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Abstract

This study identified twenty-two drivers that cause the complexity in supply chain. The level of such complexity is quantified by using hybrid AHP and GRA method. A case company is studied in order to demonstrate the applicability of the proposed method. The results from the case company were analyzed and it is seen that the level of supply chain complexity of the case company is 0.44, which is signifying that there is a considerable scope of improvement in terms of minimizing complexity in its supply chain. From the study outcomes, it is realized that the case company mainly needs substantial improvement on the issues of "government regulation," "internal communication and information sharing," and "company culture" in order to minimize the level of accompanied complexity in its supply chain.

Keywords
Supply chain complexity, Complexity measurement, Analytical hierarchy process, Grey relational analysis, Case study

1. Introduction

In the era of technological revolution, global companies are working in a distributed business environment, where they need to keep eye on every aspect of their supply networks. Supply chain (SC) is a complex system, where different entities, processes, and resources interact with one another (Khadem et al. 2017). Today's SC is getting more complex due to the advent of customization, innovation, globalization, and sustainability (Blome et al. 2014). Complexity creates uncertainties and disruptions to the SC that result in increased cost with lower customer response (Gunasekaran etl. 2015). The complexity is further exacerbated when there is a lack of strategical coordination among SC stakeholders (Surana et al., 2005). In terms of sustainability concern, SC involves consideration of environmental impacts that creates addition complexity (Kaur et al., 2018). In addition, supply chain complexity also arrives due to recent political and economic changes such as Brexit (Hunt and Wheeler, 2019) and trade-protectionist policies in the U.S. (Lambert, 2019). Such changes in business domain have raised awareness in the supply management.

There is no universal definition of SC complexity. However, most of the research studies have identified SC complexity as a multi-faceted, multi-dimensional phenomenon that is driven by several sources (Piya et al. 2017). Bozrath et al. (2009) defined SC complexity as the unpredictability of a system's response to a given set of inputs, whereas, Isik (2010) described it as the quantitative differences between the predicted and real values.

According to Drzymalski (2015), measuring the level of SC complexity is essential to manage complexity efficiently. However, before managing complexity, it is necessary to identify the drivers that create complexity to the SC. Serdarasan (2013) define SC complexity driver as any property of a SC that increases its complexity to the whole chain. According to Gunasekaran et al (2015) supply chain complexity and resilience evolves due to global sourcing strategy. Identification of drivers that create complexity and then measuring the level of SC complexity is fundamental to manage complexity in SC (Piya et al. 2019). Sivadasan et al. (2002) developed entropy-based mathematical model to measure complexity related to the manufacturing process. Isik (2010) extended an initial entropy-based model to include SC complexity with multiple SC partners. According to Serdarasan (2013), complexity in SC may be the effect of many drivers. Therefore, quantifying the SC complexity without considering the effect of all the drivers will not be comprehensive. From the literature review, it is noticed that no past research has developed a model to quantify the SC complexity level based on various complexity drivers. To fill such a research gap, this paper first identified the drivers of complexity, classify them into various dimensions and then develop a novel quantification model based on multi-criteria decision approach to measure SC complexity.

The remaining portion of the paper is structured as follows. Section 2 discusses the SC complexity drivers identified through the extensive literature review and the association of these drivers with SC complexity. Section 3 presents the novel model developed to calculate the SC complexity. Section 4 enumerates the application of the proposed method in a case company. The paper concludes with future research directions in Section 5.

2. Supply Chain Complexity Driver

Extensive literatures were reviewed with the objective to identify the drivers responsible for SC complexity. Literatures were searched using bibliographic databases, such as Science Direct, Emerald, Springer, Google Scholar, and ISI Web of Science using keyword "supply chain complexity," "complexity driver," "complexity factors," and "manufacturing/production complexity". From the literature survey, twenty-two generic drivers of SC complexity were identified. The identified drivers are then clustered into five SC complexity dimensions based on the opinion received from the experts working in the SC domain. The identified drivers, dimensions and their relationships to SC complexity are presented in Table 1.

Table 1: Identified drivers and dimensions of SC complexity

Dimension (k)	Driver (m)	Relation of driver to SC complexity
Strategic management (k1)	Organizational structure (m11)	Adopted organizational structure affects the level of SC complexity within the given organization and further to the whole chain.
	Product development(m12)	The selection of product architecture greatly affect supply chain configuration, manufacturability and assemble ability.
	Technological innovation (m13)	Any technological innovation requires to establish new production lines, materials, processes, and even new SC partners within an organization, which increase SC complexity.
	Organizational standards (m14)	Meeting organizational standards (e.g. ISO, ASME, etc.) may often create additional challenges for an organization involved with multiple SC partners. Necessary standards between the parent organization and its partners may not be at the same level.
	Government regulations (m15)	Satisfying all legal issues and laws of the entire jurisdiction where organization works creates complexity.
Production planning and control (k2)	Product variety (m21)	More product variety results into more SC partners, as well as, inventory and other logistics support for multiple products.
	Manufacturing process (m22)	Types and nature of manufacturing processes adopted by a firm affects the complexity level.
	Planning and scheduling (m23)	Inefficient planning and work scheduling leads to operational complexity, delivery delays, and increased production costs.
	Resource constraint (m24)	Frequent disruption due to the lack of resources among any SC partner affects the trust and level of collaboration.
	Logistics and transportation(m25)	Inefficient logistics and transportation system creates complexity and affects the productivity of the entire SC.
	Process synchronization (m31)	Improper synchronization of work processes between SC partners may create uncertainties, chaos and confusions.

Supplier base (k3)	Number of suppliers(m32)	Increase in the number of suppliers will increase the level of complexity in terms of SC coordination and follow-up.
	Supplier location(m33)	Distance between the supplier locations from the parent company often creates difficulty to monitor and manage the supplier.
	Company culture(m34)	Cultural differences between the partners' organizations may affects the innovation and transparency levels.
	SC network(m35)	Any mismatch among partners with respect to competency result incompatible SC network design and inefficient SC operations.
Marketing & sales (k4)	Marketing (m41)	Improper management of this driver influence the SC efficiency and impacts negatively t to organizational profitability.
	Customer need (m42)	Variety of customer needs and frequently changing needs increase heterogeneity and service options.
	Competitor action (m43)	Any actions of competitors increase complexity in the product design, production, marketing and SC integration.
	Variety of customers (m44)	More categories of customers, increases the complexity level of customer relationship, demand and order management.
Information and Communication (k5)	Communication and information sharing (m51)	Ineffective communication and information sharing leads to chaos and distorted information.
	Forecasting error (m52)	Improper method of forecasting and distorted information flow at different points in the SC network can lead to wider fluctuations in the production and results into operational complexity.
	Information technology (m53)	Incompatibility of information technologies being used by SC partner results into distorted information sharing.

3. Model to measure SC complexity

This research study is adopted a multi-criteria decision-making approach in order to develop a quantitative model, which is a combination of the Analytical Hierarchy Process (AHP) and Grey Relational Analysis (GRA) methods. After identifying the complexity drivers and clustering them into various complexity dimensions in Section 2, the weight of each dimension is calculated based on the AHP method. The results from the AHP method are then integrated to the GRA method. The details on the AHP and GRA methods are discussed next.

3.1 AHP Method

AHP is a popular and widely used multicriteria decision support tool, which works by experts assigning weights on several criteria using the concept of natural pairwise comparison. The paper uses the steps as discussed in (Arunachalam et al. 2019) to identify the weight of the criteria. In the context of this research study, dimensions of SC complexity represents the criteria. For natural pairwise comparison, this research study uses Saaty's scale that varies from 1 to 9 or their reciprocals (Saaty, 1990). As more than one experts are solicited in this study to identify the weight of SC complexity dimensions, the opinions on pairwise comparisons received from experts are unified using geometric mean, which is the most common technique used in AHP method (Grošelj et al. 2015).

Once the weight matrix for the criteria is obtained, it is essential to check the consistency of the result. Saaty (1990) defined consistency matrix as a matrix whose consistency ratio (*CR*) is lower than 0.1. *CR* can be calculated based on the consistency index of weight matrix and random inconsistency index, the value of which depends on the number of criteria.

3.2 Grey Relational Analysis (GRA) Method

The GRA method helps to convert multiple performance indicators, whether the indicators are to be maximized or minimized, into a single grey relational grade (Alam et al. 2019). This research study applied the GRA method with the objective to minimize SC complexity. SC complexity can be managed through maximizing some drivers such as "Product development" and "Process synchronization" etc., while minimizing other drivers such as "Forecasting error" and "Competitor action," etc. The procedural steps followed in the GRA method are elaborated as follows:

3.2.1 Obtain the linguistic scale on SC complexity drivers

The linguistic scale on the driver (m = 1, 2,….., M) associated with the complexity dimensions (k = 1, 2, …., K) is rated by the experts (l = 1, 2, …., L). To avoid ambiguity in dealing with imprecise data, the linguistic scale as shown in Table 2 is used. Each linguistic variable $\otimes y_{klm}$ has lower ($\otimes \underline{y}_{klm}$) and upper ($\otimes \overline{y}_{klm}$) values. The decision matrix ($\otimes D$) to calculate the GRG for dimension k is shown in Equation (1).

Table 2: Linguistic variable and associated value

Definition	Notation	Value
Very — poor, low, near, less effective	VP	0–2
Poor, low, near, less effective	P	2–4
Medium, fair	M	4–6
Good, high, far, effective	G	6–8
Very — good, high, far, effective	VG	8–10

$$\otimes D_k = \begin{pmatrix} \otimes y_{k11} & \otimes y_{k12} & \cdots & \otimes y_{k1M} \\ \otimes y_{k21} & \otimes y_{k22} & \cdots & \otimes y_{k2M} \\ \cdots & \cdots & \cdots & \cdots \\ \otimes y_{kL1} & \otimes y_{kL2} & \cdots & \otimes y_{kLM} \end{pmatrix} \quad (1)$$

3.2.2 Normalize the value

The expert's value obtained is then normalized using formulas in Equations (2) and (3). The use of formula depends on whether the effect of driver needs to be minimized or maximized.

$$\otimes x_{klm} = \frac{\{\otimes y_{klm} - \min(\otimes y_{km})\}}{\max(\otimes y_{km}) - \min(\otimes y_{km})} \quad (2)$$

$$\otimes x_{klm} = \frac{\{\max(\otimes y_{km}) - \otimes y_{klm}\}}{\max(\otimes y_{km}) - \min(\otimes y_{km})} \quad (3)$$

In Equations (2) and (3),

$$\max(\otimes y_{km}) = \max_{1 \le l \le L} (\otimes y_{klm}) \text{ and } \min(\otimes y_{km}) = \min_{1 \le l \le L} (\otimes y_{klm}) \quad (4)$$

3.2.3 Compare the normalized value with reference alternative

Reference alternative reflects the best normalized value on all SC complexity drivers related to the corresponding complexity dimension. The difference between the reference alternative and the normalized value represents the distance of the expert's normalized value from the best value.

$$\otimes \eta_{klm} = \otimes x_{km}^0 - \otimes x_{klm} \quad \text{where, } \otimes x_{km}^0 = \max_{1 \le l \le L} (\otimes x_{klm}) \quad (5)$$

In Equation (5), $\otimes \eta_{klm} = \left(\otimes \underline{\eta}_{klm}, \otimes \overline{\eta}_{klm}\right)$ which depends on the upper and lower value of $\otimes x_{klm}$.

3.2.4 Calculate the SC complexity grey relational coefficient

Grey relational coefficient (GRC) helps to express the correlation between normalized data and the ideal result for each complexity driver.

$$\otimes G_{klm} = \frac{\min\limits_{l}\min\limits_{m} \otimes \underline{\eta}_{klm} + \alpha \max\limits_{l}\max\limits_{m} \otimes \overline{\eta}_{klm}}{\otimes \eta_{klm} + \alpha \max\limits_{l}\max\limits_{m} \otimes \overline{\eta}_{klm}} \tag{6}$$

α in Equation (6) is a distinguishing coefficient, the value of which varies within (0, 1).

3.2.5 Calculate the SC complexity grey relational degree

Grey relational degree (GRD) is calculated by taking the average GRC of all the drivers associated with SCC dimension *k*.

$$\otimes G_{kl} = \frac{1}{M}\sum_{m=1}^{M} \otimes G_{klm} \tag{7}$$

In Equation (7), $\otimes G_{kl} = \left(\otimes \underline{G}_{kl}, \otimes \overline{G}_{kl}\right)$ depending on the value $\otimes \eta_{klm}$ in equation 6.

3.2.6 Calculate the SC complexity grey relational grade

Grey relational grade (GRG) is a weighted average value of the GRD of the entire SCC dimensions. The weight obtained from the AHP method is used to calculate GRG.

$$\otimes G_{l} = \sum_{k=1}^{K} \otimes G_{kl} * w_k \tag{8}$$

In Equation (8), $\otimes G_{l} = \left(\otimes \underline{G}_{l}, \otimes \overline{G}_{l}\right)$ depending on $\otimes G_{kl}$ in equation (7).

3.2.7 Calculate the grey SC complexity level

The Grey SC complexity level (δ) represents the average of the unified GRG obtained from multiple experts.

$$\delta = 1 - \sqrt[L]{\prod_{l=1}^{L} \left(\frac{1}{2}\right)\left(\otimes \underline{G}_{l} + \otimes \overline{G}_{l}\right)} \tag{9}$$

4. Case Study

The developed quantitative model is applied to a multinational company operating in the Middle East for more than four decades. Many of the products manufactured by the company have local, as well as, overseas SC partners. Five experts working at the corporate level of the company were interviewed to calculate the weight of SC complexity dimensions by using AHP method. Each of them did pairwise comparison according to the linguistic variable as discussed in section 3.1. The weighted matrices received from the five experts were then unified, the result of which is as shown in Table 3. The table also shows the weight and rank for each dimension of SC complexity.

Table 3: Experts' unified pairwise comparison matrix for AHP method

Dimension (*k*)	1	2	3	4	5	Weight (w_k)	Rank
Strategic management	-	4.47	2.83	4.47	1.73	0.40	1
Production planning and control	0.22	-	0.41	2	0.41	0.10	4
Supplier base	0.35	2.45	-	3.46	0.71	0.19	3
Marketing and sales	0.22	0.5	0.29	-	0.29	0.07	5
Information and Communication	0.58	2.45	1.41	3.46	-	0.24	2

The consistency of the pairwise comparison in Table 2 is analyzed. Based on the equation as discussed in section 3.1, CR is obtained as 0.02614, which is considerably lesser than the acceptable value of 0.1 for *n*=5 (Kannan 2010). Therefore, the pairwise comparison of experts between the dimensions is consistent.

To apply the GRA method, a questionnaire was prepared based on the identified drivers and submitted to the experts working on one of the manufacturing unit of the case company. Table 4 shows the linguistic variables received from the experts for SC complexity drivers and their associated values.

Table 4: Linguistic variables received from the experts and associated values

SC complexity dimension (k)	SC complexity Driver (m)	Expert's linguistic variable					Associated value of linguistic variable									
							Exp 1		Exp 2		Exp 3		Exp 4		Exp 5	
		1	2	3	4	5	L	H	L	H	L	H	L	H	L	H
	m11	VG	G	G	VG	G	8	10	6	8	6	8	8	10	6	8
	m12	G	M	VG	P	G	6	8	4	6	8	10	2	4	6	8
	m13	P	P	M	VP	M	2	4	2	4	4	6	0	2	4	6
	m14	G	G	G	VG	G	6	8	6	8	6	8	8	10	6	8
k1	m15	M	P	M	G	VP	4	6	2	4	4	6	6	8	0	2
	m21	P	VP	P	P	M	2	4	0	2	2	4	2	4	4	6
	m22	M	M	P	P	P	4	6	4	6	2	4	2	4	2	4
	m23	G	M	M	G	M	6	8	4	6	4	6	6	8	4	6
	m24	G	G	P	P	M	6	8	6	8	2	4	2	4	4	6
k2	m25	VP	P	P	VP	M	0	2	2	4	2	4	0	2	4	6
	m31	G	VG	M	G	VG	6	8	8	10	4	6	6	8	8	10
	m32	M	M	P	G	P	4	6	4	6	2	4	6	8	2	4
	m33	G	G	M	M	M	6	8	6	8	4	6	4	6	4	6
	m34	M	P	P	M	P	4	6	2	4	2	4	4	6	2	4
k3	m35	G	G	M	G	G	6	8	6	8	4	6	6	8	6	8
	m41	M	M	M	P	P	4	6	4	6	4	6	2	4	2	4
	m42	P	VP	VP	P	VP	2	4	0	2	0	2	2	4	0	2
	m43	M	P	G	P	M	4	6	2	4	6	8	2	4	4	6
k4	m44	G	G	M	VG	VG	6	8	6	8	4	6	8	10	8	10
	m51	VP	P	P	M	M	0	2	2	4	2	4	4	6	4	6
	m52	M	P	P	M	P	4	6	2	4	2	4	4	6	2	4
k5	m53	G	M	G	G	VG	6	8	4	6	6	8	6	8	8	10

The GRA method as discussed in section 3.2 is then implemented to the experts opinions received in Table 3. The calculated GRD of each expert for the given dimension and GRG is as shown in Table 5. Note that GRG is basically the amalgamation of GRD of five dimensions.

Table 5: SC complexity grey relational degree (GRD) and grey relational grade (GRG)

Expert	GRD for five dimensions										GRG	
	$k1$		$k2$		$k3$		$k4$		$k5$			
	$\otimes\underline{G}_{1l}$	$\otimes\overline{G}_{1l}$	$\otimes\underline{G}_{2l}$	$\otimes\overline{G}_{2l}$	$\otimes\underline{G}_{3l}$	$\otimes\overline{G}_{3l}$	$\otimes\underline{G}_{4l}$	$\otimes\overline{G}_{4l}$	$\otimes\underline{G}_{5l}$	$\otimes\overline{G}_{5l}$	$\otimes\underline{G}_{l}$	$\otimes\overline{G}_{l}$
1	0.53	0.69	0.42	0.51	0.46	0.57	0.46	0.57	0.43	0.53	0.48	0.60
2	0.50	0.63	0.48	0.60	0.48	0.62	0.53	0.68	0.43	0.53	0.48	0.60
3	0.51	0.66	0.47	0.58	0.46	0.57	0.50	0.64	0.49	0.61	0.49	0.62
4	0.51	0.66	0.44	0.54	0.46	0.57	0.46	0.57	0.51	0.63	0.49	0.62
5	0.53	0.69	0.44	0.54	0.53	0.68	0.47	0.60	0.53	0.68	0.52	0.66

Finally, the GRGs of all experts are unified to obtain the grey SC complexity level of the case company.

$$\delta = 1 - \sqrt[5]{\frac{1}{32}\left[(0.48+0.6)*(0.48+0.6)*(0.49+0.62)*(0.49+0.62)*(0.52+0.66)\right]} = 0.44$$

5. Conclusions

This study identified the drivers of SC complexity and developed a quantitative model to measure the level of complexity created by these drivers on SC. The identification of the drivers was based on an extensive literature review. In order to measure the level of SC complexity, hybrid AHP and GREY method was used. From this hybrid method, numerous drivers were identified, which need to eliminate, or minimize to remove or reduce the complexity level in SC. In order To validate this hybrid method, it was applied to study on a multinational company. From the study, the SC complexity level of the case company was found 0.44, which indicates abundance room of improvement to minimize the level of complexity in the studied case company.

The effectiveness of SC is defined based on various performance measures. In Future, this research can be extended to determine the effects of identified complexity drivers and their magnitude on various performance measures of SC such as cost, supplier responsiveness, and innovation.

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