Noida. He earned his Post Doctorate from Hanyang University, South Korea, 2016, Ph.D. (2012) from University of Delhi, India, and Post-graduation in Applied Mathematics from IIT Roorkee, India (2000). He has published more than 60 research papers in the International Journals and International Conferences. He authored one book with Narosa Publication on C language and edited three Research books with IGI Global and Springer. He has been awarded Best Faculty Award by the Amity School of Engineering and Technology, New Delhi for the year 2016-2017. He guided two PhD scholars, and 5 students working with him in the area Inventory Control and management. He also served as Dean of Students Activities at Amity School of Engineering and Technology, Delhi for nine years and as a Head, Department of Mathematics in the same institute for one year. He actively participated as a core member of organizing committees in the International Conferences in India and outside India.

Ajay Singh Yadav started his career in the education industry in 2000 with SRM Group. Currently, he is working as Head In-charge in the Department of Mathematics, SRM Institute of Science and Technology, Delhi NCR Campus, Ghaziabad. He is pursuing his post-doctorate from Srinivas University, Bangalore, Ph.D. (2011) from Banasthali University, Jaipur, Raj., India, and postgraduation in Applied Mathematics from CCS University, India (2006). He has published more than 140 research articles in the National and International Journals and International conferences and 26 patents. He has been awarded Best Faculty Award by SRM Institute of Science and Technology, Delhi NCR Campus, Ghaziabad for the year 2018–2019. He guided 5 Ph.D. scholars, and 5 students are working with him in the area of Inventory Control and Management. He actively participated as a core member of organizing committees in the international conferences in India and outside India.