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Prediction of Production Capability for Subcontractors in Automotive Rubber Part Supply Chain Using Neuro-Fuzzy System

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ABSTRACT

The paper proposes prediction production capability for automotive rubber part supply chain subcontractors in order to remain competitive in the global market. Rubber parts are used widely in automotive, motorcycles, trucks and other types of vehicles which are mostly small sizes but huge quantities to support original equipment manufacturer (OEM) brands with specific parts. The rubber part manufacturing process is complex and uncertain with compression molding and rubber curing conditions. Therefore, good conditions can predict to obtain high production capability for customer commissioning and delivery on schedule. The Neuro-fuzzy system is adopted and developed to deal with the uncertain capability under multi-criteria decision making. The methodology development can be used in the actual situation of the rubber part manufacturing supply chain environment and can predict uncertain problems that might occur in the subcontractor factories. The prediction of the production capability of the rubber part supply chain might be more effective on the real-time monitoring control system and can be tracked location part progressive for further planning both successful or has to be rescheduled. The platform was applied to audit and test in the actual industrial supply chain in Thailand. The methodology development was originally created for the particular supply chain in rubber automotive parts that can replace the existing manual approach to obtain a more efficient process of monthly performance evaluation.

Keywords: Prediction of production capability; Supply chain management (SCM) automotive rubber parts; Neuro fuzzy system

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1. Introduction

Rubber part manufacturing plays a vital role in the automotive part industrial sector. Rubber parts with special ingredient materials are extremely increased in quantity and quality and used in modern cars to obtain light weight and less energy consumption. The rubber parts are made of various types of raw materials that are mixed with different ingredients and transformed into different part shapes of the car's components. The rubber raw materials are heated and compressed by high pressure. There are two processes that are used to deform the rubber part: the injection process and the compression process. The rubber part manufacturing process is uniquely operated which compares to plastic and metal parts. The rubber part is made of compound rubber as the main raw material in which mixed additive materials are based on design specifications and can deform only once time in the production process. If the rubber part is run out of the standard, it cannot be reused or recycled. In this research, the case study is based on a rubber part automotive cluster company in Thailand. The 1st tier takes the responsibility of purchasing orders from the OEM and then, distributes to subcontractors that they are selected by contraction. The 1st tier is also responsible for raw material preparation which is mixed with product specifications as well as mould making and standard operation documents. The purchasing distribution document includes a monthly delivery planning timetable. Subcontractors take care of progressive report documents. The problem existing is that delivery is often late and delayed. Presently, the back order release solution is acceptable. It is the major cause of competitiveness reduction. There are several factors that affect the delivery's efficiency. They are mainly on quality, resources, and management. Therefore, the research objective is to develop a predictive modelling approach using Neuro-fuzzy method which is adopted to deal with the uncertainty of SCM and predict the production capability. Some previous research presented a supply chain management model with sustainability. Vafaeenezhad et al. [1] proposed multi-objective mathematical modeling for sustainable supply chain management in the paper industry. The customer value in general consists of 4 criteria such as quality, service, cost, and time. The supply chain as subcontractors commonly concerns planning and scheduling, design, new product planning, product content management, and order, together with delivery management. Awudu and Zhang [2] reviewed uncertainties and sustainability concepts in biofuel supply chain management. Modeling was proposed by analytical methods and simulation methods. Brandenburg et al. [3] proposed quantitative models for sustainable supply chain management. Sharifi et al. [4] presented a novel two-stage multi-objective optimization model for sustainable soybean supply chain design under uncertainty. It is perceptible that SCM emphasizes quality, service, cost and time which can be simulated on a mathematical model.

2. Literature reviews

This section presents previous research on SCM, SCOR criteria, fuzzy logic prediction system and production capability planning and critical comments to formulate the new conceptual idea of development model for production capacity prediction under the scope of rubber part manufacturing subcontractor.

2.1 Supply chain management

This section explains the previous study of supply chain management particularly in automotive rubber parts and the methodology to deal with current situations such as uncertainty and dynamics on both sides of the demand and supply as well as performance evaluation approach. Osiro et al. [5] proposed supplier evaluation using fuzzy logic for making decisions to increase suppliers' performance and capabilities. The fuzzy inference combined with the simple fuzzy grid method can help in decision making in supplier evaluation in the automotive industry. Jung et al. [6] proposed a simulation-based optimization approach to supply chain management under demand uncertainty because cost effective control is critical under various uncertainties of market, logistics and production. Chen and Zou [7] and Park et al. [8] presented an integration method for selecting suppliers. Good suppliers should be concerned with supplier relationship management (CRM) and purchasing strategy. Govindan et al. [5] analyzed supplier development criteria for the automobile industry. They consist of competitive pressure, evaluation and certification system, incentives, supplier development programs, buyer and supplier relationships, supplier commitment, long term strategic goals, purchasing performance and top management support. Sarkar and Mohapatra [9] determined the optimal size of the supply base with the consideration of risks of supply disruptions. Cost reduction and improving supply chain performance are important which can develop from supplier improvement and relationship management. Effective sourcing can be single and multiple sourcing to achieve competitiveness from production strategies such as JIT, lean, six sigma and so on. Effective Supplier selection is indispensable, but the methodology is complicated as multi-objective optimization problem solving [10]. Kadarova et al. [11] proposed the optimization model to select company suppliers that can deliver both quality and quantity accurately in the automotive industry. Supply chain members work with multiple subcontractors to supply the same components. KPIs performance and risk were applied and created to measure each supplier. The research methodology was simulation and modeling. Aghezzaf et al. [12] proposed models for robust tactical planning of multi-stage production systems with uncertain demands. Pan et al. [13] proposed multiple sourcing environments to determine lead times and obtained a satisfying combination of customer service, cost and long term availability. Material purchasing is one of the critical problems for supply chain management risk. The criteria are quality, price, delivery, service and technology. Quality is one of the key aspects of supply chain management. Dong et al. [14] presented quality management in multi-level supply chains with outsourced manufacturing. Supply chain and logistics are considered both inbound and outbound enterprises which focus on minimum fixed costs of facility location and transportation. Customer satisfaction is measured by lead time reduction and transportation optimization. Lee and Li [15] proposed supplier quality management from investment, inspection and incentives to meet buyer satisfaction. The improvement of supplier quality can be improved by product and process investment, quality control and quality continuous improvement. Total quality management (TQM) is another vital tool for supplier improvement of quality. Lascelles and Dale [16] reported that the barriers to buyer and supplier relationships in the automotive industry are poor communication and feedback, supplier competency, and lack of knowledge on quality improvement. Risk management in the supply chain was concerned with linking performance and social sustainability as well as customer integration [17]. It is found that supply chain management involves supplier evaluation, uncertainty demand management, customer relationship management and customer integration, purchasing strategy, and supply risk disruption. The fuzzy logic tool was used to obtain optimization.

2.2 SCOR with supply chain

SCOR model is a good tool for the supply chain to give value to customers, suppliers and makers which is effective in communicating decisions and optimizing all the process network. It encompasses the entire process of assessing customer needs, sourcing materials, creating products and distributing correctly. SCOR model can be used to evaluate the performance of agility, asset management efficiency, costs, reliability and responsiveness [18,19]. Planning is used to manage demand and supply in the chain to balance between resources and demand requirements and transportation. It is important to control capacity planning and demand planning. Sourcing involves acquiring materials and sourcing infrastructure, inventory, supplier agreement, network and performance. Making emphasizes manufacturing and production in various aspects such as make to order, make to inventory. Delivering composes of warehousing and transporting orders, and invoicing customers. Returning involves handling receiving components and sending them back to customers to ensure the satisfaction of customer services. Delipina and Kocaoglu [20] reviewed using the SCOR model to gain a competitive advantage between the supply chains of the companies in order to obtain cost reduction. General problems for supply chain companies are poor service, high inventory, unexpected costs, constrained growth and profit loss of market share. The supply chain evolves with efficient chains to improve customer service satisfaction and performance. SCOR was used together with the analytic hierarchy process (AHP) to obtain multi-criteria decision making [21–23]. Performance measurement is significant to assist competitive advantage. Bhagwat and Sharma [24] developed the platform of supply chain performance measurement using a balanced scorecard approach with 4 indicators: financial, customer, internal business process, and learning growth for the SME in India. As mentioned in the previous review, the SCOR model has been used to support SCM to increase and strengthen the ability of the organization. However, digital tools for simulation are taken into account for prediction of the future events.

2.3 Fuzzy logic prediction system

Fuzzy logic is a very useful tool to support decision making under uncertainty and complexity when information is not sufficient and imprecise. A few papers are selected to review in terms of use for operation performance evaluation and prediction in supply chain management using fuzzy logic. Ganga and Carpineti [25] proposed a fuzzy logic approach to supply chain performance management which was able to predict the performance based on causal relationships between metrics of the SCOR model. Shen et al. [26] presented a fuzzy multi criteria approach for evaluating supplier performance in the green supply chain with linguistic preferences using the TOPSIS system. Kumar et al. [27] proposed a fuzzy logic based decision support system for evaluating suppliers in supply chain management practices. Chen [28] presented fuzzy scored-based logistics management in robust SCM. A novel method of development was to evaluate the real-time overall performance of a logistics network for the supply chain. Kocamaz et al. [29] proposed an artificial neural network (ANN) to control a chaotic supply chain that used a nonlinear dynamical system. It is sensitive dependence on initial conditions and involves with infinite number of different periodic responses. An adaptive neuro fuzzy inference system (ANFIS) controller was trained according to the model. Xu et al. [30] proposed an active management strategy for supply chain systems using nonlinear control synthesis to deal with uncertainty. Butdee and Nitnara [31] proposed fuzzy logic with a linear programming (LP) model for performance evaluation to distribute purchasing orders in cluster manufacturing. The fuzzy logic was used to measure the efficiency of each factory in the aspects of capacity, quality, reliability, source and flexibility. It can be criticised that most of the prediction systems employ a fuzzy-based reasoning system to deal with multi criteria decision making including TOPSIS, ANFIS and ANN.

2.4 Production capacity planning

Production capacity planning is a strategic process proposed for determining the capacity required to meet forecasted demand, production scheduling, supply chain planning and inventory management which is linked to aggregate planning. The capacity of production operations can be measured in terms of efficiency and utilization. There are three types of capacity: design capacity, effective capacity and actual output. The design capacity expresses a maximum capacity given by the ability of machine speeds and material flow associated with labor or production system. Effective capacity concerns multiple variables such as types of product mix, schedule and order changes, disruptions in the supply chain, unplanned maintenance and labor factors of absenteeism. It is measured by maximum output. Actual output is measured by the production rate achievement of efficiency and utilization. Capacity planning can benefit supply chain planning, maintenance planning, scheduling, delivery planning and so on. Generally, capacity planning performs with MRP. Ho and Fang [32] proposed the production capacity planning for multiple products under an uncertain demand environment to obtain optimal capacity allocation under the given probability density function of specific demands and allocate limited capacity to multiple products to achieve maximize profit. Gerchak et al. [33] proposed the capacity criteria under uncertainty for earning per share, profits to asset ratio, profit per unit capacity or return on inventory investment. Song et al. [34] presented the inventory strategy of the risk averse supplier and overconfident manufacturer with uncertain demand. The study result showed that the supplier's risk reduced the number of products supplied and profit under the pull strategy. On the other hand, the makers can bring better profit and higher order quantity by push strategy. Naraharisetti et al. [35] proposed capacity management in the chemical supply chain involved with the location and allocation of production and inventory capacities. Production capacity planning is significant to impact the supply chain performance whereas predictive capacity is useful to obtain proactive delivery policy. Using a fuzzy logic base can assist enterprises in predicting and preventing stock shortages in inventory management.

3. Methodology

The research methodology development is based on the practical gap of the automotive rubber part supply chain company known as subcontractors in Thailand that need to be evaluated annually. The challenge is that the heavy competition on cost leadership every year brings about pressure on the OEM. As a result, the chain of Tier1 and Tier2 companies (subcontractors) must carry out productivity improvement and waste reduction to reduce the lower cost of the whole chain. Delivery good quality of purchasing orders is the major objective together with on-time and quantity. Presently, simulation is widely used to prepare for the future prediction. This paper proposes the ANFIS model to predict the production capacity in order to ensure that the capacities for the whole chain are sufficient. The research design consists of determining input and output criterion functions for creating membership functions of the fuzzy sets. Rules related to all membership functions are created and implemented into the workspace of the MATLAB simulation. The data sets are trained and carried out by the result of the capability of the subcontractors. One purchasing order consists of many parts distributed to many subcontractors. Therefore, the production capacity of each subcontractor should be determined by simulation frequently. A fuzzy inference system is operated and summarized. The process simulation is also tested and validates the simulation rules. **Figure 1** shows the structure of the auto rubber part supply chain and performance control & KPI system. OEM provides in order to Tier1 and distributes to Tier2 via supply chain management (SCM) which is operated as the SCM controller. Previously, the performance evaluation was done manually which was time consuming. We developed the new concept of the production capacity forecasting model by using the ANFIS system under the KPI of the supply chain of performance control.

Figure 2 shows the neuro-fuzzy system or ANFIS system for feeding forward neural networks and using fuzzification of backpropagation. It is a kind

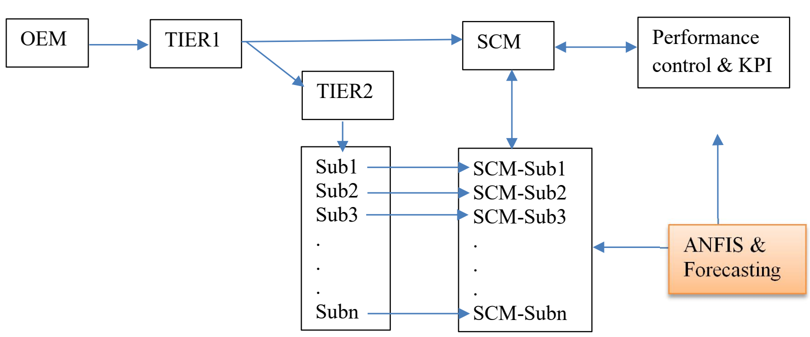


Figure 1. Structure of auto rubber part supply chain and performance control & KPI system.

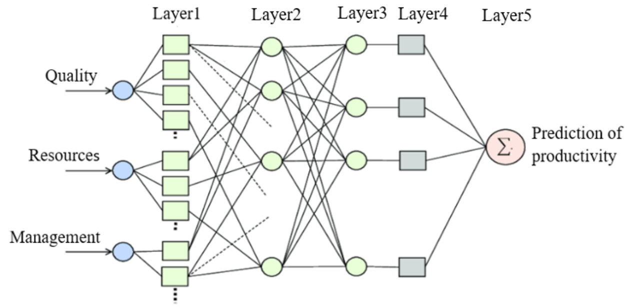


Figure 2. Neuro fuzzy systems for production capacity and productivity.

of fuzzy system which is trained by a learning algorithm using a heuristic learning procedure operated on local information. It consists of five layers. Fuzzy sets are encoded as connection weights and interpreted as a system of fuzzy rules to initialize them by prior knowledge. The ANFIS system consists of an input linguistic layer, condition layer, rule layer, consequent layer, and output linguistic layer. Fuzzy inference is performed by rule, condition and consequence layers. The learning process is composed of three stages: fuzzy membership generation, fuzzy rule identification and supervised fine-tuning. The learning procedure takes the semantic properties. It is implemented by simply the Sugeno-Takagi controller. The neuro-fuzzy system is a hybrid intelligence system that combines human reasoning as fuzzy rules of learning and connectivity of neural networks. This research paper adopts the neuro fuzzy system which is designed by using 3 inputs of quality, delivery and management whereas one output is predicted of productivity or production capacity.

Table 1 shows the linguistic variables for input and output membership functions. They are quality, delivery, management and capability respectively. The variables are divided into five levels: very high, high, medium, low and very low. The ranges are different depending on the importance of weight. Delivery is very important. It needs to perform on time, on quality and in quantity. Quality is the second rank because if the quality does not conform to the specification, the produced parts are defective and then rejected. Management is the third rank, but it is significant to associate the delivery with quality and quantity control. Traditionally, the Tier1 company evaluates subcontractors by the three variables annually by the SCM controller. In this work, we contribute a new approach to using the scientific method to predict the production capacity and evaluate performance at the same time as well as delivery and inventory control management.

Figure 3 shows the structure of a neuro-fuzzy system for the prediction of the production capacity of a rubber part manufacturing supply chain consisting of 3 inputs with five levels of membership

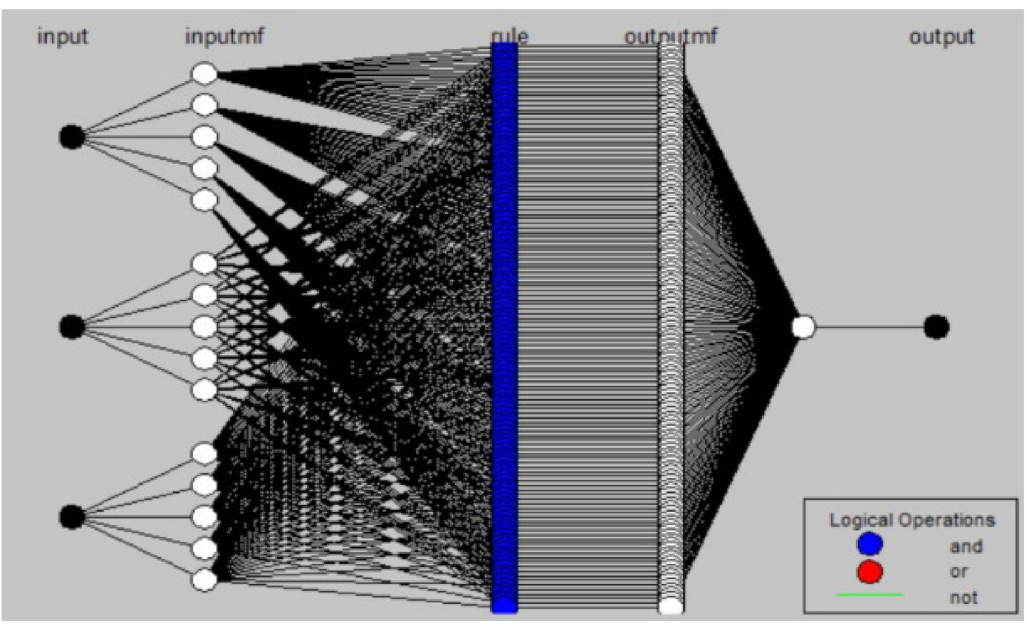


Figure 3. The structure of the Neuro-fuzzy system implemented in MATLAB.

Table 1. Linguistic variables for input membership functions.

Variables	Very high		High		Medium		Low		Very low	
	Upper	lower	upper	Lower	upper	lower	upper	lower	upper	lower
Quality	100	97.5	95	92.5	90	87.5	85	82.5	80	72.5
Delivery	100	99	98	97	96	95	94	93	92	91
Management	100	95	90	85	80	75	70	65	60	55
Capability	100	90	85	80	75	70	65	60	55	50

functions (inputmf). There are 125 rules of ANFIS decision making for the prediction of the production capacity of subcontractors. The 4th layer is done by defuzzification based on the rules in the 3rd level. Finally, the output is carried out by the model development.

Figure 4 shows the architecture of the ANFIS model for productivity simulation consisting of three inputs: quality, resources and management that influence productivity. The model is simulated by fuzzy rules of the ANFIS reasoning. The output is the score of the possibility level in the percentage of the prediction. It is then brought such quantity's percentage to calculate with the purchase order which can come out with the quantity of the parts that can be commissioned and prepared for the back-order rescheduling.

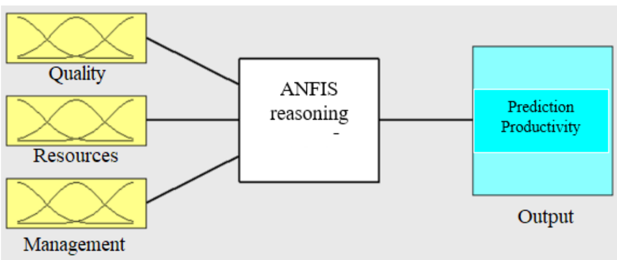


Figure 4. Architecture of ANFIS model for prediction of productivity simulation by MATLAB.

Figure 5 shows the input membership function of the quality for the rubber part manufacturing that was created by MATLAB. The scale started with 80% of quality being accepted but at a lower level whereas the very highest quality is accepted by 99% because the automotive industry performed business under a six sigma quality management system. **Figure 6** shows the input membership function of resources for the rubber part factory. The rank is set between 75% and 95% which is accepted by the availability level in order to use for making the parts from each purchase order during the period of time concerned. **Figure 7** shows the input membership function of management for the subcontractors. It is divided into 5 levels beginning with very low, low, medium, high and very high. Management in the rubber part factory is mainly concerned with the compression operation consisting of operators (man), machine availability, mold (perfect conditions) and materials.

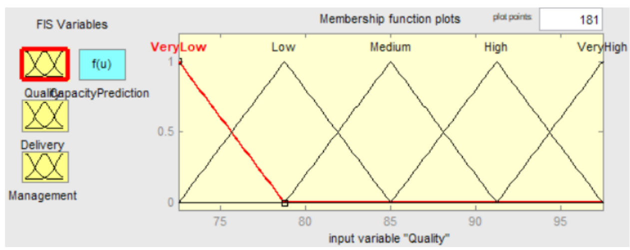


Figure 5. Input membership function of quality for the rubber part manufacturing.

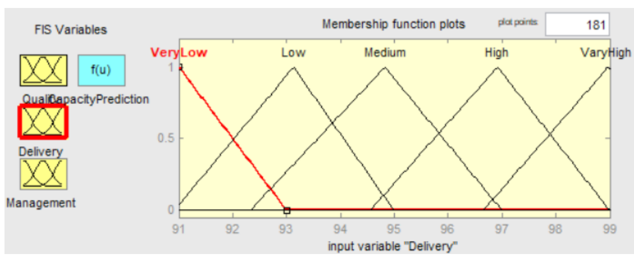


Figure 6. Input membership function of resources for the rubber part factory.

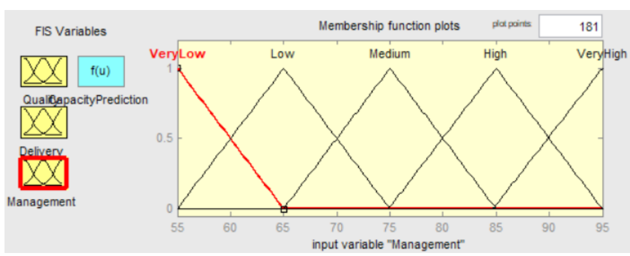


Figure 7. Input membership function of management for the subcontractors.

4. Results and discussion

This section presents the results of the ANFIS model prediction for supply chain management. Three criteria are taken into account and obtain the production capacity. The target point of capacity is more than 80%. Therefore, if the actual data are taken from the subcontractors and analyzed by the system that obtains less than 80%, then the supply chain controller needs to action by taking such parts from safety stock.

Figure 8 shows the ANFIS testing results by multi-conditions of rubber part production to obtain a capacity prediction. It shows the result of production capacity under the case specifically. The quality was 78.4% whereas the delivery was 96.1% and management was 75%. Subsequently, the model predicts that the capacity was 75.1% which was lower than it was expected to have the minimum level was 80%. Therefore, the SCM controller needs to take action to plan for extra time production or take stock parts of inventory from the safety stock level.

Figure 9 shows the impact factors of management, quality and delivery to obtain capacity prediction. **Figure 9a** shows that if the management was very good and delivery was also very good, then the capacity was predicted very high which is up to 100%. **Figure 9b** shows that if the quality is high and the management is very good, then the capacity is predicted that be very high. Finally, it can be concluded that quality is the first priority of significance, then delivery and management are the most important.

Table 2 shows the case study of a performance audit for a period of purchasing orders from 17 subcontractors. The data were shown and the capacity prediction was carried out by the ANFIS modeling on the fifth column. In addition, the risk management planning was to consider the reaming capacity of the stock and call for stock release which was shown in the sixth column.

Figure 10 shows the risk management for 100% delivery of the purchase order. There are two subcontractors that meet requirements: the sub #6 and the sub#15. As previously mentioned before, the capacity set was 80% for every subcontractor.

Figure 11 shows the result of the ANFIS model for capacity prediction of the ABC supply chain. There are 17 subcontractors producing the same parts for Tier1. The actual data from every subcontractor are collected and put into the model. It is shown that capacity is below expectations of 80%. Therefore, Tier1 needs to manage the risk management by taking stock of parts to prepare for this purchasing order.

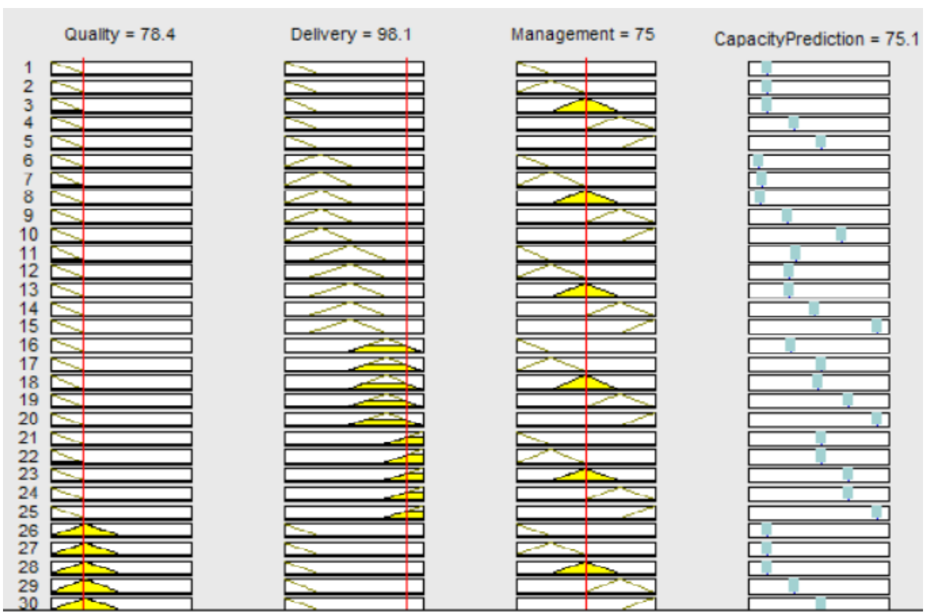
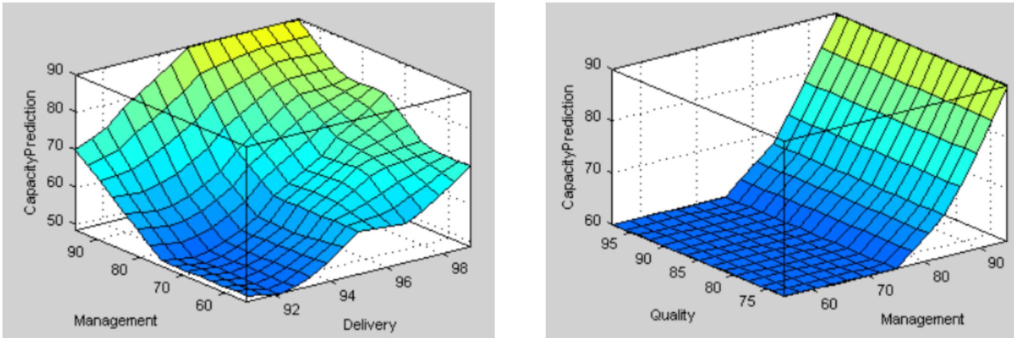


Figure 8. ANFIS testing results by multi-conditions of rubber part production at the subcontractor factory.



(a) Capacity impact by management and delivery (b) Capacity impact by quality and management

Figure 9. The impact factors of management, quality and delivery to capacity prediction.

Table 2. The case study of performance audit for a period of purchasing order.

Subcontractors	Quality	Delivery	Management	Capacity prediction	Stock release
1	80	98	85	80	0
2	90	95	78	62.8	17.2
3	100	90	95	70	10
4	75	89	90	64.9	15.1
5	85	85	95	70	10
6	95	100	98	90	0
7	96	87	94	69	11
8	87	95	87	73.9	6.1
9	70	94	85	63.4	16.6
10	100	86	93	68	12
11	88	85	98	70	10
12	98	85	84	58.6	21.4
13	76	80	87	62	18
14	95	90	94	69	11
15	86	100	96	90	0
16	74	95	87	73.9	6.1
17	93	87	89	63.9	16.1

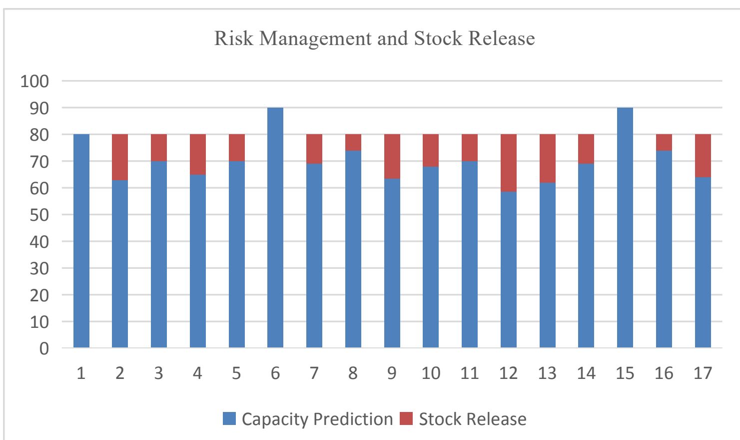


Figure 10. The risk management for 100% delivery of the purchasing order.

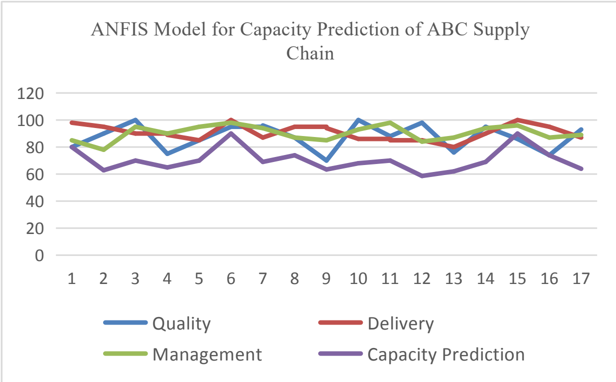


Figure 11. ANFIS model for capacity prediction of the ABC supply chain.

5. Concluding remarks

The paper presents the new model of ANFIS-based modeling for production capacity based on the main three criteria: quality, resources and management. The ranks are captured from the Tier1 company and used to assign the input membership functions. Rules are collected by the industrial site and created by the fuzzy inference system. The data sets are trained and implemented to obtain the results of capacity prediction for each subcontractor. The case study was conducted to carry out the result and designed for planning a risk management plan based on 100% delivery. Therefore, the supply chain decision-maker can deal with the dynamic situation of the supply chain and use the strategy of stock release. The minimum capacity for the safety of every subcontractor's production is set at 80%. So, if any subcontractor's performance is audited by less than 80%, the supply chain controller will need to bring the part from the stock and plan to refill for safety stock at the same time. The model development has been tested successfully compared to the traditional performance evaluation. It can save time and energy for the auditing team of the Tier1 supply chain controller. Future research will integrate the model and system with a real-time monitoring system. It is extremely believed that the ANFIS modeling for production capacity prediction is useful and beneficial to the real industry managed as supply chain management, particularly the automotive industrial cluster. The critical contribution was the scientific approach of the subcontractor's performance evaluation can assist the SCM controller in dealing with delivery risk management and benefit the whole supply chain. In this work, we contribute a new approach to using the scientific method to predict production capacity and evaluate performance at the same time as well as delivery and inventory control management. Furthermore, the concept can be modified to implement all of the supply chain industry sectors.

Author Contributions

Suthep Butdee: Conceptualization, conceived and design, methodology, writing, review & editing, summiting paper. Pichai Janmanee: Site contraction and collecting data, draft writing, data analysis and validation, formal analysis, investigation and project administration.

Conflict of Interest

There is no conflict of interest.

References

[1] Vafaeenezhad, T., Tavakkoli-Moghaddam, R., Cheikhrouhou, N., 2019. Multi-objective mathematical modeling for sustainable supply chain management in the paper industry. Computers & Industrial Engineering. 135, 1092–1102. DOI: https://doi.org/10.1016/j.cie.2019.05.027

[2] Awudu, I., Zhang, J., 2012. Uncertainties and sustainability concepts in biofuel supply chain management: A review. Renewable and Sustainable Energy Reviews. 16(2), 1359–1368. DOI: https://doi.org/10.1016/j.rser.2011.10.016

[3] Brandenburg, M., Govindan, K., Sarkis, J., et al., 2014. Quantitative models for sustainable supply chain management: Developments and directions. European Journal of Operational Research. 233(2), 299–312. DOI: https://doi.org/10.1016/j.ejor.2013.09.032

[4] Sharifi, E., Fang, L., Amin, S.H., 2023. A novel two-stage multi-objective optimization model

for sustainable soybean supply chain design under uncertainty. Sustainable Production and Consumption. 40, 297–317.
DOI: https://doi.org/10.1016/j.spc.2023.07.006

[5] Osiro, L., Lima-Junior, F.R., Carpinetti, L.C.R., 2014. A fuzzy logic approach to supplier evaluation for development. International Journal of Production Economics. 153, 95–112.
DOI: https://doi.org/10.1016/j.ijpe.2014.02.009

[6] Jung, J.Y., Blau, G., Pekny, J.F., et al., 2004. A simulation based optimization approach to supply chain management under demand uncertainty. Computers & Chemical Engineering. 28(10), 2087–2106.
DOI: https://doi.org/10.1016/j.compchemeng.2004.06.006

[7] Chen, W., Zou, Y., 2017. An integrated method for supplier selection from the perspective of risk aversion. Applied Soft Computing. 54, 449–455.
DOI: https://doi.org/10.1016/j.asoc.2016.10.036

[8] Park, J., Shin, K., Chang, T.W., et al., 2010. An integrative framework for supplier relationship management. Industrial Management & Data Systems. 110(4), 495–515.
DOI: https://doi.org/10.1108/02635571011038990

[9] Sarkar, A., Mohapatra, P.K., 2009. Determining the optimal size of supply base with the consideration of risks of supply disruptions. International Journal of Production Economics. 119(1), 122–135.
DOI: https://doi.org/10.1016/j.ijpe.2008.12.019

[10] Jadidi, O.M.I.D., Zolfaghari, S., Cavalieri, S., 2014. A new normalized goal programming model for multi-objective problems: A case of supplier selection and order allocation. International Journal of Production Economics. 148, 158–165.
DOI: https://doi.org/10.1016/j.ijpe.2013.10.005

[11] Kádárová, J., Trebuňa, P., Lachvajderová, L., 2021. Model for optimizing the ratios of the company suppliers in Slovak automotive industry. Sustainability. 13(21), 11597.
DOI: https://doi.org/10.3390/su132111597

[12] Aghezzaf, E.H., Sitompul, C., Najid, N.M., 2010. Models for robust tactical planning in multi-stage production systems with uncertain demands. Computers & Operations Research. 37(5), 880–889.
DOI: https://doi.org/10.1016/j.cor.2009.03.012

[13] Pan, A.C., Ramasesh, R.V., Hayya, J.C., et al., 1991. Multiple sourcing: The determination of lead times. Operations Research Letters. 10(1), 1–7.
DOI: https://doi.org/10.1016/0167-6377(91)90079-5

[14] Dong, Y., Xu, K., Xu, Y., et al., 2016. Quality management in multi-level supply chains with outsourced manufacturing. Production and Operations Management. 25(2), 290–305.
DOI: https://doi.org/10.1111/poms.12428

[15] Lee, H.H., Li, C., 2018. Supplier quality management: Investment, inspection, and incentives. Production and Operations Management. 27(2), 304–322.
DOI: https://doi.org/10.1111/poms.12802

[16] Lascelles, D.M., Dale, B.G., 1989. The buyer-supplier relationship in total quality management. Journal of Purchasing and Materials Management. 25(2), 10–19.
DOI: https://doi.org/10.1111/j.1745-493X.1989.tb00477.x

[17] Duong, N.H., Ha, Q.A., 2021. The links between supply chain risk management practices, supply chain integration and supply chain performance in Southern Vietnam: A moderation effect of supply chain social sustainability. Cogent Business & Management. 8(1), 1999556.
DOI: https://doi.org/10.1080/23311975.2021.1999556

[18] Arzu Akyuz, G., Erman Erkan, T., 2010. Supply chain performance measurement: A literature review. International Journal of Production Research. 48(17), 5137–5155.
DOI: https://doi.org/10.1080/00207540903089536

[19] Fatorachian, H., Kazemi, H., 2021. Impact of Industry 4.0 on supply chain performance. Production Planning & Control. 32(1), 63–81.
DOI: https://doi.org/10.1080/09537287.2020.1

712487

[20] Delipinar, G.E., Kocaoglu, B., 2016. Using SCOR model to gain competitive advantage: A literature review. Procedia-Social and Behavioral Sciences. 229, 398–406.
DOI: https://doi.org/10.1016/j.sbspro.2016.07.150

[21] Butdee, S., Phuangsalee, P., 2019. Uncertain risk assessment modelling for bus body manufacturing supply chain using AHP and fuzzy AHP. Procedia Manufacturing. 30, 663–670.
DOI: https://doi.org/10.1016/j.promfg.2019.02.094

[22] Sellitto, M.A., Pereira, G.M., Borchardt, M., et al., 2015. A SCOR-based model for supply chain performance measurement: Application in the footwear industry. International Journal of Production Research. 53(16), 4917–4926.
DOI: https://doi.org/10.1080/00207543.2015.1005251

[23] Bhagwat, R., Sharma, M.K., 2007. Performance measurement of supply chain management using the analytical hierarchy process. Production Planning and Control. 18(8), 666–680.
DOI: https://doi.org/10.1080/09537280701614407

[24] Bhagwat, R., Sharma, M.K., 2007. Performance measurement of supply chain management: A balanced scorecard approach. Computers & Industrial Engineering. 53(1), 43–62.
DOI: https://doi.org/10.1016/j.cie.2007.04.001

[25] Ganga, G.M.D., Carpinetti, L.C.R., 2011. A fuzzy logic approach to supply chain performance management. International Journal of Production Economics. 134(1), 177–187.
DOI: https://doi.org/10.1016/j.ijpe.2011.06.011

[26] Shen, L., Olfat, L., Govindan, K., et al., 2013. A fuzzy multi criteria approach for evaluating green supplier's performance in green supply chain with linguistic preferences. Resources, Conservation and Recycling. 74, 170–179.
DOI: https://doi.org/10.1016/j.resconrec.2012.09.006

[27] Kumar, D., Singh, J., Singh, O.P., 2013. A fuzzy logic based decision support system for evaluation of suppliers in supply chain management practices. Mathematical and Computer Modelling. 58(11–12), 1679–1695.
DOI: https://doi.org/10.1016/j.mcm.2013.03.002

[28] Chen, S.G., 2012. Fuzzy-scorecard based logistics management in robust SCM. Computers & Industrial Engineering. 62(3), 740–745.
DOI: https://doi.org/10.1016/j.cie.2011.11.011

[29] Kocamaz, U.E., Taşkın, H., Uyaroğlu, Y., et al., 2016. Control and synchronization of chaotic supply chains using intelligent approaches. Computers & Industrial Engineering. 102, 476–487.
DOI: https://doi.org/10.1016/j.cie.2016.03.014

[30] Xu, X., Kim, H.S., You, S.S., et al., 2022. Active management strategy for supply chain system using nonlinear control synthesis. International Journal of Dynamics and Control. 10(6), 1981–1995.
DOI: https://doi.org/10.1007/s40435-021-00901-5

[31] Butdee, S., Nitnara, C., 2019. A fuzzy logic combined with LP model for performance evaluation to distribute purchase orders in cluster manufacturing. Procedia Manufacturing. 30, 19–25.
DOI: https://doi.org/10.1016/j.promfg.2019.02.004

[32] Ho, J.W., Fang, C.C., 2013. Production capacity planning for multiple products under uncertain demand conditions. International Journal of Production Economics. 141(2), 593–604.
DOI: https://doi.org/10.1016/j.ijpe.2012.09.016

[33] Gerchak, Y., Hassini, E., Ray, S., 2002. Capacity selection under uncertainty with ratio objectives. European Journal of Operational Research. 143(1), 138–147.
DOI: https://doi.org/10.1016/S0377-2217(01)00337-X

[34] Song, Z., Tang, W., Zhao, R., et al., 2021. Inventory strategy of the risk averse supplier and overconfident manufacturer with uncertain demand. International Journal of Production Economics. 234, 108066.
DOI: https://doi.org/10.1016/j.ijpe.2021.108066

[35] Naraharisetti, P.K., Karimi, I.A., Srinivasan, R., 2006. Capacity management in the chemical supply chain. IFAC Proceedings Volumes. 39(2), 253–258.
DOI: https://doi.org/10.3182/20060402-4-BR-2902.00253