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Nagesh Shukla
University of Wollongong, nshukla@uow.edu.au

Senevi Kiridena
University of Wollongong, skiriden@uow.edu.au

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Keywords

multi, configuration, sets, fuzzy, rough, chain, supply, dynamic, framework, analytics, agent

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A Fuzzy Rough Sets-based Multi-agent Analytics Framework for Dynamic Supply Chain Configuration

Nagesh Shukla[1*], Senevi Kiridena[2]

[1]SMART Infrastructure Facility, Faculty of Engineering and Information Sciences, University of Wollongong, Wollongong, NSW 2522, Australia
[2] School of Mechanical, Materials and Mechatronics Engineering, Faculty of Engineering and Information Sciences, University of Wollongong, Wollongong, NSW 2522, Australia

[*] Corresponding Author

Abstract

Considering the need for more effective decision support in the context of distributed manufacturing, this paper develops an advanced analytics framework for configuring supply chain networks. The proposed framework utilizes a distributed multi-agent system architecture to deploy fuzzy rough sets-based algorithms for knowledge elicitation and representation. A set of historical sales data, including network node-related information, is used together with the relevant details of product families to predict supply chain configurations capable of fulfilling desired customer orders. Multiple agents such as data retrieval agent, knowledge acquisition agent, knowledge representation agent, configuration predictor agent, evaluator agent and dispatching agent are used to help execute a broad spectrum of supply chain configuration decisions. The proposed framework considers multiple product variants and sourcing options at each network node, as well as multiple performance objectives. It also captures decisions that span the entire supply chain simultaneously and, by implication, represents multiple network links. Using an industry test case, the paper demonstrates the effectiveness of the proposed framework in terms of fulfilling customer orders with lower production and emissions costs, compared to the results generated using existing tools.

Keyword: manufacturing processes, multi-agent systems, supply chain

1. Introduction

With the emerging technological advancements that enable distributed manufacturing come opportunities for businesses to explore new sources of competitive advantage. To successfully explore such opportunities organisations must possess the capacity to make robust decisions. In an environment where distributed manufacturing networks operate at a global scale, due to the diverse range of factors that need to be considered and the pace at which they change, the need for effective decision-making becomes even greater (Olhager *et al.*, 2015; Wang and Chan, 2010). Supply chain (SC) management research can make a significant contribution to advance this cause by way of developing suitable decision support systems (DSS).

The call for more effective decision support in the context of distributed manufacturing is justified on a number of accounts. First, shifting competitive dynamics and ongoing industry consolidations exert increasing pressure on manufacturing enterprises to integrate into global SC networks (Wang and Chan, 2010; Shen *et al.*, 2006). Second, addressing the trade-offs concerning the need for upholding the commercial interests (opportunism) of partner entities while being able to optimise the performance of the entire SC network demands innovative approaches to SC management (Mustafee *et al.*, 2012; Qu *et al.*, 2010). Third, current developments on the social, economic and technological fronts that enhance the accessibility to numerous forms of data (from multiple sources) create new opportunities for such data to be productively used for decision support (Mortenson *et al.*, 2015; Bose, 2009). The work pursued through this paper is motivated by the need for responding to the challenges and opportunities presented by these developments (Fawcett and Waller, 2014).

To this end, this paper develops an advanced analytics framework that can be used to support SC configuration decisions. The paper first presents a summary account of the state-of-the-art in SC configuration decision support, including major limitations of the existing approaches. It then introduces the proposed agent-based architecture, accompanied by a detailed description of its constituent elements. Application of this framework is then illustrated using a test case and sample data drawn from the literature. The paper concludes with an assessment of the efficacy of the proposed framework in light of the results generated and further opportunities for improving and extending the framework.

2. Literature Review

There is a substantive body of knowledge to inform SC network design decisions such as facilities location, capacity planning and supplier selection (Olhager *et al.*, 2015; Meixell and Gargeya, 2005). This body of knowledge is complemented by the extensive work undertaken in the areas of mathematical optimisation and simulation modelling (Acar *et al.*, 2010; Iannone *et al.*, 2007; Shen *et al.*, 2006; Terzi and Cavalieri, 2004). By comparison, much less attention has been paid to research concerning SC network configuration decisions. The interest in configuration decisions arises out of the situation where, in response to the changes in the internal and external business environments, organisations need to assess the alignment between their competitive priorities and SC structure on an ongoing basis, to remain competitive. Inevitably, any consequent adjustments of network nodes or links do affect the performance of the whole SC. Most of the available analytical models and mathematical optimisation techniques do not have the capacity to account for such adaptive and dynamic dimensions of SC network configuration (Zhang *et al.*, 2009; Akanle and Zhang, 2008; Piramuthu, 2005).

Supply chain configuration decisions involve the determination of network nodes and links to meet a set of product-related functional, as well as organisational, objectives while recognising the adaptive nature of SC networks and being able to respond to the dynamics of the business environment. Therefore, configuration decisions are still considered as those concerning the SC network structure; however, compared to design decisions, they transpire more frequently. Thus, the aim of optimisation is to generate a number of alternative (feasible) configurations decision-makers can choose from to suit a given set of circumstances, instead of a single globally-optimised configuration which is often the case in SC design.

Most of the DSS developed within the context of SC design have been based on the assumption that once a network is configured to suit a given product architecture it would remain the same for the foreseeable future (Blackhurst *et al.*, 2005; Huang *et al.*, 2005). Given that configuration, subsequent research efforts generally aim at optimising operations performance. Research focusing on static network designs has also employed analytical methods (both deterministic and stochastic) such as mixed-integer programming and multi-objective optimisation algorithms, as well as systems modelling and simulation to derive the best globally-optimised network configuration (Olhager *et al.*, 2015; Mustafee *et al.*, 2012; Beamon, 1998). In most cases, these optimisations have been achieved against a single performance objective such as cost (Meixell and Gargeya, 2005; Beamon, 1998).

However, a number of authors have pointed out that such an approach is insufficient to provide effective support required for robust decision-making in a dynamic global environment. For instance, Akanle and Zhang (2008) emphasized the need for recognising the evolving nature of SCs when developing methodologies to address the configuration problem. Olhager *et al.* (2015), as well as Meixell and Gargeya (2005), noted the need for extending current decision support models to capture multiple decisions and multiple objectives across the SC in their entirety, while accounting for contingency factors. Similarly, Piramuttu (2005) called for studies that deal with the dynamic configuration of SCs and "extending the research focus to handle more stages, several nodes in each stage and variability [in order size or type]" (p. 229). More broadly, the literature has also highlighted the limitations of existing analytical methods used for dealing with the above challenges (Qu *et al.*, 2015; Long and Zhang, 2014; Mustafee *et al.*, 2012).

A few authors have attempted to comprehensively tackle the above challenges using novel methodological approaches. For example, Akanle and Zhang (2008) developed a multi-agent system to optimise configuration decisions considering anticipated changes in customer demand, as well as ongoing adjustments in the resource profiles of SC entities and their operational environment. Troung and Azadivar (2005) proposed a SC model builder combining genetic algorithms, mixed integer programing and discrete-event simulation to address multiple configuration decisions (of both qualitative and quantitative nature) simultaneously. Piramuttu (2005) applied machine learning algorithms to identify the nodes of a SC network that best aligns with a given combination of order attributes, which was shown to deliver better SC-wide performance. The current status of SC design/configuration research, as revealed through the literature review, is summarised in Figure 1 below with the research gaps this paper aims to address largely falling in quadrant 4 (Q4).

		Spatial dimension	
		Narrow scope (reductionist)	**Broad scope (holistic)**
Temporal dimension	**Static**	Q1 • assume stable entities and relationships • driven by product architectures and performance improvement goals • focus on single-objective optimisation • well-researched; mature knowledge base • a wide range of tools and techniques are available to choose from	Q2 • assume stable entities and networks • driven by product architectures and competitive priorities • focus on global optimisation, few objectives and centralised external control • limited-research; emerging knowledge base • some tools and techniques
	Dynamic	Q3 • assume evolving entities and relationships • driven by product architectures and technology platforms • focus on local optimisation, many objectives and distributed control • limited-research; emerging knowledge base • some tools and techniques	Q4 • assume evolving entities and networks • driven by competitive priorities, organisational capabilities, product architectures and technology platforms • focus on scenario-based optimisation, multiple objectives and self-control • little research; no tools and techniques

Figure 1: State-of-the-art in SC configuration research

The work reported in this paper aims to contribute to this stream of literature by addressing the problem of generating a suit of network configurations capable of delivering a given mix of customer orders that could be evaluated against multiple performance goals. In doing so, we extend the work of Akanle and Zhang (2008), Troung and Azadivar (2005) and Piramuttu (2005) by way of enhancing their scope and methodology. Previous studies have employed individual methods such as machine learning and genetic algorithms, as well as agent-based approaches, to account for the dynamic and adaptive dimensions of the network configuration problem. Agent-based approaches in particular have been found to be useful in representing the distinctive behaviour of individual entities within the SC network (Dai *et al.*, 2014; Long and Zhang, 2014; Shen *et al.*, 2006). Following our evaluation of the available tools to ascertain their capacity to meet the multiple requirements discussed above, we selected a fuzzy rough sets-based multi-agent approach. In the following section, we illustrate how this approach is used to solve the SC configuration problem.

3. Multi-agent architecture for SC configuration

In general, agents are defined as independent problem-solvers with capabilities for sensing and acting within their environment, which include communicating with other agents, to decide their course of action in an autonomous way (Monostori *et al.*, 2006). The multi-agent system (MAS) architecture proposed in this paper is based on: (*i*) knowledge handling by agents; (*ii*) a data-based intuitive analytics approach; and (*iii*) a number of similarly coordinating/communicating agents. As such, it comprises a group of agents namely: data retrieval agent, knowledge acquisition agent, knowledge representation agent, configuration predictor agent, SC configuration evaluator agent and dispatcher agent. Each of these agents is assigned to perform specific tasks that facilitate SC configuration decisions. Collectively these agents provide SC configuration solutions to satisfy a mix of customer orders, which are driven by chosen competitive priorities, while meeting multiple performance objectives (*e.g.* total cost, CO_2 emissions and total delivery time, among others).

Due to the advancement of data acquisition and storage technologies, SC organisations are typically capturing and storing various datasets related to product sourcing, design, manufacturing, logistics and field performances. These datasets can potentially be used to inform SCM decisions. In this paper, we demonstrate the use of some historical product data sets for generating SC configurations that are aligned with an organisation's competitive priorities. We employ an innovative set of techniques from fuzzy rough sets theory (FRST) (Cornelis *et al.,* 2010; 2008) to mine rules and associations from such historical datasets. Rough set theory (RST) was first introduced by Pawlak (1982) for mining data based on the information theory-based approximations. It allows an effective mechanism for distinguishing objects based on their attribute values. These are then used to form simple intuitive rules (IF-THEN) for classifying objects. FRST is a generalised form of RST where imprecision or vagueness is represented by membership degrees in fuzzy sets rather than discretisation for the real-valued attributes. More information about FRST is presented later in this section.

Figure 2 illustrates the MAS architecture proposed for supporting SC configuration decisions.

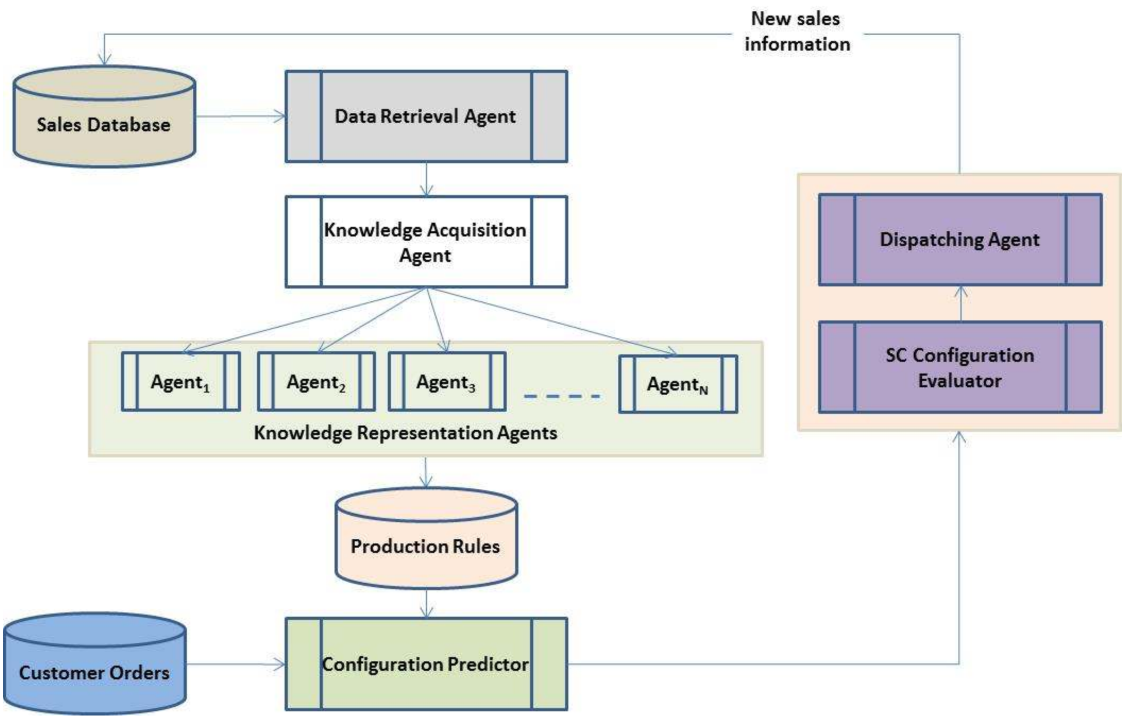

Figure 2: MAS Architecture for Dynamic SC Configuration

3.1. Data retrieval agent

The data retrieval agent retrieves historical product sales data and SC network node information. It pre-processes the raw records so that they can be used by the knowledge acquisition agent to prepare the dataset for analysis.

3.2. Knowledge acquisition agent

The knowledge acquisition agent performs some processing on the datasets retrieved by the data retrieval agent based on the FRST principles of discernibility, *i.e.*, ability to distinguish objects based on measured attributes. The notations of FRST used throughout this paper are, therefore, introduced first. Let us assume that the dataset from the data retrieval agent is represented as $\mathcal{A} = (U, A \cup \{d\})$, where U is a finite set of objects (data instances), A is the finite non-empty set of attributes (a) and d is the decision attribute such that $d \notin A$. Mathematically, $a: U \to V_a\ \forall\ a \in A$ and V_a is the set of values that an attribute a can take. Decision variable d can take only nominal/categorical values. The indiscernibility relations are established based on decision system $\mathcal{A}$. To model indiscernibility in decision classes (B-indiscernibility), an equivalence relation R_B is defined for RST for set $B \subseteq A$:

$$R_B(x, y) = \{(x, y) \in U^2 | a \in B, a(x) = a(y)\} \quad (1)$$

According to this equivalence relation, if $(x, y) \in R_B(x, y)$, then x and y have exactly the same values for attributes in B. In the case of decision system $\mathcal{A} = (U, A \cup \{d\})$, equivalence classes are defined based on the designated attribute called the decision attribute. These equivalence classes are represented as $[x]_{R_d}$.

However, in FRST, fuzzy indiscernibility relation is used to determine the degree to which two objects are indiscernible. The relation R is assumed to be reflexive (Eqn. 2) and symmetric (Eqn. 3) with further tolerance conditions (Eqn. 4) imposed as needed.

That is,

$$R(x,x) = 1 \; \forall x \in U \tag{2}$$

$$R(x,y) = R(y,x) \; \forall x,y \in U \tag{3}$$

$$\mathcal{T}(R(x,y), R(y,z)) \leq R(x,z) \quad \forall x,y,z \in U \tag{4}$$

where, the relation R is called $\mathcal{T}$-equivalence relation and $\mathcal{T}(.)$ is a given triangular norm operator.

In FRST, *approximate equality* relation (R) for objects is measured instead of indiscernibility used in RST (Eqn. 1). To create fuzzy B-indiscernibility relation or approximate equality relation for $B \subseteq A$ with respect to quantitative attribute $a \in A$ is defined by R_a. According to Jensen and Shen (2009), this relation is typically represented as:

$$R_a(x,y) = \max\left(\min\left(\frac{a(y)-a(x)+\sigma_a}{\sigma_a}, \frac{a(x)-a(y)+\sigma_a}{\sigma_a}\right), 0\right) \tag{5}$$

where, σ_a is the standard deviation of attribute a. In the case of nominal attributes, $R(x,y) = 1$ if $a(x) = a(y)$ and $R(x,y) = 0$ otherwise. Therefore, fuzzy B-indiscernibility relation is represented by:

$$R_B(x,y) = \mathcal{T}\left(\underbrace{R_a(x,y)}_{a \in B}\right) \tag{6}$$

where, $\mathcal{T}(.)$ is a t-norm.

The upper and lower approximation sets for fuzzy rough set theory is generally given by an implicator function $\mathcal{J}$ and a t-norm function $\mathcal{T}$ (Radzikowska and Kerre, 2002). The fuzzy lower and upper approximations are given by:

$$(R_B \downarrow X)(y) = inf_{x \in U} \mathcal{J}(R_B(x,y), X(x)) \tag{7}$$

$$(R_B \uparrow X)(y) = sup_{x \in U} \mathcal{T}(R_B(x,y), X(x)) \tag{8}$$

where, X is a fuzzy set in U.

In FRST, fuzzy B-positive regions are defined as the fuzzy set of objects in U that can be unequivocally classified using conditional attributes B. The fuzzy B-boundary region is defined to be the fuzzy set of objects in U that can potentially, but not certainly, be classified using conditional attributes B. The fuzzy positive region (POS) can be defined based on the fuzzy B-indiscernibility relations for $y \in U$,

$$POS_B(y) = \left(\bigcup_{x \in U} R_B \downarrow [x]_{R_d}\right)(y). \tag{9}$$

The fuzzy B-boundary region is defined as:

$$BND_B(y) = \left(\bigcup_{x \in U} R_B \uparrow [x]_{R_d} \setminus \bigcup_{x \in U} R_B \downarrow [x]_{R_d}\right)(y). \tag{10}$$

Once the fuzzy B-indiscernibility relationships are established, the decision-relative discernibility matrix is defined. Mathematically, discernibility matrix ($n \times n$) is defined as

$$c_{ij} = \begin{cases} \{a \in A: 1 - R_B(x_i, x_j) \leq \lambda_i\}, & \text{if } d(x_i) \neq d(x_j) \\ \emptyset & \text{otherwise,} \end{cases}. \tag{11}$$

where, $\lambda_i = (R_B \downarrow [x_i]_d)(x_i)$.

The continuous attributes in the decision system $\mathcal{A} = (U, A \cup \{d\})$ is discretised based on the rough set approach. For instance, for $a \in A$ and the sequence of values it can take is defined by $\{v_1^a, v_2^a, \dots, v_{n_a}^a\}$ and $v_1^a < v_2^a < \cdots < v_{n_a}^a$, the set of cuts on a is denoted by:

$$C_a = \left\{\left(a, \frac{v_1^a + v_2^a}{2}\right), \left(a, \frac{v_2^a + v_3^a}{2}\right), \dots, \left(a, \frac{v_{n_a-1}^a + v_{n_a}^a}{2}\right)\right\}. \tag{12}$$

Therefore, the set of all possible cuts $\forall a \in A$ is represented as

$$C_A = \bigcup_{a \in A} C_a. \tag{13}$$

The discretised values in the decision system are then passed on to the knowledge representation agent for knowledge representation based on rule induction.

3.3. Knowledge representation agents

Knowledge representation agents use the information received from the acquisition agent (historical datasets) to create knowledge in the form of production rules. Each knowledge representation agent works with this information to represent knowledge for each node in the SC network. One of the popular knowledge representation techniques is the production rules commonly represented as *IF <condition> THEN <action>*. Advantages of rule-based representation include their simplicity and ease of use: e.g. interpretation and manipulation.

The algorithm used in this paper for generating decision rules is similar to the generalized fuzzy rough set rule induction (Zhao *et al.,* 2010) and QuickRules algorithm (Jensen *et al.,* 2009a,b). The method proposed by Zhao *et al.* (2010) can be briefly described as (see Fig. 3a):

Step 1: General lower approximation sets are developed to deal with misclassification and perturbation;
Step 2: Discernibility matrix is computed based on the consistency degree; and
Step 3: Rules based on consistency degrees of the associated objects are evaluated.

This algorithm is applied by agents to generate production rules for each node (supplier, manufacturers, retailer, others) in a distributed manner. The distributed nature of knowledge representation agents is achieved through adopting a bottom-up approach (i.e. from individual SC nodes to configuring the whole SC). The resulting knowledge is stored in the production rules database for its use in SC configuration predictions.

3.4. Configuration predictor agent

Configuration predictor agent takes two types of input: (*i*) customer orders and (*ii*) production rules. The production rules are used together with the customer order attributes to predict appropriate SC configurations that are aligned with the SC performance objectives considered (see Fig. 3b). In this paper, we have used time, SC cost and carbon emissions as the three main indicators to assess SC-level performance. The customer orders are generally represented by the time window that customers are prepared to wait and the type of product that has been requested. More information about customer order attributes and production rules is presented in the results and discussion section.

3.5. SC configuration evaluator agent

Once the SC configurations for a given mix of customer orders are generated, these configurations are evaluated against the three performance metrics identified above (see Section 3.4). The total SC cost is used together with the selling price of the product to compute the total profit generated for the organisation by following the SC configurations concerned. At this stage, decision-makers can also consider other indicators such as carbon emissions and total production time before selecting an appropriate SC configuration to fulfil the desired mix of customer orders (see Fig. 3c).

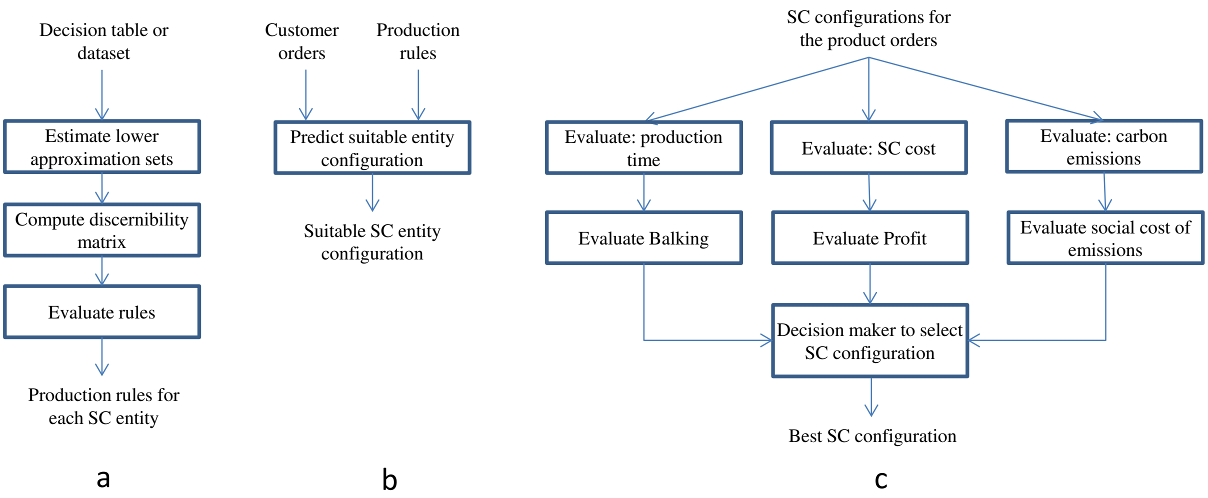

Figure 3: Agent actions for (a) knowledge representation agents, (b) configuration predictor, and (c) configuration evaluator agent

3.6. Dispatching agent

Based on the SC configuration decided by the configuration evaluator agent, subject to decision-makers preferences, the customer order is fulfilled. The dispatching agent sends information about the order and SC configuration to the relevant nodes in the SC network.

4. Numerical Example

In this section, we illustrate the implementation of the proposed framework using a popular example adapted from literature (Akanle and Zhang, 2008; Huang *et al.,* 2005; Troung and

Azadivar, 2005). In this example, the SC network considered involves the production of two product variants; Laptop-CD and Laptop-DVD. Both of these products require similar components and sub-assemblies until they reach the final stage of assembly where either CD or DVD subassembly is used. Figure 4 illustrates the structure of the SC network. We have adapted the example to suit the purpose of our paper with the changes listed below.

1. Both Laptop-CD and Laptop-DVD can be sold in all markets
2. There can be multiple suppliers with varying profiles (attributes) available to produce the required parts within the SC
3. Multiple assembly plants are available to produce subassemblies within the SC

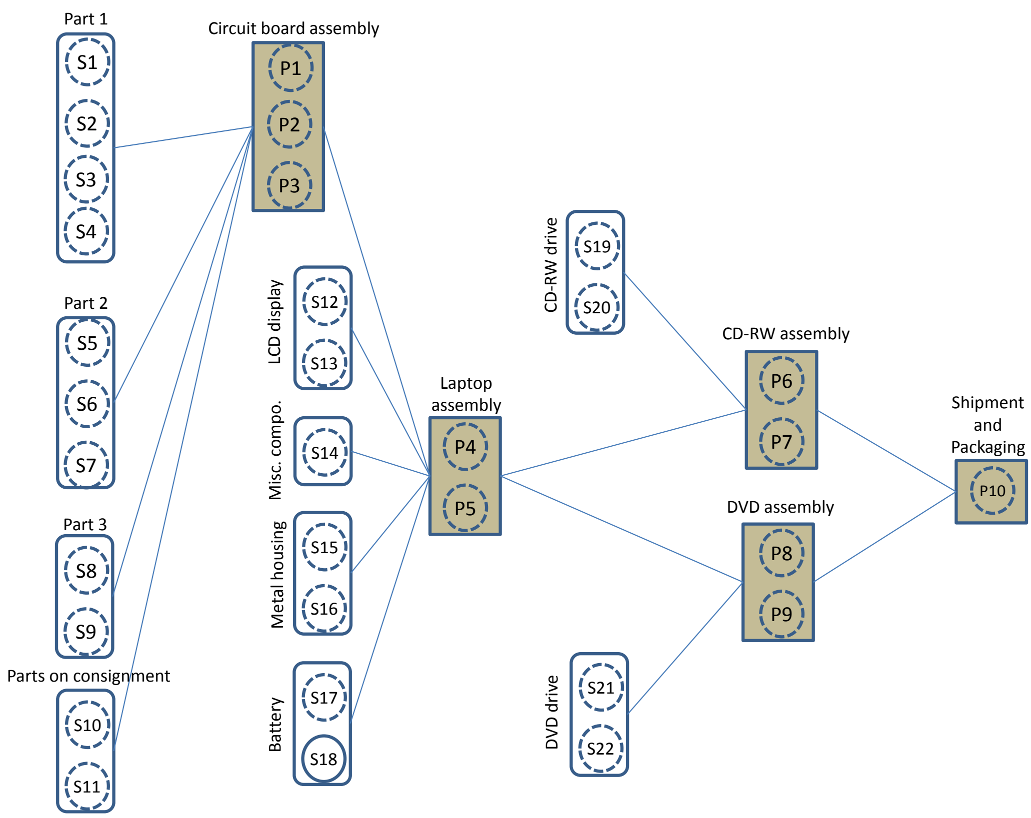

Figure 4: SC network for Laptops

As shown in Figure 4, the modified example has multiple options (in terms of suppliers and assemblers) to choose from at each network node when configuring the SC. For example, for part 1, the available sources are S1, S2, S3 and S4; and for the circuit board assembly, the available sources are P1, P2 and P3. Each of these alternative sources represents different values for lead times, costs and supply quantity.

The distance between two nodes, as an attribute to compute carbon emissions, has also been considered. However, it was assumed that road-based freight is the only transport option available. Table 1 illustrates the configuration dataset sample for suppliers for parts 1 and 2 only.

The data retrieval agent extracts raw production and sourcing information of relevant network entities such as suppliers and assemblers. This information is passed on to the knowledge acquisition agent to perform pre-processing of the raw product structure information. In pre-processing, the knowledge acquisition agent derives the fuzzy B-discernibility matrix from the raw information based on generalised fuzzy rough sets. The dataset for each node (SC entity) is divided into 70% for training and 30% for validation/testing. This helps in generalising the results from the classification system and to avoid over-fitting. The resulting matrix is then used to induct rule-based classifiers for each node in the SC network.

Table 1: Aggregated configuration data on suppliers for parts 1 and 2 (only)

Stage	Node	Components	Supplier	Lead time	Quantity	Cost ($)	Distance (Km)
1	1	Part 1	S1	1-10	50	145	148.36
1	1	Part 1	S1	11-20	100	139	148.36
1	1	Part 1	S1	21-40	150	125	148.36
1	1	Part 1	S2	1-5	60	144	175.36
1	1	Part 1	S2	6-25	95	140	175.36
1	1	Part 1	S2	26-40	150	125	175.36
1	1	Part 1	S3	1-25	40	140	223.23
1	1	Part 1	S3	26-35	115	138	223.23
1	1	Part 1	S3	36-40	150	132	223.23
1	1	Part 1	S4	1-15	80	141	184.23
1	1	Part 1	S4	16-40	150	133	184.23
1	2	Part 2	S5	1-5	40	50	123.63
1	2	Part 2	S5	6-9	90	45	123.63
1	2	Part 2	S5	10-12	120	43	123.63
1	2	Part 2	S5	13-15	150	42	123.63
1	2	Part 2	S6	1-7	30	49	145.96
1	2	Part 2	S6	8-10	80	43	145.96
1	2	Part 2	S6	11-15	150	42	145.96
1	2	Part 2	S7	1-10	75	50	123.23
1	2	Part 2	S7	11-15	150	40	123.23

Table 2: Prediction accuracy (percentage correctly classified) for all the nodes in the SC

Node	Component/process description	Fuzzy Rough Sets Theory (GFRS)
1	Part 1	68.23
2	Part 2	67.9035
3	Part 3	82.243
4	Parts on consignment	93.33
5	Circuit board assembly	72.02
6	LCD display	94.061
7	Miscellaneous components	100.00
8	Metal housing	89.074
9	Battery	75.647
10	Laptop assembly	71.1838
11	CD-RW drive	99.17695
12	DVD drive	86.104
13	CD-RW assembly	80.939

14	DVD assembly	83.07692
15	Shipment and Packaging	100.00

The knowledge representation agent runs the rule induction algorithm individually for each SC network node in a distributed manner (on training dataset) and the production rules generated are stored in the database at the end. The rules generated are tested with the help of the test dataset (30% of the raw dataset). The results of the classification (i.e. percentage correctly classified for test dataset) for each node of the SC network are shown in Table 2. It should be noted that there is only one configuration option available for SC entity at nodes 7 and 15. Therefore the classification is 100%. On average, the accuracy of the classifiers used for all the nodes (excluding nodes 7 and 15) is 81.77. This means that the proposed classifier system is able to predict the configuration for SC entities accurately.

The rules generated are then stored in a production rules database. The configuration predictor agent retrieves information about the product orders from the customers and applies the rule-based classification to obtain suitable SC configurations. The customer orders for the two product variants (Laptop-CD and Laptop-DVD) are shown in Table 3. The results obtained after the application of stored production rules to each customer order is presented in Table 4. For each order, a suitable SC entity configuration is obtained to fulfil the customer order in a cost-effective and timely manner. From Table 4, it is clear that there is no one particular configuration of SC entities that suit all orders. The most common SC configuration (based on Table 4), however, is S4, S7, S9, S11, P1, S13, S14, S16, S17, P4, S20, S21, P6, P8 and P10.

Table 3: Customer orders for laptops

ID	Product Type	Lead Time	Quantity
1	Laptop-CD	8	142
2	Laptop-CD	56	136
3	Laptop-CD	8	148
4	Laptop-CD	37	140
5	Laptop-CD	19	60
6	Laptop-CD	26	9
7	Laptop-CD	77	100
8	Laptop-CD	59	131
9	Laptop-CD	57	96
10	Laptop-CD	68	35
11	Laptop-DVD	44	137
12	Laptop-DVD	57	43
13	Laptop-DVD	7	135
14	Laptop-DVD	61	94
15	Laptop-DVD	20	57
16	Laptop-DVD	8	125
17	Laptop-DVD	22	27
18	Laptop-DVD	40	7
19	Laptop-DVD	47	147
20	Laptop-DVD	80	41

The SC configuration evaluator agent takes the results of the SC configuration (Table 4) and evaluates them against balking criteria based on the actual lead times required to match the customer's expected delivery time. Table 5 illustrates this evaluation, where order ID 1,3,4,5 for Laptop-CD and 11, 13, 15, 16 for Laptop-DVD is balked. Then the production cost per product is evaluated for the two cases: (i) when dynamic SC configuration is used, and (ii) when fixed common SC configuration is used. Table 5 shows the results of the SC evaluation process, where savings of $7,337 (for Laptop-CD) and $5,069.5 (for Laptop-DVD) can be achieved by dynamically configuring the SCs. The scenario where only sales profit and delivery time are used to evaluate the SC configuration is termed as ***scenario (i)*** and it would be used for comparisons against other scenarios (where carbon emissions is also considered).

Table 4: SC configuration results for the orders in *scenario (i)*, where, N_1 represents node 1

ID	N_1	N_2	N_3	N_4	N_5	N_6	N_7	N_8	N_9	N_10	N_ 11	N_12	N_13	N_14	N_15
1	S4	S5	S8	S10	P3	S13	S14	S16	S17	P4	S19	S21	P6		P10
2	S4	S7	S9	S11	P1	S13	S14	S16	S17	P5	S20	S21	P6		P10
3	S4	S5	S8	S10	P3	S13	S14	S16	S17	P4	S19	S21	P6		P10
4	S4	S7	S9	S11	P2	S13	S14	S16	S17	P4	S19	S22	P6		P10
5	S3	S6	S9	S11	P1	S13	S14	S16	S17	P4	S19	S22	P7		P10
6	S1	S7	S9	S11	P1	S13	S14	S16	S17	P4	S19	S21	P6		P10
7	S2	S7	S8	S11	P2	S12	S14	S16	S17	P4	S20	S21	P7		P10
8	S2	S7	S9	S11	P1	S13	S14	S16	S17	P4	S20	S21	P6		P10
9	S2	S7	S9	S11	P1	S13	S14	S16	S17	P4	S20	S21	P6		P10
10	S1	S7	S9	S11	P2	S13	S14	S16	S17	P5	S20	S21	P7		P10
11	S4	S7	S9	S11	P1	S13	S14	S16	S17	P5	S20	S21		P8	P10
12	S2	S7	S9	S11	P1	S13	S14	S16	S17	P4	S20	S21		P9	P10
13	S4	S5	S9	S11	P3	S13	S14	S16	S17	P4	S19	S22		P8	P10
14	S2	S7	S8	S11	P3	S13	S14	S16	S17	P4	S20	S21		P9	P10
15	S3	S5	S9	S11	P1	S13	S14	S16	S17	P4	S19	S21		P8	P10
16	S4	S5	S9	S10	P3	S13	S14	S16	S17	P4	S19	S21		P8	P10
17	S1	S7	S9	S11	P1	S13	S14	S16	S18	P5	S19	S21		P8	P10
18	S4	S7	S9	S11	P2	S13	S14	S16	S17	P5	S19	S22		P8	P10
19	S1	S7	S9	S11	P1	S13	S14	S16	S17	P4	S20	S21		P8	P10
20	S1	S7	S9	S11	P2	S12	S14	S15	S17	P4	S20	S21		P9	P10

The social cost of carbon emissions arising out of manufacturing and logistics activities is also used to configure SCs using the proposed framework. An average CO_2 emission factor of 62 g CO_2/tonne-km (CEFIC, 2011), used for activity-based CO_2 emission estimations, is considered. This estimate was used for computing the transportation-related emissions. For the purposes of this paper, we have only considered road-based transport. Additionally, manufacturing-related emissions were calculated using an estimate of 61.1 tonnes of CO_2 when a ton of product, by mass, is produced (CO_2List, 2012). The weight of a laptop is considered to be 2.2078 Kg. The social cost of CO_2 emissions is used in this study to estimate the reduction of net social welfare due to emissions. A recent study by Moore and Diaz (2015) estimates that one additional ton of CO_2 emitted in 2015 reduces net social welfare by

US$220. This estimate is used to compute the dollar equivalent of the harm caused by CO_2 emissions.

Table 5: Order results evaluation for scenario (i)

ID	***Order status***	***Estimated Production Cost based on Proposed SC configuration ($, per product)***	***Estimated Production Cost based on most common SC configuration ($, per product)***	***Savings ($)***
1	BALK	1142	1147.5	781
2	OK	1149.5	1147.5	-272
3	BALK	1142	1147.5	814
4	BALK	1137.5	1147.5	1400
5	BALK	1214.25	1240.5	1575
6	OK	1237	1246	81
7	OK	1180.25	1169.5	-1075
8	OK	1129.5	1147.5	2358
9	OK	1149.5	1169.5	1920
10	OK	1253	1246	-245
			Total	**7,337**
11	BALK	1151.5	1147.5	-548
12	OK	1237.5	1244	279.5
13	BALK	1143.5	1147.5	540
14	OK	1165	1169.5	423
15	BALK	1221.5	1240.5	1083
16	BALK	1147	1151.5	562.5
17	OK	1252	1246	-162
18	OK	1248	1246	-14
19	OK	1131.5	1147.5	2352
20	OK	1230.5	1244	553.5
			Total	**5,069.5**

The proposed framework is used again in the scenario where social cost from CO_2 emission is used together with the production cost in evaluating SCs. This scenario is termed as ***scenario (ii)***. The results obtained from the SC configuration agent for scenarios (i) and (ii) are presented in Table 6. It is evident from Table 6 that although the production cost per product based on SC configuration is comparatively higher for scenario (ii) the combined cost is lower in scenario (ii). This is true for most of the orders. It can also be seen that the number of orders that are balking is lower in scenario (ii) when compared to scenario (i).

Table 6: Comparison between scenarios (i) when production cost only, and (ii) combined production cost and social cost of CO_2, is used for SC configuration

	Scenario (i)			*Scenario (ii)*		
ID	***Order status***	***Estimated Production Cost ($, per product)***	***Estimated Combined Cost ($, per product)***	***Order status***	***Estimated Production Cost ($, per product)***	***Estimated Combined Cost ($, per product)***
1	BALK	1142	1228.80	BALK	1151.5	1214.45
2	OK	1149.5	1233.06	OK	1139.5	1199.87
3	BALK	1142	1232.05	BALK	1151.5	1217.53
4	BALK	1137.5	1223.32	OK	1149	1210.47
5	BALK	1214.25	1258.85	OK	1235.5	1254.16
6	OK	1237	1253.85	OK	1249	1241.60
7	OK	1180.25	1246.64	OK	1174.25	1216.19
8	OK	1129.5	1210.31	OK	1139.25	1197.05
9	OK	1149.5	1211.26	OK	1158.25	1198.21
10	OK	1253	1284.02	OK	1250.5	1256.03
11	BALK	1151.5	1234.11	BALK	1152	1214.38
12	OK	1237.5	1270.91	OK	1246.5	1257.66
13	BALK	1143.5	1224.61	BALK	1151.5	1212.85
14	OK	1165	1223.98	OK	1173.25	1213.93
15	BALK	1221.5	1262.37	OK	1235.5	1254.63
16	BALK	1147	1222.53	BALK	1151.5	1207.72
17	OK	1252	1276.58	OK	1249	1252.78
18	OK	1248	1261.79	OK	1257	1250.58
19	OK	1131.5	1219.15	OK	1152	1219.52
20	OK	1230.5	1263.70	OK	1251.5	1261.59

The comparative summary of the SC configuration for scenarios (i) and (ii) is presented in Table 7. It can be seen that balking percentage is reduced when production cost and social cost is considered for both of the products. In scenario (ii), the average social cost for CO_2 emissions per product is significantly reduced (from 76.32 to 52.53 for Laptop-CD and from 68.91 to 48.77 for Laptop-DVD). The net reduction in social cost (per product) is 31.17% and +29.23. The unit production cost has slightly increased under scenario (ii). However, the production cost losses for the two products are 0.506% and 0.795% under scenario (ii). It can be seen that the production losses are less compared to the gain achieved through the reduction in social costs under scenario (ii). As such, the decision-makers need to consider both of these costs in determining the preferred SC configuration.

Table 7: SC configuration based on production costs and social costs of emissions

Scenario	**Laptop-CD**			**Laptop-DVD**		
	Balking (%)	**Average Production Cost ($, product)**	**Average Social Cost for Emission ($, product)**	**Balking (%)**	**Average Production Cost ($, product)**	**Average Social Cost for Emission ($, product)**
Scenario (i)	*40*	*1,154.41*	*76.32*	*40*	*1,165.03*	*68.91*
Scenario (ii)	*20*	*1,160.25*	*52.53*	*30*	*1,174.29*	*48.77*

Savings	*+50*	*-0.506 %*	*+31.17*	*+25*	*-0.795 %*	*+29.23 %*

5. Conclusions and Future Directions

Considering the diverse challenges faced by manufacturing enterprises seeking to sustain their competiveness in a dynamic global business environment, we proposed an advanced agent-based analytics framework to aid their SC network configuration decisions. As we set out to develop an advance analytics framework to support robust configuration decisions we relaxed a number of assumptions used in the extant studies, which our framework was built on (i.e. Akanle and Zhang, 2008; Troung and Azadivar, 2005; Piramuttu, 2005). For instance, the proposed framework accounted for two product variants, multiple sourcing options at each network node, as well as multiple performance objectives. It also captured decisions that span the entire SC network simultaneously and, by implication, represented multiple network links. In effect, this paper contributes to SC configuration research by addressing most of the research gaps identified through the literature review (listed in Q4 of Fig. 1). The framework first generated alternative SC configurations that aligned with competitive priorities, which were then evaluated against SC-level performance metrics. This approach provides an opportunity for organisations to appreciate the impact of a range of factors in the broader decision environment on SC configuration decisions and make strategic choices aimed at leveraging or mitigating such impacts.

Results generated through the application of the test case demonstrated that the configuration choices made using the proposed framework can yield significantly superior financial gains and SC-wide performance outcomes. It was demonstrated that the methodological approach and the constituent knowledge acquisition and representation rules employed are capable of handling sophisticated configuration problems involving multiple product types, sourcing options and performance objectives. As such, the proposed analytics framework has the potential to serve as a more effective decision support tool that help manufacturing enterprises address the challenges associated with responding to changing competitive dynamics while accounting for nuances of the decision environment. Overall, we believe, the proposed framework responds well to the calls made in the literature in that it has demonstrated its efficacy in terms of generating alternative configurations that are feasible (i.e. capable of fulfilling required customer orders) and circumstantially optimal (i.e. capable of delivering desired performance outcomes under a given set of circumstances).

Building on the results of this study, we aim to validate the proposed framework using a full-scale empirical case study in future research. The agent-based modelling approach proposed in the paper is fairly generic and hence can be applied to real world examples with minimal modifications, for example, to input parameters and data. There is also a further opportunity for more comprehensively comparing the results of a full-scale empirical study against those of previous studies that have used other comparable methodological approaches. This may help identify areas for further improvements which will lead to establishing the superiority and generalisability of the proposed analytic framework in unequivocal terms.

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