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A multi-agent optimisation model for solving supply network configuration problems

Subodha Dharmapriya
University of Wollongong

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Subodha Dharmapriya
MPhil, BSc Engineering (specialised in Production Engineering)

Supervisor: Dr Senevi Kiridena
Co-supervisor: Dr Nagesh Shukla

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DEDICATION

To

all my teachers

ABSTRACT

Supply chain literature highlights the increasing importance of effective supply network configuration decisions that take into account such realities as market turbulence and demand volatility, as well as ever-expanding global production networks. These realities have been extensively discussed in the supply network literature under the structural (i.e., physical characteristics), spatial (i.e., geographical positions), and temporal (i.e., changing supply network conditions) dimensions. Supply network configuration decisions that account for these contingencies are expected to meet the evolving needs of consumers while delivering better outcomes for all parties involved and enhancing supply network performance against the key metrics of efficiency, speed and responsiveness. However, making supply network configuration decisions in the situations described above is an ongoing challenge.

Taking a systems perspective, supply networks are typically viewed as socio-technical systems where SN entities (e.g., suppliers, manufacturers) are autonomous individuals with distinct goals, practices and policies, physically inter-connected transferring goods (e.g., raw materials, finished products), as well as socially connected with formal and informal interactions and information sharing. Since the structure and behaviour of such social and technical sub-systems of a supply network, as well as the interactions between those subsystems, determine the overall behaviour of the supply network, both systems should be considered in analysing the overall system.

Accordingly, the first and the most significant research need addressed in this study is enhancing the performance of a geographically dispersed, multi-echelon supply network in a distributed decision-making environment, where individual supply network entities aim to satisfy their own organisational goals. The second research need addressed in this study is to achieve the above goals with minimal information sharing between supply network entities, which reflects the real-world situation of organisations' reluctance to disclose commercially sensitive information. The third research need addressed in this study is to provide analytical insights for SN decision-makers to sustain SN-level competitiveness in the face of changing SN conditions (e.g., uncertainties and dynamics).

In the literature, approaches such as multi-agent systems and intelligent systems have been proposed as suitable for dealing with complex and dynamic systems and distributed decision-making problem contexts. The structure and behaviour of supply networks, which is also consistent with the characteristics and principles of multi-agent systems, make them particularly suitable for studying in the form of distributed systems. Therefore, this study

proposes a comprehensive multi-agent optimisation approach in combination with intelligent auctioning and bidding strategies to address the research needs mentioned above.

To this end, a multi-stage, multi-echelon supply network consisting of geographically dispersed supply network entities catering to distinct product-market profiles was modelled. In modelling the supply network configuration decision problems, two types of agents, physical and auxiliary agents, each having distinct attributes and functions were introduced with the purpose of modelling the supply network entity behaviour and the supply network configuration decision-making process. Agents were modelled with an architecture, which consists of a decision-making module, a learning module and a communication module. Physical agents were modelled with all three modules, whereas auxiliary agents were modelled using the decision-making and communication modules. Decision-making modules of the physical agents were implemented through a rule-based approach, and the learning modules were implemented using the Q-learning algorithm. The communication modules of both agents were used for routing messages between them. Decision-making modules of auxiliary agents were executed with evolutionary algorithms and a rule-based approach. Furthermore, the modelling approach incorporated an intelligent bidding mechanism with a reverse-auctioning process. This simulated the behaviour of autonomous supply network entities collectively contributing to enhancing supply network-level performance, by means of setting reserve values generated through the application of a Genetic Algorithm. A set of Pareto-optimal supply network configurations catering to distinct product-market profiles was generated using the Non-dominated Sorting Genetic Algorithm-II. Further evaluation of these supply network configurations against additional criteria, using a rule-based approach, allowed the selection of the most appropriate supply network configuration to meet a broader set of conditions. The proposed model was tested on a case study of a refrigerator production network to draw lead time and cost comparisons under changing supply network conditions.

The majority of studies in the supply network configuration literature have developed supply network configuration models for static and deterministic supply network conditions using combinatorial optimisation techniques while adopting a centralised decision-making approach. This study, in contrast, developed a comprehensive multi-agent optimisation approach, as mentioned above, addressing the research needs as specified. In terms of contribution to theory, synthesising the state-of-the-art information on the topic of supply network configuration modelling and then identifying the key factors that drive supply network configuration decisions is a primary contribution of this study. Additionally, a number of theoretical insights such as a deeper understanding of the relationships among supply network entity-level decisions, and contextual factors and supply network-level performance were drawn from the analysis of SN literature. Compared to the existing decision support tools, the proposed multi-agent-based optimisation approach effectively addresses the three key challenges referred to earlier, which is a significant contribution to practice. Potentially, this model can be used to enhance supply network configuration decisions by any supply network entity, as well as other parties such as analysts, policymakers or consultants by providing useful analytical insights to sustain supply network-level competitiveness under changing supply network conditions. The proposed approach could be extended to incorporate other emerging techniques and to solve other variants of the supply network configuration problem in future studies.

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LIST OF PUBLICATIONS

Refereed journal publications:

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Refereed conference publications:

1. Dharmapriya, S, Kiridena, S & Shukla, N 2018, 'Modelling sustainable supply networks with adaptive agents', in *2018 International Conference on Production and Operations Management Society (POMS),* pp. 1-8, IEEE. **[The best track paper award]**

2. Dharmapriya, S, Kiridena, S & Shukla, N 2018, 'Modeling supply network configuration problems with varying demand profiles', in *2018 IEEE Technology and Engineering Management Conference (TEMSCON)*, pp. 1-6, IEEE - **[Student paper award – the first place]**

3. Dharmapriya, USS, Kiridena, SB & Shukla, N 2016, 'A review of supply network configuration literature and decision support tools', in *2016 Industrial Engineering and Engineering Management (IEEM)*, pp. 149-153, IEEE.

Refereed abstract publications:

1. Dharmapriya, USS, Kiridena, SB & Shukla, N 2017, 'Agent-based model for dynamic supply network configuration', in *2017 International Conference on Production and Operations Management Society (POMS), Sydney, Australia*.

CERTIFICATION

I, Subodha Dharmapriya, declare that this thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy from the School of Mechanical, Materials, Mechatronic and Biomedical Engineering, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. This document has not been submitted for qualifications at any other academic institution.

Subodha Dharmapriya

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LIST OF NOTATIONS

Acronyms

ABM	Agent-based modelling
ACO	Ant colony optimisation
AHP	Analytical hierarchy process
AI	Artificial intelligence
ATC	Analytical target cascading
AU	Auctioning agent
BOM	Bill of material
CM	Communication module
CNP	Contract net protocols
COGS	Cost of goods sold
DA	Distributor agent
DE	Deterministic-analytical
DM	Decision-making module
EA	Exact algorithms
EVA	Evaluation agent
GA	Genetic algorithm
ID	Identification index
LM	Learning module
LT	Lead-time
MA	Manufacturer agent
MAS	Multi-agent system
MAOM	Multi-agent optimisation model
MDP	Markov decision process
MH	Meta-heuristics
ML	Machine learning
NSGA-II	Non-dominated sorting genetic algorithm-II

OP	Order processing agent
OPT	Optimisation agent
RL	Reinforcement learning
SA	Supplier agent
SC	Supply chain
SES	Supply entity selection
SI	Simulation
SN	Supply network
SNC	Supply network configuration
SP	Software platforms
ST	Stochastic-analytical
TA	Transportation agent
TSNC	Total supply network cost
WTP	Willing-to-pay

Indices

i	Stages ($i = 1,2,3,\dots,I$)
j	Nodes ($j = 1,2,3,\dots,J$)
k	Entity options ($k = 1,2,3,\dots,K_j$)
m	Capacity status ($m = 1,2,3,\dots,5$)
n	Profit ranges ($n = 1,2,3$)
$\mathbf{S} = (\mathbf{S}_1 \dots \mathbf{S}_i \dots \mathbf{S}_I)$	Set of stages; $\mathbf{S}_i \in \mathbf{S}$
$\mathbf{S}_i = (\mathbf{N}_{im} \dots \mathbf{N}_{ij} \dots \mathbf{N}_{in})$	Set of nodes; $\mathbf{N}_{ij} \in \mathbf{S}_i$
$\mathbf{N}_{ij} = \{R_{ij1} \dots R_{ijk} \dots R_{ijp}\}$	Set of available entity options; $R_{ijk} \in \mathbf{N}_{ij}$
$\mathbf{L} = \{L_1 \dots L_l \dots L_L\}$	Set of consumer regions

Parameters

AC_{ijk}	Capacity level of entity option R_{ijk}
AAC_{ijk}	Available annual capacity of entity option R_{ijk}
A_n	Set of actions
A_n^t	The preferred action at the iteration *t*
BP_{ijk}	Unit bidding price of entity option R_{ijk}
BT_{ijk}	Unit bidding time of entity option R_{ijk}
$D_{ijk\rightarrow i'j'k'}$	Distance between two entity options *k* and *k'*
F_l	Dispatching frequency
LT_l	Lead-time attribute of the product-market profile at consumer region *l*
NC_{ijk}	Planned annual capacity of entity option R_{ijk}
PC_{ijk}	Operations cost of entity option R_{ijk}
P_l	WTP attribute of the product-market profile at consumer region *l*
P_{mn}	Profit margins for capacity state *m* and action/profit range *n*
PT_{ijk}	Operations time of entity option R_{ijk}
PP_{ij}	Percentage price of node *j*
PPT_{ijk}	Percentage time of node *j*
Q_{mn}	Q-value corresponding to capacity status *m* and profit range *n*
Q_{mn}^t	Q-value corresponding to state *m* and action *n* in iteration *t*
RC_{ij}	The number of units required from node *j*
RP_{ij}	Reserve price for node *j*
RT_{ij}	Reserve time for node *j*
$TC_{ijk\rightarrow i'j'k'}$	Transportation cost between two entity options *k* and *k'*
$TC_{ijk\rightarrow i'j'k'}$	Transportation time between two entity options *k* and *k'*
T_n	Reward for action *n*
V_l	Volume attribute of the product-market profile at consumer region *l*
V_s	Transport speed

X_m	Set of states
$x_{ijk \to i'j'k'}$	A decision variable; 1: if there is a connection between two entity options; 0:
λ_{ijk}^1	Size of capacity addition of entity option R_{ijk}
λ_{ijk}^2	Percentage utilised capacity of entity option R_{ijk}
β_m	A coeficient representing capacity utilisation levels
δ_{ij}	The number of units required from node j
μ_{ijk}^1	Percentage contribution of the overall profit corresponding to the previous
μ_{ijk}^2	Percentage contribution of the overall loss
μ_{ijk}^3	Percentage contribution of the overall profit corresponding to the final selection
γ	Discount factor
$\propto_2$	Unit distance transportation cost
z_{ijk}	A decision variable; 1: if entity option is shortlisted; 0: otherwise
y_{ijk}	A decision variable; 1: if entity option is selected; 0: otherwise
Π	Optimal policy

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CHAPTER 1: INTRODUCTION

1.1 Background of the study

1.1.1 Supply networks, challenges and opportunities

The typical definition of a supply chain (SC) is the arrangement of business entities such as suppliers, manufacturers, distributors and retailers to acquire raw materials, transform them into components and assemblies, and then distribute the final products to end-users. Examining the way businesses operate and compete in the form of SCs draws attention to a number of issues that would otherwise have not been captured and/or given adequate consideration. For example, the need for aligning the strategic goals of business entities, and process integration and information sharing across the SC, which are critical to delivering a superior customer value proposition (i.e., providing better product or service for the price), is often overlooked when businesses compete as individual entities. These aspects and others such as coordination, communication, and collaboration between business entities have been dealt with extensively in SC literature over a long period (Mustafa & Irani 2014; Maleki & Cruz-Machado 2013; Meixell & Gargeya 2005).

Furthermore, the way global production systems have evolved over the past few decades highlights that many business entities are part of more than one SC; they are, in effect, entities in supply networks (SNs) (MacCarthy et al. 2016; Braziotis et al. 2013). The notion of SNs introduces further challenges, as well as opportunities, for businesses in terms of creating, delivering and capturing value. On the one hand, the inherent complexities of SNs can exacerbate challenges such as alignment, coordination, communication, and integration between business entities. On the other hand, when businesses operate as a well-organised network, they can not only leverage their complementary strengths to deliver better customer value but also can utilise their combined capacity towards mitigating risks, guarding against disruptions and the like.

Hence, the capacity of a SN to deliver superior customer value is largely determined by the way that the SN is organised. More specifically, the real value-adding potential of a SN as a whole lies in the way it is configured – i.e., how the various elements (SN entities, processes etc.) in the SN are combined to create and deliver a superior customer value proposition while taking into account the contingencies driven by evolving product-market profiles and changing organisational and environmental conditions (Surana et al. 2005; Kemppainen & Vepsäläinen 2003). In recognition of the above perspectives, many authors have emphasised the significance of supply network configuration (SNC) decisions and the need for research that informs SNC decisions (Yao & Askin 2019; Shukla & Kiridena 2016; Akanle & Zhang 2008; Piramuthu 2005a).

1.1.2 Supply network configuration

In general, SNCs refer to the alternative ways in which the entities within a SN are organised, considering the varied and often changing needs of end-customer (i.e., consumer) requirements. The most common definition for SNC used in the literature is the alternative arrangements of SN entities, processes and resources in the SN when there are multiple options available, in order to differentiate between the SN entities in terms of key performance metrics such as cost and lead-time (Moncayo-Martínez & Recio 2014; Mastrocinque et al. 2013; Nepal et al. 2011; Akanle & Zhang 2008). In practical terms, SNC decisions aim to enhance the expected SN performance (e.g., responsiveness and efficiency) across a SN by building SN capabilities to be: flexible by effectively dealing with customised orders; robust by being able to withstand uncertainties in the internal and external environment; and agile by exploring and adopting new business practices (Chandra & Grabis 2009a; Lou et al. 2004).

1.2 **Problem statement and research questions**

The competitiveness and sustainability of SNs depend on their success (i.e., effectiveness) in terms of delivering a superior customer value proposition. Consumer requirements are distinct and varied; the product-market profile of a consumer region can capture the estimated consumer requirements in multiple attributes such as price, volume and lead-time. However, the pace of changing product-market profiles with the ongoing advancements in technology and information systems, as well as the pursuit of broad-based initiatives such as Industry 4.0, introduce both opportunities and challenges to SNs to be competitive and sustainable (Frank, Dalenogare & Ayala 2019; Tjahjono et al. 2017). The varied and often changing product-market profiles have been dealt with in the SN literature giving attention to both product-specific needs and expected SN-level performance (Vaidya, Ambad & Bhosl 2018). The product-specific needs represent the distinct requirements of consumers in terms of product specifications such as functionality, durability and quality, which have been catered for through mass customisation and faster introduction of new products (Yao & Ronald 2019). Other attributes of the product-market profile determine the desired SN-level performance. For example, a certain SN needs to be more efficient if the consumers are more sensitive to price, whereas another SN needs to be more responsive if the consumers demand timely and flexible responses to their requirements.

Along with the technological advancements and varied and often changing product-market profiles, SNs have been subjected to many structural changes such as an increased number of SN echelons and SN entities. Also, SNs are spread across multiple geographical regions with the involvement of SN entities from different locations due to potential advantages such as low manufacturing costs, tariff levels and trade concessions (Yao & Askin 2017; Rauch et al. 2015; Mourtzis & Doukas 2013). SNs are growing structurally and spatially, however, challenges associated with changing conditions in the broader SN environment are also unavoidable. The two key challenges in this regard are dealing with the effects of uncertainties (e.g., changing SN entity attributes such as operations cost and operations time) and dynamics (e.g., shifting product-market profiles, entering and losing SN entities) due to disruptions such as natural calamities, industrial actions and technological advancements. Overall, the challenges associated with evolving SNs have been discussed in the SN literature under the structural (i.e., physical characteristics), spatial (i.e., geographical positions) and temporal (i.e., changing SN conditions) dimensions (Garcia & You 2015; Klibi, Martel & Guitouni 2010; Coe, Dicken & Hess 2008).

Despite the circumstances discussed above, SN entities still tend to operate based on the premise that once a SN is configured to suit a given product-market profile, it would remain the same for the foreseeable future (Braziotis et al. 2013; Huang et al. 2005). This is mainly because of such factors as the benefits of maintaining long-term relationships, contractual arrangements and ease of coordination and communication (Braziotis et al. 2013). However, on the one hand, sticking to the same SC for too long can lead to the loss of competitiveness at the SN-level due to both advancements in technology and unforeseen reasons, which have significantly altered the overall competitiveness of alternative SCs. On the other hand, shifting product-market profiles means that a certain SC, that has been configured to serve a given product-market profile at a particular point in time, could become less competitive if it no longer fulfils the requirements of the current product-market profile (Melnyk, Narasimhan & DeCampos 2014; Ballou 2007). Accordingly, retaining the same level of SN conditions has been found ineffective in terms of catering to varied and changing product-market profiles and responding to changing SN conditions, and hence not achieving the expected SN-level performance goals. The significance of SNC has been highlighted in the SN literature with respect to its role in reconfiguring SNs, considering the circumstances referred to above (Zhang et al. 2009; Chandra & Grabis 2009a).

As such, effective SNC decisions have the potential to enhance SN-level performance in the face of changing SN conditions while catering to varied and often changing product-market profiles. Hence, developing models to support SNC decisions has been identified as a pertinent research need (Yao & Askin 2019; Garcia & You 2015; Klibi, Martel & Guitouni 2010). In spite of the substantial body of scholarly work available in the area of SN design and optimisation, there have been limited studies addressing SNC decisions (Yao & Askin 2019; Shukla & Kiridena 2016; Chandra & Grabis 2009a). Review of extant literature reveals the limitations in capturing the SN characteristics in terms of structural, spatial and temporal dimensions (Yao & Askin 2019). Certain factors affecting the structural complexities of SNs such as product variants, multiple echelons and multiple SN entities have been addressed to some extent in the SNC literature; however, spatial and temporal dimension have been addressed sparsely (Yao & Askin 2019; Klibi, Martel & Guitouni 2010). The importance of modelling multi-echelon SNs including both upstream and downstream entities located in different geographical regions; and accounting for autonomous decisions made at the SN-entity level, with minimum need to share information between them, towards enhancing SN-level performance, have been identified as major research needs (Yao & Askin 2019; Fuenfschilling & Binz 2018; Sáenz, Revilla & Acero 2018).

The majority of the currently available SNC models have attempted to address the research needs referred to above by adopting combinatorial optimisation approaches to find optimal SNCs in terms of efficiency and responsiveness assuming static and deterministic SN conditions (Yao & Askin 2019; Sheremetov & Rocha-Mier 2008). A number of authors have highlighted the limitations of such optimisation approaches in the context of SNC, particularly with respect to handling the autonomous decision-making behaviour of SN entities and addressing changing SN conditions (Akanle & Zhang 2008; Sheremetov & Rocha-Mier 2008).

In summary, the limited body of published work in the SN literature related to SNC problems suggests the need to generate alternative optimal SNCs dealing with varied and changing product-market profiles, changing SN conditions, and disparities between SN entities in terms of their behaviour and decision-making, in order to achieve expected SN-level performance by the diligent selection of appropriate modelling approaches and solution methodologies.

Having considered the abovementioned research needs, this study focuses on addressing two key research questions:

I. What are the key factors that underpin SNC decisions?

II. How can SNC decisions be supported through the identification of SNs that are optimally configured to cater to different product-market profiles, under changing SN conditions?

1.3 Research aim and objectives

To address the two research questions stated in Section 1.2, the aim and objectives of this research study are formulated as follows.

Aim: to develop a comprehensive approach that is capable of generating alternative SNCs for varied product-market profiles, optimised against a selected set of parameters under a given set of organisational and environmental conditions.

Objectives:

I. define and conceptually model a typical SN to sufficiently represent the key drivers of SNC decisions;

II. formulate the conceptual model developed in (I) above mathematically using appropriate modelling approaches;

III. implement the conceptual model developed in (I) above using a suitable programming language and/or software tools; and

IV. test the veracity of alternative optimal SCNs generated using the computer-based model developed in (III) above, by way of following appropriate verification and other analysis protocols.

1.4 Research methodology

The research problem presented in Section 1.2 highlights the necessity of suitable modelling approaches and solution methodologies that can generate alternative SNCs for varied product-market profiles in the face of changing SN conditions. It also requires evaluating the decisions made by autonomous SN entities against achieving optimal SN-level performance with minimum information shared between the SN entities. Accordingly, the need for modelling decision-making at the SN entity level and capturing its impact at the SN-level is recognised. The majority of studies in the SNC literature have developed SNC models for static SN conditions using combinatorial optimisation techniques aimed at finding optimal SNC(s) based on the desired performance attributes of SN entities. This indicates that existing SNC models address decision-making only at the SN-level towards achieving the expected SN-level performance.

In the systems perspective, supply networks are typically viewed as socio-technical systems where SN entities (e.g., suppliers, manufacturers) are autonomous individuals with distinct goals, practices and policies, physically inter-connected transferring goods (e.g., raw materials, finished products), as well as socially connected with formal and informal interactions and information sharing (Behdani 2012). Since the structure and behaviour of such social and technical subsystems determine the overall behaviour of the SN (Otten et al. 2006), both systems should be considered in studying the overall system. The structure and the behaviour of SNs take the form of distributed decision-making, which is more consistent with the characteristics and principles of a multi-agent system (MAS). Also, techniques such as MAS and agent-based modelling (ABM) are recommended in the literature to represent such complex, dynamic and distributed decision-making problems (Juneja et al. 2017). Therefore, this study undertakes a comprehensive approach to developing a multi-agent optimisation model (MAOM), employing a multi-agent optimisation modelling approach in combination with an intelligent auctioning and bidding strategies. Accordingly, the MAOM models the decisions of SN entities and evaluates the effects of those decisions at the SN-level when catering to varied product-market profiles.

To this end, a multi-stage, multi-echelon SN consisting of geographically dispersed SN entities catering to distinct product-market profiles was modelled. Two types of agents were modelled under the proposed modelling framework - physical and auxiliary agents. Physical agents represent the supply entities of the SN, whereas auxiliary agents handle the computational aspects of the framework. Agents were modelled with a novel architecture comprising of a decision-making module (DM), a learning module (LM) and a communication module (CM). The modelling approach incorporated a reverse-auctioning and bidding process to simulate the adaptive and competitive behaviour of SN entities with differing individual goals, collectively contributing to achieving expected SN-level performance. Further, a set of Pareto-optimal SNCs catering to distinct product-market profiles was generated at the final stages using Non-dominated Sorting Genetic Algorithm-II (NSGA-II). Evaluation of these SNCs against additional criteria, using a rule-based approach, allowed the selection of the most appropriate SNC to meet a broader set of conditions.

The proposed MAOM was tested using a refrigerator SN case study drawn from the literature, first verifying the model using appropriate protocols, and then scenario analysis were performed to test the robustness of the proposed MAOM and sensitivity analysis were performed to estimate the extent to which, the SN-level performance is vulnerable to the changes in SN characteristics.

1.5 Contributions of the study

As outlined in Section 1.2, contingencies for the evolution of SN such as by the expansion of SNs with an increased number of autonomous SN entities and changing SN conditions highlight the need for SNC models with suitable modelling approaches and solution methodologies. Similar to other models dealing with the SN design decisions, the appropriateness of SNC models is mainly determined by the extent to which the SN characteristics have been incorporated, as well as the efficiency and effectiveness of the modelling approaches and solution methodologies used (Barbati, Bruno & Genovese 2012; Klibi, Martel & Guitouni 2010). The review of SNC literature (as will be presented in Chapter 2) has revealed a number of limitations of the existing SNC models in terms of accounting for real-life SN characteristics and solution methodologies that have been partially addressed in previous studies.

The first and the most significant research need addressed in this study is enhancing SN-level performance in a geographically dispersed, multi-echelon distributed decision-making SN environment, where individual SN entities aim to satisfy their own organisational goals. The second research need was to achieve the above goals with a minimal requirement for sharing information between SN entities, which reflects the real-world situation of organisations' reluctance to disclose commercially sensitive information. The third research need addressed in this study is to provide analytical insights for SN decision-makers to sustain SN-level competitiveness in the face of changing SN conditions (e.g., uncertainties and dynamics).

These research gaps are addressed through developing the MAOM using a MAS based optimisation modelling approach in combination with an intelligent auctioning and bidding strategies. Accordingly, the proposed MAOM in this study can be benchmarked against existing comparable SNC models, considering the level of detail at which it addresses the aspects of SN characteristics, SNC decisions, SN-level performance measures, SN modelling approaches and solution methodologies. Figure 1.1 presents a summary of the existing literature (the contribution of the majority of the literature) and the contributions of the proposed approach to SNC literature. As indicated in Figure 1.1, the input used in the SNC model is the product-market profile of a given consumer region, and the output is Pareto-optimal SNCs with respect to the desired SN-level performance. Accordingly, the proposed MAOM is capable of generating Pareto-optimal SNCs for a given product-market profile incorporating structural, spatial and temporal SN dimension.

The product-market profile, which represents the consumer requirements, has been limited to cover the volume attribute in the extant literature (Dharmapriya, Kiridena & Shukla 2016). However, this study identifies the need for a more comprehensive representation of product-market profiles, including other attributes such as expected lead time and willing-to-pay (WTP) price. Capturing product-market profile through multiple attributes serves three key purposes: primarily, it provides a complete representation of consumer requirements; secondly, these product-market profile attributes represent SN-level performance metrics rather than product-specific performance measures such as quality and functionality; finally, these product-market profile attributes provide guidance in relation to making SNC decisions and setting the desired SN-level performance metrics.

Additionally, in this study, a number of other limitations reported in the SNC literature have been addressed: i.e., modelling multi-stage (upstream, midstream and downstream), multi-echelon SNs with geographically dispersed autonomous SN entities. Furthermore, compared to the static (e.g., same set of SN entities stay in business over time) and deterministic (e.g., constant SN entity attributes), SN contexts used in previous studies, this study modelled changing SN conditions incorporating SN uncertainties and dynamics pertaining to the SN context. Moreover, SNC models which have been developed in the literature commonly adopted a centralised approach using combinatorial optimisation techniques to generate optimal SNC(s). Those SNC models addressed only SN-level decision making; the primary limitation of that approach is not incorporating the effects of the autonomous behaviour of SN entities at the SN entity-level. Instead, the modelling approach used in this study simulates the adaptive and competitive behaviour of SN entities with differing individual goals, collectively contributing to enhancing SN-level performance. In addressing these limitations, the novelty of the proposed comprehensive approach to deal with SNC decisions come from its capacity to account for the comprehensive representation of

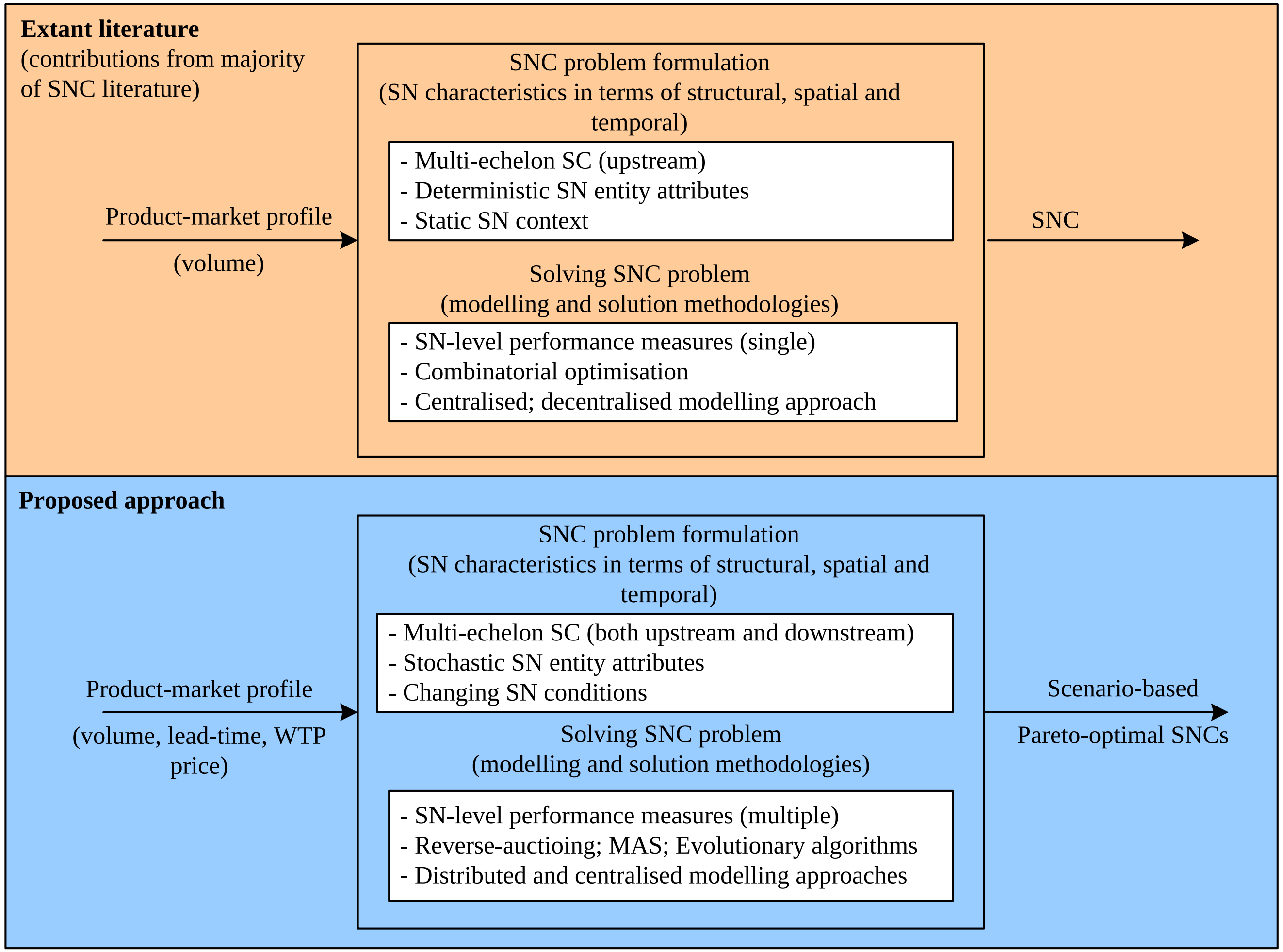


Figure 1.1: Existing literature vs the proposed approach

SN characteristics, and the autonomous decisions of individual SN entities, changing SN conditions, varied and often changing product-market profile, by the diligent selection and application of 'state-of-the-art' knowledge and technology.

In terms of contribution to theory, synthesising the state-of-the-art information on the topic of supply network configuration modelling and then identifying the key factors that drive supply network configuration decisions is a primary contribution. Additionally, a number of theoretical insights were also drawn such as a deeper understanding of the relationships among SN-entity level decisions, and contextual factors and SN-level performance. Compared to the existing SNC models, the proposed approach effectively addresses the three key challenges referred to earlier, which is a significant contribution to practice. Potentially, this model can be used to enhance SNC decisions by any SN entity, as well as other parties such as SC analysts, policymakers or consultants by providing useful analytical insights to sustain supply network-level competitiveness under changing SN conditions. In terms of the contribution of this study to knowledge, there is a distinct advantage in applying this type of decision support tools in relation to enhancing SNC decision making.

1.6 Limitations of the study

This study addresses a number of significant research gaps identified through the review of extant SNC literature while contributing to both theory and practice, as outlined in Section 1.5. Despite such contributions, there are some limitations relating to the generalisability of the proposed MAOM.

The first limitation of this study is the lack of real-life data to validate the developed MAOM. Nevertheless, the model was validated in the form of face validity and conceptual model validity (see Chapter 4 and 5). There are a number of reasons for not being able to validate the proposed MAOM using real-life data. Mainly, the broad scope of this study which considers SN entities involved in the end-to-end SC functions. Depending on the bill of material (BOM) of the product, there are a number of upstream, midstream and downstream SN entities arranged into echelons. These SN entities are reluctant to reveal their capabilities as well as attributes of their upstream SN entities (e.g., location, operations cost) as this information is commercially sensitive. Also, the approach adopted in practice to configure the SN is different from the approach proposed in this study. The current practice is each SN entity selects the upstream SN entities depending on the requirements of downstream SN entities; however, this study adopts a reverse-auctioning and bidding strategies based holistic approach to select SN entities from each SN node depending on the requirements of the product-market profile. To overcome this limitation, certain data is partly taken from the extant literature, and others are estimated. Furthermore, in order to minimise the implications of not having real-life data, scenario analysis and sensitivity analysis are performed to test the robustness of the proposed MAOM and to estimate to which SN characteristics that the SN-level performance is sensitive.

The second limitation of this study is, the developed MAOM is not generalised to any SN or a standard product structure. SNs are different from one to another in terms of structure depending on the BOM, practices and policies. Hence, a single model cannot be developed to account for all such differences. However, for demonstration purposes, the proposed MAOM is tested on a variant of a refrigerator product, which could be modified to suit other variants of a refrigerator with minimal additional work.

The third limitation of this study relates to the conditions and constraints which SN entities (modelled as physical agents) consider in making their bidding decisions. Physical agents use a Q-table which consists of capacity levels and profit ranges to extract knowledge from past bidding experience. In determining the capacity levels, physical agents only consider in-house capacity subject to normal working hours. However, physical agents could also bid considering a few other options such as outsourcing or using overtime, which are not considered in this study.

The fourth limitation of this study is about the constraint in relation to selecting physical agents from a SN node to satisfy a product-market profile. Candidate physical agents for each product-market profile are selected from each SN node through the reverse-auctioning process, given the condition that a physical agent could bid only if the total number of units could be supplied. This means the number of units required from a SN node cannot be split between several physical agents or multiple sourcing is not possible. Multiple sourcing has not been considered in this study as it does not make a significant contribution to the set aim of the study.

1.7 Thesis Outline

This thesis has seven chapters: Introduction, Literature Review, Conceptual Framework, Methodology, Simulation Results, Discussion and Conclusions. References and appendixes follow these main chapters.

Chapter 1 gives an overall introduction to the thesis with a brief overview of both opportunities and challenges associated with evolving SNs and recognises the SNC decisions in such SN contexts. This is followed by the research problem, research questions and aim and objectives. A brief account of the adopted methodology to solve the SNC problem is also presented, followed by the contributions of the study. Finally, limitations of the study are acknowledged.

Chapter 2 of this thesis presents a summary of the current body of knowledge in the domain of SNC with a focus on SNC models in particular. This chapter first presents SN decisions that apply at different levels with particular attention to SN design decisions and associated challenges in modelling these decisions. The ways in which those challenges have been addressed in the literature is dealt with next, while also discussing the limitations of current modelling approaches and solution methodologies. SNC decisions are then discussed and compared and contrasted with the SN design decisions. The key elements of past SNC models are then reviewed, summarised and analysed under four classification criteria, namely SN characteristics, SNC decisions, SN performance measures, modelling approaches, and solution methodologies. Finally, research gaps are identified by evaluating and synthesising the contributions of the existing literature under each classification criteria.

Chapter 3 of this thesis presents the conceptual framework which guides the overall methodological approach adopted in this study to deal with SNC decisions. The proposed conceptual framework consists of three components focusing on establishing product-market profiles, generating alternative Pareto-optimal SNCs, and scenario-based optimisation. Finally, the proposed approach is compared with the existing approaches in the SNC literature.

Chapter 4 presents the overall methodology employed in achieving the aim of this study. First, the rationale for selecting the methodology is discussed, and then the modelling framework used to implement the proposed MAOM is presented. The proposed framework consists of four steps: conceptual definition, mathematical formulation, computer-based implementation, and model verification and other analysis protocols. Finally, a brief account of the case study used in testing the proposed MAOM is presented, followed by simulation experiments carried out and the presentation of findings.

Chapter 5 is devoted to the presentation of simulation results. First, the case study of a refrigerator SN where the proposed MAOM has been applied is presented, including the implementation details of the MAOM. Then a detailed account of simulation experiments: verification, base-line model, scenario analysis and sensitivity analysis are presented followed by the presentation of the simulation results.

Chapter 6 presents the discussion of the findings of this study, including an account of how these findings relate to those of the comparable previous studies. First, the set-up of the experiment design, along with the key findings are presented. Then, the adopted methodological approach including modelling approaches and solution methodologies used in this study is discussed and compared with those used in the extant literature.

Chapter 7 concludes the thesis summarising the research effort and findings, while providing some concluding remarks on the research questions addressed, followed by an account of the contributions and limitations of this study, as well as with future research directions.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter presents the current body of knowledge in the domain of SNC literature with a particular focus on SNC models. Initially, relevant literature was identified through a structured literature search, and then that literature was summarised, evaluated and synthesised to identify the research gaps.

Section 2.2 of this chapter presents an overview of SN decisions at the different planning levels. Section 2.3 draws attention to SN design decisions and associated research challenges in the context of evolving SNs. Section 2.4 contains a brief account of existing SN design models and their limitations in relation to addressing practical needs. Section 2.5 contrasts and compares SNC decisions against SN design decisions. It is followed by Section 2.6, which summarises, evaluates and collates SNC models according to a proposed classification. An overall summary of the literature is presented in Section 2.7, and key research gaps are presented in Section 2.8. Finally, Section 2.9 summarises the chapter.

2.2 Supply network decisions

SN decisions are often considered at strategic, tactical and operational planning levels depending on the enduring time horizon of such decisions and the extent of their influence on SN performance (Schmidt & Wilhelm 2000). The strategic level decisions, called long-term decisions, hold for a considerably long period (typically three to five years), which has a significant impact on the overall SN performance and creates a considerable impact on other planning-level decisions (Farahani et al. 2014). Typical strategic-level decisions include: determining the number of SN facilities to be set up, including their locations and capacities; identifying the supplier base; and deciding on appropriate technologies to be used (Farahani et al. 2014; Sahebi, Nickel & Ashayeri 2014; Melo, Nickel & Saldanha-Da-Gama 2009). Tactical level decisions, called medium-term decisions, endure for a relatively shorter period than strategic decisions (typically six months to three years) and deal with aspects such as inventory policy and controlling parameters; equipment/machinery upgrades; and production and distribution planning (Farahani et al. 2014; Sahebi, Nickel & Ashayeri 2014). However, depending on the circumstances that apply to each business organisation or the context in which they operate, a particular strategic decision of one organisation could be a tactical decision for another organisation (Bashiri, Badri & Talebi 2012). Operational level decisions, called short-term decisions, are made quite frequently, usually on a daily, weekly or monthly basis. Examples of decisions taken at the operational level include vehicle routing, operations scheduling and workforce assignment (Farahani et al. 2014; Min & Zhou 2002; Schmidt & Wilhelm 2000).

While operational level decisions are supported by commercial software packages such as enterprise resource planning, warehouse management systems and transport management systems (Ardalan & Ardalan 2009), most of the strategic level decisions are often made based on managerial judgement (Shapiro 2004). However, the need for more advanced models that support strategic and tactical level decisions have gained considerable attention due to a number of factors such as the high capital investment involved in certain strategic decisions (e.g., locations of facilities, adopting new technologies) (Sahebi, Nickel & Ashayeri 2014; Shapiro 2004) and their impact on decisions at tactical and operational levels (Farahani et al. 2014; Bashiri, Badri & Talebi 2012).

2.3 Supply network design decisions and associated research challenges

SN design decisions are mostly the strategic level decisions that determine the structure of the SN (Melnyk, Narasimhan & DeCampos 2014; Ballou 2001). Some of the pertinent questions that need to be answered concerning SN design decisions are: how many facilities should be set up; where should those facilities be located; what are the suitable and alternative transportation modes to be used (Klibi, Martel & Guitouni 2010). These SN design decisions are expected to be effective for a considerable period. However, their potency is increasingly challenged by the contingencies of evolving SNs.

As highlighted in Section 1.2, SNs evolve in structural, spatial and temporal dimensions due to factors such as advancements of technology and information systems, as well as changing market conditions and competitive dynamics. As a result, SNs grow structurally with an increased number of SN entities in a given SN while dealing with complex and distinct product architectures. Also, SNs spread across multiple geographical regions, having spatially distributed SN entities. These trends in evolving SNs form a more distributed decision-making context having autonomous SN entities with distinct objectives and behaviours. Also, SNs are continuously subject to changes due to SN uncertainties and SN dynamics (Garcia & You 2015; Klibi, Martel & Guitouni 2010). Accounting for such changes in all three dimensions in the context of modelling SNs is a challenging undertaking.

Additionally, SN design decisions result in certain levels of SN performance with respect to speed, responsiveness and efficiency through the way the SNs are structured and run. Traditionally, SN design decisions have focused on economic objectives such as cost minimisation and profit maximisation. However, changes in product-market profile demand the consideration of the multiple and distinct objectives such as speed, responsiveness and sustainability (Eskandarpour et al. 2015; Garcia & You 2015), which also helps in competing with other SNs. Therefore, the effectiveness of SN design decisions is challenged in such a SN context, particularly in terms of achieving SN performance with respect to the expected consumer needs (Oliveira, Lima & Montevechi 2016; Gerschberger et al. 2012; Choi, Dooley & Rungtusanatham 2001).

Accommodating the above-mentioned factors into SN design models helps assess the effectiveness of SN design decisions in delivering a superior customer value proposition. Nonetheless, it has been found in the literature that SN design models accommodate these aspects at different levels of abstraction and there are a number of limitations in the existing SN design models with respect to delivering realistic and meaningful solutions (Eskandarpour et al. 2015; Garcia & You 2015; Melnyk, Narasimhan & DeCampos 2013; Klibi, Martel & Guitouni 2010).

2.4 Existing supply network design models and their limitations

Regardless of the many structural and functional complexities of SNs, the majority of existing SN design models are largely simplified, static and deterministic models (Yao & Askin 2019; Behncke, Ehrhardt & Lindemann 2013). These models consider rather narrowly defined SN structures (i.e., with few echelons) within a confined geographical area giving limited attention to global SNs (Yao & Askin 2019; Meixell & Gargeya 2005). In most cases, a static SN environment has also been considered with assumptions such as the presence of the same set of SN entities throughout the period, without accounting for uncertainties and dynamics caused by disruptions or market turbulence. Therefore, these models have been presented in the form of deterministic-analytical with linear relationships and a number of assumptions to make the model scalable (Goetschalckx, Vidal & Dogan 2002). These deterministic-analytical models have been solved using commercial solvers, exact algorithms, meta-heuristics and evolutionary algorithms. Practical use of the solutions derived from these deterministic-analytical SN models is quite limited as the assumptions made are unrealistic in light of the changing conditions experienced by real-world SNs (Afrouzy et al. 2016; Salem & Haouari 2016; Gupta & Maranas 2003).

This issue has been addressed through stochastic models to a certain degree by modelling uncertainties in multiple ways (Salem & Haouari 2016). Melo, Nickel and Saldanha-Da-Gama (2009) introduced three clusters of stochastic models namely: (a) single period planning and using stochastic modelling approaches and solution methodologies (e.g., Santoso et al. 2005); (b) multiple time period planning and using deterministic modelling approaches and solution methodologies (e.g., Fattahi et al. 2015); and (c) multiple time period planning and using stochastic modelling approaches and solution methodologies (e.g., Pasandideh, Niaki & Asadi 2015). According to the above classification, studies have dealt with uncertainties pertaining to the SN context by dividing the planning horizon into single and multiple periods. Most of the early studies belong to Cluster (a) assuming that the same pattern of uncertainty applies over time (Govindan, Fattahi & Keyvanshokooh 2017). Later, Cluster (b) studies have become popular in a way that divides the planning horizon into multiple segments. However, most recent and a limited number of studies fall into Cluster (c) which have dealt with multi-period planning using stochastic modelling approaches and solution methodologies (Govindan, Fattahi & Keyvanshokooh 2017). The solution methodologies proposed in these studies are different in terms of the way relevant parameters are modelled, and they fall into three categories namely those that: (i) consider the probability distribution of parameters (e.g., stochastic programming); (ii) use subjective opinions when no information related to the probability distribution is available (e.g., interval-uncertainty modelling, scenario-based approach); and (iii) consider a fuzzy decision environment (e.g., fuzzy programming) (Melo, Nickel and Saldanha-Da-Gama 2009; Govindan, Fattahi & Keyvanshokooh 2017).

Even though uncertainties have been incorporated through stochastic models, most of these SN design models have adopted centralised decision-making approaches assuming a single decision-maker making the decisions for all SN entities/ SN functions in the SN (Qu et al. 2009). Despite the fact that this is suitable in a vertically integrated SN context, those SNs which consist of autonomous SN entities, have their own goals, policies and practices demand modelling approaches that represent distributed decision-making (Akanle & Zhang 2008). Other approaches such as simulation and artificial intelligence-based modelling (e.g., MAS) have been used in handling various decision problems in distributed decision-making contexts and a large number of deterministic/stochastic variables and their non-linear relationships (Pourhejazy & Kwon, 2016). Meta-heuristics, simulation software platforms, general-purpose programming languages are the most popular solution methodologies used in such modelling contexts. Meta-heuristics based solution methodologies have been widely used in dealing with problems with a large number of variables and in accounting for their non-linear relationships. Simulation software platforms and general-purpose programming languages have been used in dealing with simulation models, MASs etc. Additionally, due to the pertinent SN uncertainties and dynamics, SN design models are expected to be more robust, resilient and responsive. Although stochastic models have partially addressed this requirement, more advanced models are yet to be developed to handle the autonomous and adaptive behaviour of SN entities and changing SN conditions (Yao & Askin 2019; Klibi, Martel & Guitouni 2010; Akyuz & Erkan 2010). Although the application of certain modelling approaches and solution methodologies such as MAS and ABM are still at a relatively early stage in terms of delivering fully-developed industry solutions, their achievements so far have been impressive in studying more complex phenomena such as population growth, the spread of disease, financial markets and traffic systems and their potential contribution can be significant (Mostafa et al. 2017; Macal & North, 2010).

Apart from incorporating the above requirements in terms of modelling SN characteristics, one of the other the primary objectives of a SN design model is to structure and run the SN, to deliver superior customer value. In the SN literature, consumer requirements have been represented only by volume attributes, paying no attention to other equally relevant attributes such as lead-time and WTP price to comprehensively represent the consumer's requirements. Also, most of the SN design models have been developed focusing on economic objectives such as cost minimisation or profit maximisation. However, the multiple attributes of product-market profile and associated changes demand the consideration of multiple performance objectives such as responsiveness and sustainability (Eskandarpour et al. 2015; Garcia & You 2015).

In summary, the extant literature highlights the need for developing SN design models incorporating more realistic SN characteristics in terms of structural, spatial and temporal dimensions with particular attention to the autonomous decision-making of SN entities and changing SN conditions (i.e., SN uncertainties and dynamics) while achieving SN-level performance to suit product-market profile attributes. In this regard, SNC decisions have been identified as an effective way of dealing with these needs with appropriate modelling approaches and solution methodologies.

2.5 Supply network design decisions vs supply network configuration decisions

As presented in Section 2.2, SN design decisions determine the structure of the SN or the way the SN should be organised to deliver the desired consumer requirements. Hence, SN design decisions are expected to be effective for a substantial period; however, there are many reasons as to why it may not be the case. As discussed in Section

2.3, SNs have been evolving into more distributed and global contexts with the involvement of individual SN entities who make their own decisions. In such a SN environment, SN uncertainties and dynamics are unavoidable and these make a significant impact on SN-level performance with respect to meeting specific product-market profile requirements. For example, certain facilities could shut down permanently due to natural calamities or certain suppliers may not be profitable any longer in light of the shifting product-market profiles. Therefore, the need for dynamic SN design models or SNC decisions which could cater for changing SN conditions is identified as a research need (Melnyk, Narasimhan & DeCampos 2014).

In the SNC literature, the use of SNC decisions is highlighted mainly from two different perspectives. Some studies have claimed that SNC decisions are important in instances where new products are introduced (e.g., Graves & William 2005) and the others have emphasised the need for SNC decisions in the face of SN uncertainties and SN dynamics (e.g., Xia, Liu & Matsukawa 2014; Wang et al. 2009). Both of these perspectives can be addressed by configuring the SN by considering the alternative sourcing options available at each node to deliver a given product-market profile.

Upon identifying the need for considering SNC decisions, the next question is to focus on the way SNs are configured or what SNC decisions are to be addressed. The literature converged on the point that the intended purpose of SNC is to enhance SN capabilities to be: flexible, by effectively dealing with customised orders; robust, by being able to withstand uncertainties in the internal and external environment; and agile, by exploring and adopting new business opportunities (Chandra & Grabis 2009a; Lou et al. 2004). However, the same level of consensus does not seem to be there in terms of the way SNC is defined or SNC decisions are identified. The term SNC was introduced by Graves and Willems (2005) with the definition of alternative options for accomplishing SC functions at each stage and the amount of safety stock to be placed at each node of the SN. A number of studies (e.g., Moncayo–Martínez et al. 2011; Nepal, Monplaisir & Famuyiwa 2011; Huang & Qu 2008) have since then followed this definition. Zhang et al. (2009) defined SNC as the integration of product, process and logistics decisions. However, the most common and widely adopted definition used by researchers, which is also adopted by this thesis study, is the alternative arrangements of SN entities, processes and resources when there are multiple options available, differentiated by their performance metrics such as cost and lead time (Moncayo-Martínez & Recio 2014; Nepal et al. 2011; Akanle & Zhang 2008).

As per the definitions referred to above and the use of SNC decisions in the literature, SNC can be considered as an effective means of dealing with the changing SN conditions (e.g., uncertainties, dynamics). Accordingly, typical SNC decisions are: from where to source materials/parts/sub-assemblies; where to manufacture/assemble products; where to locate storage/distribution facilities; and what transport alternatives to be considered/used. As stated earlier in this section, since these SNC decisions are made mainly to deal with changing SN conditions, the frequency of making these decisions can not be determined precisely due to the difficulty in the timing of such changing SN conditions. It has been found in the literature that certain studies have considered SNC as a strategic level decision (Akanle & Zhang 2008; Truong & Azadivar 2005) whereas others have considered it as a tactical level decision (Graves & Willems 2005). However, given the facts relating to the evolving nature of the SN context and the role of SNC decisions, this study considers SNC decisions fall in between the strategic and tactical planning levels.

2.6 The proposed classification to analyse the existing SNC models

The aim of this study is to develop a comprehensive approach to support SNC decisions, which is capable of generating alternative SNCs to be optimised against a selected set of parameters under a given set of organisational and environmental conditions. Therefore, the existing SNC models identified from a structured literature search were reviewed to identify the contribution of existing SNC models to address a number of requirements.

A number of classifications have been proposed in the SN literature to evaluate the models developed to support SN decisions (e.g., Govindan, Fattahi & Keyvanshokooh 2017; Mula et al. 2010; Peidro et al. 2009; Huang, Lau & Mak 2003; Min & Zhou 2002). Among such classifications, two comprehensive reviews have been adapted in this study. Mula et al. (2010) had reviewed models related to production and transportation planning. The proposed classification of Mula et al. (2010) included the SC structure (i.e., the overall arrangement of SN nodes), SN decision planning level (i.e., strategic, tactical, operational), modelling approach, purpose (i.e., objective/s defined in the mathematical model), types of shared information between SN nodes, limitations of the model, the novelty in terms of contribution to SN literature and the applications of the proposed model. The review of quantitative models used for SC planning under uncertainty by Peidro et al. (2009) used a classification which includes the source of SN uncertainty (i.e., demand, process/ manufacturing and supply); SN decision planning level; and the modelling approach.

In this study, a classification to review SNC models was proposed by examing the classifications in the SN literature to identify the strengths and limitations of existing SNC models in catering for the needs of industry requirements and achieving improved SN-level performance. Accordingly, the proposed classification to review existing SNC models consists of SN characteristics, the type of SNC decisions, SN-level performance metrics, modelling approaches and solution methodologies.

2.6.1 Supply network characteristics

Previous studies have dealt with a number of challenges associated with SN decisions which can be discussed in terms of the structural, spatial and temporal dimensions as introduced in Section 1.2. In this section, each of these dimensions is discussed, investigating to what extent the SN characteristics have been incorporated by the existing SNC models.

Structural dimension**:** SC structure varies depending on a number of factors such as product architecture, logistics network, and the nature of the business context (e.g., service providers) (Montoya-Torres & Ortiz-Vargas 2014). Multiple types of SC structure have been identified within classifications reported in the literature. For example, Huang, Lau and Mak (2003) identified five types of SC structure: dyadic (i.e., a SC with two nodes which are mostly the buyer and vendor), serial (i.e., a SC which is a combination of multiple dyadic structures), divergent (i.e., each node has at most one predecessor and several successors), convergent (i.e., each node has at least one successor and several predecessors) and network (i.e., a combination of convergent and divergent structures in the upstream and downstream respectively). Beamon and Chen (2001) proposed four types of SC structures, namely convergent, divergent, conjoined and general. There is a minor difference in the two classifications referred to above with respect to the term used to refer to SC structures that combine both convergent and divergent structures. Huang, Lau and Mak (2003) defined the SC structure, which combines both convergent and divergent structures as “network” structure, whereas Beamon and Chen (2001) termed it as the conjoined structure. Apart from that Beamon and Chen (2001) proposed “general” as another type of SC structure which is neither strictly convergent, divergent, nor conjoined as stated above, however, it had multiple combinations of convergent and divergent structures in upstream and downstream of the SN. Considering both these classifications, this study has used types of SC structures as shown in Figure 2.1 to review the SNC models in the literature. A given SC structure type is further considered in terms of its horizontal structure (i.e., a number of echelons) and vertical structure (i.e., a number of nodes in an echelon) (Lambert, Cooper & Pagh 1998). Additionally, the number of product flows, consumer regions and SN entities are considered as elements of the structural dimension (Serdarasan 2013; Zhang

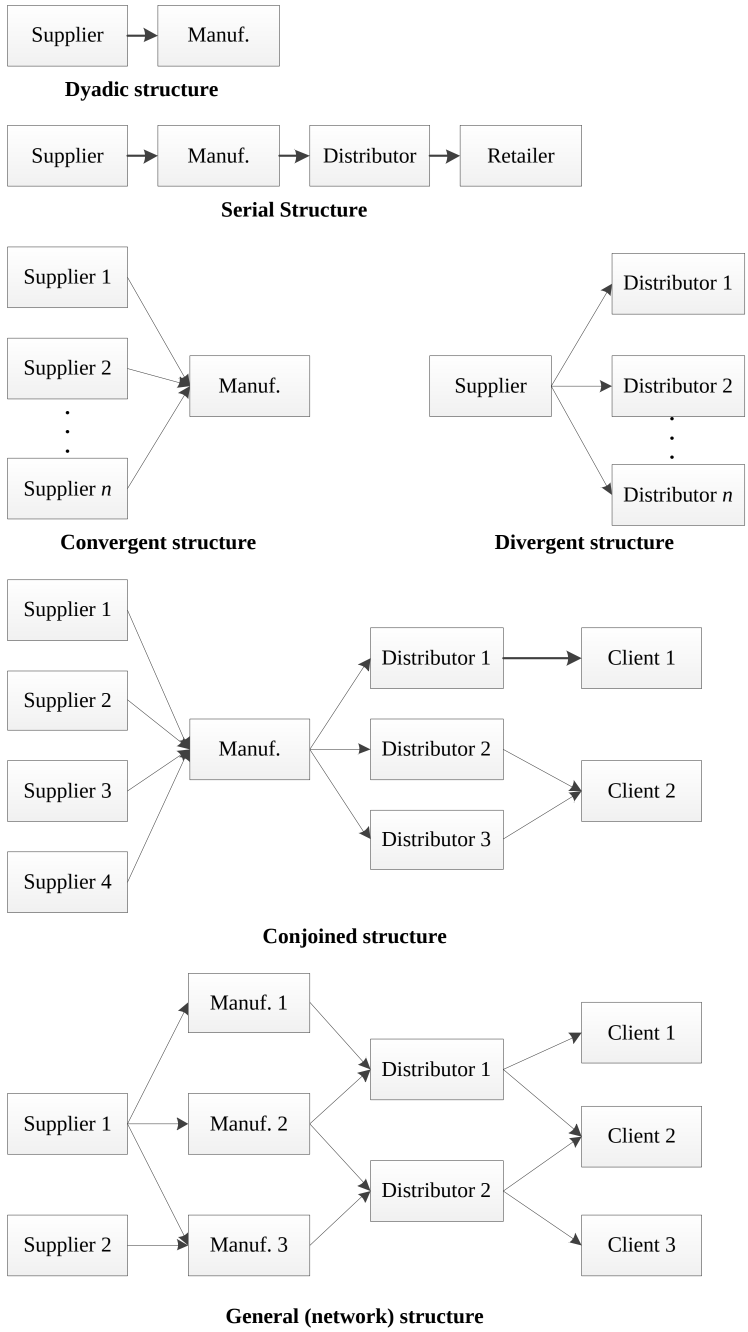


Figure 2.1: Different SC structures

et al. 2009; Min & Zhou 2002). The analysis of the above dimensions in SNs indicates the complexity of SNs in terms of coordination and communication.

In SNC literature, different SC structures have been considered in the proposed models depending on the research problem framed. As listed in Table 2.1, SC structures considered in the SNC models in the literature are mostly either convergent or conjoined. Those studies that consider convergent or conjoined SC structures have multi-echelon supplier bases (i.e., varying from one to eight). These echelons are responsible for extracting raw material, producing parts or components, which then assemble into a final product. The only study that has also accounted for a multi-echelon downstream SN is Truong and Azadivar (2005). Apart from the composition of the overall SC structure, one other important factor is the size of the SN, which indicates the number of nodes, SN entities and product flows in the SC.

Among all the studies reviewed, the largest upstream SN stage (i.e., supply base) consists of 26 parts/components (which represent sourcing nodes) whereas the smallest supply base consists of one node. The largest structure dealt with in SNC models has 118 SN entities. The highest number of consumer regions that have been dealt with in previous studies is six. The product-market profiles of those consumer regions are represented in terms of the type of the product (i.e., product variant) and volume (i.e., the total number of units required). A few studies have considered multiple product types, as well.

Spatial dimension: Over the past several decades, SNs have evolved in a way that the constituent SN entities are spread across many geographical regions around the world (Tjahjono 2017; Mourtzis & Doukas 2012). Globalisation of SNs is associated with many advantages such as lower manufacturing costs, tariff concessions, access to technology and other free-trade facilities, which offer opportunities to procure and produce components/products more competitively (Tjahjono, 2017; Rauch et al. 2015; Mourtzis & Doukas 2012). Despite such opportunities, there are also certain risks associated with globalised SCs as the entities and the connections between these entities are prone to various forms of disruptions such as those caused by bankruptcies, breakdowns, macroeconomic and political changes and disasters (Manuj & Mentzer 2008). Another major challenge associated with global SCs is managing the logistics functions with the cost and time involved in long-distance transportation and storing of goods, which have a direct impact on SN performance in terms of efficiency, responsiveness and speed. However, SNC literature has emphasised that global SCs are benefited by having alternative suppliers dispersed across the world in the face of disruptions, as well (Aguila & ElMaraghy 2018). Even though the SN literature has identified that having developed SNC models to accommodate the spatial dimension is one of the most important aspects, the spatial dimension has not been incorporated into SNC models directly.

Table 2.1: Structural dimension of SCs

Reference	Overall SC structure	Horizontal			Vertical			No.of SN entities	No. of consumer regions	No. of product variants handled
		No.of tiers in each stage			No.of nodes in each stage					
		U	M	D	U	M	D			
Akanle & Zhang 2008	Conjoined	3	1	1	12	2	2	33	2	2
Ameri & McArthur 2013	Serial	1	1	-	3	1	-	7	-	3
Fujita et al. 2013	Conjoined	1	1	1	3	1	3	10	4	4
Graves & Willems 2005	Conjoined	3	1	1	13	1	2	31	2	2
Greco et al. 2013	Convergent	1	1	-	2	1	-	4	-	1
Huang et al. 2005	Conjoined	3	1	1	12	2	2	33	2	2
Huang & Qu 2008	Conjoined	3	1	1	13	1	1	28	2	2
Jiao, You & Kumar 2006	Convergent	1	1	-	3	1	-	9	4	1
Jiang et al. 2018	Conjoined	6	1	1	23	1	1	88	4	3
Lou, Chen & Ai 2004	Convergent	1	1	-	1	1	-	4	-	1
Li & Womer 2008	Conjoined	3	1	1	13	1	2	31	2	2
Mastrocinque et al. 2013	Conjoined	5	1	1	23	1	1	105	4	3
Moncayo-Martínez & Zhang 2011	Conjoined	6	1	1	23	1	1	105	4	3
Moncayo-Martínez & Zhang 2013	Convergent	5	1	-	26	3	-	109	0	1
Moncayo-Martínez & Recio 2014	Conjoined	3	1	1	13	1	2	33	2	2
Moncayo–Martínez et al. 2016	Convergent	8	1	1	26	2	1	74	1	1
Moncayo–Martínez et al. 2016	Conjoined	6	1	1	23	1	1	105	4	3

Note: U – upstream stage; M – midstream stage; D – downstream stage

Table 2.1: Structural dimension of SCs (continued)

Reference	Overall SC structure	Horizontal			Vertical			No.of SN entities	No. of consumer regions	No. of product variants handled
		No.of tiers in each stage			No.of nodes in each stage					
		U	M	D	U	M	D			
Nepal et al. 2011	Convergent	4	1	-	21	1	-	40	-	1
Piramuthu 2005a	Convergent	1	1	-	1	1	-	5	-	1
Piramuthu 2005b	Convergent	1	1	-	1	1	-	4	-	1
Qu et al. 2009	Convergent	3	1	1	13	1	-	33	-	
Qu et al. 2010	Convergent	3	1	1	11	1	2	25	1	1
Qu et al. 2010	Convergent	2	1	-	-	-	-	-	-	1
Ruiqing et al. 2014	Conjoined	3	1	1	7	1	1	28	2	1
Sheremetov & Rocha-Mier 2008	Conjoined	1	1	-	3	1	-	3	-	2
Shukla & Kiridena 2016	Conjoined	3	1	1	13	1		31	1	2
Truong & Azadivar 2005	Conjoined	6	1	2	19	1	2	72	6	1
Vanteddu, Chinnam & Gushikin 2011	Convergent	1	1	-	1	1	-	3	-	1
Wang et al. 2009	Serial	2	1	-	2	1	-	-	-	1
Wang et al 2016	Conjoined	2	1	1	11	1	1	118	-	3
Wang & Shu 2007	Conjoined	3	1	1	13	1	2	31	2	2
Yang et al. 2015	Convergent	3	1	-	13	1	-	-	1	-
Yuce et al. 2014	Conjoined	5	1	1	18	1	4	105	4	3
Zhang et al. 2009	Conjoined	2	1	1	6	1	4	19	4	1
Zhang et al. 2017	Convergent	1	1		3	1	-	31	-	1

Note: U – upstream stage; M – midstream stage; D – downstream stage

In configuring the SN, the majority of existing SNC models have considered SN entities with two attributes, namely, operations cost and operations time. Although travel distance and time vary depending on the selected upstream/downstream SN entities, studies have included transportation cost into operations cost, assuming a fixed amount (distance). This assumption indicates a somewhat unrealistic situation as transportation cost and time vary significantly depending on the geographical location of the selected upstream/downstream SN entity. The only study which has considered the spatial dimension to some extent is Shukla and Kiridena (2016) accounting for the social cost of transportation-related carbon-dioxide emission between SN entities. Even though this study explicitly accounts for the impact of the spatial dimension in terms of the sustainability aspect, the effect of spatial dimension on other SN performance parameters such as efficiency and speed have not been considered.

Temporal dimension: Changing conditions in SNs overtime are considered as the temporal dimension in this study, which have been discussed in the literature under the topics of SN uncertainties and SN dynamics (Shishebori & Babadi 2018; Salem & Haouari 2017; Dai & Li 2017; Peidro et al. 2009). Uncertainties pertaining to the SN context have been identified through a number of classifications. For example, Salem and Haouari (2017) presented SN uncertainties in terms of general environment uncertainties, industry uncertainties and firm-specific uncertainties.

Dai and Li (2017) classified uncertainties into environmental (which includes supply and demand) and system (e.g., production, distribution) related aspects. Peidro et al. (2009) categorised SN uncertainties into demand, process/manufacturing and supply. Irrespective of the way SN uncertainties were classified, these studies have reviewed the SN uncertainties pertaining to the entire SN. SN dynamics have also been identified and researched in the SN literature as changes to SN structure overtime with entities entering or leaving the SN as a result of disruptions and technological advancement, shifting product-market profiles, mergers and acquisition of SN entities (Choi, Dooley & Rungtusanatham 2001).

An essential SN design (and SNC) requirement stated in the SN literature is to build the SN capacity to be robust and resilient in the face of uncertainties and dynamics (Klibi, Martel & Guitouni 2010). However, only a few studies have explicitly accounted for these aspects. Even though existing models have considered one or both of the operations costs and operations time as attributes of SN entities, they have been assumed to remain the same over time. The conventional approach used with these SNC models is to configure the SN considering static and deterministic SN contexts. However, typically, SN entities are autonomous business organisations with distinct attributes, characteristics and behaviours. They interact with other SN entities and make decisions such as adopting new technologies, expanding facility capacities and changing business models to cope with challenges such as market reactions or competitor manoeuvres (Yao & Askin 2019; Swaminathan, Smith & Sadeh 1998). This could change the SN entity attributes and behaviour over time, resulting in different levels of performance at the whole of SN level.

A few studies have attempted to model the stochastic nature of SN entities. Wang and Shu (2007) modelled the SNC problem considering a scenario where each SN node has multiple SN entities that differ in terms of their operations costs and lead-times. They have accounted for uncertainty in relation to lead-times of SN entities and consumer demand using a fuzzy set modelling approach. Greco et al. (2013) adopted Bayesian decision networks and modelled the SN as a tree using MAS where agents represent SN entities. The entire SN was configured by the successful creation of sub-chains (which consist of upstream SN entities) by each SN entity considering both the reputation and selling price for the product. Reputation of a SN entity was determined by analysing the previous experience of collaborations with trading partners. Selling price was determined by each agent based on both the expected minimum profit and the past experience in bidding. Depending on the success or failure of the previous bid, the agent increases (subject to the number of previous successful bids) or decreases (subject to the cost of production) the selling price. Ruiqing, Tang and Matsukawa (2014) developed a dynamic programming model and is the only study which accounted for SN disruptions in the context of making SNC decisions. In their approach, first, the SNC was developed in a static manner, and then the impact of SN disruptions to SNC decisions was tested using scenario analysis with a given probability of holding the functioning of SN entities at each stage.

Additionally, to uncertainties related to SN entity attributes, existing SNC models have considered uncertainties in consumer requirements, modelling the product-market profiles with uncertainties related to one or more attributes of volume (i.e., the number of unit required), lead-time and WTP price. For example, Graves and Williams (2005) have modelled the product-market profile using the volume attribute and assumed it follows the normal distribution. In this study, multiple studies have been reviewed and analysed based on the nature of the attributes of the product-market profiles used. Accordingly, two types of product-market profiles were identified: (i) static, i.e., attributes of product-market profile remain the same over an extended period; (ii) dynamic, i.e., attributes of the product-market profile are changing over time. The distribution of SNC models concerning the type (i.e., static or dynamic) and attributes (i.e., volume, lead-time and WTP price) of the product-market profile is shown in Figure 2.2. There are 15 studies out of the 35 which have dealt with static product-market profiles whereas 10 studies have dealt with dynamic product-market profiles. Jiao, You and Kumar (2006) and Zhang et al. (2009) had considered a static product-market profile with all three product-market profile attributes. There are no studies that have used dynamic product-market profiles accounting for all three attributes.

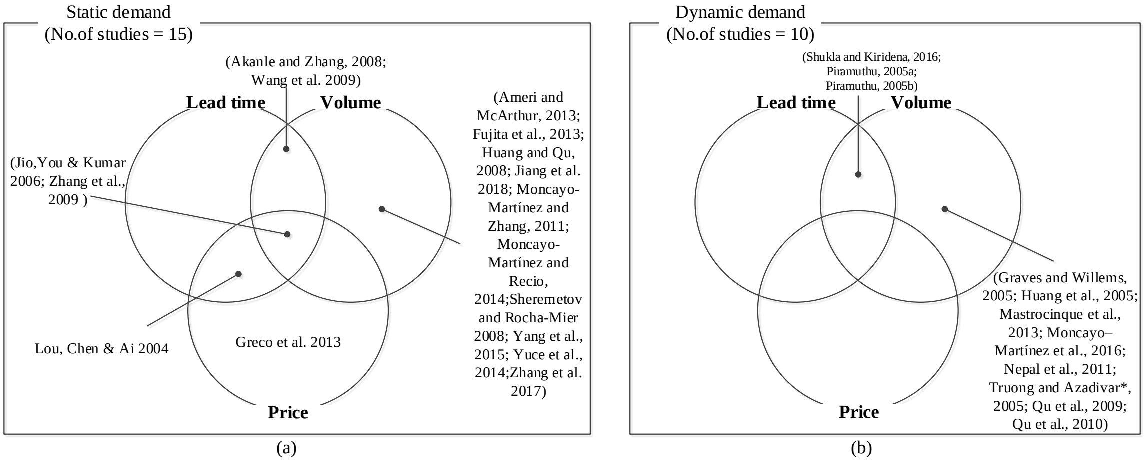


Figure 2.2: Studies with different product-market profiles (a) static (b) dynamic

2.6.2 Supply network configuration decisions

SNC decisions addressed by each of the 35 studies reviewed are listed in Table 2.2. The entries show that most of the proposed models (17 out of 35) have dealt with the three key decisions: supplier selection, determination of facility locations, and the choice of transport mode(s). For example, the supplier selection decision deals with the selection of the 1st tier suppliers, determination of facility location deals with the selection of location to manufacture products and the choice of transportation mode deals with the selection of the mode of transportation to dispatch products to consumers. Additionally, the three key decisions mentioned above, Truong and Azadivar (2005), however, have also considered production policy (make-to-order or make-to-stock) and selection of facilities considering their capacity. There are other studies (e.g., Moncayo–Martínez & Zhang 2013; Graves & Willems 2005; Huang et al. 2005) that have considered inventory planning as one of the SNC decisions, indicating that some authors have incorporated both strategic and tactical level decisions into SNC decisions. This analysis indicates that the type of SNC decisions considered in SNC models varies depending on the definitions for SNC adopted by the study and the perspective of the authors.

Eight studies have dealt with only the supplier selection decision considering simple SCs consisting of single echelon supply and manufacturing stages. For example, Piramuthu (2005b) has considered a supplier selection decision which was tested on a convergent SC with three nodes in a single echelon supply stage and one node in the manufacturing stage. Despite the fact that these studies have used simple SC structures, they have made distinct contributions to the SNC literature. For example, both Piramuthu (2005b) and Lou, Chen and Ai (2004) accounted

Table 2.2: SNC decisions

References	SNC decisions					
	SS	**FL**	**TM**	**IP**	**CP**	**PP**
Akanle & Zhang 2008	×	×	×			
Ameri & McArthur 2013	×					
Fujita et al. 2013	×	×				
Graves & Willems 2005	×	×	×	×		
Greco et al. 2013	×					
Huang, Zhang & Liang 2005	×	×	×	×		
Huang & Qu 2008	×	×	×			
Jiao, You & Kumar 2006	×					
Jiang et al. 2018	×	×				
Lou, Chen & Ai 2004	×					
Li & Womer 2008	×	×	×			
Mastrocinque et al. 2013	×	×	×			
Moncayo-Martínez & Zhang 2011	×	×	×			
Moncayo-Martínez & Zhang 2013	×	×	×	×		
Moncayo-Martínez & Recio 2014	×	×	×			
Moncayo–Martínez et al. 2016	×	×	×	×		
Moncayo–Martínez et al. 2016	×	×	×			
Nepal et al. 2011	×	×				
Piramuthu 2005a	×	×				
Piramuthu 2005b	×					
Qu et al. 2009	×	×	×			
Qu et al. 2010	×	×	×			
Qu et al. 2010	×	×				
Ruiqing et al. 2014	×	×	×			
Sheremetov & Rocha-Mier 2008	×					
Shukla & Kiridena 2016	×	×				
Truong & Azadivar 2005	×	×	×		×	×
Vanteddu, Chinnam & Gushikin 2011	×					
Wang et al. 2009	×					
Wang et al 2016	×	×				
Wang & Shu 2007	×	×	×	×		
Yang et al. 2015	×	×				
Yuce et al. 2014	×	×	×			
Zhang et al. 2009	×	×				
Zhang et al. 2017	×	×				

SS – Supplier selection; FL – Facility location selection; TM – Transport mode selection; IP – Inventory planning; CP – Capacity planning; PP – Production planning for product-market profiles with three attributes volume, lead-time and WTP price (see Section 2.6.1).

Additionally, Lou, Chen and Ai (2004) selected multiple SN entities (i.e., adopting multiple sourcing strategies) to supply the same component/parts aimed at finding the best coalition between SN entities (see Section 2.6.4). Other studies such as Ameri and McArthur (2013) and Jiao, You and Kumar (2006) have contributed to the SNC literature by adopting a distributed decision-making approach using MAS. Furthermore, Jiao, You and Kumar (2006) employed bidding and negotiation protocols in handling SNC decisions.

Those studies which dealt with the three most common decisions (i.e., supplier selection, facility location selection, transport mode selection) have addressed the SNC problem rather holistically in dealing with large scale SC (i.e., SC with more than 100 SN entities) structures. The other distinct feature in those studies is the use of combinatorial optimisation based modelling approaches and meta-heuristics as the solution methodology (see Section 2.6.4).

2.6.3 Supply network performance measures

There are a number of performance measures that have been reported in the SN literature both at SN entity-level (e.g., Akyuz & Erkan 2010) and the whole of the SN-level (e.g., Klibi, Martel & Guitouni 2010). SN entities are independent business organisations with their own goals, hence, each has its performance measures. However, the performance measures applicable at the SN-level for a target product-market profile are quite common. With the broader goals of improved profitability and market share, a given SN is expected to outperform other competing SNs in terms of speed, efficiency and responsiveness (Ketchen Jr et al. 2008).

Table 2.3 lists the SN-level performance measure(s) that have been considered in SNC literature, these include minimising SN cost, lead-time and energy consumption, as well as maximising the compatibility index which is a measure of compatibility between SN entities in terms of structural (e.g., cultural) and managerial (e.g., strategic) goals and financial (e.g., profit margin) aspects.

Close examination of SN costs reveals three key constituent elements, namely, cost of goods sold (COGS), distribution cost and inventory cost. COGS is defined as the direct costs related to the production of goods which

Table 2.3: SN performance metrics

References	Cost	Time	Compatibility index	Energy consumption
Akanle & Zhang 2008	×			
Ameri & McArthur 2013	×			
Fujita et al. 2013	×			
Graves & Willems 2005	×			
Greco et al. 2013	×			
Huang et al. 2005	×			
Huang & Qu 2008	×			
Jio, You & Kumar 2006	×			
Jiang et al. 2018	×	×		
Lou, Chen & Ai 2004	×			
Li & Womer 2008	×			
Mastrocinque et al. 2013	×	×		
Moncayo-Martínez & Zhang 2011	×	×		
Moncayo-Martínez & Zhang 2013	×	×		
Moncayo-Martínez & Recio 2014	×	×		
Moncayo–Martínez et al. 2016	×	×		
Moncayo–Martínez et al. 2016	×	×		
Nepal et al. 2011	×		×	
Piramuthu 2005a	×			
Piramuthu 2005b	×			
Qu et al. 2009	×			
Qu et al. 2010	×	×		
Qu et al. 2010	×			
Ruiqing et al. 2014	×			
Sheremetov & Rocha-Mier 2008	×			
Shukla & Kiridena 2016	×			×
Truong & Azadivar 2005	×			
Vanteddu, Chinnam & Gushikin 2011	×			
Wang et al. 2009	×			
Wang et al 2016	×			
Wang & Shu 2007	×			
Yang et al. 2015	×	×		
Yuce et al. 2014	×	×		
Zhang et al. 2009	×			
Zhang et al. 2017	×	×		×

include raw material cost, and other direct (value-adding) costs incurred in manufacturing (i.e., operations cost). The distribution cost is usually explicitly accounted only at the distribution stage in relation to the transportation of finished goods from manufacturer to consumer, not having considered the transportation cost between other SN stages. In many cases, inventory cost comprises of the holding cost only. Accordingly, the studies are grouped into three categories based on cost elements considered: (i) COGS only (e.g., Nepal et al., 2011); (ii) COGS and the distribution cost (e.g., Moncayo-Martínez & Zhang 2013; Moncayo-Martínez & Zhang 2011; Akanle & Zhang 2008); (iii) COGS, distribution and inventory cost (e.g., Huang, Zhang & Liang 2005; Graves & Willems 2005). These cost elements also indicate the characteristics of the relevant SC structure, as mentioned in Section 2.8.1. For example, those studies with convergent SC structures have considered only COGS.

Lead-time is defined as the lapsed time between the time when an order is placed and when it is actually available for satisfying the customer demand (Zheng et al. 2019). In the SNC literature, lead-time of an individual SN entity is modelled in a way that assumes the delivery lead-time of supplying a particular component to its immediate down-stream operation is fixed regardless of whichever optional down-stream SN entity is considered (Akanle & Zhang 2008).

As given in Table 2.3, all studies have accounted for SN cost and 12 studies have considered both SN cost and lead-time. Additionally, Nepal, Monplaisir and Famuyiwa (2011) have considered the compatibility of firms represented by the cultural alignment, information sharing, and cooperation. Shukla and Kiridena (2016) and Zhang et al. (2017) are the only studies that have also considered a sustainability measure in terms of energy consumption.

2.6.4 Modelling approaches and solution methodologies

In general, modelling approaches are selected based on a number of factors such as the type and number of variables required to model the problem at hand; the relevant parameters and their nature; the number of objective(s) to be achieved; and the computational efficiency with which the model can be run considering the scale of the problem and the nature of the variables and parameters involved (Sahebi et al. 2014; Barbati, Bruno & Genovese 2012). Solution methodologies explain the methods used to solve the models concerned in arriving at a solution while dealing with the computational complexity and the quality of the solution obtained (Barbati, Bruno & Genovese 2012).

Many modelling approaches and solution methodologies have been used in the SN literature to deal with SN decisions. A number of classifications have been used in the SN literature to evaluate the range of modelling approaches available against the criteria referred to above. Beamon (1998) classified the modelling approaches used in SN design models into deterministic-analytical, stochastic-analytical, economic and simulation. This classification focuses on the types of quantitative models, considering the nature of the input (i.e., parameters), the objective of the modelling approach and the nature of the solution. However, this classification did not consider the more advanced modelling approaches which are currently in use. Giannocaro and Pontrandolfo (2003) classified models in terms of conceptual, analytical, artificial intelligence-based, and simulation. This classification has covered the modelling approaches used in both qualitative and quantitative SN contexts. Although this classification did not pay particular attention to the nature of the parameters involved, compared to Beamon (1998), more focus was given to the nature of the solution obtained while also accounting for more recent modelling approaches. This classification has been modified by Peidro et al. (2009) with a particular focus on the quantitative context by introducing hybrid modelling approaches in which a combination of many modelling approaches are involved. Having considered all these classifications, this study proposes a classification schema to review SNC models that considers only quantitative modelling approaches as per the aim of this study. Accordingly, this study clusters the modelling approaches used in SNC models into deterministic-analytical (i.e., parameters are known and specified) (DE), stochastic-analytical (i.e., at least one parameter is unknown but follows a certain probabilistic distribution) (ST), simulation (SI) and artificial intelligence-based (AI). Table 2.4 shows the modelling approach adopted by each of the studies.

Solution methodologies explain the methods used to solve the models concerned in arriving at a solution. There are a number of classifications for solution methodologies proposed in the SN literature. Melo, Nickel and Saldanha-Da-Gama (2009) divided solution methodologies used in the SN literature into exact algorithms and heuristics which are solved using general-purpose software and tailored algorithms. This classification has covered solution methodologies used in solving a few modelling approaches. In comparison, Govindan, Fattahi and Keyvanshokooh (2017) have presented four clusters of solution methodologies used in SN literature under uncertainties, they are: exact algorithms, heuristics, meta-heuristics, and commercial solvers. This classification also has not considered solution methodologies for all of the modelling approaches listed above. Considering these classifications and solution methodologies that have been used in the SNC literature, this study grouped solution methodologies into exact algorithms (EA), meta-heuristics (MH), software platforms (SP), and machine learning (ML) clusters. Deterministic models have been solved using both exact algorithms and meta-heuristics, depending on the nature and scale of the problem being modelled.

Table 2.4: Modelling approaches and solution methodologies used in SNC literature

Reference	Modelling approaches				Name of the modelling approach	Solution methodologies				Name of the solution methodology
	DE	ST	AI	SI		EA	MH	SP	ML	
Akanle & Zhang 2008			×		Multi-agent system		×			Genetic Algorithm
Ameri & McArthur 2013			×		Multi-agent system			×		Similarity algorithm
Fujita et al. 2013	×		×		Mixed-integer linear	×	×			Simplex Algorithm, Genetic Algorithm
Graves & Willems 2005	×				Dynamic programming	×				Dynamic Programming
Greco et al. 2013			×		Multi-agent system				×	Bayesian Decision Network
Huang et al. 2005			×		Evolutionary optimisation		×			Genetic Algorithm
Huang & Qu 2008	×				Analytical target cascading		×			Genetic Algorithm
Jio, You & Kumar 2006			×		Multi-agent system					Bidding (Contract net protocols)
Jiang et al. 2018			×		Meta-heuristics optimisation		×			Bee Algorithm; Simulated Annealing;
Lou, Chen & Ai 2004			×		Multi-agent system			×		Bidding (case based contract net protocols)
Li & Womer 2008	×				Integer programming	×				Constraint programming
Mastrocinque et al. 2013	×		×		Mixed-integer non-linear		×			Bee Algorithm
Moncayo-Martínez & Zhang 2011			×		Meta-heuristics optimisation		×			Ant Colony Optimisation
Moncayo-Martínez & Zhang 2013			×		Meta-heuristics optimisation		×			Ant Colony Optimisation
Moncayo-Martínez & Recio 2014			×		Meta-heuristics optimisation		×			Ant Colony Optimisation
Moncayo–Martínez et al. 2016			×		Meta-heuristics optimisation		×			Ant Colony Optimisation; Intelligent
Moncayo–Martínez et al. 2016			×		Meta-heuristics optimisation		×			Intelligent Water Drop
Nepal et al. 2011			×		Meta-heuristics optimisation		×			Genetic Algorithm
Piramuthu 2005a			×		Multi-agent system				×	Decision rules

Table 2.4: Modelling approaches and solution methodologies used in SNC literature (continued)

Reference	Modelling approaches				Name of the modelling approach	Solution methodologies				Name of the solution methodology
	DE	ST	AI	SI		EA	MH	SP	ML	
Piramuthu 2005b			×		Multi-agent system				×	Decision rules
Qu et al. 2009	×				Analytical target cascading		×			Genetic Algorithm
Qu et al. 2010	×				Analytical target cascading		×			Genetic Algorithm
Qu et al. 2010	×				Analytical target cascading		×			Genetic Algorithm
Ruiqing et al. 2014	×				Dynamic programming	×				Dynamic Programming
Sheremetov & Rocha-Mier 2008			×		Multi-agent system					Collective intelligence
Shukla & Kiridena 2016			×		Multi-agent system			×	×	Rough Set
Truong & Azadivar 2005	×		×	×	Mixed Integer Linear Program, Evolutionary algorithm, Simulation		×	×		Genetic Algorithm; Discrete Event Simulation
Vanteddu, Chinnam & Gushikin 2011		×				-	-			
Wang et al. 2009			×		Multi-agent system			×		Negotiation
Wang et al 2016	×				Mixed-integer non-linear Program		×			Genetic Algorithm
Wang & Shu 2007			×		Fuzzy rough set theory		×			Genetic Algorithm
Yang et al. 2015	×				Mixed-integer linear program		×			Genetic Algorithm
Yuce et al. 2014			×		Evolutionary optimisation		×			Bee Algorithm
Zhang et al. 2009				×	Peri nets			×		Petri.NET Simulator
Zhang et al. 2017	×				Analytical target cascading		×			Genetic Algorithm

AI-based modelling approaches and solution methodologies have been used in a number of studies, while treating the SNC problem as a combinatorial optimisation problem, from the mathematical point of view (Nepal et al. 2011; Huang et al. 2005). Those studies that consider the SNC problem to be of a combinatorial optimisation type have adopted a centralised decision-making approach assuming that a single decision-maker selects the best set of SN entities for a given product-market profile. Additionally, the SN context has been assumed to be static and deterministic. These models have used evolutionary, and meta-heuristics optimisation solution approaches for solving the SNC problem. Genetic algorithm (GA) has been used in many studies, and Ant Colony Optimisation (ACO) was the second most popular meta-heuristics reported in the literature. MAS has also been used as an AI-based modelling approach to model the SNC problems in distributed decision-making environments. These have often been implemented on software platforms with communication and coordination mechanisms, as well as decision rules. The commonly used modelling approaches and solution methodologies will be further discussed in Section 2.6.4.1.

From a practical point of view, to arrive at an effective solution for SNC problems, it is required to evaluate the SN entity-level decisions at the SN-level, considering the product-market profile attributes. The decisions of SN entities can change over time which in turn has an impact on SN-level performance. However, the majority of studies have addressed only SN-level decisions adopting a centralised decision-making approach and considering the SNC problem to be of a combinatorial optimisation type. A few other studies have attempted to model SN-level decision-making in a de-centralised manner using MAS and analytical target cascading (ATC) modelling approaches. However, this practical context has not been modelled at an adequate level of detail in the SNC literature except for a few studies such as Akanle and Zhang (2008) and Sheremetov and Luis (2008) who modelled both SN entity-level decisions and SN-level decisions.

2.6.4.1 Widely used modelling approaches and solution methodologies in SNC models

In this section, the most common modelling approaches and solution methodologies used in the SNC literature are discussed. The AI-based modelling approach is the most common modelling approach category in which meta-heuristic optimisation and MAS have been widely employed. ATC is also a modelling approach which has been used in many studies. With respect to solution methodologies, GA and ACO have been used in many studies. Each modelling approach and solution methodology has its own distinct advantages and limitations. Meta-heuristics and evolutionary algorithms have the capacity to deal with large-scale problems, and are considered as computationally efficient techniques. Also, these solution methodologies offer near-optimal solutions. ATC is also an effective method in arriving at an optimal solution; yet, is not as efficient in terms of computational efficiency. MAS has high computational efficiency and is also a potential approach to model distributed decision-making contexts with the flexibility to accommodate any solution methodologies depending on the requirement. Nonetheless, proper coordination and communication mechanisms have to be implemented to integrate distributed autonomous decisions.

MAS: This approach refers to a collection of agents (self-contained, modular, and uniquely identifiable individuals) who independently make decisions co-operating and competing with other agents to achieve individual or common goals (Mostafa et al. 2017). The MAS modelling approach has been recognised as an approach particularly suitable for complex and dynamic problem contexts. It deals with developing modular components (agents) for executing specific and defined sets of tasks in a rather autonomous manner. The salient features of the MAS modelling environment are the agent environment; agent attributes and characteristics; and the agent architecture (Macal 2016). Agent environment is defined in the literature as the context which is considered to fall outside the control of the agent (Van Otterlo 2009; Sutton 1998). Agent characteristics are such that they display autonomous and adaptive behaviour (i.e., they independently make their own decisions and change their behaviour/decisions upon external influences). This behaviour may take the form of reactive (i.e., respond to the external influences through quick decisions) and/or pro-active responses (i.e., take prior initiatives to cope with future changes), as well as social (i.e., with other SN entities) interactions (Wooldridge & Jennings 1995). Agent architecture is the make-up of an agent in terms of modules and the mechanisms through which these modules interact with each other (Maes, 1991). Alternatively, agent architecture can be considered as a way of implementing the agent attributes and characteristics (Chin et al. 2014). There are a number of agent interaction protocols available in the literature such as blackboard systems, contract net, negotiation, and multi-agent belief maintenance and market mechanisms (Weiss 1999). These communication protocols are selected and applied to suit the type of problem and its context.

MAS modelling has been used in nine studies in the SNC literature. The majority of such studies (e.g., Ameri & McArthur 2013; Greco 2013; Wang et al. 2009; Jiao, You & Kumar 2006; Lou, Chen & Ai 2004) has been undertaken in the context of rather narrowly defined SNs with limited SC tiers (mostly upstream of the SC having a maximum of two stages) and simple product structures. Also, many of them have focused on coordination/configuration of the entire SN using negotiation protocols (Huang & Qu, 2008). These studies have used negotiation protocols such as argumentation-based negotiation (see Wang et al. 2009), contract net protocol (CNP) with negotiation (see Jiao, You & Kumar 2006), case-based reasoning with CNP (see Lou, Chen & Ai 2004). These protocols have their distinct advantages and limitations. CNP is a task sharing method, where nodes become a manager or a contractor situationally where managers decompose, announce and allocate tasks, and then contractors perform the task (Smith, 1980). Jiao, You and Kumar (2006) introduced an improved version of CNP by introducing a multi-contract negotiation process. This study introduces multiple negotiation agents to negotiate with multiple SN entities which enhances the efficiency of the negotiation process. The highest utility value is used to select candidate SN entities subject to meeting the consumer order requirements. If any of the selected SN entities is not compatible with other SN entities in meeting the customer requirements, then the negotiation occurs iteratively until meeting the consumer requirements. Lou, Chen and Ai (2004) used case-based reasoning with CNP in order to enhance coordination efficiency. This method maintains a database which has the history (i.e., information on SN entities to fulfil a given order) of past fulfilled orders (referred to as cases). When a new order is received, the requirements of that order are first compared with the cases in the database. Then depending on the availability of similar cases in the database, the same set of SN entities are used for the new order; otherwise, the steps of the general CNP are followed to find the suitable SN entities. The compatibility of these SN entities across the SN is tested using an index for coalition ranking (i.e., SN entities are rated by the number of effective coalitions) subject to the constraints.

A few studies have used MAS in rather complex SCs with multiple echelons while incorporating certain advanced/significant features into the model. Greco et al. (2013) modelled the SC as a tree representing SN entities as agents. Once a SN entity in the SC receives an order, that SN entity is responsible for selecting the corresponding upstream SN entities (i.e., creating the sub-chain) in order to fulfil the order requirements. For example, a SN entity needs to create a sub-chain if that SN entity needs raw material or sub-assemblies to fulfil the order requirement. The order is accepted by the SN entity, checking the availability of resources. If the resources are available, then the selling price is decided by considering both the expected minimum profit and the past experience in bidding. Depending on the success or failure of the previous bid, the agent increases (subject to the number of previous successful bids) or decreases (subject to the cost of production) the selling price. This decision-making process is modelled using Bayesian decision networks. Studies of Akanle and Zhang (2008), Shukla and Kiridena (2016) more holistically addressed SNC decisions in the context of multi-tiered SNs. Apart from addressing multi-tier SC, Akanle and Zhang (2008) introduced a coordinated iterative bidding process to find an optimal set of SN entities for a given customer order. A set of reserve values were generated using a GA, upon which SN entities presented their bids given the condition that a minimum threshold of profit was gained. Otherwise, SN entities do not bid for the given customer order. This bidding process was continued for a given number of iterations in order to find an optimal set of SN entities. Shukla and Kiridena (2016) introduced multiple agents such as data retrieval agent, knowledge acquisition agent, knowledge representation agent etc to make SNC decisions. Fuzzy rough sets-based algorithms have been used for knowledge elicitation and representation dealing with multiple product variants. Additionally, this is the only study which has considered the spatial dimension to account to some extent for the social cost of transportation-related to carbon-dioxide emission between SN entities.

Although these studies contribute to solving SNC problems in a number of ways, most of them have fallen short of modelling the autonomous decisions of SN entities at the required level of detail. However, Sheremetov and Rocha-Mier (2008) developed a model based on collective intelligence theory by considering autonomous SN entity decisions at SN-level to achieve SN-level performance. A reinforcement algorithm is used to model the decisions of SN entities and a generalised version of the Q-neutral algorithm is used for SN-level optimisation.

GA: First introduced by Holland (1975), GA has been extensively used in optimisation-based problem-solving applications in areas such as engineering and business (Mirjalili 2019). It is an evolutionary adaptive algorithm inspired by the process of natural selection observed in biological systems (Kumar et al. 2010). A chromosome represents a candidate solution (i.e., individual) which consists of a series of genes. These genes represent the basic characteristics of the candidate solution in the solution space. A fitness value is calculated for each chromosome which indicates the degree of "goodness" of the chromosome. A chromosome with high fitness has a higher likelihood to yield a good-quality offspring (i.e., a better candidate solution). GA is a population-based evolutionary algorithm which means GA initiates with a population of chromosomes which then subjects to local search. The size of the population varies depending on the application (Mahfoud 1994). A new generation of individuals (i.e., children population) is created through the three key genetic operators of selection, crossover and mutation from the current population (i.e., from parent population). Chromosomes from the parent population are selected using roulette wheel selection (Kumar et al. 2010). These evolutionary iterations continue until a defined convergence criterion are met (Davis 1991). This convergence criterion includes the number of function evaluations (i.e., computational iterations), the difference between fitness value of two generations of population, the predefined value of fitness can also be set by the number of evolution cycles (computational runs), the amount of variation of individuals between different generations, or a predefined value of fitness (Chan et al. 2018).

As Table 2.4 indicates, GA has been used as a solution methodology in a number of SNC models, including MAS, mixed-integer linear/nonlinear programming models, ATC, and fuzzy rough set theory. Additionally, the role of GA in these SNC models is different. Akanle and Zhang (2008) used GA in the proposed multi-agent model to tune the control parameters (i.e., a set of virtual prices and profits) and use them as reserve values for bidding to select the best set of SN entities minimizing the SN cost. Fijita et al. (2013) and Huang, Zhang & Liang (2005) used GA to solves the SNC problem as a combinatorial optimisation problem dealing with a single objective.

ACO: This is an optimisation technique introduced in the early 1990s. ACO is especially used in discrete optimisation problems (Mullen et al. 2009). This technique is inspired by ants' behavior in searching for food. Ants have the capability of smelling and depositing a chemical substance called pheromone, as a way of communicating with each other. Ants move randomly when they leave the nest to forage for food, but when ants find a pheromone trail, they decide whether or not to follow it. The probability that an ant selects one path over the other is based on the strength of the pheromone smelt on paths. The stronger the pheromone smelt of a path, the more likely the ant will select the path. If they decide to do so, they deposit their own pheromone over the trail. Over time, the amount of pheromone on a path also evaporates. Before the colony finds the shortest path between the nest and the food, ants use all potential paths in equal numbers, depositing pheromone as they travel. The ant that takes the shortest path at a time will return to the nest first, with food. The shortest path at that time will have the highest pheromone strength because the path has ‘‘fresh’’ pheromone which has not yet evaporated and will be more attractive to other ants that look for the food source (Zang, Zhang & Hapeshi 2010; Angus & Woodward 2009; Dorigo, Maniezzo & Colorni 1996)

ACO is also a common solution methodology used within the SNC problem context, which optimises multiple objectives in arriving at a SN level solution. Alternative SNCs are generated based on the pre-defined attributes of SN entities which means that ACO has been applied in deterministic SN context. However, ACO based solution methodologies have dealt with large scale SNs (i.e., SNs with more than 100 SN entities) effectively generating alternative optimal SNCs within a reasonable computational time.

ATC: This is a hierarchical, decomposition-based optimisation method (Kim 2001). The first step of ATC is breaking a system (e.g., SN) into hierarchies (e.g., SN echelons) which has ATC elements (e.g., SN nodes) and the second step is to identify the key links between ATC elements in the hierarchy. Key links are those variables shared by two or more elements (such as lead-time and cost in the context of SNC) in the ATC model and should be kept consistent during the optimisation phase (Allison et al. 2005). Key links include responses and linking variables. Responses are the variables shared by parent and child elements vertically in the ATC. The third step of an ATC analysis is to formulate the local optimisation problems for each element in the ATC. Deviations of responses and linking variables are included in the objective function for minimization of an element (Allison et al. 2005). These deviations are reduced through each iteration of cascading, eventually becoming acceptable according to the given tolerances.

ATC follows a decentralized decision-making approach where a given SN entity has the decision-making autonomy to configure the upstream stage (Huang & Qu 2008). GA has been used in solving the ATC model to take both SN entity decisions and SN level configuration decisions. However, ATC is capable of dealing with only convergent SCs and only with one objective (Huang & Qu 2008).

2.7 Literature review summary

Among the available definitions of SNC the most common one found in the literature is: SNC is alternative arrangements of SN entities, processes and resources differentiated by their performance metrics such as cost and lead-time when multiple options are available. Extant SNC literature was reviewed and presented using the classification consisting of SN characteristics, SNC decisions, SN performance measures, modelling approaches and solution methodologies.

SN characteristics were discussed under structural, spatial and temporal dimensions. Most of the structures considered in the SNC models are either convergent or conjoined. Even though such structures consider multiple echelons in upstream, downstream has not been treated as such. A considerable number of the models available dealt with SCs with over 20 different SN nodes (e.g., raw material, part/component/subassemblies etc). The total number of SN entities considered ranged from less than 30 in the majority of studies to more than 100 in a few studies. The maximum number of consumer regions considered was six. Furthermore, all studies were limited to a single product platform; however, a number of product variants (maximum is four) have been considered.

Although the structural dimension was modelled to some extent in SNC models, both the spatial dimension and temporal dimension were poorly addressed. Most of the studies had configured the SN based on two attributes (i.e., operations cost and operations lead-time) of SN entities, and these attributes were assumed to remain the same over time. This indicates the lack of attention to the impact of uncertainties pertaining to those attributes. Furthermore, the operations cost attribute of each SN entity was calculated, taking into account one or more of the constituent components, COGS, inventory cost and distribution cost. Except at the distribution stage, transportation cost between other SN stages was not considered. However, uncertainties related to the product-market profile has been accounted for in most of the models but considering the volume attribute only.

Most of the studies had dealt with the three key SNC decisions: supplier selection, the determination of facility locations and the choice of transport modes. Additionally, a few studies had also dealt with inventory planning and capacity planning decisions. SN cost was the only performance metric which had been optimised in the context of SNC decisions. The majority of SNC models proposed in the literature had focused on a single objective (i.e., SN cost), and 12 studies out of 35 considered two objectives, including SN costs. Among the multi-objective based studies, the majority accounted for the cost and lead-time, whereas a few studies also considered the compatibility index between SN entities and energy consumption.

The majority of the studies had formulated the SNC problem as a combinatorial optimisation problem (adopting a centralised decision-making approach). It solved using meta-heuristic techniques (e.g., GA, ACO), assuming that one central decision-maker selects the best set of SN entities (from all SN nodes) to achieve expected SN-level performance. However, a few other studies had attempted to model SN-level decision-making adopting a de-centralised approach. For example, studies which used ATC had adopted a de-centralised decision-making approach by assigning the SN entity selection decision to SN stages. A few studies had attempted to integrate both SN entity-level decisions and SN-level decisions. Those studies, using MAS as a modelling approach, attempted to accommodate the autonomous decisions of SN entities. Despite certain limitations, those models have made distinct contributions to the literature. For example, MAS based models applied on small-scale problems (i.e., simplified SN structures); however, they have also made unique contributions from other perspectives (e.g., dealing with multiple product variants, modelling the adaptive behaviour of SN entities, employing iterative bidding mechanisms), which may better reflect industry practice.

2.8 Key research gaps in the SNC literature

Research efforts that incorporate SN characteristics (in terms of structural, spatial and temporal) into the models supporting SNC decisions can deliver more practically useful results. Although the structural dimension is adequately incorporated into existing SNC models, the spatial and temporal dimensions of SNs are under-researched. This literature review further established the need for modelling the distinct attributes of SN entities to achieve a more realistic representation of SNs, as each SN entity can be quite unique in terms of the decision-making style adopted, strategic goals pursued and the organisational practices in place. More importantly, changing SN conditions (e.g., uncertainties and dynamics) have an impact on the performance of SN entities which in turn make an impact on the overall SN-level performance. However, these aspects have not been incorporated into the majority of existing SNC models. Therefore, the need was identified for modelling a multi-stage, multi-echelon SN consisting of geographically dispersed autonomous SN entities catering to distinct product-market profiles.

SNs compete with other SNs in terms of offering a superior customer value proposition to sustain their competitiveness in a changing business context. Therefore, addressing the varied and often changing product-market profiles is another crucial aspect which needs to be incorporated into SNC models. However, there are many limitations in modelling product-market profiles in the existing SNC literature, which include inadequate representation of the realistic SN conditions, as well as consumer requirements. The product-market profile is mostly specified only by the volume attribute, giving no attention to the characteristics of its multiple attributes, each with a varying and changing nature. Additionally, setting up the expected SN performance in alignment with the attributes of the product-market profile is identified as another important aspect in SNC literature.

In conclusion, since distinct and dynamic behaviour of individual SN entities can create complex aggregate behaviour at the SN level, to arrive at an optimal solution for a given SNC problem, both the SN entity-level (local) and SN-level (global) decisions need to be aligned. However, the majority of studies holistically addressed the key SN decisions such as supplier selection, facility location selection and transport mode selection with limited attention to the impact of the individual behaviour of SN entities. In most cases, SNC problems are considered to be of combinatorial optimisation type aimed at finding optimal SNC(s) based on the desired SN entity attributes. As such, researchers have often used meta-heuristic approaches for solving SNC problems. The challenge of integrating both SN entity-level decisions and SN-level decisions demands solution approaches that extend beyond the realm of solely simulation-based numerical modelling and optimisation (Barbati, Bruno & Genovese 2012).

2.9 Chapter summary

SNC as a research area is still in the early stages of its development thus drawing the attention of both researchers and practitioners, particularly in relation to its potential for supporting SNC decisions towards sustaining competitiveness in dynamic business environments. In this chapter, with the use of the proposed classification, SNC literature was reviewed under the topics of SN characteristics, SNC decisions, SN performance measures, modelling approaches and solution methodologies.

The main research gap in the SNC literature is the lack of the required representation of SN characteristics, especially in terms of spatial and temporal dimensions, in modelling the SNC problem. Even though the unique attributes of SN entities can make a significant impact on the SN-level performance, the majority of studies have not accounted for these aspects in SNC models. Most of the existing SNC models have adopted centralised decision-making approaches to configure the SN by finding an optimal SNC(s) based on the desired SN entity attributes. The major limitation of this approach is that it is not able to accommodate the autonomous decisions of each SN entity and evaluate their effects at the SN-level. Therefore, lack of using suitable modelling approaches and solution methodologies for developing SNC models for supporting autonomous decisions of SN entities and methods to configure the SN on a needs basis have been identified as an important area of research.

The two key aspects that require particular attention when modelling product-market profiles are the comprehensive representation of consumer requirements using multiple attributes and accounting for the varied and changing nature of those attributes across different geographical regions. The majority of the SNC literature modelled consumer requirements only in terms of volume; however, there are a number of other attributes such as lead time and price which could be used in capturing the realistic nature of consumer requirements. Another important requirement in relation to meeting consumer requirements is by setting up SN-level performance aligning with the product-market attributes.

CHAPTER 3: CONCEPTUAL FRAMEWORK

3.1 Introduction

As presented in Chapter 2, key research gaps identified in this study inform the need of incorporating SN characteristics and the autonomous behaviour of SN entities in SNC models to achieve expected SN-level performance catering for diverse consumer requirements. Accordingly, this study identifies three key areas for particular attention in developing SNC models. This chapter presents the overall conceptual framework that guided the development of the proposed modelling approach. The conceptual framework consists of three components which represent the key areas that need to be addressed to achieve the aim of this study. These three components are individually discussed in the sub-sections in Section 3.2. Finally, the chapter summary is presented in Section 3.3.

3.2 The proposed conceptual framework

The three components of the proposed conceptual framework are as depicted in Figure 3.1 deal with:

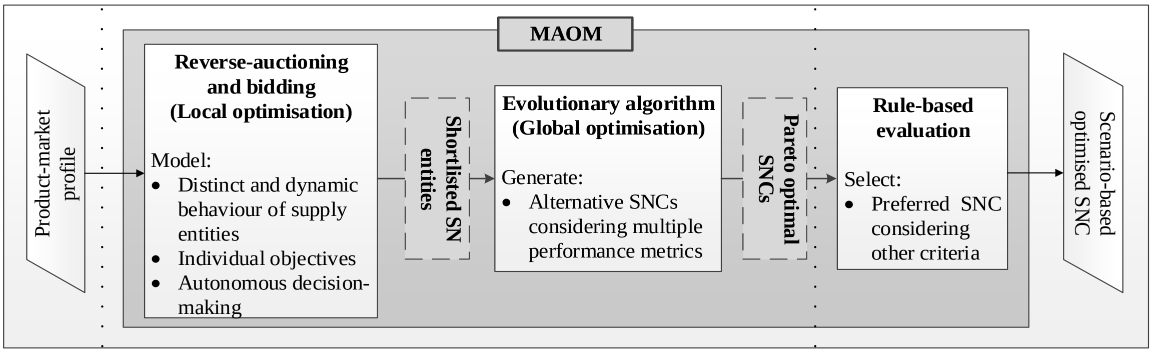


Figure 3.1: Conceptual framework guiding the proposed methodological approach

(i) Establishing the product-market profiles representing different consumer regions;

(ii) Generating alternative Pareto-optimal SNCs catering to specific product-market profile; and

(iii) Evaluating the SNCs generated in (ii) against a set of metrics representing the chosen SN performance criteria applicable to a given context.

As stated in Section 3.1, these three components represent key areas which need to be focused on to achieve the aim of this study while addressing the key research gaps presented in Section 2.8. Accordingly, consumer requirements are captured in multiple attributes by establishing a product-market profile. Then, the individual decisions of SN entities (accounting for their adaptive behaviour) are evaluated at the SN-level by generating alternative Pareto-optimal SNCs for a given product-market profile. Finally, out of these alternative optimal SNCs, one SNC is selected based on other evaluation criteria as per the preference of the decision-maker. Each of these key components of the conceptual framework is explained in detail in the following subsections.

3.2.1 Establishing the product-market profiles

The product-market profile of a consumer region captures consumer requirements, with reference to a given product, using multiple dimensions, which are taken as the input to the MAOM. Within the context of the above framework, the product-market profile of a given consumer region l represents the estimated consumer requirements, with respect to the three key attributes, aggregate demand (V_l), expected lead-time (LT_l) and WTP price (P_l). Capturing the product-market profile this way serves two key purposes: primarily, it provides a complete representation of consumer requirements; secondly, these product-market profile attributes provide guidance for making SNC decisions so as to meet desired SN-level performance targets. It is common practice to derive the values of such attributes using demographic and historical data. However, given that such historical data is not readily available to be used in this study, a set of alternative methods has been used to estimate the required values, as outlined below.

The base parameters used to derive the attributes of the product-market profile are per capita income (www.imf.org), price level index, which is the ratio of purchasing power parity to market exchange rate (www.ec.europa.eu), energy consumption (data.worldbank.org) and population density (www.worldometers.info). Attribute P_l for the target consumer region is taken as proportionate to the price level index of that region. Attribute LT_l is estimated considering per capita income, assuming that populations with high income (i.e., affluent consumers) expect a shorter delivery lead-time. Analytical Hierarchy Process (AHP) is employed to estimate the aggregate demand (volume attribute) of the product-market profile, using several base parameters, as further detailed below.

AHP is a widely used multi-criteria problem-solving technique, originally proposed by Thomas L. Saaty (Saaty

1986). The use of AHP for estimating V_l allows accounting for multiple base parameters representative of a market-segment and the differences between consumer regions to arrive at a more robust estimate of the aggregate demand, compared to assuming that the demand is proportional to the population density of the target consumer region alone. AHP has been used in a number of applications such as selecting the best alternative, allocating resources and forecasting sales (Zhang et al. 2017; Podvezko 2009). Especially, AHP is designed to model a problem, which has criteria, sub-criteria and alternatives, in a hierarchical manner following a series of steps. Such criteria and sub-criteria could be quantitative or qualitative, where quantitative (e.g., cost, speed) factors are derived using statistical data and qualitative factors (e.g., comfortability, appearance) are assessed based on expert opinions.

The fundamental mathematical theory of AHP is to use consistent matrices and Eigenvectors to generate a weight for each alternative with respect to the given criteria. The primary mechanism of constructing a matrix in AHP is by deriving a ratio-scale weight between a pair of alternatives for each given criterion. The principle Eigenvector of such a matrix gives the ratio (i.e., weight) across all alternatives. Weights derived from multiple Eigenvectors give the linear additive weight of an alternative with respect to all criteria. In certain applications, this resultant additive weight of each alternative is used to rank the alternatives in a way that allows the decision-maker to make a choice. In this study, the proportional difference between these additive weights is used to allocate demand among each consumer regions. A detailed account of the process followed in applying the AHP process, including relevant calculations, is provided in Appendix 1.

3.2.2 Generating alternative Pareto-optimal SNCs catering to product-market profiles

Generating alternative Pareto-optimal SNCs for a given product-market profile means identifying the best set of SN entities to meet the expected SN-level performance levels while meeting the product-market profile attributes. To accomplish this requirement, modelling the adaptive behaviour of SN entities in the face of changing SN conditions was identified as an important requirement. As discussed in Section 1.4, a SN can be considered as a socio-technical system consisting of a number of autonomous or semi-autonomous business organizations (i.e., SN entities) with distinct characteristics, such as capabilities, resources and processes, which functions based on a set of competitive priorities. Typically, these SN entities independently make decisions while interacting with other SN entities and take necessary actions, e.g., adopting new technologies, expanding the capacity of facilities and updating business models, to cope with the challenges such as market forces or competitor manoeuvres (Swaminathan, Smith & Sadeh 1998). Such distinct and dynamic behaviour of individual SN entities can create complex aggregate behaviour at the SN level. It is the cumulative effect of these collective decisions and actions that manifest in the form of SNs that are competing against each other in terms of satisfying a given product-market profile. As such, to arrive at an optimal solution for a given SNC problem, both the SN-entity (local) decision-making and SN-level (global) performance need to be aligned. The challenging nature of such problems, such as e.g., distributed decision-making in a global context, demands solution approaches that extend beyond the realm of mathematical programming (Barbati, Bruno & Genovese 2012). However, integration of these perspectives cannot be achieved by using either meta-heuristics, MASs, or any other similar technique, alone, hence the need for a combined approach.

This study adopts MAS in combination with intelligent auctioning and bidding strategies and evolutionary algorithms to determine the optimal SNCs catering to specific product-market profiles while accounting for the diverse goals and autonomous decision-making behaviour of individual SN entities of a given SN. SN entities are modelled using MASs, representing the SN entities as computational agents and these agents are considered to be discrete entities having distinct characteristics and behaviours that learn and adapt to survive under changing SN conditions (Sheremetov & Rocha-Mier 2008). As such, MAS can overcome the limitations in other modelling techniques due to its capacity to accommodate such computational agents, complex SN structures and changing SN conditions. While adopting such a distributed decision-making approach in modelling SN entity-level decisions, a centralised decision-making approach is adopted to make SN-level decisions, which is to generate alternative Pareto-optimal SNCs. Therefore, MAOM is developed in this study to generate alternative Pareto-optimal SNCs for given product-market profile, integrating both MAS and optimisation approaches to model SN entity-level decisions and evaluate these decisions at the SN-level.

MAS has been implemented in MAOM by employing Q-learning algorithms and rule-based reasoning to model SN entity behaviour in presenting bids; the reverse-auctioning process is used for two purposes in relation to identifying a set of SN entities: one is to determine reserve values for each node in the bidding process with the aim of optimising SN-level performance with minimum information available; and the other is to ensure that a competitive bidding process takes place. Optimisation based solution approach has been used in selecting competitive bids at the SN-level while achieving expected SN-level performance metrics.

Accordingly, the SN-level optimisation is in the form of a binary programming model, which belong to the combinatorial optimisation type problem cluster. Therefore, applying exact algorithms such as branch-and-cut and branch-and-bound is practically infeasible due to exhaustive search which is not tractable as the computational time could increase exponentially with the problem size (El Motaki et al. 2019). Additionally, for the purpose of dealing with two objectives, the applicability of evolutionary multi-objective optimisation techniques have been identified as appropriate over the exact algorithms such as goal programming. Moreover, dealing with multiple fronts of SN-level performance requires dealing with trade-off solutions. In mathematical terms, such solutions are called Pareto-optimal solutions or non-dominated solutions which are widely dealt with using evolutionary multi-objective optimisation techniques (Niyomubyeyi et al. 2020). In this study, a widely used evolutionary multi-objective optimisation algorithm, NSGA-II has been used to generate alternative Pareto-optimal SNCs to achieve the expected SN-level performance.

3.2.3 Scenario-based optimisation

The changing SN conditions, the uncertainties in operational parameters, disruptions, structural changes of SN, and inter-dependencies between various entities within the context of SNC make SN design decisions such as supplier selection, facility location and order allocation particularly challenging. Among the mix of modelling approaches and solution methodologies proposed in the literature to deal with SN uncertainties and dynamics, as discussed in Section 2.4, evaluating “what-if” situations supported by scenario-based approaches is considered to be appropriate for solving SNC problems under changing SN conditions (Gabrel, Murat & Thiele 2014). The proposed MAOM approach first determines alternative optimal SNCs considering a selected set of SN-level performance metrics for a given product-market profile; these SNCs are then subject to further evaluation based on other criteria considered important for the type of industry concerned, e.g., energy consumption or carbon footprint, as needed.

Speed, efficiency and responsiveness are the SN-level performance dimensions that are widely used in the literature (Avelar-Sosa, García-Alcaraz & Maldonado-Macías 2019; Tseng et al. 2019). The two objectives used in the proposed MAOM, total SN cost (TSNC) and lead time (LT), represent the efficiency and speed dimensions of the SN-level performance, respectively. These metrics have been chosen to demonstrate the efficacy of the proposed MAOM, in line with the product-market profile concerned. However, depending on the type of product portfolio, industry or the SN strategy pursued pertaining to a given situation, a different set of objectives could be selected to represent the relevant SN-level performance dimensions.

3.3 The proposed approach vs existing approaches

The merits of the proposed approach were compared against those of the approaches used in the existing SNC models. The characteristics of existing approaches were identified through the review of SNC literature and referring to the study by Hang and Qu (2008). Accordingly, the significance of the proposed approach is benchmarked on multiple criteria (based on the classification used in Chapter 2) as listed below:

(i) SN characteristics: considers structural, spatial and temporal characteristics;

(ii) decision-making autonomy of SN entities: indicates the level of detail of the individual decisions incorporated into modelling;

(iii) SN-level decision-making autonomy: informs the approach adopted in SN-level optimisation;

(iv) adopted modelling approaches and solution methodologies: consider the methods/ techniques used to model both SN entity-level decisions and SN-level decisions;

(v) SNC objectives: represent the SN-level performance measures;

(vi) product-market profile: indicates the aggregate consumer requirements in multiple attributes.

Figure 3.2 compares the proposed approach with existing approaches with respect to the above criteria. Based on these criteria, the existing approaches can be clustered into two approaches where the most common one is adopting a centralised decision-making approach to SN-level optimisation assuming static and deterministic SN context while giving no attention to the autonomous behaviour of SN entities. The next common approach is adopting de-centralised decision-making to SN-level optimisation assuming static and deterministic SN context while giving no attention to the autonomous behaviour SN entities. As the research problem highlighted in Section 1.2, the need for modelling SN entity-level decisions and evaluating them at SN-level to generate alternative optimal SNCs in the face of changing SN conditions has been addressed in the proposed approach. Additionally, to this primary contribution, the majority of the existing literature has considered only one attribute (i.e., aggregate

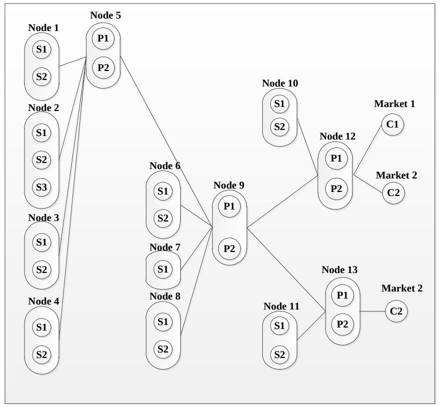
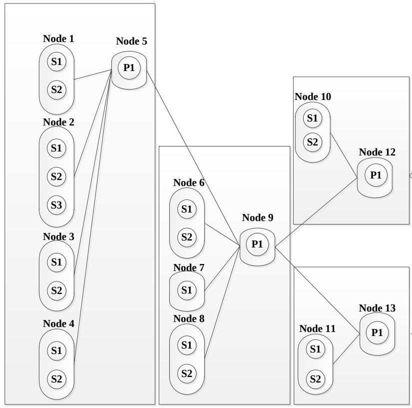
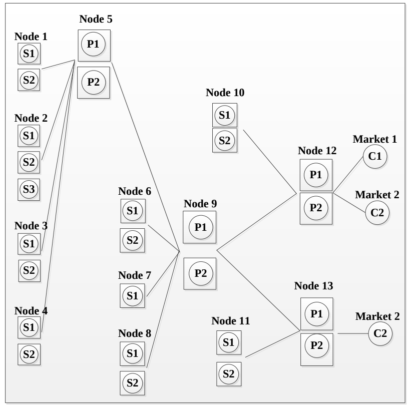
	 **Existing approach (1)**	 **Existing approach (2)**	 **Proposed approach (MAOM)**
Notations	Decision-making autonomy/ the scope of decision; S Supplier; P Manufacturing plant; C Consumer region		
SN characteristics (structural, spatial, temporal)	multi-stage, multi-echelon SN (both upstream and downstream); no spatial attribute; static and deterministic SN context	multi-stage, multi-echelon SN (only upstream); no spatial attribute static and deterministic SN context	multi-stage, multi-echelon SN (both upstream and downstream); geographically dispersed; dynamic and stochastic SN context
SN entity level decision-making autonomy	not modelled	not modelled	modelled (adaptive behaviour)
SN-level decision-making autonomy	modelled (centralised)	modelled (de-centralised)	modelled (centralised)
Modelling approaches and solution methodologies	deterministic-analytical (e.g., dynamic programming) and combinatorial optimisation (e.g., GA, ACO)	deterministic-analytical (e.g., ATC) and MAS (e.g., negotiation protocols)	MAS (Q-learning, rule-based reasoning, intelligent auctioning and bidding) and combinatorial optimisation (GA, NSGA-II)
SNC objectives	single and multiple objectives	single objective	multiple objectives
Product-market profile	single attributed	single attributed	multi-attributed

Figure 3.2: Comparison between existing approaches and the proposed approach

demand) to represent the product-market profile, this study considered a multi-attribute product-market profile representing volume, lead-time and WTP price. Accordingly, in comparison, the proposed approach is expected to make distinct contributions to the SNC literature through its comprehensive approach.

3.4 Chapter summary

This chapter presented the conceptual framework proposed in this study as a holistic approach to achieving its aims. The proposed conceptual framework consists of three steps namely, establishing the product-market profiles for different consumer regions, generating alternative Pareto-optimal SNCs for each product-market profile, evaluating the SNCs generated against a set of performance metrics applicable to a given context. Out of the three steps presented in the conceptual framework in Figure 3.1, the primary focus of this study is to generate alternative SNCs catering to specific product-market profiles, which are achieved in this study with the proposed MAOM. Two common modelling approaches have been found in the extant SNC literature as presented in Figure 3.2 and these approaches are compared and contrasted with the proposed approach against six criteria namely: SN characteristics, SN entity-level decision-making autonomy, SN-level decision-making autonomy, adopted modelling and solution methodologies, SNC objectives, and product-market profiles. In response to a number of limitations in the existing SNC models, the proposed approach stands out on a number of accounts. Primarily, MAOM is significant in terms of generating alternative optimal SNCs accounting for the autonomous decisions of SN entities sharing minimum information with other SN entities, while incorporating the changing SN conditions. This was achieved by adopting a distributed decision-making approach to model SN entity-level decisions and a centralised decision-making approach to model SN-level optimisation. To serve these purposes, MAS and combinatorial optimisation modelling approaches were used with solution methodologies including Q-learning, rule-based reasoning, reverse-auctioning and bidding and evolutionary algorithms.

CHAPTER 4: METHODOLOGY

4.1 Introduction

This chapter presents the methodology adopted to achieve the aim of this study, which is to develop a comprehensive approach to the generation of alternative SNCs for varied product-market profiles optimised under a given set of organisational and environmental conditions. The overall approach to achieve the aim of this study has already been discussed in some detail in Chapter 3 in terms of the proposed conceptual framework.

This chapter is arranged as follows. In Section 4.2, the rationale for the selected methodology is presented. The modelling framework developed to implement MAOM is presented in Section 4.3. This is followed by presenting the four steps of the modelling framework: conceptualisation in Section 4.3.1, mathematical representation in Section 4.3.2, computer-based implementation in Section 4.3.3, and model verification and analysis of other experimental results in Section 4.3.4. Finally, the sub-sections (4.4.1, 4.4.2, 4.4.3) in Section 4.4 briefly present the sources of data used to test MAOM, the types of experiments and analysis performed and brief accounts of the presentation of the results and discussion. Section 4.5 summarises the chapter highlighting the key areas of the methodology.

4.2 Rationale for the chosen methodology

In general, the methodology of a research study is decided based on a number of factors such as the nature of the research problem (i.e., exploratory and explanatory), the aim of the study, the type of research question(s), and the state-of-the-art literature. There are other factors such as time frame of the project, technical facilities (e.g., software) and the availability/accessibility of data which also make an impact on the selection of the methodology.

The research problem stated in Section 1.2 indicates the need for modelling SN entity-level decisions and evaluating them at SN-level to generate alternative Pareto-optimal SNCs in the face of changing SN conditions. The review of SNC literature presented in Chapter 2 highlighted a number of limitations in the existing approaches. Among them, certain research gaps were identified to address in this study considering their importance to the current body of knowledge and practice while being feasible to address within the time frame of the project. Accordingly, this study identified three challenges discussed in the literature (as listed below) as significant in generating alternative SNCs.

I. The first and the most significant research need addressed in this study was enhancing SN-level performance in a geographically dispersed, multi-echelon distributed decision-making SN environment, where individual SN entities aim to satisfy their own organisational goals.

II. The second research need was achieving the above goals in a way that required minimal information sharing between SN entities, which reflects the real-world situation of organisations' reluctance to disclose commercially sensitive information.

III. The third research need was to provide analytical insights for SN decision-makers (e.g., SN entities, SN analysts, consultants) in regards to sustaining SN-level competitiveness in the face of changing SN conditions (e.g., uncertainties and dynamics).

The above-mentioned challenges have been addressed using appropriate modelling approaches and solution methodologies. Strengths and limitations of the available modelling approaches and solution methodologies in the SN literature were discussed in Section 2.4. Additionally, section 2.6.4 and 2.6.4.1 paid particular attention to the modelling approaches and solution methodologies used in SNC models and discussed their strengths and limitations in addressing the real SN requirements. In summary, both analytical models (e.g., Graves & Willems 2005) and numerical models (e.g., Moncayo–Martínez and Mastrocinque 2016) fall short of addressing changing SN conditions, distributed decision-making requirements and desired computational efficiencies, together. This prevailing situation has indicated that the capacity of such models alone to address the SNC problem is quite limited and not practically appropriate. Therefore, to address the above research needs, this study has selected the MAS-based optimisation modelling approach with the integration of intelligent auctioning and bidding strategies. Accordingly, MAOM has been developed in this study, which is further elaborated in the forthcoming sections.

4.3 MAOM modelling framework

The proposed MAOM modelling framework is shown in Figure 4.1. This framework was developed following the approaches used in comparable studies. For example, Persson and Olhager (2002) developed a simulation model which evaluates alternative supply chain designs with respect to different performance measures following the steps of: (i) project planning (i.e., deciding a set of tasks to develop the simulation model and relevant completion times); (ii) conceptual modelling (i.e., describing the problem context using flowcharts or text documents); (iii) conceptual model validation (i.e., assessing and correcting the conceptual model); (iv) computer-based model development; (v) verification (i.e., testing the computer-based model to confirm the accurate implementation of the conceptual model); (vi) model validation (i.e., testing the computer-based model with the real system); (vii) sensitivity analysis (i.e., examining the changes of input to the output); (viii) experimentation and analysing the output data (i.e., analysing the output data and re-run the experiments if necessary); (ix) implementation (i.e., making recommendations or implementations based on the analysed results).

Having considered the above approach and its applicability to implement MAOM to address the SNC problem, four major steps were followed in this study. These steps are conceptualisation; mathematical formulation; computer-based implementation; and verification of the proposed MAOM and the analysis of experimental results. The literature has reported successful implementations of MAS modelling approaches in a number of applications in different disciplines (Barbbati, Bruno & Genovese 2012; Lee & Kim 2008). Accordingly, the salient features of the modelling approaches used in these applications can be differentiated in terms of the agent environment, agent attributes, agent characteristics, and agent architecture. A similar approach has been adopted in developing the proposed MAOM in this study. The implementation of each step falls into five phases: agent and agent environment; agent characteristics; agent types, attributes and architectures; agent communication; and agent model execution.

4.3.1 Step 1 – Conceptualisation

Conceptualisation is a communication method which enables the researcher to convey the intended meaning of concepts or terms used in the research (Sequeira 2014; Onen 2016). Onen (2016) holds a broader view on conceptualisation, which is "starting with the process of forming concepts that describe the identified research problem and proceeding to the derivation of agreed-on meanings of concepts, as well as the operationalisation of study variables, in order to avoid ambiguity and misinterpretation in a researcher's work" (Onen 2016, p.28). In recognition of the importance of conceptualisation, the initial step of this study was to conceptualise the SNC problem in relation to concepts and terminologies used in the development of the MAOM.

Accordingly, in the first step, the SNC problem is conceptualised across the five phases identified above. Phase 1 considers the agent and the agent environment, which is the structural and spatial characteristics of the SN.

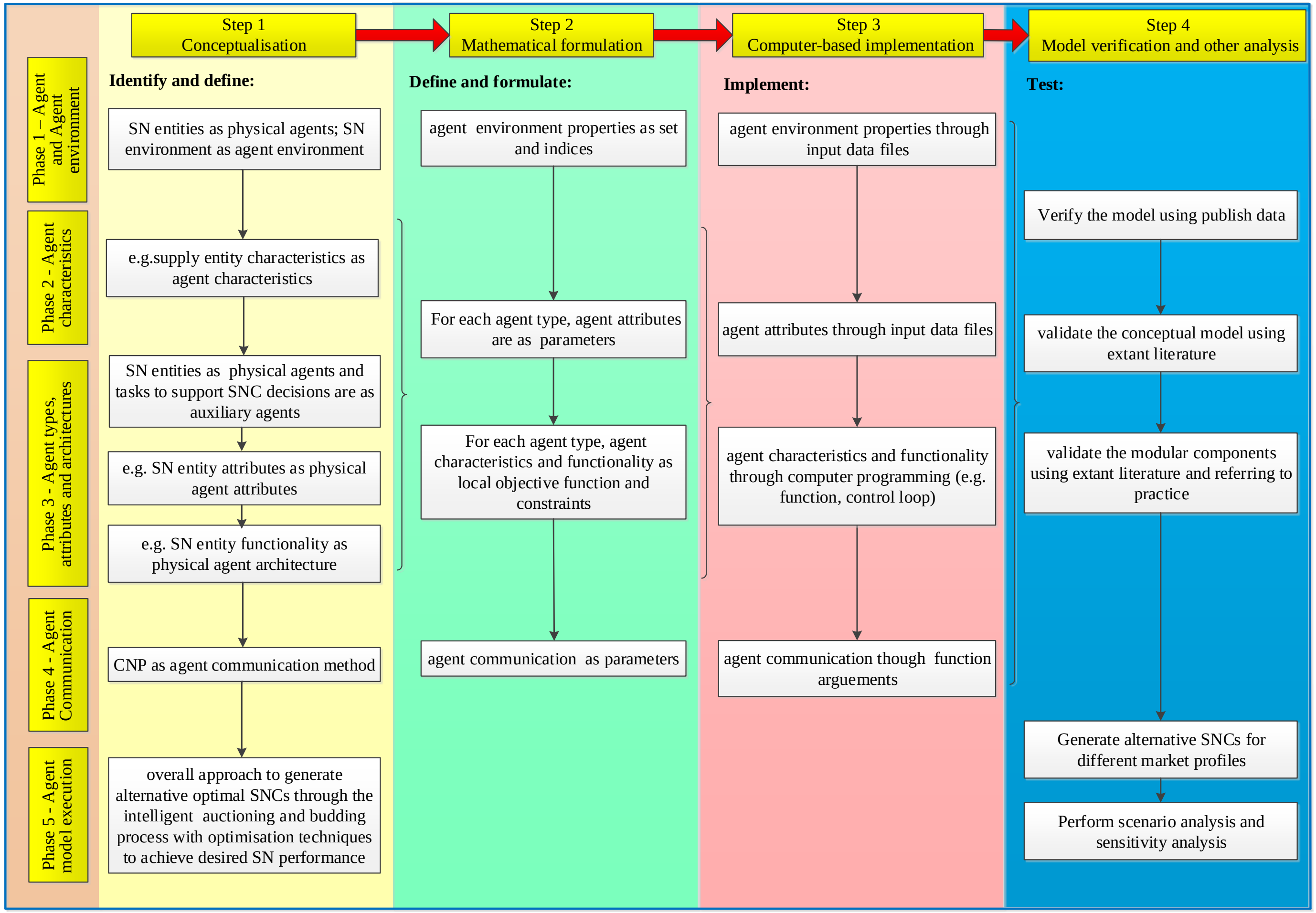


Figure 4.1: The proposed framework for the implementation of MAOM

Phase 2 presents agent characteristics. Phase 3 introduces agent types, which are specific to this SNC problem context their attributes and architectures. Phase 4 presents communication between SNC agents identified in Phase 1 through the interaction protocols (i.e., CNP). Phase 5 informs the execution of the MAOM to generate alternative SNCs for varied product-market profiles.

4.3.1.1 Phase 1 – Agent and Agent environment

Two major views on 'what an agent is' can be gleaned from the extant literature: one is focusing on the attributes and behaviours of agents and the other focusing on their applications; i.e., how agents are used in solving problems within a particular domain (Marks et al. 2018; Mostafa et al. 2017; Russell & Norvig 2016). Based on the review of the definitions currently available in the literature, agents are considered to be entities representing human representatives or tasks (mutually exclusive) with certain inherent characteristics, which are typically executed using software applications. An agent environment is defined in the literature as the modelling context that falls outside the control of agents (Macal & North 2010; Van Otterlo 2009; Sutton 1998). In relation to the SN context, individual SN entities are considered as agents and the SN environment as the agent environment. The SN environment is illustrated in Figure 4.2, which is explained in terms of structural and spatial characteristics. The structural dimension of the environment reflects the composition of the SN, which includes: the number of stages and echelons in the SN; the number of SN entities and their relationships; and multiple product platforms and product variants involved (Serdarasan 2013). A typical SN has multiple stages which could be responsible for: supplying raw materials; producing parts, components or sub-assemblies; assembling final products; or delivering finished goods through various intermediate points to the final consumer. Depending on the product architecture or BOM of a product, there could be multiple raw material, component or sub-assembly types which are sourced/manufactured in respective stages. Each of these raw material, component and sub-assembly types is represented as a node. Accordingly, there could be multiple nodes at any stage, and at a given node, there are a number of competing SN entities, who perform similar functions, termed as entity options. These entity options are dispersed in different geographical locations (representing the spatial characteristics of the SN) and capable of performing the required value-adding functions at the respective node. Depending on factors such as the location of facilities, capacity of their plants, and the processes or technologies utilised, these entities can compete with each other on the basis of cost, lead-time or quality parameters. For example, a local supplier may be able to supply a component at a higher price with a shorter lead-time, whereas an overseas supplier may be able to supply

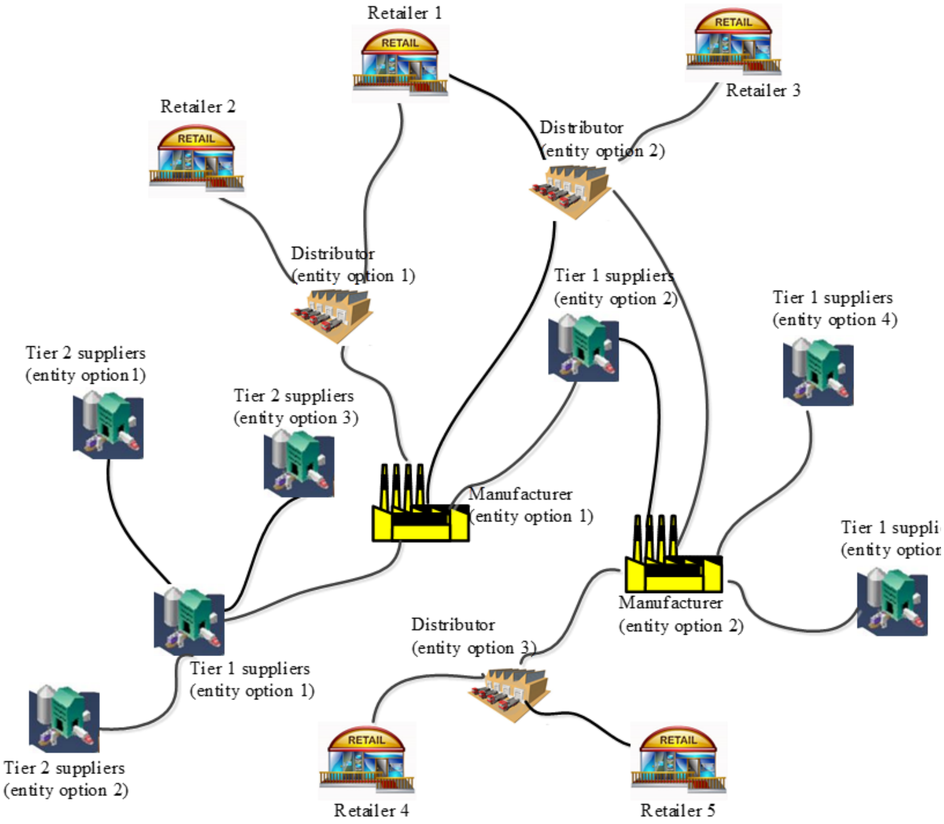


Figure 4.2: Conceptual representation of a SN

it at a much lower price but with a considerably longer lead-time. Consumers are spread across the world, and as such, in this study, consumer demand is considered as the aggregate regional demand.

4.3.1.2 Phase 2 – Agent characteristics

In line with the way agents are defined, a range of agent characteristics are presented in the literature. This study adopted the suite of characteristics proposed by Wooldridge and Jennings (1994) and interprets each of them here with respect to the SN context introduced above.

- Autonomous: SN entities independently make their own decisions considering their competitive priorities, organisational strategies and available resources.

- Adaptive: SN entities change their behaviour/decisions in light of external factors such as business trends, regulatory frameworks and economic conditions.

- Reactive: SN entities make a timely and appropriate response to external influences such as plant breakdowns, loss of suppliers and transport delays.

- Pro-active: SN entities review their operations from time to time and implement new initiatives (e.g., capacity additions) to cope up with future changes.

- Social: SN entities interact with each other for fulfilling customer requirements, for example, in relation to placing orders for raw materials and/or parts.

4.3.1.3 Phase 3 - Agent types, attributes and architectures

In the literature, agent classifications are proposed based on the role of the agent within the system concerned (Caridi & Calieri 2004). From the purpose of modelling, Swaminathan, Smith and Sadeh (1998) classified SNs in terms of structural (e.g., retailer, distributor) and control (e.g., inventory control) elements. Madejski (2007) proposed a classification in terms of physical (e.g., distributors, manufacturers) and functional (e.g., order acquisition, production scheduling) agents. In this study, two types of agents are introduced, namely, physical and auxiliary. SN entities (e.g., suppliers, manufactures) performing typical SN operations and physically located in different geographical regions are considered as physical agents, and those who support SNC decision-making in satisfying different product-market profiles are considered as auxiliary agents.

The attributes of an agent establish the identity of the agent, which allows it to be distinguished from and recognised by other agents (Macal & North 2010). The proposed agents in this study have distinct attributes which will be explained later in this section. Agent architecture is another important aspect of the modelling approaches used, which reflects how an agent is constructed thus giving rise to certain properties, Additionally, the behavioural or functional attributes (Chin et al. 2014; Wooldridge & Jennings 1994; Maes 1991). Maes (1991) proposed a succinct definition of agent architecture, which was adopted in this study: a collection of modules with a mechanism to interact with each other to perform a particular function. The architecture of the proposed agents in this study consist of multiple modules, namely, DM, LM and CM, which are explained along with each agent type.

Physical agents: In relation to the SNC problem studied, a set of three physical agents are introduced, namely, supplier (SA) agent, manufacturer (MA) agent and distributor (DA) agent to represent suppliers, manufacturers and distributors of the SN respectively. These physical agents are located in different geographical regions. The primary function of these agents is to perform the core value-adding operations in relation to satisfying a given product-market profile. As such, SA agents are arranged into a number of tiers according to the BOM of the product involved. For example, if there are multiple tiers in the supply stage; first-tier suppliers supply sub-assemblies; second-tier suppliers supply the required parts and/or components and third-tier suppliers supply raw materials. Similarly, MA agents produce final products, and DA agents are responsible for storing finished products ready to be dispatched to relevant consumer regions. These physical agents have distinct capacity levels applicable to their value-adding operations (e.g., processing, assembly, storage and handling) depending on the node they belong to. Additionally, certain physical agents periodically upgrade their capacity through the purchase of new machinery, adopting new technology and expanding facilities etc. Given these capacity levels, each agent will then have a distinct unit operations cost and operations time related to processing, assembly, storage and handling. In this study, operations cost and operations time of the SN entities have been treated as order winning attributes, considering their relevance to the particular product-market profile, with respect to achieving the individual SN entity-level goals. Accordingly, other product attributes such as quality, delivery, flexibility and service are treated as order qualifiers, which are assumed to meet the threshold (satisfactory) levels of performance. Additionally, these physical agents take part in the reverse-auctioning process to explore business opportunities. The functionality of physical agents in the context of reverse-auctioning is executed with the help of the three modules in the agent architecture shown in Figure 4.3.

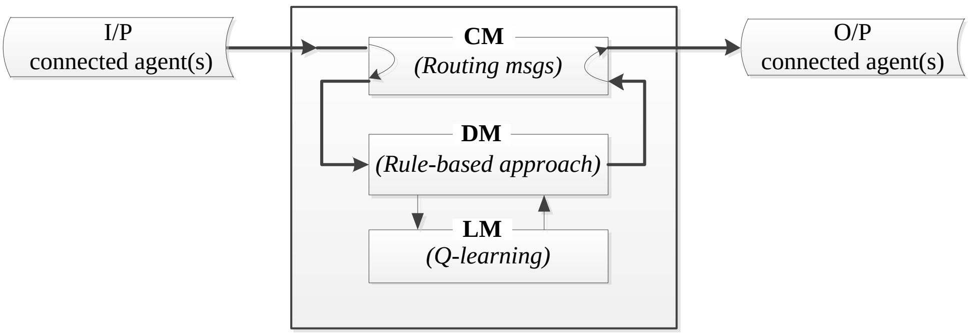


Figure 4.3: The architecture of the physical agents

DM, LM and CM of physical agents: DM supports an agent to bid for orders pertaining to the given product-market profiles using the knowledge-base of that agent. It makes the bidding decisions take the form of sequential decision-making within the dynamic SN context, and the decision-making of an agent is modelled using Markov decision process (MDP) (Puterman 2014).

MDP is considered to be a mathematical framework (as indicated in Figure 4.4) for stochastic dynamic programs, which models dynamic systems using a sequential decision-making approach (Puterman 2014). MDP consists of a set of states (X_m), a set of actions (A_n), a transition function (f (X_m, A_n)) and a reward (T_n) (Puterman 2014; Van Otterlo 2009). A given state can be considered as an observation space of the problem, which represents the capacity level of an SN entity of this study. There could be a number of actions to take (i.e., profit ranges in this study) in relation to transferring from one state to the other. The transition function indicates the transition from one state to the other, and it is a probability distribution across a set of action/transitions. The system will receive a reward (i.e., positive or negative) depending on the action taken at the given state. A policy is a function which maps a state to an action and solving MDP means finding the optimal policy which maximizes the expected utility (Puterman 2014).

A set X of world states representing the capacity levels of an agent

A set A of actions representing profit ranges of an agent

A transition function - f (X_m, A_n)

$X_{m-1} \times A_n \times X_m \rightarrow [0,1]$ such that

$$\sum_{x' \in X} \Pr(x' | x, a) = 1 \quad \forall x \in X, \forall a \in A$$

A reward T_n

Optimal policy Π

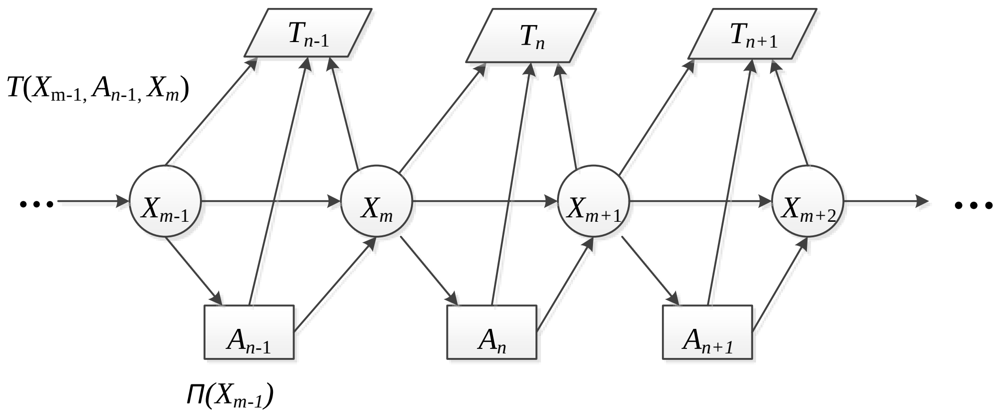


Figure 4.4: Illustration of MDP with mathematical notations

MDPs are solved using learning algorithms which are in two forms, namely, model-based and model-free (Chin et al. 2014). Model-based algorithms (e.g., dynamic programming) are used when all the elements of the MDP discussed above are known in relation to finding an optimal policy whereas model-free algorithms (e.g., reinforcement learning) work in situations of incomplete information (Van Otterlo 2009). Model-free learning uses rewards gained through the interactions with the environment to reinforce the learning process. Considering the non-deterministic nature of the SNC problem and the variability associated with the behaviour of SN entities, in this study, a model-free algorithm is used to make the bidding process-related decisions.

Reinforcement learning, which is adopted in this study, is widely used in model-free learning environments (Diallo, Sugiyama & Sugawara 2019). Reinforcement learning requires clever exploration mechanisms (e.g., temporal learning, monte-carlo, direct policy search) to explore the solution (state-action) space to find optimal policies (Puterman 2014). Among them, the temporal-difference learning is selected, which is an unsupervised learning technique, predicting the outcome of an action at the end of a series of states (Van Otterlo 2009). There are a number of different temporal difference methods available such as Q-learning (Watkins & Dayan 1992), SARSA (Sutton 1996) and actor-critic learning (Konda & Tsitsiklis 2003). The Q-learning algorithm has a simple value iteration process by updating the Q-function in the Q-table using the reward gained from the selected action at a given state. The Q-function helps in predicting the best action in a given state to maximize the cumulative reward. In this study, the Q-table (as given in Table 4.1) is defined in the form of a matrix to store state-actions. States of the Q-table are capacity levels, and the actions are the defined profit ranges which will be discussed more in detail in Section 4.3.2.2. The Q-value corresponding to each state-action is updated based on the reward that the agent gained through the bidding process. At the very first bidding of a physical agent for a new product-market profile, the value of each entry (i.e., Q-value) is set to zero, and for a regular product-market profile, the previous knowledge is used along with the updated Q-table. After each action, the Q-table is updated with a positive or negative reward depending on the outcome of the bids.

Figure 4.5 presents the bidding process of the physical agent. Upon receiving an invitation to bid, at iteration 1, the decision-making module of physical agents first chooses to follow either an exploration or an exploitation strategy, depending on whether the invitation is for a new product-market profile or not (i.e., whether they have bid in the past). Exploration strategy is appropriate in the case of a new product-market profile due to the absence of prior bidding outcomes, in situations such as the introduction of a new product, a new physical agent joining

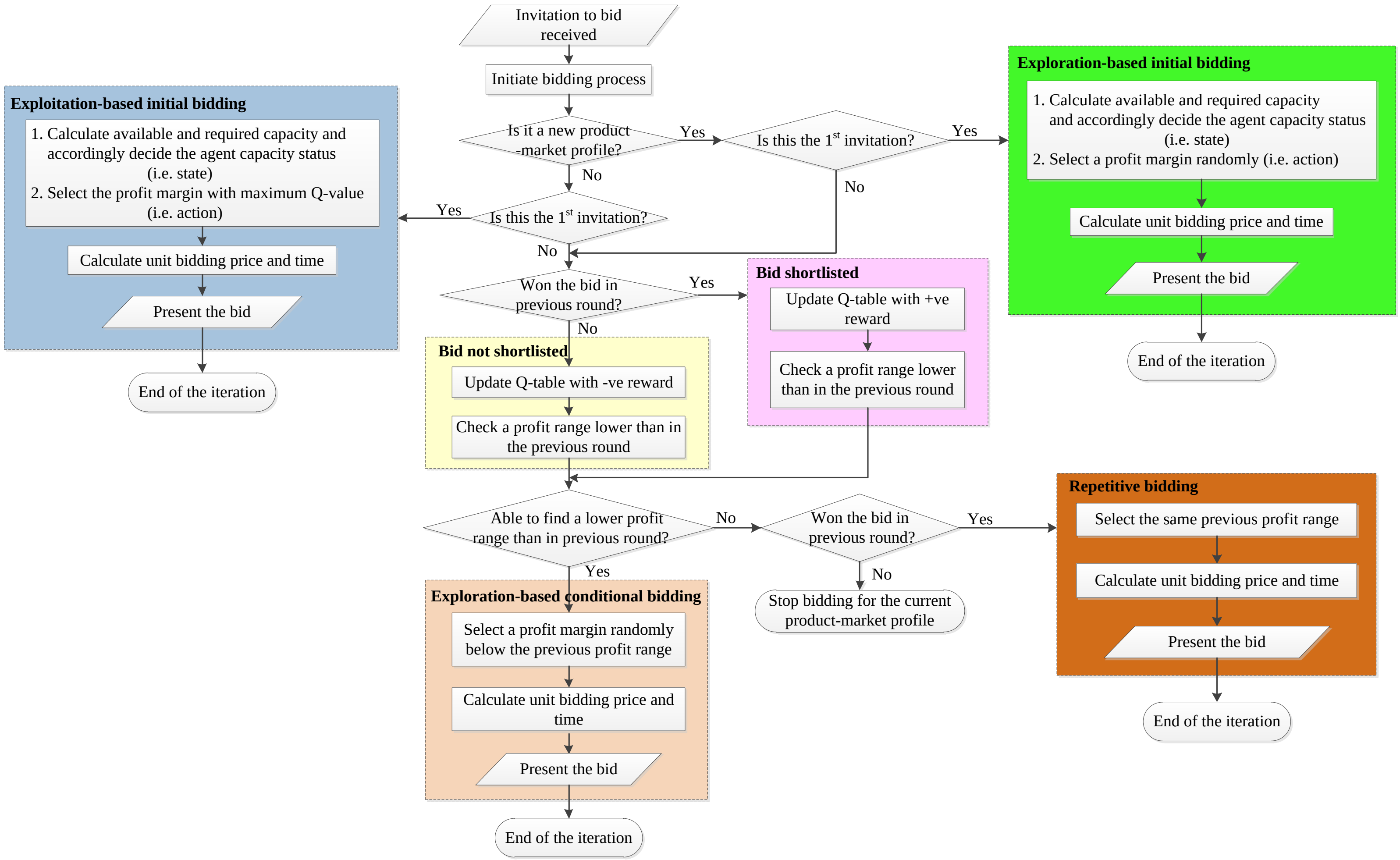


Figure 4.5: Steps involved in the decision-making process (bidding process) of physical agents

the SN or an existing physical agent bidding for the first time on a given product. Exploitation strategy is employed to make use of the physical agent's experience acquired through participation in past auctions or the earlier iterations of the current reverse-auction process. Under exploitation strategy, once the action is selected, unit bidding price and bidding time are calculated. Detailed explanations on all the relevant steps, conditions and constraints used in this process are mathematically presented in Section 4.3.2.2. Once the bids generated as above are presented to the corresponding SN entity selection (SES) agents for consideration, iteration 1 of the bidding process is complete. Upon evaluation of all bids received in iteration 1, the SES agent informs respective physical agents as to whether they are invited to bid in the next iteration of the auctioning process. Shortlisting of bids to proceed to the next iterations is made based on the comparison of bids received against the reservereserve values of price and time. Subsequent iterations of the bidding process may follow multiple paths as illustrated in Figure 4.5, depending on the outcomes of the previous iteration. At the start of each subsequent iteration, the physical agents update their Q-table with a positive or negative reward depending on whether or not the bid was shortlisted to proceed to the next iteration. The physical agent then reads the updated Q-table to see if there is a lower profit range available than was used to bid in the previous iteration. If a lower profit range in the previous iteration can be found, then an *exploration-based conditional bidding* strategy is followed. Under this strategy, the physical agent randomly selects an action, based on a profit range which is less than that used in the previous iteration, and bidding values are again calculated. In case that a lower profit range cannot be found, the physical agent considers whether the bid in the previous iteration was shortlisted or not. If the bid was shortlisted, then the *repetitive bidding strategy* is followed. Under this strategy, the physical agent presents the same values used in the previous iteration of auctioning in response to the current invitation. Otherwise, the agent decides to stop further bidding for the given product-market profile. This brings the reverse-auctioning process to its conclusion.

Auxiliary agents: A set of six auxiliary agents are introduced in the proposed approach namely, SES agent, order processing (OP) agent, auctioning (AU) agent, optimisation (OPT) agent, transportation (TA) agent and evaluation (EA) agent. The role of auxiliary agents is to support SNC decisions in relation to the generation, optimisation and evaluation of alternative SNCs for different product-market profiles. Auxiliary agent architecture consists of DM and CM as shown in Figure 4.6. The way in which each of these agents' functions is elaborated in the following sub-sections.

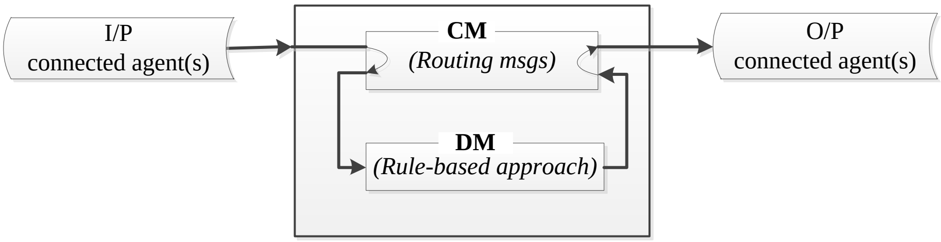


Figure 4.6: The architecture of the auxiliary agents

OP agent: The architecture of the OP agent is shown in Figure 4.7. As presented in the conceptual framework in Chapter 3, initially, the product-market profile of each consumer region was estimated. Then, the volume attribute of such product-market profile is fed to the OP agent to calculate the number of units required from each SN node using the information in the BOM of the product. Figure 4.8 shows a sample BOM which indicates that A_{11} number of units are required from node 1 to produce product A. Then the OP agent contacts both SES agents and the AU agent to pass the relevant information (i.e., SN node indices and the number of units required from each SN node) via the communication module.

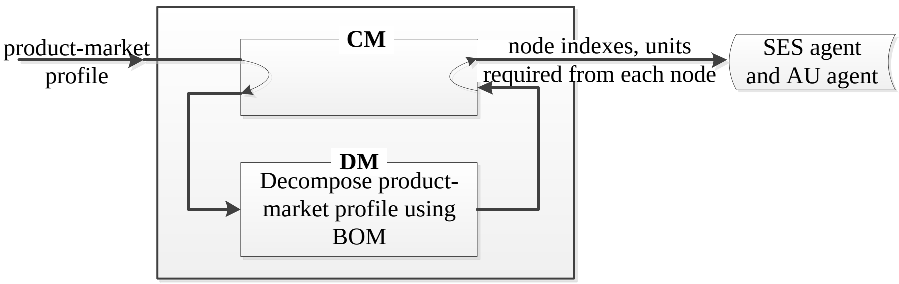


Figure 4.7: OP agent architecture

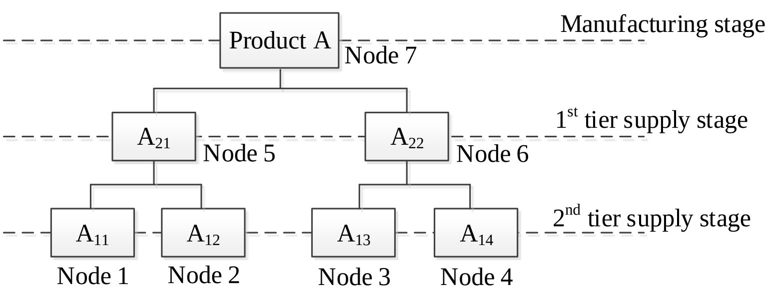


Figure 4.8: BOM of product A (an example)

AU agent: The architecture of the AU agent is shown in Figure 4.9. The primary responsibility of the AU agent is to perform the reverse-auctioning. Once the AU agent receives relevant SN node indices from the OP agent, a set of reserve prices and reserve times are generated based on the product-market profile attributes to those SN nodes in order to execute the reverse-auctioning process. The proposed reverse-auctioning process serves two purposes: one is optimising the SN level performance sharing the minimum information; and the other is to motivate physical agents to bid with the best value they can offer which indirectly creates a competition between physical agents. The AU agent generates a set of feasible optimal reserve prices and reserve times based on the attributes of the product-market profile using a GA for relevant SN nodes as given in Figure 4.10. The initial population to execute the GA is a set of reserve prices and times (i.e., chromosomes) which are generated as given in Figure 4.11 and Figure 4.12, respectively. Those two reserve values are random numbers which are defined within the specified upper and lower threshold value. The lower threshold value is 85% of the upper threshold value. The upper threshold value of reserve price/ reserve processing time of each node is calculated by taking the willing-to-pay price/ expected lead time of the product-market profile of the respective region and the percentage processing cost/ percentage processing time allocated to each node, respectively.

The process of generating a set of feasible optimal reserve prices and reserve processing times starts with initialising the relevant control parameters such as the size of the initial population, the number of offspring to be generated, the number of generations to be used (termination criterion) and the probabilities of crossover and mutation. Once these parameters are set, the chromosomes representing reserve prices and reserve processing times are generated. The feasibility of each of these chromosomes is checked by comparing their fitness value with the willing-to-pay price and expected lead time of the product-market profile, respectively. The fitness value

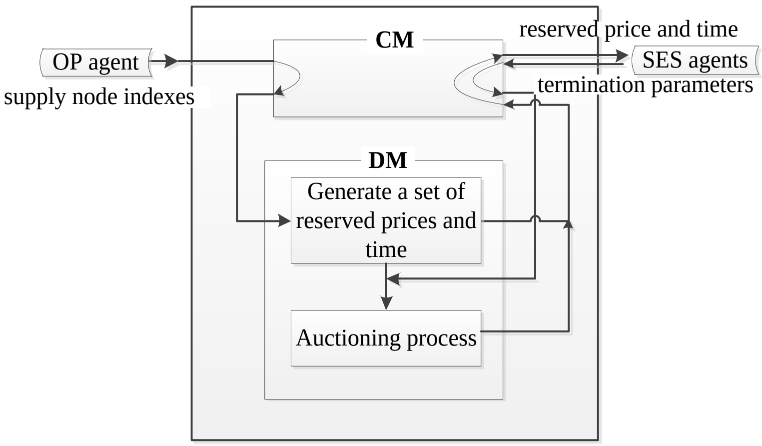


Figure 4.9: The architecture of AU agent

of each chromosome is computed taking the summation of the reserve price/ processing time at every SN node for a given SNC. Then the initial feasible population is subjected to the two genetic operators, mutation and crossover, in order to generate a predefined number of offspring. The fitness values of the offspring generated as above are computed, before combining them with the initial/parent population to form the new population to be used in the next step. Out of this population, a predetermined set of parents with the highest fitness values is selected to form the next generation and the two genetic operators are used again to create a new set of offspring. This procedure is continued until the termination criterion is met.

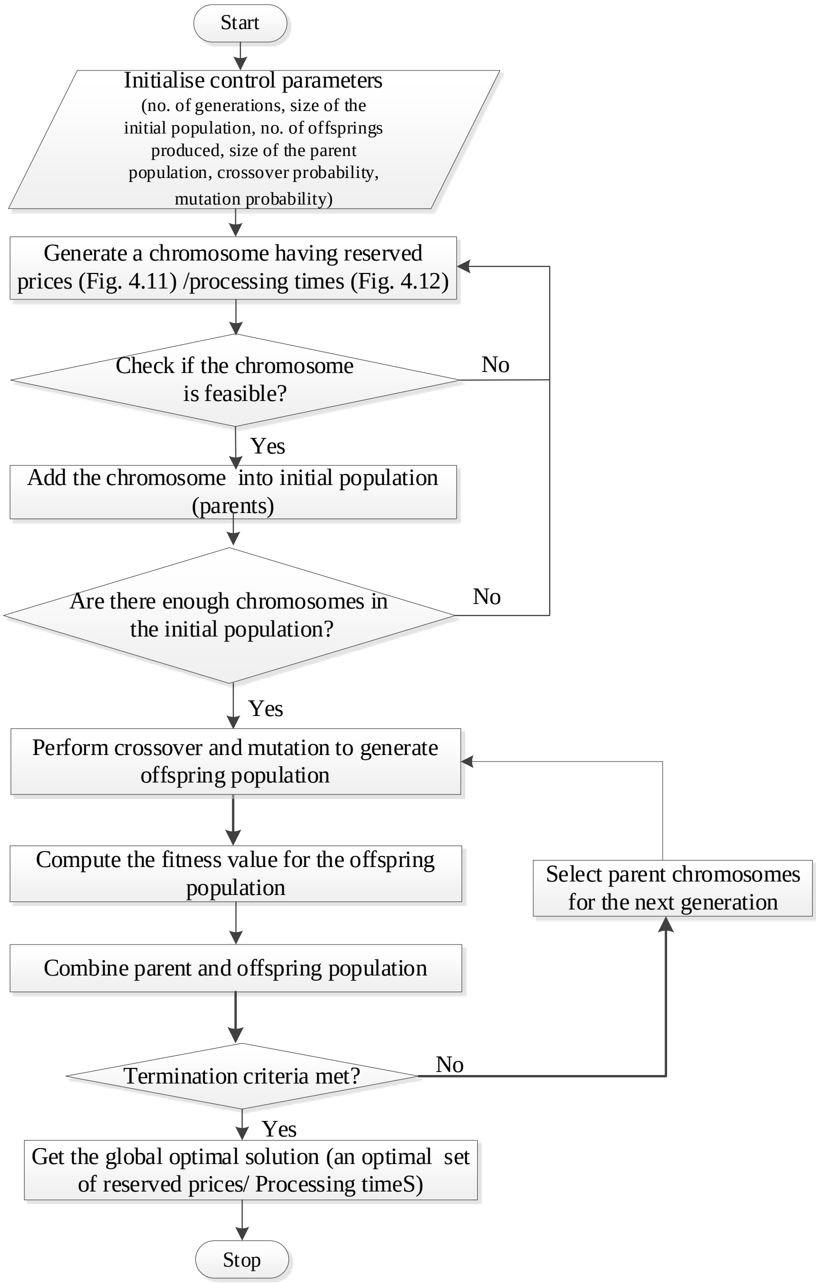


Figure 4.10: The process of generating a feasible optimal set of reserve prices and processing times

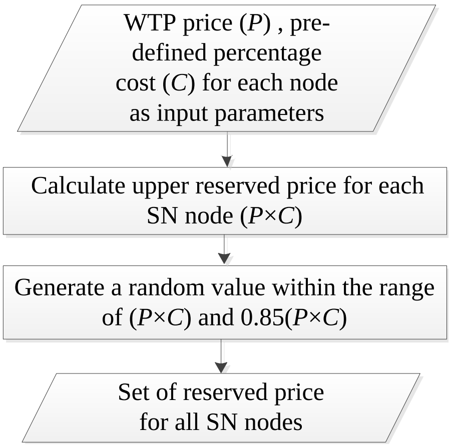


Figure 4.11: The process of generating a set of reserve prices

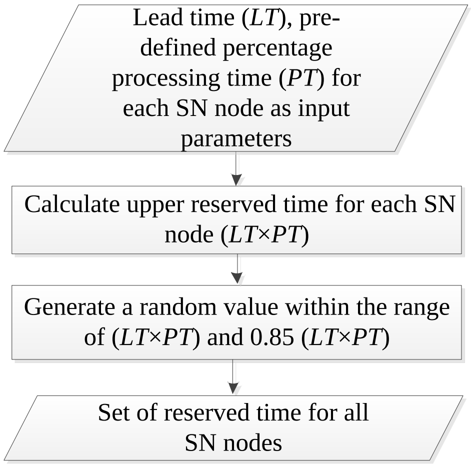


Figure 4.12: The process of generating a set of reserve times

Once the AU agent has generated a set of feasible optimal reserve prices and reserve processing times, as shown in the in Figure 4.13, it starts the reverse-auctioning process using those values as the first set of reserve values which correspond to the first invitation. The invitations are sent to the physical agents through SES agents, and new invitations are made by lowering the initial reserve values by a certain percentage. Then the auction continues until the termination criteria are met (i.e., the pre- defined number of invitations) or at the time when there are no more eligible physical agents to bid.

SES agents: The supplier/manufacturing facility/distribution centre selection agents are considered as SESs. The architecture of a SES agent is shown in Figure 4.14. The primary task of SES agents is to shortlist the physical agents by comparing reserve values (generated by the AU agent) with the bids presented by the physical agents.

Each type of SES communicates with the respective physical agent type. For example, SES of suppliers communicates only with SAs.

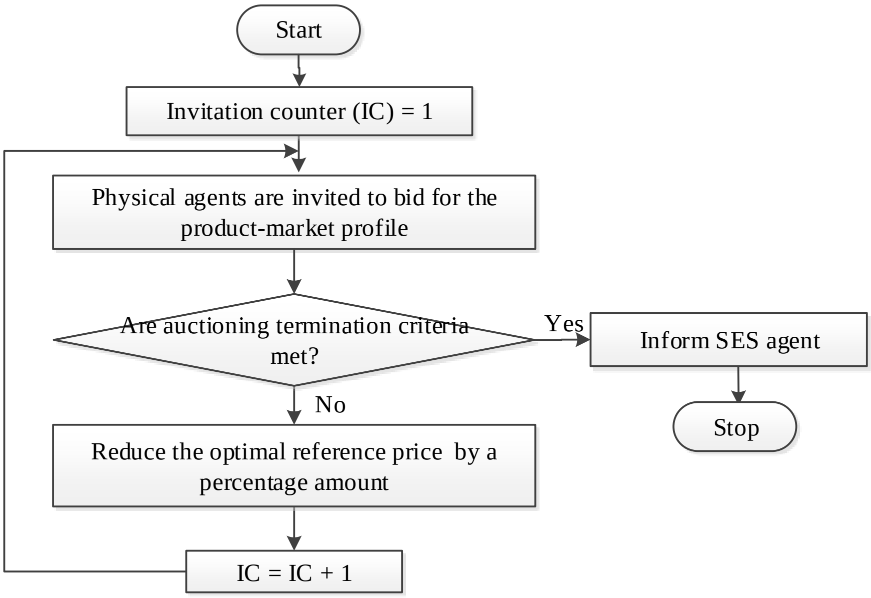


Figure 4.13: Steps involved in the reverse-auctioning process

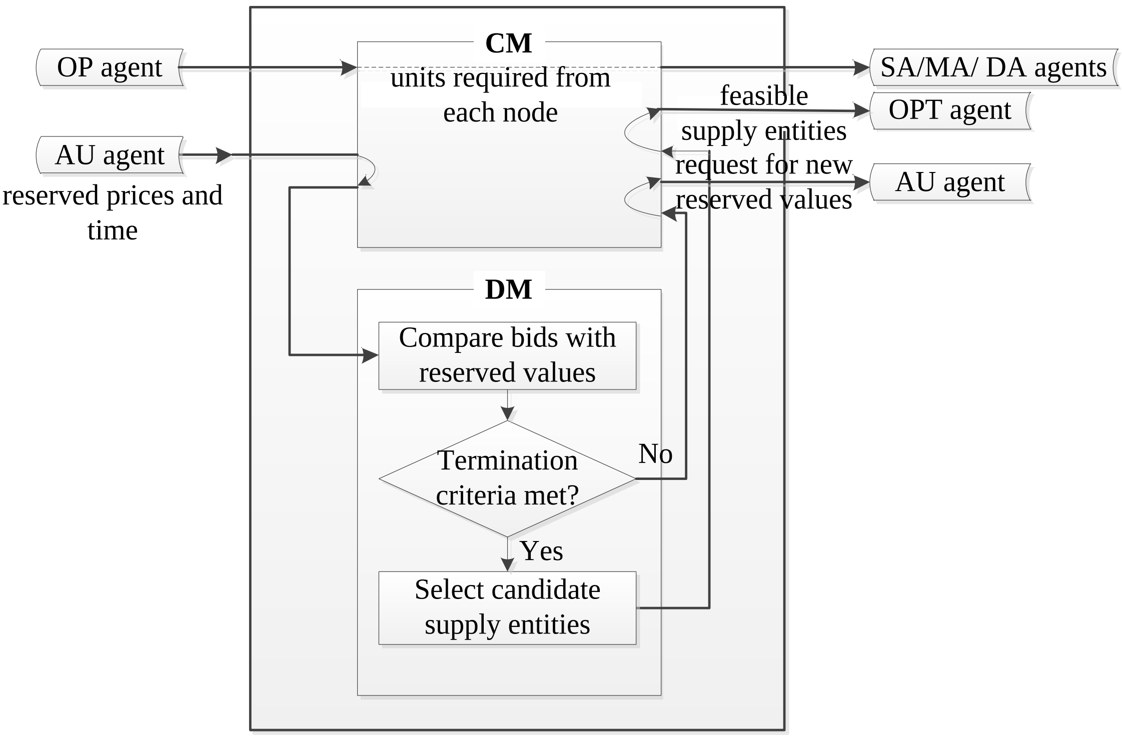


Figure 4.14: Architecture of SES agent

Initially, SES invites relevant physical agents to bid informing them of the number of units required. Upon receiving bids from those physical agents, bids are compared with reserve values and then shortlisted. That bidding outcome is informed to relevant physical agents and the AU agent. This process continues until the AU agent stops the auctioning process upon meeting the relevant termination criteria. At the end of the auctioning process, respective SES agents send a set of shortlisted physical agents to the OPT agent to generate alternative SNCs for the given product-market profile.

OPT agent: The architecture of the OPT agent is shown in Figure 4.15. The OPT agent is responsible for finding a global (i.e., SN-level) solution to the SNC problem in a way that generates optimal alternative SNCs against the multiple SN-level performance objectives (TSNC and LT), while meeting the product-market profile-specific requirements. The OPT agent receives shortlisted physical agents from the AU agent at the end of the auctioning process and the details (cost and time) related to the transportation function are obtained from the TA agent.

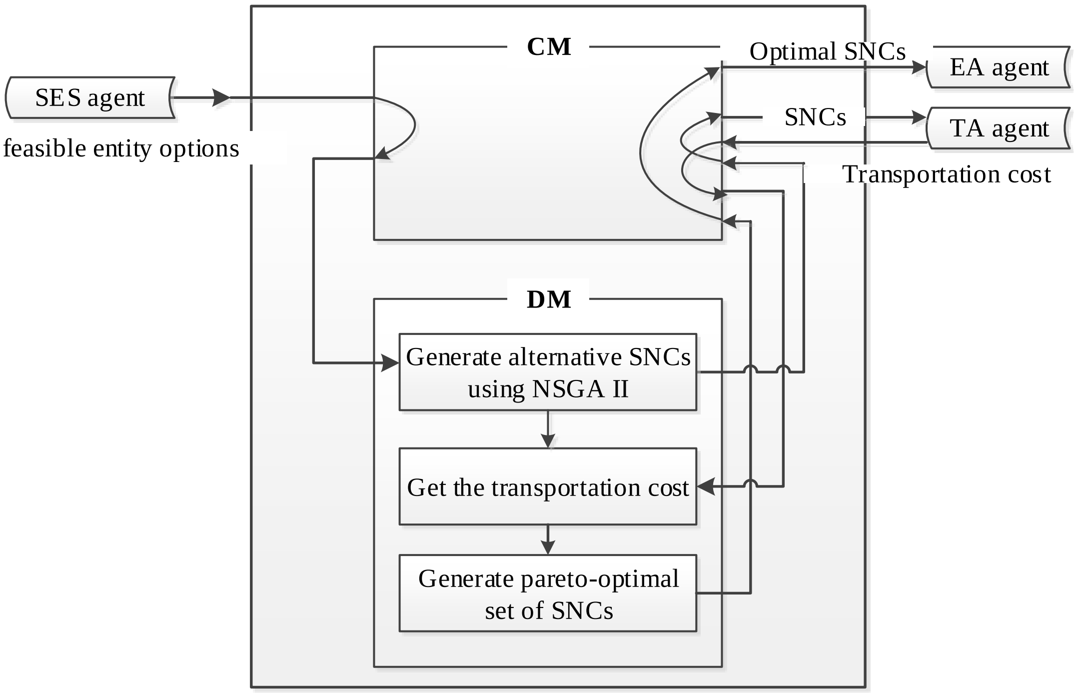


Figure 4.15: The architecture of OPT agent

From a mathematical point of view, the problem of finding optimal alternative SNCs belongs to the combinatorial optimisation type, which cannot be solved with an exhaustive search approach in polynomial time. Therefore, this study has employed NSGA-II (as outlined in Figure 4.16), a widely used evolutionary multi-objective optimisation algorithm (Deb et al. 2002), which has proven to be effective in solving combinatorial type optimisation problems (Niyomubyeyi et al. 2020). NSGA-II has also been used for multiple applications and found to be particularly suitable for dealing with two objectives, compared to the comparable meta-heuristics such as Strength Pareto Evolutionary Algorithm (SPEA) and Pareto archived evolution strategy (PAES) (Matin, Nezafat & Golroo 2017; Hajipour et al. 2016; Subashini & Bhuvaneswari 2012). The three key characteristics associated with NSGA-II namely, elitism (i.e., fast non-dominated sorting approach), crowding distance metric (i.e., fast crowded distance estimation procedure) and simple crowded comparison operator, are employed to arrive at a high-quality set of Pareto-optimal solutions more efficiently, compared to the other evolutionary algorithms referred to above (Audet et al. 2018; Yusoff, Ngadiman & Zain 2011). The fast non-dominated sorting approach segregates the population into many non-dominated sets and then a ranking algorithm is used to select high-performing individuals from these sets to generate a new population using genetic operators. Crowding distance and comparison operators are used to measure the distance between individual solutions in the same non-dominated set and to select the solutions with higher crowding distance in order to maximise the diversity of the selected solutions. Apart from the superior functionality and solution quality achieved through the above algorithmic strategies, it is relatively simpler to implement NSGA-II, due to the relatively smaller number of algorithmic parameters (i.e., control parameters) that need to be defined by the user (Audet et al. 2018). For the same reason, the effort needed in calibrating the algorithm is also minimal, thereby reducing the potential biases in algorithmic performance (Ramesh, Kannan & Baskar 2012).

As shown in Figure 4.16, NSGA-II starts with an initial population (i.e., parents), which is the set of SNCs having one physical agent (i.e., entity option) from each node. Then, fitness values (TSNC and LT) are calculated to rank the population using the sorting algorithm known as Pareto-fast non-dominated (PF-ND). Then, the standard genetic operators are applied (i.e., selection, crossover and mutation) to generate the offspring. Elitism is achieved by combining the chosen attributes of parents and children, that are ranked with the use of PF-ND sorting passed on to the subsequent generation. This process continues until the ceasing criteria are met. Finally, the solutions from the Pareto front are taken as the optimal SNCs for a given set of product-market profile requirements.

TA agent: The architecture of the TA agent is shown in Figure 4.17. The TA is responsible for the overall transportation function across the SN. The TA agent calculates the transportation-related cost and time for a certain SNC on the request of OPT agent.

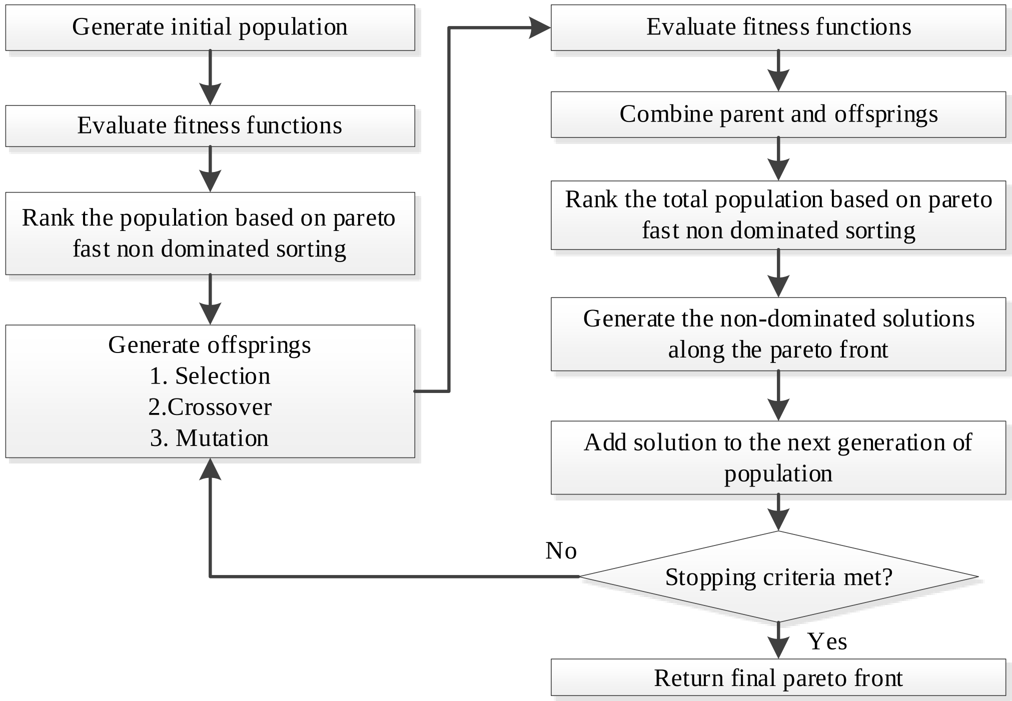


Figure 4.16: Overall steps in NSGA - II algorithm

EA agent: The architecture of the EA agent is shown in Figure 4.18. The EA agent evaluates the alternative Pareto-optimal SNCs generated by the OPT agent, based on additional expected SN-level performance metrics (in addition to cost and lead-time) and selects the best SNC that aligns with the given product-market profile. After a particular SNC is selected, all physical agents are informed, through relevant SES agents, to update their occupied production capacities and Q-table with positive rewards.

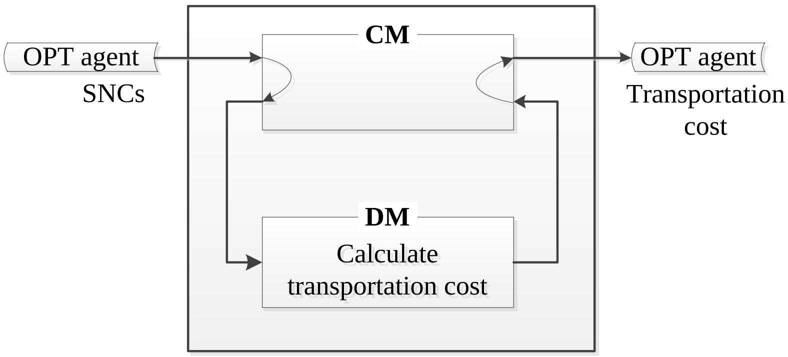


Figure 4.17: The architecture of TA agent

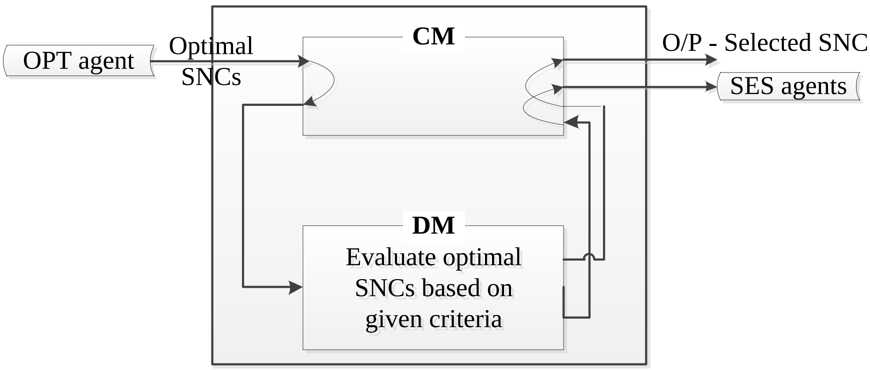


Figure 4.18: The architecture of EA agent

4.3.1.4 Phase 4 - Agent interactions

There are a number of agent interaction protocols available in the agent-related literature such as blackboard systems, CNP, negotiation, multi-agent belief maintenance and market mechanisms (Weiss, 1999). These communication protocols are selected and applied based on the characteristics and requirements of the given problem and its context. Among them, CNP is widely applied in distributed systems. In general terms, CNP is a task sharing method, where nodes situationally become a manager or a contractor (Smith, 1980). This has been used in a number of studies in the SNC literature (Jiao, You & Kumar 2006; Lou, Chen & Ai 2004). When a composite task is received by a node, the node acts as a manager and the task is broken down into a number of sub-tasks to be allocated to other nodes who are considered to be contractors. Potential contractors submit their bids and winning contractors are awarded the tasks. Accordingly, the responsibilities of a manager are: to announce a task; collect and evaluate bids from potential contractors; award the bid to a suitable contractor; and collect and synthesize results. The responsibilities of the contractors are to: evaluate their own capability of performing the task; respond to the bid (accept/reject); perform the task upon accepting the bid, and report results.

Considering the tasks of both the manager and contractors, the steps of the CNP can be listed in the order of recognition, auctioning and bidding, and awarding. In the proposed MAOM, agent interactions occur following CNP. Figure 4.19 shows the overall communication mechanism used in the MAOM and Figure 4.20 shows agent connectivity. Figure 4.21 shows how information passes through relevant agents when performing the reverse-auctioning process. Interactions are executed by the communication modules of each agent.

Recognition: According to CNP, first, the necessity for breaking/sharing the main task into sub-tasks has to be recognised. In this study, catering to a given product-market profile is the main task received by the OPT agent, which is then decomposed and allocated, via auxiliary agents, among supply nodes, based on the BOM.

Reverse-auctioning and bidding: Reverse-auctioning and bidding occur between the AU agent and physical agents through SES agents. First, based on the BOM, the OP agent sends information regarding the supply nodes that are participating in the bidding process to the AU agent to generate a set of reserve values for each SN node. When the reverse-auctioning starts, the SES agent starts sending invitations to relevant physical agents inviting bids for a given product-market profile. Upon receiving invitations, each physical agent will follow their own strategies and procedures and prepare their bids. Then those bids are communicated to the SES agent who then assesses those bids against reserve values. This reverse-auctioning process continues through a series of bidding rounds (iterations) until the termination criteria are met. Finally, shortlisted bids are sent to the OPT agent so as to generate Pareto-optimal SNCs.

Awarding: The OPT agent uses NSGA-II to find the optimal alternative SNCs considering the multiple bids received at each node. These SNCs are then sent to the EA agent, who determines the most suitable SNC considering other possible criteria such as carbon emissions and the compatibility between SN entities. Once the desired SNC is determined, the outcome is passed on to physical agents so as to update their occupied production capacities Q-table.

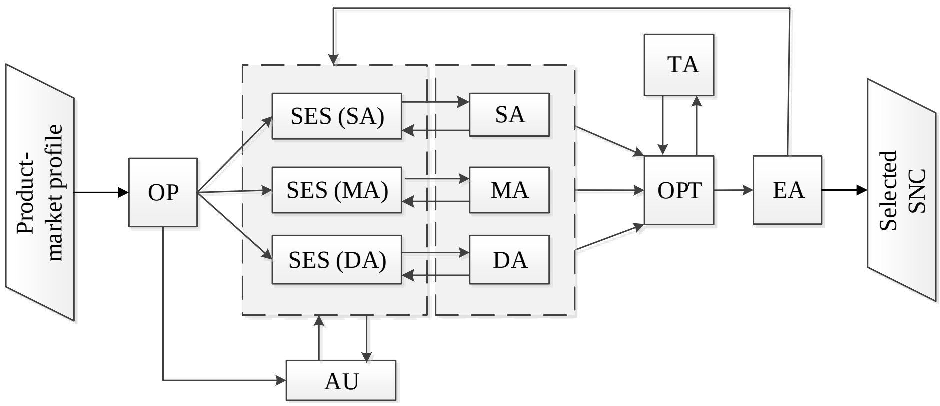


Figure 4.19: Agent connectivity in the overall system

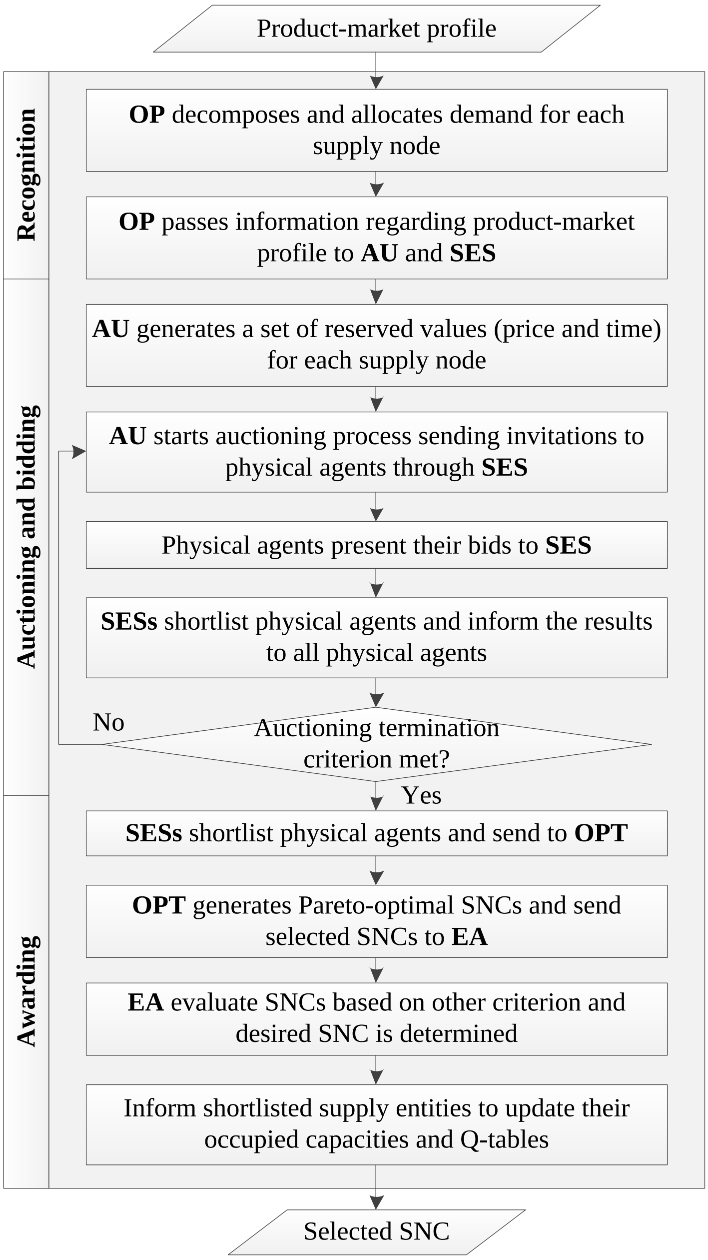


Figure 4.20: The process of Contract Net Protocols

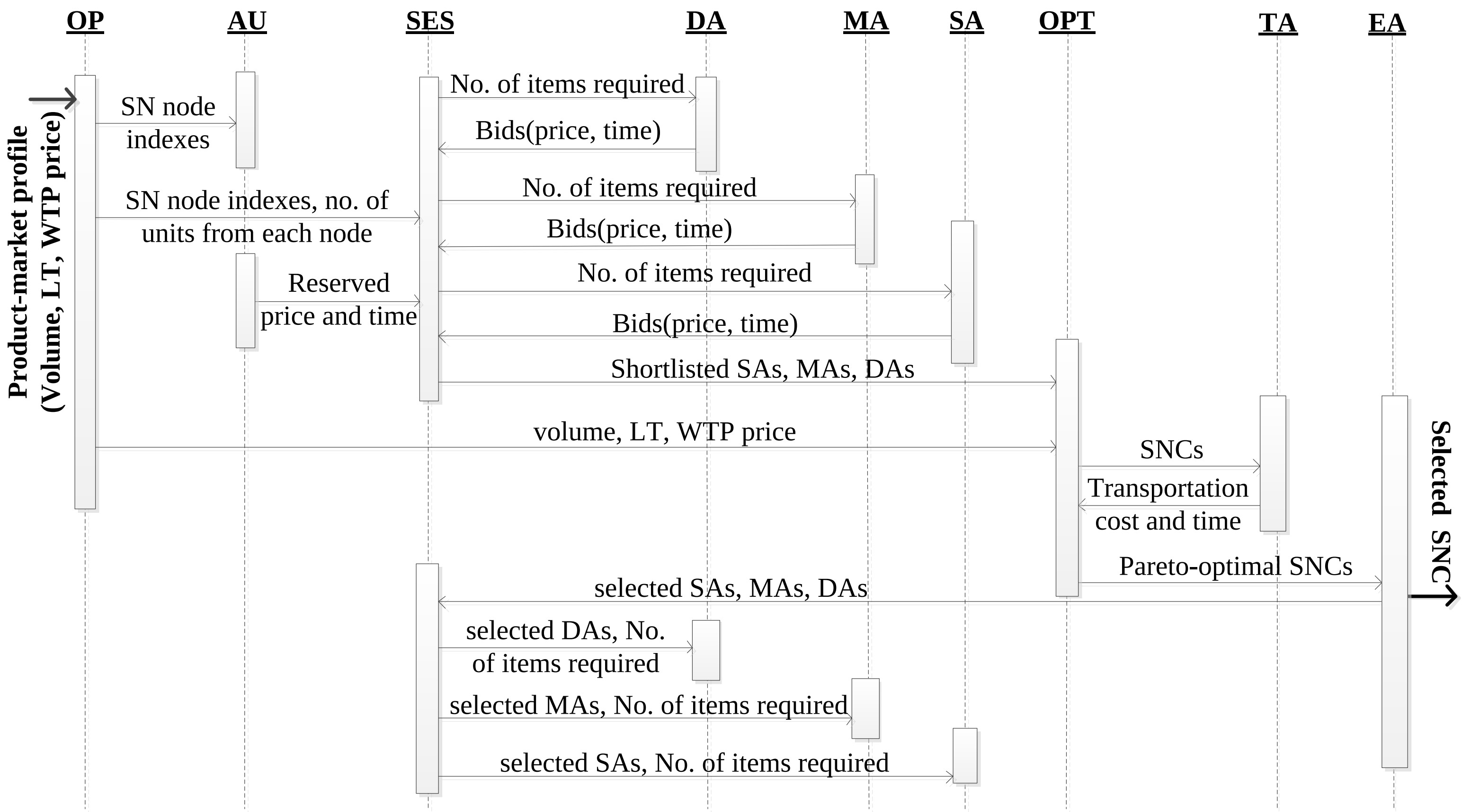


Figure 4.21: Information exchange between agents (agent interactions)

4.3.1.5 Phase 5 – Execution

In previous sections, the functionality of each agent and their interactions were presented. This section explains the overall execution of the MAOM while concisely restating the agent functionality. All agents in the MAOM are connected, as shown in Figure 4.20. Initially, the estimated product-market profile of each consumer region is passed on to the OP agent for processing to determine the SN nodes to be involved and the number of units required from each of the relevant SN nodes. The OP agent communicates with both the AU agent and the SES agent. According to the BOM and attributes of the product-market profile (i.e., WTP price and lead-time), the AU agent is informed of the indices of the relevant SN nodes and SES agents are informed of both indices of the relevant SN nodes and the number of units required from each SN node. Then SES agents send invitations to all physical agents to bid for the given product-market profile requirements. Physical agents make their own bidding decisions (i.e., bidding price and time) based on their available resources and past bidding experience (supported by the Q-table). These decisions are then informed to relevant SES agents so that they can shortlist the physical agents to be invited to bid in the next round. After every iteration, all physical agents are informed of the outcome of their bids. This process continues until the AU agent stops generating reserve values when the terminating criteria are met (i.e., the pre-defined number of invitations, availability of shortlisted physical agents). At the end of the auctioning process, the shortlisted physical agents are sent to the OPT agent. The OPT agent contacts the TA agent on needs basis to get the transportation cost and time. Once the OPT agent generates alternative optimal SNCs using NSGA-II, thus optimising the SN performance in terms of TSNC and LT, the EA agent is informed to select the most suitable SNC based on the preference of the decision-maker. Upon selecting the best SNC based on an evaluation criterion, relevant physical agents are informed to update their occupied capacity and their knowledge base (i.e., Q-table). In any instance where the OPT agent is not able to find feasible optimal SNCs for a given product-market profile, then the AU agent is asked to run the auction until the termination criteria is met. If it is not possible to generate feasible SNCs at the end of the auctioning process, the attributes of the product-market profile are re-evaluated, or such product-market profiles are discarded.

4.3.2 Step 2 - Mathematical formulation

Following the conceptual definitions relevant to each phase of the framework proposed in Figure 4.1, Step 2 presents the mathematical formulation of MAOM across the five introduced phases.

4.3.2.1 Phase 1 – Agent and Agent environment

As presented in Section 4.3.1.1, in relation to the SN context, individual SN entities are considered as agents and the SN environment as the agent environment. The representative SN considered in this study has I number of stages (S) where $\mathbf{S} = (\mathbf{S}_1 \ldots \mathbf{S}_i \ldots \mathbf{S}_I)$ and $\mathbf{S}_i$ is the ith stage of the supply network, which spans across the entire value-adding chain. Accordingly, there could be multiple nodes at any stage, and there are J number of nodes in total in the SN. The nodes in the ith stage of the SN are represented by $\mathbf{S}_i = (\mathbf{N}_{im} \ldots \mathbf{N}_{ij} \ldots \mathbf{N}_{in})$. At a given node $\mathbf{N}_{ij}$, there are a number of entity options (R_{ijk}) which is denoted by $\mathbf{N}_{ij} = \{R_{ij1} \ldots R_{ijk} \ldots R_{ijp}\}$ where R_{ijk} is the k^{th} entity option at node j in stage i. Here, p is the maximum number of entity options available at $\mathbf{N}_{ij}$. Additionally, consumer regions (L) are located across the world, and are presented as consumers. There are L number of consumer regions where $\boldsymbol{L} = \{L_1 \ldots L_l \ldots L_L\}$. Figure 4.22 illustrates the SN environment indicating i, j, k, and l.

4.3.2.2 Phase 2 and 3 - Agent types, attributes and architectures

Physical agents: Attributes and behaviour of physical agents (SA, MA and DA) in MAOM are mathematically explained in this section.

DA agents: are located in different geographical regions designated with an identification index (ID) which is 'ijk' indicating their stage index (i), node index (j), and entity option index (k) respectively. The main function of DA agents is storing the finished products to be able to dispatch to consumers. Each DA agent has distinct capacity levels (i.e., storage) (AC_{ijk}), operations cost (i.e., unit handling) (PC_{ijk}) and operations time (i.e., unit handling) (PT_{ijk}). Additionally, certain DA agents periodically expand their capacity (i.e., storage) by an increment expressed as a percentage of their current capacity.

MA agents: are located in different geographical regions designated with an ID which is 'ijk' indicating their stage index (i), node index (j), and entity option index (k) respectively. The main function of MA agents is assembling the final product and dispatching it to relevant DA agents on request. Each MA agent has distinct capacity levels (i.e., in manufacturing) (AC_{ijk}), operations (i.e., unit assembly) cost (PC_{ijk}), and operations (i.e., unit assembly) time (PT_{ijk}). Additionally, certain MA agents periodically expand their capacity (i.e., assembly) by an increment expressed as a percentage of their current capacity.

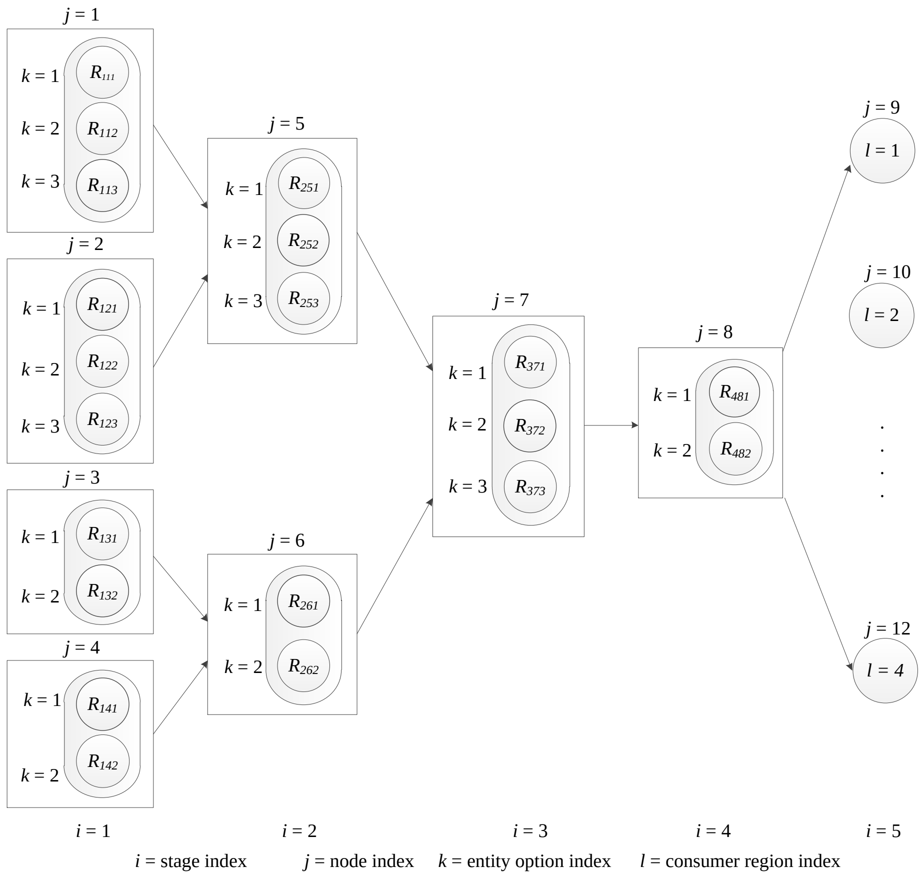


Figure 4.22: Representation of SN environment with mathematical notations

SA agents: supplier agents may be organized in multiple tiers depending on the BOM of the product. For example, a product may need components (that is the 1^{st} tier of the supply stage) to assemble a final product, and those components are made up of different parts or raw material types (that is the 2^{nd} tier of the supply stage). Those SA agents are located in a number of different regions depending on their distinct capabilities (e.g., availability of raw material, low-cost labour). For the purpose of this study, SA agents are introduced with an ID which is 'ijk'indicating their stage index (i), node index (j), and entity option index (k) respectively. Each SA agent has a distinct capacity level (e.g., production) (AC_{ijk}), operations cost (e.g., unit production) (PC_{ijk}) and operations time (e.g., unit production) (PT_{ijk}). Additionally, certain SA agents periodically expand their (e.g., production) capacity by an increment expressed as a percentage of their current capacity.

Additionally, to performing core value-adding functions, these physical agents take part in the reverse-auctioning process to explore business opportunities. As presented in Section 4.3.1.3, the functionality of physical agents in the context of reverse-auctioning (as shown in Figure 4.5) is executed with the help of the three modules: DM, LM and CM. Upon receiving an invitation, physical agents bid in terms of unit price (BP_{ijk}) and unit time (BT_{ijk}) corresponding to a given product-market profile. When bidding, physical agents consider the state of their available capacity and past bidding outcomes.

As indicated in Figure 4.5, upon receiving an invitation to bid, the DM of physical agents first chooses to follow either an exploration or an exploitation strategy, depending on whether the invitation is for a new product-market profile or not (i.e., whether they have bid in the past). In both cases, the physical agent generates a bid (i.e., the values of BP_{ijk} and BT_{ijk}) for the first round of bidding, taking into account the desired profit margin, cost, time and the current capacity status. The current capacity status m is determined situationally following a rule-based reasoning approach using Eqns. (1) and (2), supported by the Q-table shown in Table 4.1.

$$AAC_{ijk} = \left(1 + \lambda_{ijk}^{1} - \lambda_{ijk}^{2}\right) \times AC_{ijk} \tag{1}$$

$$RC_{ij} = \delta_{ij} \times V_l \tag{2}$$

Equation (1) refers to the available annual capacity AAC_{ijk}, which is the difference between planned annual capacity (where, λ_{ijk}^{1} is the size of capacity addition, expressed as a percentage of current annual capacity) and utilised capacity expressed as a percentage (λ_{ijk}^{2}) of the current annual capacity. Equation (2) refers to the RC_{ij}, which is the number of units required from node j (i.e., δ_{ij}), according to BOM and volume (V_l) required as per the product-market profile. Once the relevant capacity status m is determined, the corresponding profit range n is read from the Q-table leading to the preferred action A_n^t, depending on the iteration t of the reverse-auctioning process at which the bid is considered, and the experience of the agent reflected in the Q-table.

Table 4.1: Illustration of the Q-table*

Capacity Status (m) \ **Action/Profit range(n)**		**Low (5-10%)**	**Medium (10-15%)**	**High (15-20%)**
Under-utilized $AAC_{ijk} \geq 0.5 \times NC_{ijk}$	$AAC_{ijk} \geq RC_{ij}$	Q_{11} (5%)	Q_{12} (10%)	Q_{13} (15%)
	$AAC_{ijk} < RC_{ij}$	Q_{21} (6%)	Q_{22} (11%)	Q_{23} (16%)
Utilized $(0.25 \times NC_{ijk}) \leq AAC_{ijk} < (0.5 \times NC_{ijk})$	$AAC_{ijk} \geq RC_{ij}$	Q_{31} (7%)	Q_{32} (12%)	Q_{33} (17%)
	$AAC_{ijk} < RC_{ij}$	Q_{41} (8%)	Q_{42} (13%)	Q_{43} (18%)
Fully-utilized $AAC_{ijk} < (0.25 \times NC_{ijk})$	$AAC_{ijk} \geq RC_{ij}$	Q_{51} (9%)	Q_{52} (14%)	Q_{53} (19%)
	$AAC_{ijk} < RC_{ij}$	Q_{61} (10%)	Q_{62} (15%)	Q_{63} (20%)

*each cell contains a Q-value (Q_{mn}) corresponding to capacity status m and profit range n. Percentage values in each cell are read as profit margins (P_{mn}) for capacity state m and action/profit range n. NC_{ijk} represents planned annual capacity

Initially, at iteration 1, action A_n^t is taken following either the exploration or exploitation strategy, as per the conditions shown Eqn. (3).

$$A_n^t = \begin{cases} random(A_{1\to n}^t), & \text{if exploration} \\ \max(Q_{mn}^t), & \text{if exploitation} \end{cases} \tag{3}$$

Exploration strategy is more appropriate in the case of a new product market profile due to the absence of prior bidding outcomes, in situations such as the introduction of a new product, a new physical agent attempting to join the SN or an existing physical agent bidding for the first time.

Exploitation strategy is employed to make use of the physical agent's experience acquired through participation in past reverse-auctions or the earlier iterations of the current reverse-auction process. Under the exploitation strategy, once the action A_n^t is selected, unit bidding price (BP_{ijk}) and bidding time (BT_{ijk}) are calculated as per Eqns. (4) and (5). BP_{ijk} is calculated taking PC_{ijk} and the relevant profit percentage (P_{mn}) with respect to the capacity status (m) and profit ranges (n).

$$BP_{ijk} = PC_{ijk}\,(1 + P_{mn}) \tag{4}$$

$$BT_{ijk} = \beta_m \times PC_{ijk} \tag{5}$$

BT_{ijk} is calculated considering PT_{ijk} and a coefficient (β_m). The coefficient β_m is introduced to account for the variation in production time with respect to the capacity status. To illustrate this variation, β_m values representing six states reflecting the three utilization levels shown in Table 4.1 are used; i.e., $\beta_{m;m=1\to 6} = \{1, 1.15, 1.3, 1.45, 1.6, 1.75\}$. Once the bids generated as above are presented to the corresponding SES agents for consideration, iteration 1 of the bidding process is completed. Upon evaluation of all bids received in iteration 1, the SES agent informs the respective physical agents as to whether they are invited to bid in the next iteration of the reverse-auctioning process. Shortlisting of bids to proceed to the next iterations is made based on the comparison of bids received against the reserve values of price (RP_{ij}) and time (RT_{ij}). Subsequent iterations of the bidding process may follow multiple paths as illustrated in Figure 4.5, depending on the outcomes of the previous iteration, as elaborated below.

At the start of each subsequent iteration, the physical agents update their Q-table based on the outcome in the previous iteration, as outlined below. Depending on whether or not the bid was shortlisted to proceed to the next iteration, the relevant Q-value, Q_{mn}^t, (i.e., corresponding to relevant state m and action n in iteration t) of the Q-table is updated with a positive or negative reward as per Eqns. (6) and (7).

$$Q_{mn}^{t} = Q_{mn}^{t-1} + \mu_{ijk}^{1}\left(\delta_{ij} \times V_l \times P_{mn}\right) + \gamma \times \max(Q_{mn}^{t+1}) \tag{6}$$

$$Q_{mn}^{t} = Q_{mn}^{t-1} - \mu_{ijk}^{2}(\delta_{ij} \times V_l \times P_{mn}) \tag{7}$$

Here, μ_{ijk}^{1} is the percentage contribution of the overall profit corresponding to the previous action, γ is the discount factor, which is applied to future rewards (represented as max (Q_{mn}^{t+1}) for iteration $t+1$), where, μ_{ijk}^{2} is the percentage contribution of the overall loss as a reward where $\mu_{ijk}^{1} \geq \mu_{ijk}^{2}$.

The physical agents then read the updated Q-table to see if there is a lower profit range available than that was used to bid in iteration $t-1$ (i.e., $n > 1$ in iteration $t-1$). If a lower profit range in iteration $t-1$ can be found then an exploration-based conditional bidding strategy is followed. Under this strategy, the physical agent randomly select an action, A_n^t, based on a profit range (A_n^{t-1}), which is less than that used in the previous iteration, as per Eqn. (8) and bidding values are again calculated according to Eqns. (4) and (5).

$$A_n^t = random\ (A) \mid A = (A_1^{t-1}, \ldots A_{n-1}^{t-1}) \qquad \forall\ t > 1 \tag{8}$$

In case that a lower profit range cannot be found, the physical agent considers whether the bid in the previous iteration was shortlisted or not. If the bid was shortlisted, then the repetitive bidding strategy is followed. Under this strategy, the physical agent presents the same values used in the previous iteration of bidding in response to the current invitation, *i.e.*:

$$A_n^t = A_n^{t-1} \mid \forall\ t > 1 \tag{9}$$

Otherwise, the agent decides to stop further bidding for the given product-market profile. This brings the reverse-auctioning process to its conclusion.

Auxiliary agents: As introduced in Section 4.3.1.3, the six auxiliary agents proposed in this study are SES agents, OP agent, AU agent, OPT agent, TA agent and EA agent. The role of those auxiliary agents is to support SNC decisions in relation to the generation, optimisation and evaluation of alternative SNCs for different product-market profiles and those individual roles are presented in mathematical form in this section.

The OP agent processes the product-market profile information to determine the number of units required at each supply node (i.e., RC_{ij}) taking into account both V_l and δ_{ij} as per Eqn. 2. For the first iteration, the AU agent generates RP_{ij} and RT_{ij} corresponding to a given product-market profile using the GA for relevant SN nodes. The initial population of GA is a set of RP_{ij} and RT_{ij} values derived for each node as per Eqns. (10) and (11).

$$RP_{ij} \sim rnd\ [PP_{ij} \times P_l\,, 0.85 \times PP_{ij} \times P_l] \tag{10}$$

$$RT_{ij} \sim rnd\ [PPT_{ij} \times LT_l \times F_l/V_l, 0.85 \times PPT_{ij} \times LT_l \times F_l/V_l] \tag{11}$$

The two reserve values are randomly selected from those falling within the specified upper and lower threshold values. The upper threshold of RP_{ij} is calculated taking P_l for each product from the corresponding consumer demand region and PP_{ij} for each node. The lower threshold value is 85% of the upper threshold value. Similarly, RT_{ij} is also a random value within the upper and lower threshold values, which are calculated based on the overall lead-time (LT_l) as per the given product-market profile and the percentage time (PPT_{ij}) allocated for each node. Here, F_l is the dispatching frequency of region l. The feasibility of each chromosome in the initial population is checked as given in Eqns. (12) and (13) by comparing the fitness value of the chromosome against the willing-to-pay price and expected lead time of the product-market profile concerned. The fitness value of each chromosome in the initial population (consists of RP_{ij}s/ RT_{ij}s) is computed taking the summation of RP_{ij}s/ RT_{ij}s of all SN nodes. As presented in the Section 4.3.1.3, a set of feasible optimal reservereserve prices and processing times are generated following the steps of GA shown in Figure 4.10.

$$\sum RPij \ \leq P_l \tag{12}$$

$$\sum RTij \ \leq LT_l \tag{13}$$

Once the AU agent has generated a set of feasible optimal reserve prices and times, as shown in the in Figure 4.13, it starts the reverse-auctioning process using those values as the first set of reserve values which correspond to the first invitation. The invitations are sent to physical agents through SES agents. Reserve values for subsequent invitations are determined by lowering the initial set of reserve values by a certain percentage, and the reverse-auctioning continues until the termination criteria are met (i.e., on completion of a pre-defined number of iterations or when there are no more physical agents to bid). The SES agent corresponding to each physical agent shortlists physical agents that proceed to the next iteration of bidding (i.e., R_{ijk}s) by comparing reserve values (generated by the AU agent) with the bids presented by physical agents in each iteration, as per Eqns. (14) and

(15). Here, z_{ijk} is a decision variable which has value 1 when the physical agent R_{ijk} is shortlisted to fulfil a given product-market profile; otherwise, it is 0.

$$BP_{ijk} \times z_{ijk} \leq RP_{ij} \tag{14}$$

$$BT_{ijk} \times z_{ijk} \leq RT_{ij} \tag{15}$$

At the end of the reverse-auctioning process, the OPT agent receives the final list of R_{ijk}s representing shortlisted bids from the SES agent. Given this list of R_{ijk}s, the cost ($TC_{ijk \to i'j'k'}$) and time ($TT_{ijk \to i'j'k'}$) representing the transportation function is obtained from the TA agent.

The TA generates transportation costs and times corresponding to a given product-market profile, which are calculated as per Eqns. (16) and (17) for a given SNC on the request of the OPT. Transportation cost is proportionate to the distance between physical agents R_{ijk}. The distance between two selected physical agents (R_{ijk} and $R_{i'j'k'}$) at two consecutive stages i and $i'(= i + 1)$ is indicated by $D_{ijk \to i'j'k'}$ and unit distance transportation cost is taken as $\propto_2$ and speed is taken as V_s. Here, $x_{ijk \to i'j'k'}$ is the decision variable which has value 1 when R_{ijk} in stage i and $R_{i'j'k'}$ in stage i' are selected to fulfil a given order; otherwise, it is 0. A database is maintained by the TA, including a distance matrix, α_2 and V_s. The OPT agent then generates alternative optimal SNCs, considering the total SN cost (TSNC) and the overall lead-time (LT) satisfying the product-market profile of the given region.

$$TC_{ijk \to i'j'k'} = D_{ijk \to i'j'k'} \times x_{ijk \to i'j'k'} \times \alpha_2 \times F_l \tag{16}$$

$$TT_{ijk \to i'j'k'} = (D_{ijk \to i'j'k'} \times x_{ijk \to i'j'k'})/V_2 \tag{17}$$

The TSNC is the sum of the costs of individual operations (e.g., processing, assembly, storage and handling) at each R_{ijk} and transportation costs between relevant SN stages. The overall LT of the SN is the sum of the: operations time of the selected R_{ijk} in the final operational node (j); transportation time between SN stages (i.e., i and i'); and the maximum delivery LT time of all connected nodes from the previous stage i'' ($= i - 1$). Eqns. (18) and (19) represent the objectives of the OPT, which are to minimize TSNC and LT. The OPT achieves the above SNC objectives subject to the constraint expressed in Eqn. (20), which represents the selection of only one physical agent at each node to generate the SNC satisfying a given product-market profile. Here, y_{ijk} is a decision variable which has value 1 when the R_{ijk} is selected to fulfil a given product-market profile; otherwise, it is 0.

$$\text{Minimise TSNC} = \sum_{S_i \in S} \sum_{N_{ij} \in S_i} \sum_{R_{ijk} \in N_{ij}} y_{ijk} . BP_{ijk} . \delta_{ij} . V_l + \sum_{S_{i,i'} \in S} \sum_{N_{ij} \in S_i} \sum_{N_{i'j'} \in S_{i'}} \sum_{R_{i'j'k'} \in N_{i'j'}} D_{ijk \to i'j'k'} . x_{ijk \to i'j'k'} . \propto_2 . F_l \tag{18}$$

$$\text{Minimise LT} = \sum_{R_{ijk} \in N_{ij}} y_{ijk}\, BT_{ijk} . \delta_{ij} . V_l / F_l + \sum_{\substack{R_{ijk} \in N_{ij} \\ R_{i'j'k'} \in N_{i'j'}}} D_{ijk \to i'j'k'} . x_{ijk \to i'j'k'} / V_s + \max_{N_{i''j''} \in S_{i''}} LT_{i''} \tag{19}$$

Subject to:

$$\sum_{k \in K_j} y_{ijk} = 1 \tag{20}$$

In generating optimal alternative SNCs, NSGA-II starts with the initial population (i.e., parents), which is the set of SNCs having one entity option from each node and follows the process outlined in Figure 4.16. After a particular SNC is selected, all physical agents are informed through relevant SESs to update their occupied production capacities (as in Eqn. 21), as well as the Q-table, using Eqn. 22, where $\mu_{ijk}^3 > \mu_{ijk}^1 > \mu_{ijk}^2$.

$$\lambda_{ijk}^2 = \lambda_{\text{ijk}}^2 + RC_{ij} / (1 + \lambda_{\text{ijk}}^1)\, AC_{ijk} \tag{21}$$

$$Q_{mn} = Q_{mn} + \mu_{ijk}^3 (\delta_{ij} \times V_l \times P_{mn}) \tag{22}$$

4.3.3 Step 3 - Computer based implementation

This step presents an overview of the implementation of MAOM on the MATLAB 2016b software platform. As indicated in Figure 4.23, the primary input to the computer-based implementation of the model is the product-market profile of a region, and the output is alternative Pareto-optimal SNCs which satisfy the relevant product-market profile attributes. Alternative optimal SNCs are generated so as to optimise SN-level performance in terms of TSNC and LT.

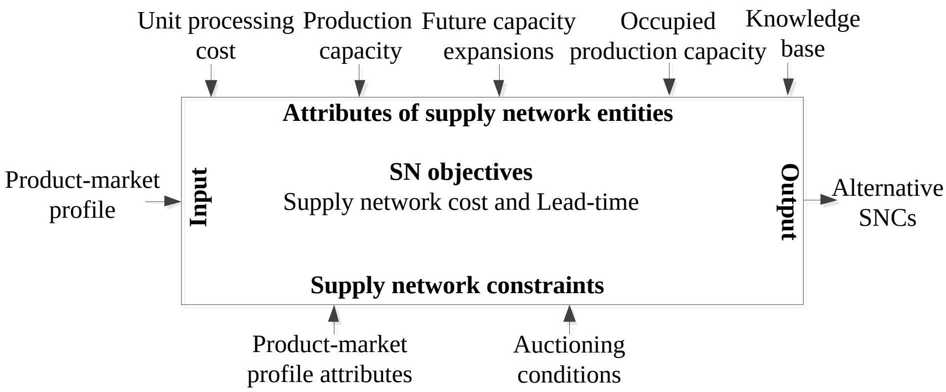


Figure 4.23: Software-based implementation framework

As explained in Chapter 4, the reverse-auctioning procedure was used in shortlisting the physical agents that could satisfy the product-market profile. Accordingly, bidding related decisions of physical agents were constrained by auctioning conditions and the relevant attributes of the product-market profile, apart from the attributes of physical agents and their past experience.

The model is implemented using scripts (basic programming files), functions (programs that accept inputs and return outputs), and control flows (conditional statements, loops). Scripts are used to programme the functionality of the physical agents using functions and control flows following the agent architecture. Control flows are used to implement iterative decision-making while considering the given termination criteria. The communication between physical agents is implemented through functions sending communication parameters as arguments. The organisation of functions and control flows in the script are shown in Figure 4.24.

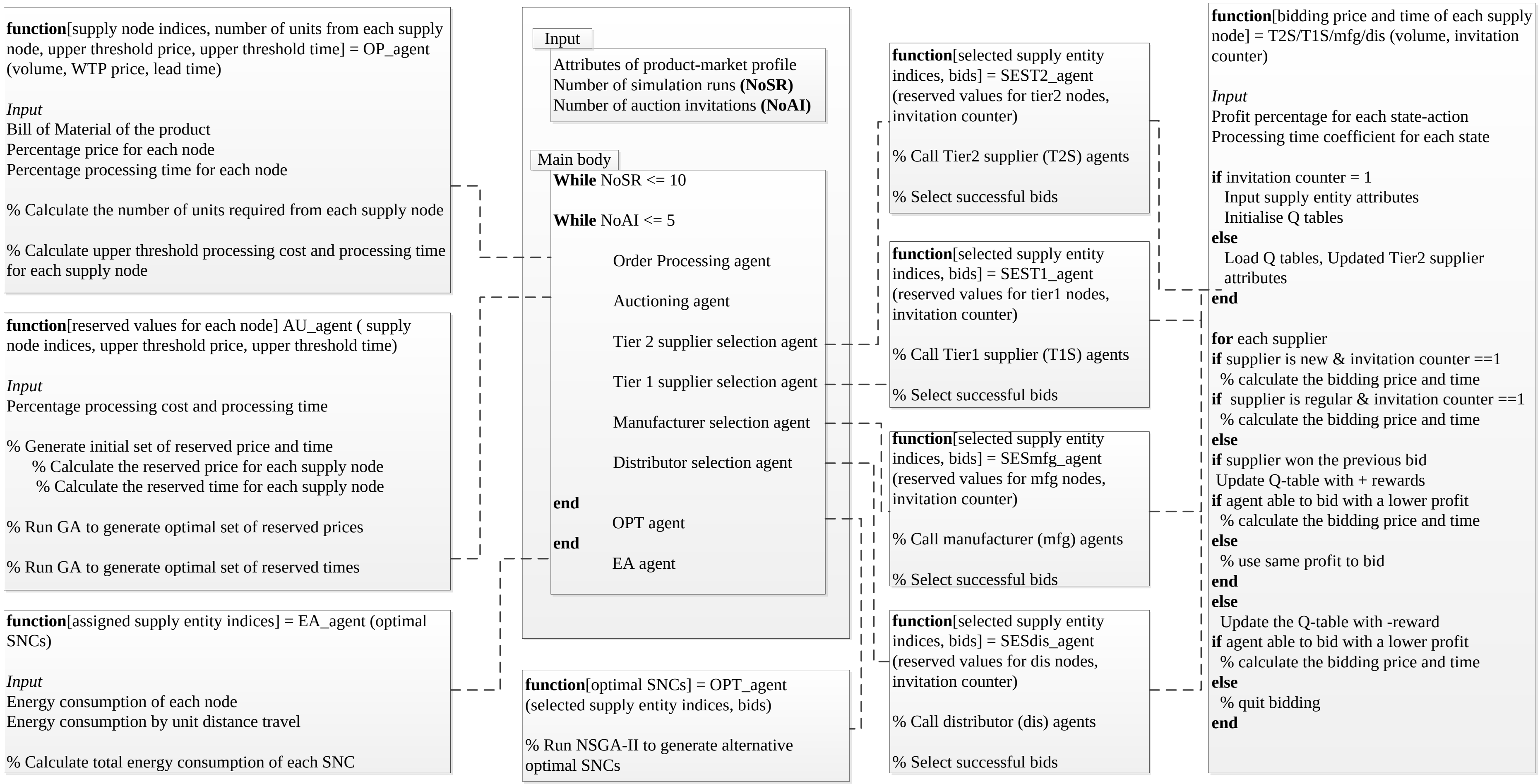


Figure 4.24: Outline of the coding for implementing MAOM on MATLAB

4.3.4 Step 4 – Verification and simulation experiments

Any developed model has to be tested for accuracy and robustness to ensure its use in a given problem context. Widely used testing methods reported in the literature are verification, validation, scenario analysis and sensitivity analysis. Verification (as in Figure 4.25) is the process to confirm that the proposed conceptual model is implemented through a computer programme with an adequate level of accuracy (Davis, 1992) or in simple terms correct implementation of the model. The verification of the model is done mainly through finding and fixing model implementation errors through a number of ways. Some of the practices are: comparing the conceptual model and the simulation model, observing the model output for different input parameters or scenarios, checking the code in detail, and getting expert opinion/judgements (Oliveira et al. 2016; Tannock et al. 2007). In this study, the debug mode of the software was used to identify implementation errors, including syntax and execution errors. The proposed MAOM model was further verified by testing the functionality of agents with respect to the simulation outcome of the given agent. For example, the bidding price and time of physical agents for specific product-market profiles were recorded over the auctioning iterations. A number of authors (Law & Kelton 2000; Davis 1992) have presented definitions for validation, which is broadly defined as building the right model that meets the intended purpose/objective. A detailed definition given by Davis (1992) was "Validation is the process of determining: (a) the manner in which and the degree to which a model (and its data) is an accurate representation of the real world from the perspective of the intended uses of the model and order to test whether the right model is implemented in the software environment, Robinson (2006) presented a number of validation methods as indicated in Figure 4.26 namely, conceptual model validation (i.e., confirmation of the theories and assumptions are correct and meet the intended purpose of the model); data validation (i.e., confirmation of the suitability of data in terms of their reliability, sufficiency and accuracy to validate the model); white-box validation (i.e., confirmation of the modular part of the complete model which represents the real system in the required level of accuracy); black-box validation (i.e., confirmation that the complete model represents the real system with the required level of accuracy). Previous studies have used one or more of these validation methods depending on a number of factors such as the existence of the proposed model, in reality, availability of data in the required format, and the ability to identify the modular components. There are a few other methods such as face validity and sensitivity analysis, proposed in the literature, to be employed when, for whatever reasons, the other types of validation cannot be performed.

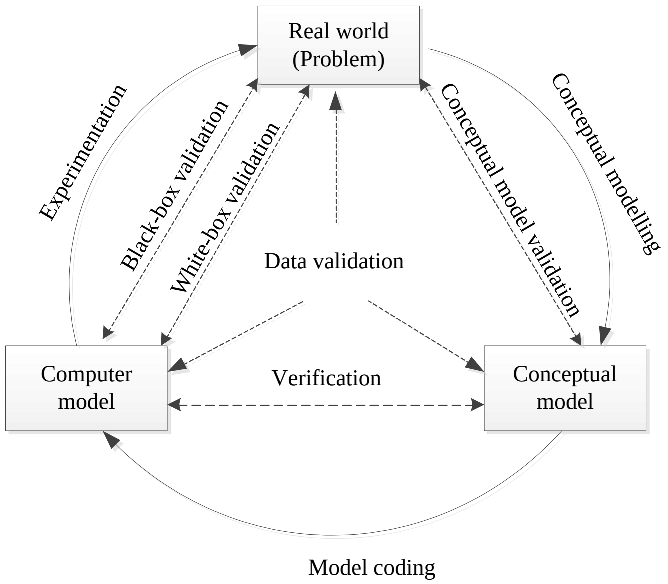


Figure 4.2: Simulation model verification and validation in the modelling process (sourced from Sargent 1992)

The validation of MAOM was done in the form of conceptual model validation and face validation. Other validation methods were not practically feasible to perform in this study due to a number of factors. Mainly, the proposed model does not exist in practice; hence, data are not available in the required format or not in a form which can be extracted. The lack of interest in disclosing the SN information, including those related to the supplier base, logistics network and product architecture is another factor that hinders validation. Conceptual model validation was done by examining the MAOM with respect to the intended purpose (i.e., scope, aim and objectives) of the study. This study considers a multi-stage, multi-echelon SN range spanning the full length and breadth of the SN with SN entities from different geographical regions. Incorporating structural, spatial and temporal characteristics as explained in Section 4.3.1.1, this model has face validity. Also, as presented in Figure 3.1, the developed conceptual framework addresses the aim of this study which is to generate alternative Pareto-optimal SNCs for different product-market profiles considering the distinct decisions of SN entities. Accordingly, the conceptual model is validated.

However, apart from the verification and validation methods, scenario analysis and sensitivity analysis were performed to test the robustness of the MAOM and to estimate the extent to which the SN-level performance is vulnerable to the changes in the attributes of SN entities collectively in each stage and/or individually as entities of the SN. Scenario analysis and sensitivity analysis are important in this study due to the impact of uncertainties and disruptions on SNC decisions which, in turn, could have an adverse impact on SN performance. By definition, scenarios are hypothetical contexts, which describe alternative future situations (Spaniol & Rowland 2018). There are a number of different ways to define scenarios namely, normative (i.e., prescriptive, which identifies the pathways to achieve a desirable or pre-specified future); exploratory (i.e., descriptive, which identifies different pathways to a probable future); and predictive, which identifies a more preferable future considering both present and past. In general, testing scenarios help decision-makers to identify long term requirements; adopt strategies to avoid problematic situations and disruptions and deal with uncertainties in a practical context. In this study, the exploratory scenario approach was adopted as the SN is continuously subject to changes due to uncertainties and disruptions, which are known to induce significant risks in terms of their impact on SN performance. SN disruptions reported in the literature include unforeseen incidents such as transportation mishaps, natural calamities and intentional attacks (Schmitt et al. 2017), as well as anticipated circumstances like facility breakdowns, failures of the supplier base, offensive actions of competitors and abrupt changes in demand (Rezapour, Farahani & Pourakbar 2017; Govindan & Fattahi 2017). Therefore, the robustness of the MAOM was tested using multiple scenarios that incorporated the consequences of one or more of the disruptions referred to above.

Sensitivity analysis is performed on a model to investigate the impact of changes in parameters and assumptions on the output of the model (Pannell 1997). Sensitivity analysis is performed in this study to estimate the extent to which the SN-level performance is vulnerable to the changes in the attributes of SN entities collectively in each stage and/or individually as entities of the SN. Results of both scenario analysis and sensitivity analysis help in assessing the robustness of the optimal SNCs; and making more credible and persuasive recommendations such as the circumstances for changing the optimal SNCs and how it should change (plus the underlying reasons for such changes); the consequences of using the same derived optimal SNC ignoring the changing circumstances. If the results of the analysis reveal that the selected SNC is robust, that is SN performance does not change significantly against SN uncertainties, it provides credibility to accept/ adhere to the selected SNC. In an instance where the selected SNC does not display the desired level of robustness, then opportunities are available to know under what circumstances (e.g., attributes of SN entities) the selected optimal SNC would be effective or what alternative SNCs would be effective.

4.4 **Data collection and analysis**

4.4.1 Data sources

The proposed MAOM was tested using data published in the literature, and this will be discussed in Chapter 5 in a detailed manner. The primary data source used in this study pertains to a refrigerator production network, which was originally used by Umeda et al. (2000) to estimate life cycle cost. The logistics network of the refrigerator production network was proposed by Krikke et al. (2001) and Fleischmann et al. (2001). A number of other new parameters were introduced to suit the SNC problem addressed in this study, which are further explained in Chapter 5.

The refrigerator SN consists of five stages including two supply stages, raw material and components, the final assembly stage and a distribution stage before the finished products reach end-users via individual consumer regions (virtual retail outlets). There are 18 nodes and 120 SN entities (i.e., entity options) in this network. The attributes of SN entities are agent ID (i.e., 'ijk'), $PC_{ijk}, PT_{ijk}, AAC_{ijk}, NC_{ijk}$. As stated in Section 4.3.1.3, PC_{ijk}, PT_{ijk} represent different types of value-adding operations depending on the SN stage. For example, PC_{ijk} of manufacturer refers to manufacturing cost and PC_{ijk} of distributor refers to storing and handling related cost. Seven consumer regions in Europe are considered in this study, adapted from Krikke et al. (2001). For each consumer region, a product-market profile was estimated, including the attributes of volume, lead-time and WTP price as explained in Chapter 3.2.1.

4.4.2 Simulation experiment design

As presented in step 4 of the conceptual framework, simulation experiments were designed primarily to: 1) verify the proposed MAOM and illustrate the agents' behaviours; 2) test the baseline model under static and deterministic conditions; 3) test the robustness of MAOM by conducting scenario analysis; and 4) estimate the extent to which the SN-level performance is vulnerable to the changes in SN characteristics. Accordingly, a set of four simulation experiments were carried out in relation to verification, sensitivity analysis and scenario analysis. An introduction to each of the above analyses was presented in Section 4.3.4. and simulation results of each analysis are presented in Chapter 5.

The first set of experiments were conducted for the verification of the model. The model verification was done through debugging, detailed code checking, and testing the behavior of agents as proposed in MAOM. The second set of experiments was conducted considering a deterministic SN context which is considered as the baseline model, assuming SN entities available at the time of initial consideration and their attributes remain the same over time. The third set of experiments was performed to analyse multiple scenarios, which incorporate both SN uncertainties and disruptions. The designed scenarios were distinct, depending on the type of the SN uncertainty or disruptions considered and how they originate in the SN (i.e., upstream, midstream and downstream). Altogether, there were seven scenarios tested in this experiment. The fourth set of experiments focuses on the sensitivity analysis. Having performed four types of analysis, the extent to which the SN-level performance is vulnerable to the changes in SN characteristics were estimated.

4.4.3 Reporting results and discussion

Multiple presentation formats are used to report the results of the experiments undertaken. Verification-related experimental results are presented mainly using graphs to illustrate the behaviour of the selected physical agents. In the base-case analysis, results are reported in tabular format with respect to: the relevant product-market profiles, the performance of SNCs in terms of the average and the range of SN performance, the number of optimal SNCs in the Pareto front, and SN entities in the most energy-efficient SNC with the total energy consumption of that SNC. Results of scenario analysis are presented in tabular format for each product-market profile, accounting for the average of SN performance, percentage difference from the base-line model, and the number of optimal SNCs in the Pareto front. Results of the sensitivity analysis are presented in terms of the average SN performance with respect to each percentage change of SN entity attributes, and the percentage difference in SN performance. Accordingly, the results are analysed in the form of: identifying the impact of uncertainties and disruptions on SN-level performance; identifying the robustness of the MAOM in the face of SN uncertainties and disruptions; and identifying, to which SN characteristics, the SN-level performance is more sensitive.

4.5 Chapter Summary

This chapter presented the methodology adopted to achieve the aim of this study, which is to generate alternative optimal SNCs for different product-market profiles in a given set of organisational and environmental conditions. The need for taking a distributed decision-making approach was identified as a critical aspect of modelling the behaviour of the SN entities. Accordingly, MAOM was proposed to achieve the aim of the study. A modelling framework was developed to implement the MAOM which consisted of four steps (i.e., conceptualisation, mathematical formulation, computer-based implementation and model execution), each step was executed across five phases (i.e., agent and agent environment; agent characteristics; agent types, attributes and architecture; agent communication; and execution). Two types of agent were introduced to serve the distinct purposes of the SNC problem context. SN entities were modelled as physical agents whereas supportive decisions for SNC were modelled as auxiliary agents. Both these agent types were modelled incorporating distinct agent attributes, characteristics and architectures. Agent communication was implemented using CNP in a way that selected agents through the intelligent reverse-auctioning and bidding strategies. MAOM was tested on a refrigerator production network. Initially, verification of the model was performed, followed by scenario analysis and sensitivity analysis.

CHAPTER 5: SIMULATION RESULTS

5.1 Introduction

This chapter presents the case study of a refrigerator SN where the proposed MAOM has been applied, including the implementation details of the MAOM and the results of the simulation experiments. Simulation experiments were designed to 1) verify the proposed MAOM including the agents' behaviours, 2) test the baseline model under static and deterministic conditions, 3) test the robustness of MAOM by conducting scenario analysis, and 4) test to which SN characteristics that overall SN-level performance is more sensitive. This chapter first provides information about the case study of the refrigerator SN in Section 5.2, followed by the simulation experiments and results in Section 5.3. Section 5.4 summarises and concludes this chapter.

5.2 Case study – refrigerator supply network

As introduced in Section 4.4.1, this study, adapted the dataset pertaining to a refrigerator SN, which was initially used by Umeda et al. (2000), and later modified by Krikke et al. (2001) and Fleischmann et al. (2001). Those modifications include additional parameters related to logistics networks for optimizing lifecycle costs. To help demonstrate the efficacy of the proposed MAOM, several new parameters were introduced considering the specific SNC problem introduced in this study.

There are five stages ($I = 5$) in the refrigerator SN: two supply stages (i.e., raw material and components), the final assembly stage, and a distribution stage before the finished products reach end-users via the respective consumer regions (virtual retail outlets). There are 18 nodes in the refrigerator SN including four raw material supply nodes, five-components supply nodes, one manufacturing node, one distribution node and seven retailer nodes. There are 25 different components manufactured at the components supply stage using four different types of raw material, namely, iron, plastic, aluminum and copper. In order to reduce the complexity of the SN for demonstration purposes, these 25 components were categorised into five groups based on the type of raw material used and the manufacturing process employed. The final assembled products are sent to distribution centres through which retailers at each consumer region receive goods. Accordingly, there are multiple nodes ($\mathbf{N_{ij}}$) in each stage, and there are multiple entity options ($R_{ijk}s$) capable of performing the required value-adding functions at each node, which are modelled as physical agents in this study. A detailed description of the nodes and entity options of the refrigerator SN are presented in Section 5.2.1 and Section 5.2.2, respectively. The connectivity between nodes is shown in Figure 5.1. Krikke et al. (2001) proposed 10 consumer regions in Europe in their study. Out of those 10 consumer regions, seven consumer regions ($l = 1 \rightarrow 7$) were considered in this study (see Section 5.2.3) considering the accessibility through land transportation. Seven consumer regions in Europe were considered with distinct product-market profiles attributed by V_l, LT_l and P_l, which were derived using the four base parameters as presented in Section 3.2.1.

5.2.1 Nodes of the refrigerator supply network

This section presents a detailed description of the nodes of the refrigerator SN in addition to the introduction provided above. There are 18 nodes in this SN, and those nodes are distributed across five stages. In the 2nd tier supply stage, there are four supply nodes, which supply four main types of raw material, namely iron, plastic, aluminum and copper. These raw material types are supplied in different forms; for example, iron is sourced as a metal sheet and plastic in the form of powder. There are 25 different components in the 1st tier supply stage, and they have been assigned to five nodes, considering the similarities in the material used and the manufacturing processes involved. Table A2.1 lists the details of each of the 25 components with their attributes, including the material used, weight, price, manufacturing cost and energy consumption. Figure A2.1 presents the graphical representation of each of these components.

At the final product assembly stage, all components produced by the nodes in the 1st tier supply stage are assembled to form the final product. Then, the finished products are sent to different retailers (in each consumer region) via distribution centres to satisfy consumer requirements. Table 5.1 presents details about each node including the item (e.g., material or components) produced, primary function involved, a description of each item, operations cost (PC_{ij}) and operations time (PT_{ij}). The given PC_{ij} and PT_{ij} for each node of the SN were estimated using the data published by Umeda et al. (2000), online sources and logical assumptions. These estimates of PC_{ij} and PT_{ij} were taken as the base values in estimating operations cost (PC_{ijk}) and operations time (PT_{ijk}) of each entity option of the $\mathbf{N_{ij}}$ with certain adjustments to account for region-specific characteristics (see Section 5.2.2). A detailed description of the base values used ($PC_{ij}, PT_{ij}, EC_{ij}$) is listed in Table A2.2, A2.3 and A2.4. Illustration of the connectivity between nodes of the refrigerator supply network

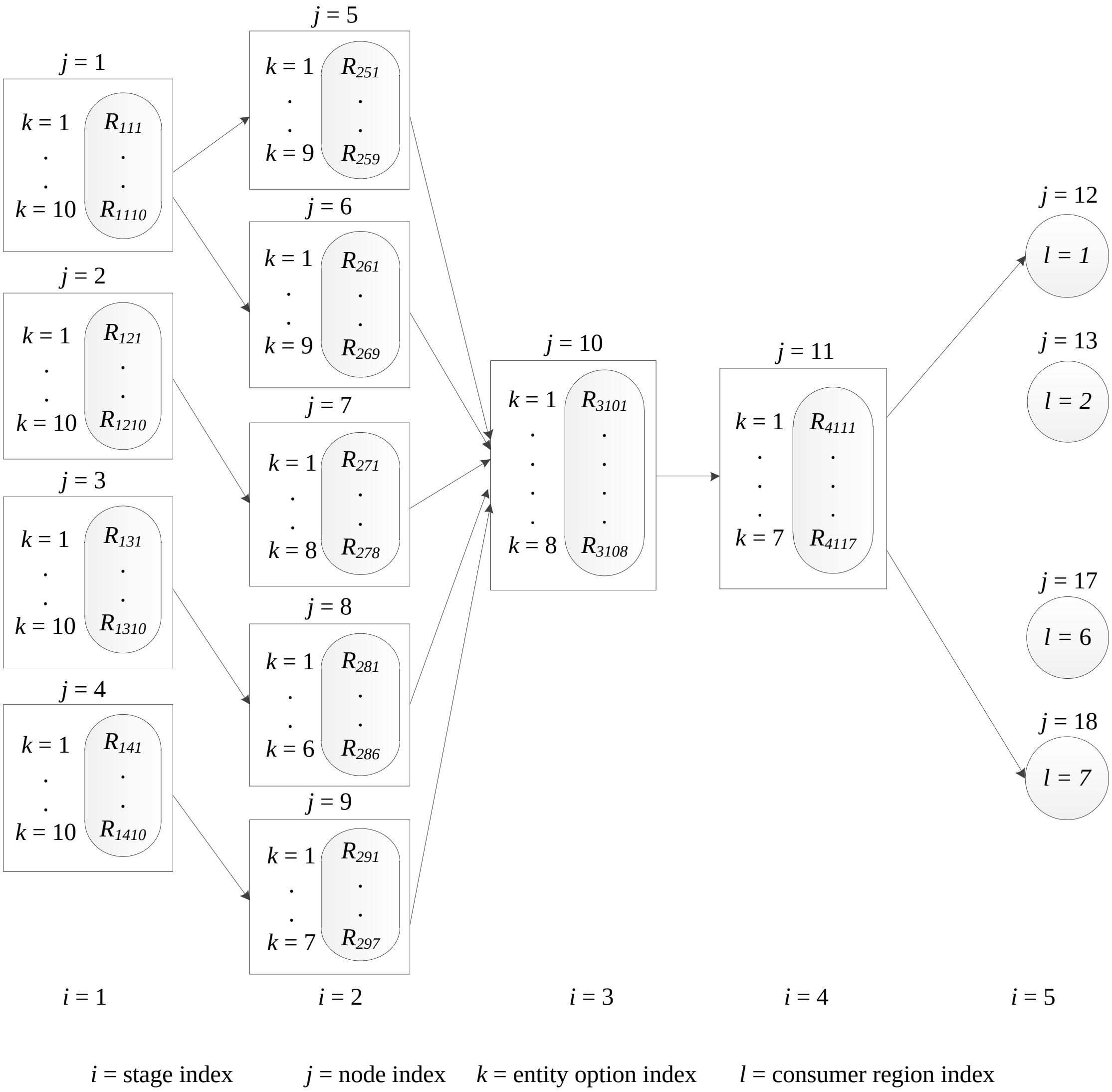


Figure 5.1: Illustration of the connectivity between nodes of the refrigerator supply network

5.2.2 Entity options of the refrigerator supply network

Each node of the refrigerator SN is served by more than one SN entity, termed as entity options in this study (see Section 4.3.1). Entity options in all nodes are commonly referred to as SN entities in this chapter, and they were modelled as physical agents in MAOM. Altogether, there are 120 SN entities in this refrigerator SN. The attributes of SN entities are ID, PC_{ijk}, PT_{ijk}, AC_{ijk}, $\lambda^1_{ijk}, \lambda^2_{ijk}$ and EC_{ijk} as listed in Table A2.5.

The selection of the locations of SN entities in the 2nd tier supply stage (i.e., raw material supplying nodes) was based on the availability of raw material identified through publicly available data sources. It was found that

Table 5.1: Description of nodes of the refrigerator SN

j	Item produced	Function involved	Description on each item	PC_{ijk} ($)	PT_{ijk} (mins)
1	Raw material 1	Manufacturing	Fe	49	30
2	Raw material 2	Manufacturing	Plastic	88	50
3	Raw material 3	Manufacturing	Cu	5	10
4	Raw material 4	Manufacturing	Al	15	20
5	Component 1 (Fe)	Manufacturing	Door1, Door2, Door3, Door4, Base, Sideboard, Back Grill, Cabinet Frame, mpcb	186	147
6	Component 2 (Fe)	Manufacturing	Compressor, Radiator, Fan Motor, Accumulator	50	135
7	Component 3 (Plastic)	Manufacturing	Cabinet, Duct in room, Evaporator case, Duct, Gasket, Door plastic, SPCB, Tank	413	77
8	Component 4 (Cu)	Manufacturing	Cabinet pipe, Dryer	10	10
9	Component 5 (Al)	Manufacturing	Evaporator, Heater	28	15
10	Final product	Final assembly	Refrigerator	10	45
11	Final product	Distribution	Refrigerator	5	5

Note: j – node index; PC_{ij} – operations cost of node j; PT_{ij} – operations time of node j; Al – Aluminium; Fe – Iron; Cu – Copper

aluminium producing countries are Ukraine, Spain, Romania, Italy, Greece, Germany and France (www.world-aluminium.org). Iron producing countries are Germany, Turkey, Ukraine, Italy, France, Spain, Poland, Belgium, Austria (www.statista.com). Plastic raw material producing countries are Turkey, Switzerland, Spain, Poland, France, Italy, Germany (www.worldstopexports.com). Copper producing countries are Chile and Peru (investingnews.com). The locations of the 1st tier SN entities were determined considering the raw material used for production and supplier information available on online databases (e.g., www.directindustry.com). Accordingly, candidate countries are Portugal, Spain, France, Belgium, Switzerland, Italy, Germany, Netherland, Poland, Czechia, Slovakia, Hungary, Romania, Ukraine, Bulgaria, Greece, Lithuania, Austria, Turkey, and Denmark. The locations of final assembly plants were determined referring to the refrigerator supplier databases (e.g., www.environmental-expert.com), and distribution centres were located requiring at least one distribution centre in each consumer region (l).

As mentioned in Section 5.2.1, other attributes of the entity options of a node were determined using the base value of each node adjusted to account for the location-specific characteristics. As listed in Table A2.6, these regional characteristics were represented by a number of indicators namely, the hourly labour cost in each country (ec.europa.eu), global manufacturing competitive index (www2.deloitte.com) and annual investment in high-tech manufacturing (ec.europa.eu). The labour cost of a country was used to estimate the PC_{ij} and the competitive index and annual growth rate of high technology usage were used to estimate the PT_{ij}. Considering the above factors, the attributes of each SN entity were estimated, and the complete list is presented in Table A2.5.

5.2.3 Product-market profile

The product-market profile of a consumer region was defined in terms of V_l, LT_l and P_l and those product-market profile attributes were derived using both AHP and logical assumptions as presented in Section 3.2.1 and Appendix 1. The V_l was derived using AHP, P_l was taken as proportionate to the price level index and LT_l was estimated considering per capita income, assuming that populations with high income (i.e., affluent consumers) expect a shorter delivery lead-time. Apart from these three main attributes, each consumer region has a dispatching frequency (F_l) which was calculated assuming a fleet of vehicles having identical vehicle capacity available to transport goods to all consumer regions. The estimated values for each attribute of the product-market profile in seven consumer regions are given in Table 5.2.

Table 5.2: Attributes (with mean and standard deviation) of product-market profile of each consumer region

l	Consumer region name	V_l (units) (mean, std)	LT_l (days) (mean, std)	P_l (dollars) (mean, std)	F_l (trips) (mean, std)
1	Zaragoza	(15000, 500)	(80,10)	(1200,75)	(30,1)
2	Milan	(30000, 800)	(150,15)	(1300,45)	(60,1)
3	Munich	(35000, 400)	(120,10)	(1200,50)	(70,1)
4	Hannover	(12000, 200)	(100,12)	(1200,40)	(24,1)
5	Nuremberg	(19000, 1000)	(110,5)	(1200,55)	(38,1)
6	Paris	(57000, 600)	(250,20)	(1300,35)	(114,1)
7	Prague	930000, 200)	(160,15)	(1100,30)	(60,1)

5.3 Simulation experiments and results

This section initially presents the verification of the proposed MAOM, followed by the simulation experiments related to the baseline model, scenario analysis and sensitivity analysis. In Section 5.3.1, the implementation of MAOM in the refrigerator SN context is explained. Section 5.3.2 presents the verification of the MAOM, including the behaviour of agents in the MAOM. Then, in Section 5.3.3, simulation experiments related to the baseline model are presented, followed by scenario analysis in Section 5.3.4 and sensitivity analysis in Section 5.3.5.

5.3.1 Implementation of MAOM within the refrigerator SN context

Section 4.3.1 conceptualised the SNC problem within the context of MAS modelling in terms of the agent environment, agent characteristics, agent types, agent attributes and agent architectures. As stated at the beginning of this chapter, the proposed MAOM was applied on a refrigerator SN where the agent environment represents the refrigerator SN environment, physical agents are SN entities in the refrigerator SN, and auxiliary agents are those supporting the decisions related to the configuration of the refrigerator SN concerned. Following the description of the refrigerator SN provided in Section 5.2, Table 5.3 in this section presents a summary of all parameters used in modelling the SN characteristics, physical agents and auxiliary agents.

5.3.2 Verification of the proposed MAOM

A number of verification methods have been used in the literature (as presented in Section 4.3.4) to test the efficacy of a proposed model. The MAOM was implemented on the MATLAB 2016b software platform, and the initial verification of the MAOM served the purpose of testing the accuracy of implementation of the conceptual model on the MATLAB 2016b. In this study, the 'debug' mode of the above software programme was used to identify implementation errors, including syntax and execution errors. The MAOM was further verified by testing the behaviour of agents (both physical and auxiliary agents) with respect to their intended behaviour as defined in Section 4.3.1.3. For illustration purposes, behaviours of the key agents, that is the physical agents, AU agent, and OPT agent are presented in this section. These agents' behaviours were modelled using Q-learning algorithm and evolutionary algorithms (i.e., GA and NSGA-II). The value of the parameters related to these algorithms and other settings related to the SN environment are as provided in Table 5.3.

Table 5.3: Parameter settings in the simulation environment

<table>
<tr><th rowspan="2">SN characteristics</th><th colspan="4">Implementation details of MAOM</th></tr>
<tr><th>Key features</th><th>Solution methodologies</th><th>Parameter name</th><th>Parameter value</th></tr>
<tr><td rowspan="4">SN environment</td><td rowspan="4">Agent environment</td><td rowspan="4"></td><td>I</td><td>5</td></tr>
<tr><td>J</td><td>18</td></tr>
<tr><td>$\sum R_{ijk}$</td><td>120</td></tr>
<tr><td>L</td><td>7</td></tr>
<tr><td rowspan="6">SN entities</td><td rowspan="6">Physical agents</td><td rowspan="6">Q-learning algorithm</td><td>m</td><td>6</td></tr>
<tr><td>n</td><td>3</td></tr>
<tr><td>μ_{ijk}^{1}</td><td>100</td></tr>
<tr><td>μ_{ijk}^{2}</td><td>10</td></tr>
<tr><td>μ_{ijk}^{3}</td><td>1000</td></tr>
<tr><td>γ</td><td>10</td></tr>
<tr><td rowspan="8">SNC decisions</td><td rowspan="5">AU agent</td><td>Reverse auctioning</td><td>No. of iterations (invitations)</td><td>5</td></tr>
<tr><td rowspan="4">GA</td><td>Population size</td><td>200</td></tr>
<tr><td>Crossover probability</td><td>0.6</td></tr>
<tr><td>Mutation probability</td><td>0.04</td></tr>
<tr><td>Reproduction probability</td><td>0.5</td></tr>
<tr><td rowspan="3">OPT agent</td><td rowspan="3">NSGA-II</td><td>Population size</td><td>200</td></tr>
<tr><td>Crossover probability</td><td>0.8</td></tr>
<tr><td>Mutation probability</td><td>0.04</td></tr>
</table>

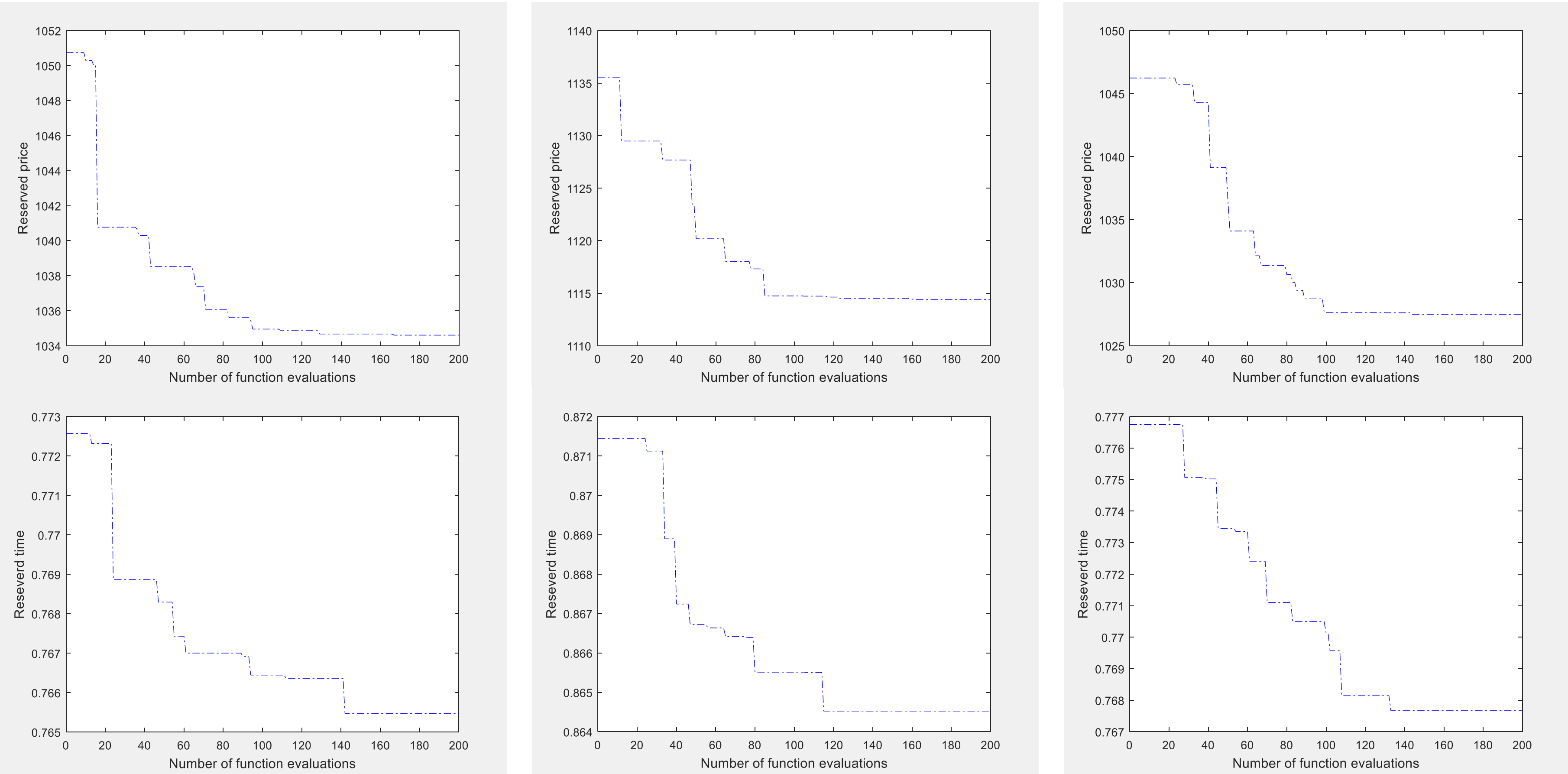
As introduced in Section 4.3.1.3, reverse-auctioning was employed to select the best bids from the competing physical agents to optimise SN-level performance. The initial set of reserve values (i.e., RP_{ij} and RT_{ij}) required to execute the reverse-auctioning process, were generated using GA. Then the AU agent sent invitations to all physical agents through the respective SES agents. The reverse-auctioning process for each product-market profile was run for a maximum of five invitations by lowering the reserve values until the termination criteria were met. Then this reverse-auctioning process was repeated 100 times (i.e., iterations) with a different set of initial reserve values. Figure 5.2 presents the optimal reserve values (price and time) generated by the AU agent for the product-market profiles in consumer region 1, 2 and 3. In all the above-illustrated instances, the GA process converged before reaching 200 algorithmic iterations.

Physical agents (as introduced in Section 4.3.1.3) were implemented with an architecture, which consists of the three modules, DM, LM and CM. These modules help physical agents to make competitive bids using past bidding experience and to communicate with relevant SES agents. Figure 5.3 shows the bidding values (which were determined following the steps shown in Figure 4.5) of physical agents (ID: 119 and 126) for the product-market profile of consumer region 1, 2, 3 and 4. Figure 5.4 and Figure 5.5 show the corresponding Q-tables of Agent ID 119 and 126, respectively. These agents were selected for illustration purposes as they were found to be shortlisted candidates for many product-market profiles and also they are a good representation of the distinct behaviour of agents. For example, for the product-market profile of consumer region 1 and 2, agent ID 119 reduced the bidding price (BP_{ijk}) in response to the first two auctioning invitations and then used the same bidding price for the other invitations. In the case of consumer region 3, the agent used the same BP_{ijk} for all auctioning invitations and for consumer region 4, the agent used the same BP_{ijk} up to the third invitation and then stopped bidding for the product-market profile concerned.

As explained in Section 4.3.1.3, physical agents use a Q-table (i.e., their knowledge base in the form illustrated in Table 4.1) to make bidding decisions when participating in the auctioning process. When referring to the Q-table, the physical agent initially decides the capacity level (based on Eqn. 1 and 2) and then follows either an exploration or exploitation strategy depending on whether the invitation is for a new product-market profile or not. For example, Agent ID 119 selected capacity status 2 as it's current capacity level with respect to the demand of the consumer region 1.

Then the agent selected an action (i.e., profit margin) in order to calculate the BP_{ijk}. Since Agent ID 119 was an experienced agent (as per agent's attributes given in Table A2.5) in bidding for consumer region 1 (see Figure 5.4.), action 3 (i.e., Q_{31}) which has Q-value of 922.2 (the highest Q-value in capacity status 2) was selected. In response to the second invitation, the same agent used exploration strategy and action 1 was selected (see Figure 5.4.). Accordingly, as shown in Figure 5.3, the new BP_{ijk} is lower than the previous one.

Since the bid for the second invitation was also successful, Q-table (i.e., Q_{21}) was updated to 842.7 with a positive reward (see Figure 5.4). From the second auction invitation onwards, this agent used the same action (i.e., action 1) which means the same BP_{ijk} as the agent was shortlisted by the SES agent, but agent ID 119 was not able to lower the profit range any further. By comparison, when Agent ID 119 presented bids for the product-market profile of consumer region 2, capacity level 4 and action 3 were selected as per the Q-tables in Figure 5.4. Hence,



Consumer region 1 **Consumer region 2** **Consumer region 3**

Figure 5.2: Optimal set of reserve values (price and time) generated by the AU agent using GA for product-market profiles in consumer region 1, 2 and 3

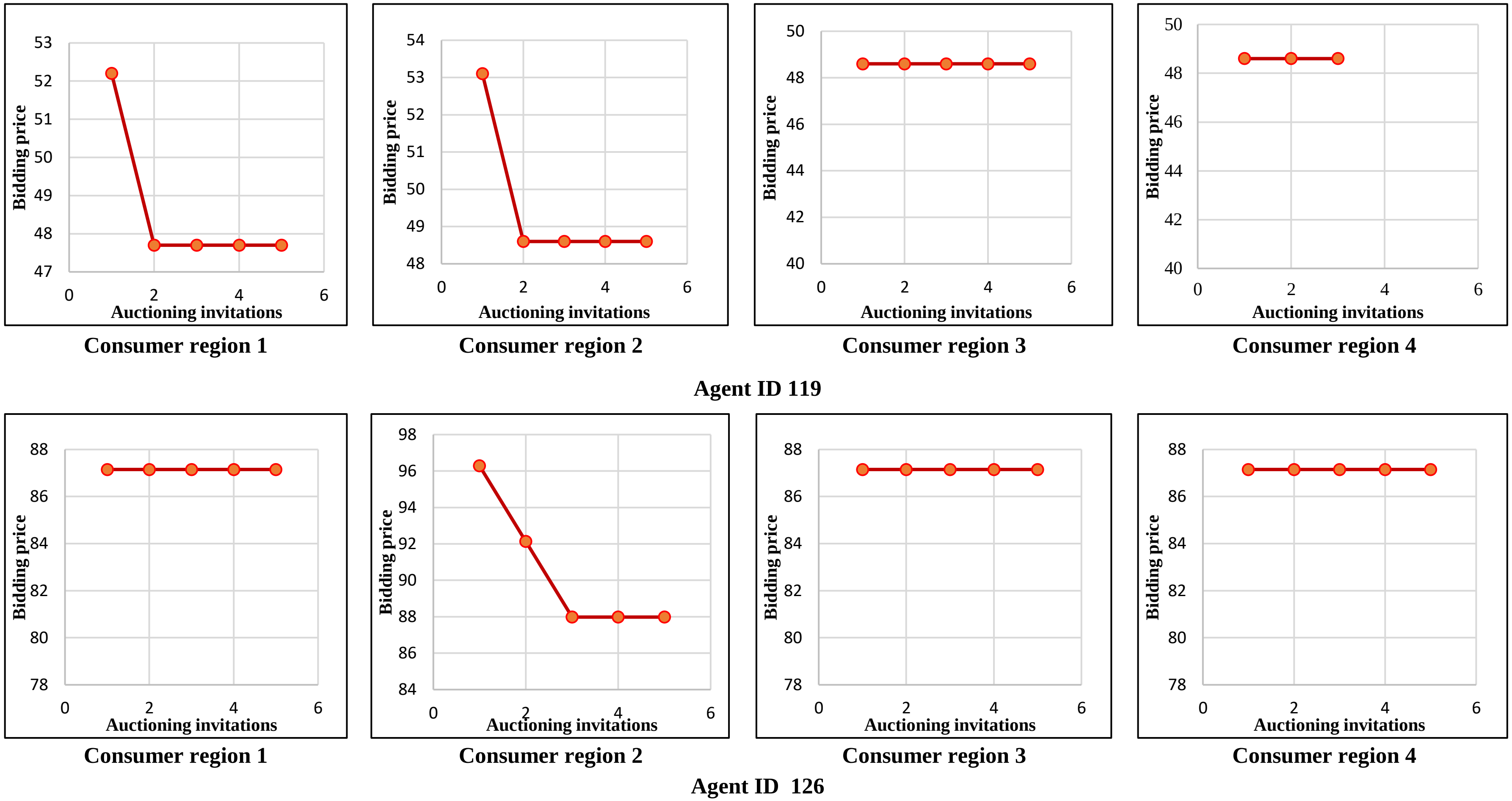


Figure 5.3: Illustration of bidding price decision of Agent ID 111 and 126 for product-market profile of consumer region 1 and 2

	Action				Action				Action				Action				Action		
Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75
	47.7	49.95	**922.2**		**842.7**	49.95	922.2		**1637**	49.95	922.2		**2432**	49.95	922.2		**3227**	49.95	922.2
	48.15	50.4	52.65		48.15	50.4	52.65		48.15	50.4	52.65		48.15	50.4	52.65		48.15	50.4	52.65
	48.6	50.85	53.1		48.6	50.85	53.1		48.6	50.85	53.1		48.6	50.85	53.1		48.6	50.85	53.1
	49.05	51.3	53.55		49.05	51.3	53.55		49.05	51.3	53.55		49.05	51.3	53.55		49.05	51.3	53.55
	49.5	51.75	54		49.5	51.75	54		49.5	51.75	54		49.5	51.75	54		49.5	51.75	54

Consumer region 1

	Action				Action				Action				Action				Action		
Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75
	3227	49.95	922.2		3227	49.95	922.2		3227	49.95	922.2		3227	49.95	922.2		3227	49.95	922.2
	48.15	50.4	52.65		48.15	50.4	52.65		48.15	50.4	52.65		48.15	50.4	52.65		48.15	50.4	52.65
	48.6	50.85	**1823**		**1668**	50.85	1823		**3288**	50.85	1823		**4908**	50.85	1823		**6528**	50.85	1823
	49.05	51.3	53.55		49.05	51.3	53.55		49.05	51.3	53.55		49.05	51.3	53.55		49.05	51.3	53.55
	49.5	51.75	54		49.5	51.75	54		49.5	51.75	54		49.5	51.75	54		49.5	51.75	54

Consumer region 2

	Action				Action				Action				Action				Action		
Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75
	3227	49.95	922.2		3227	49.95	922.2		3227	49.95	922.2		3227	49.95	922.2		3227	49.95	922.2
	48.15	50.4	52.65		48.15	50.4	52.65		48.15	50.4	52.65		48.15	50.4	52.65		48.15	50.4	52.65
	8418	50.85	1823		**10308**	50.85	1823		**12198**	50.85	1823		**14088**	50.85	1823		**15978**	50.85	1823
	49.05	51.3	53.55		49.05	51.3	53.55		49.05	51.3	53.55		49.05	51.3	53.55		49.05	51.3	53.55
	49.5	51.75	54		49.5	51.75	54		49.5	51.75	54		49.5	51.75	54		49.5	51.75	54

Consumer region 3

	Action				Action				Action				Action				Action		
Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75	Capacity status	47.25	49.5	51.75
	3227	49.95	922.2		3227	49.95	922.2		3227	49.95	922.2		3227	49.95	922.2		3227	49.95	922.2
	48.15	50.4	52.65		48.15	50.4	52.65		48.15	50.4	52.65		48.15	50.4	52.65		48.15	50.4	52.65
	18570	50.85	1823		**19218**	50.85	1823		**20832**	50.85	1823		**20832**	50.85	1823		**20832**	50.85	1823
	49.05	51.3	53.55		49.05	51.3	53.55		49.05	51.3	53.55		49.05	51.3	53.55		49.05	51.3	53.55
	49.5	51.75	54		49.5	51.75	54		49.5	51.75	54		49.5	51.75	54		49.5	51.75	54

Consumer region 4

Figure 5.4: Illustration of Q-tables of Agent ID 119 in product-market profile of consumer region 1,2,3 and 4

	Action		
Capacity status	87.15	91.3	**957.95**
	87.98	92.13	96.28
	88.81	92.96	97.11
	89.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	**874.65**	91.3	957.95
	87.98	92.13	96.28
	88.81	92.96	97.11
	89.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	**1662.15**	91.3	957.95
	87.98	92.13	96.28
	88.81	92.96	97.11
	89.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	**3237**	91.3	957.95
	87.98	92.13	96.28
	88.81	92.96	97.11
	89.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	**2449.65**	91.3	957.95
	87.98	92.13	96.28
	88.81	92.96	97.11
	89.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

Consumer region 1

	Action		
Capacity status	3237.15	91.3	957.95
	87.98	92.13	**1836.2**
	88.81	92.96	97.11
	89.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	3237.15	91.3	957.95
	87.98	**1757.13**	1836.28
	88.81	92.96	97.11
	89.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	3237.15	91.3	957.95
	1677.98	1757.	1836.28
	88.81	92.96	97.11
	89.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	3237	91.3	957.95
	3267.	1757.13	1836.28
	88.81	92.96	97.11
	1709.	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	3237.15	91.3	957.95
	3267.98	1757.13	1836.28
	88.81	92.96	97.11
	89.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

Consumer region 2

	Action		
Capacity status	3237.15	91.3	957.95
	5122.98	1757.13	1836.2
	88.81	92.96	97.11
	1709.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	3237.15	91.3	957.95
	6977.98	1757.13	1836.28
	88.81	92.96	97.11
	1709.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	3237.15	91.3	957.95
	8832.98	1757.	1836.28
	88.81	92.96	97.11
	1709.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	3237	91.3	957.95
	10687	1757.13	1836.28
	88.81	92.96	97.11
	3599.	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	3237.15	91.3	957.95
	10687.9	1757.13	1836.28
	88.81	92.96	97.11
	1709.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

Consumer region 3

	Action		
Capacity status	**3867.15**	91.3	957.95
	10687.9	1757.13	1836.2
	88.81	92.96	97.11
	3599.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	**4497.15**	91.3	957.95
	10687.9	1757.13	1836.28
	88.81	92.96	97.11
	3599.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	**5127.15**	91.3	957.95
	10687.9	1757.	1836.28
	88.81	92.96	97.11
	3599.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	**5757**	91.3	957.95
	10687	1757.13	1836.28
	88.81	92.96	97.11
	3599.	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

	Action		
Capacity status	**6157.25**	91.3	957.95
	10687.9	1757.13	1836.28
	88.81	92.96	97.11
	3599.64	93.79	97.94
	90.47	94.62	98.77
	91.3	95.45	99.6

Consumer region 1

Figure 5.5: Illustration of Q-tables of Agent ID 126 in product-market profile of consumer region 1,2,3 and 4

the BP_{ijk} (i.e., \$ 53.10) for the first invitation for the product-market profile in consumer region 2 is higher than that of the product-market profile in consumer region 1 (see Figure 5.3). In the second round of bidding, the agent selected action 1 following the exploration strategy. Hence, as shown in Figure 5.4, Q_{41} was updated to 1668, and the agent continued to choose the action 1 in the remaining auctioning invitations and Q_{41} was updated accordingly.

As presented in Section 4.3.1.3, at the end of the auctioning process, the SES agent communicates the shortlisted physical agents to the OPT agent so as to generate Pareto-optimal SNCs. Figure 5.6 shows the Pareto-optimal SNCs for the product-market profile of consumer region 1,2,3 and 4. Figure 5.7 shows the Pareto-optimal SNCs for the product-market profile of consumer region 5, 6 and 7. It turned out that all the consumer regions have feasible Pareto-optimal SNCs satisfying the attributes of the product-market profile. As presented above, the behaviours of the AU, physical and OPT agents indicate that each agent serves the intended purpose as defined in Section 4.3.1.3, which also verifies the proposed MAOM in the MATLAB 2016b environment.

5.3.3 Baseline model

This section presents the results of the baseline model which considers a static and deterministic SN context, assuming that the existing SN entities (i.e., physical agents in MAOM) remain functioning and no uncertainty is associated with their attributes (e.g., PC_{ijk}, PT_{ijk}, AC_{ijk}). These assumptions represent the situation that SNs tend to operate in, based on the premise that once a network is formed to suit a given product-market profile, it would remain the same for the foreseeable future (Braziotis et al. 2013; Huang, Zhang & Liang 2005).

The baseline model was run in the simulation environment with the given parameter settings assumed to be present, and attributes of those SN entities (PC_{ijk}, PT_{ijk}, AC_{ijk}) were assumed to be deterministic so that the mean values of the relevant parameters were used as listed in Table A2.5. Also, unique product-market profiles for seven consumer regions (as introduced in section 5.2.3) were considered using the mean value of each product-market profile attribute. Table 5.3 summarises the parameters related to SN characteristics and algorithms used to implement the behaviours of SN entities. In the baseline model, Pareto-optimal SNCs were generated for the product-market profile of each consumer region by repeating the reverse-auctioning process 100 times (i.e., iterations).

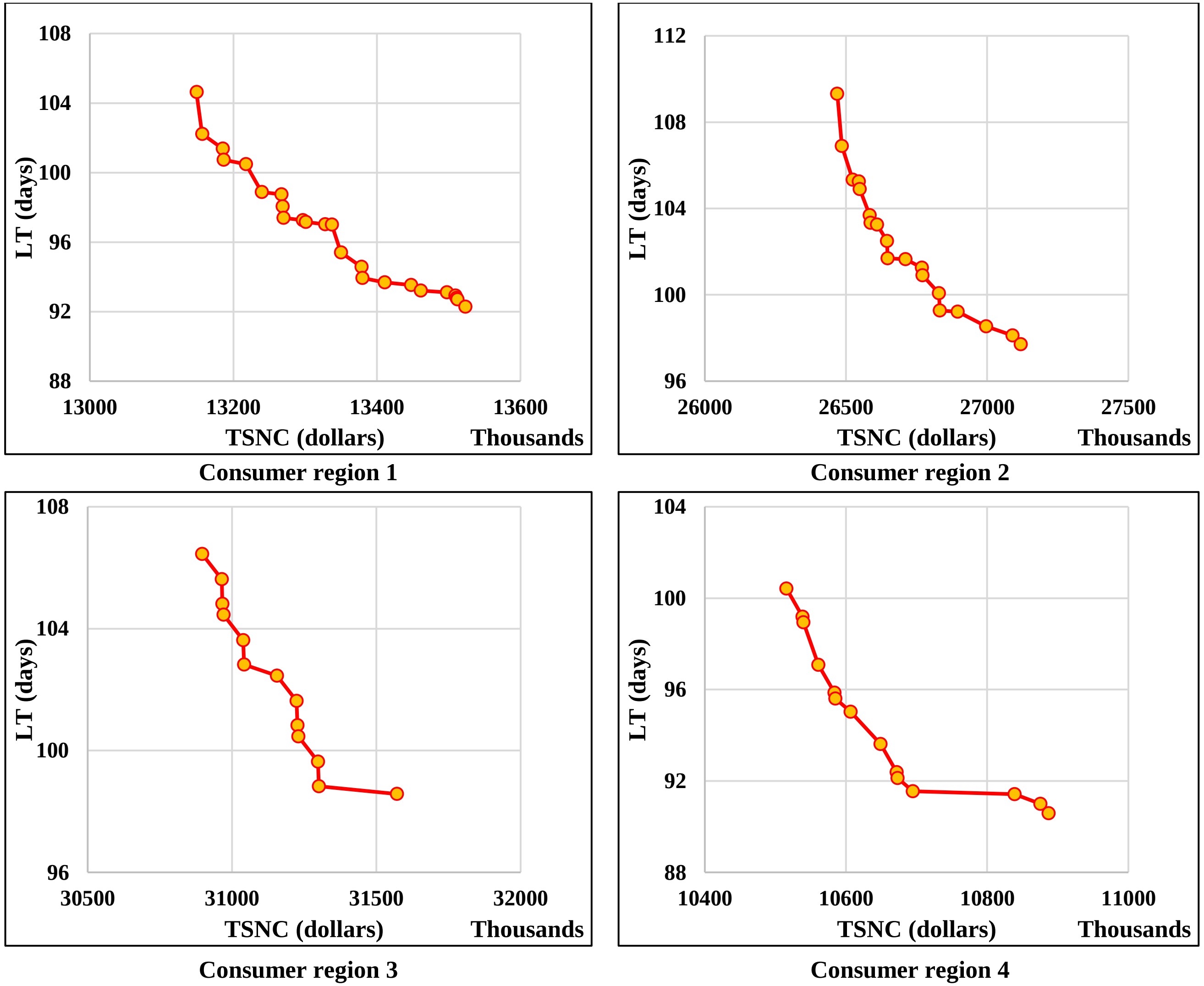


Figure 5.6: Illustration of Pareto front generated by OPT agent for product-market profile in consumer region 1, 2, 3 and 4

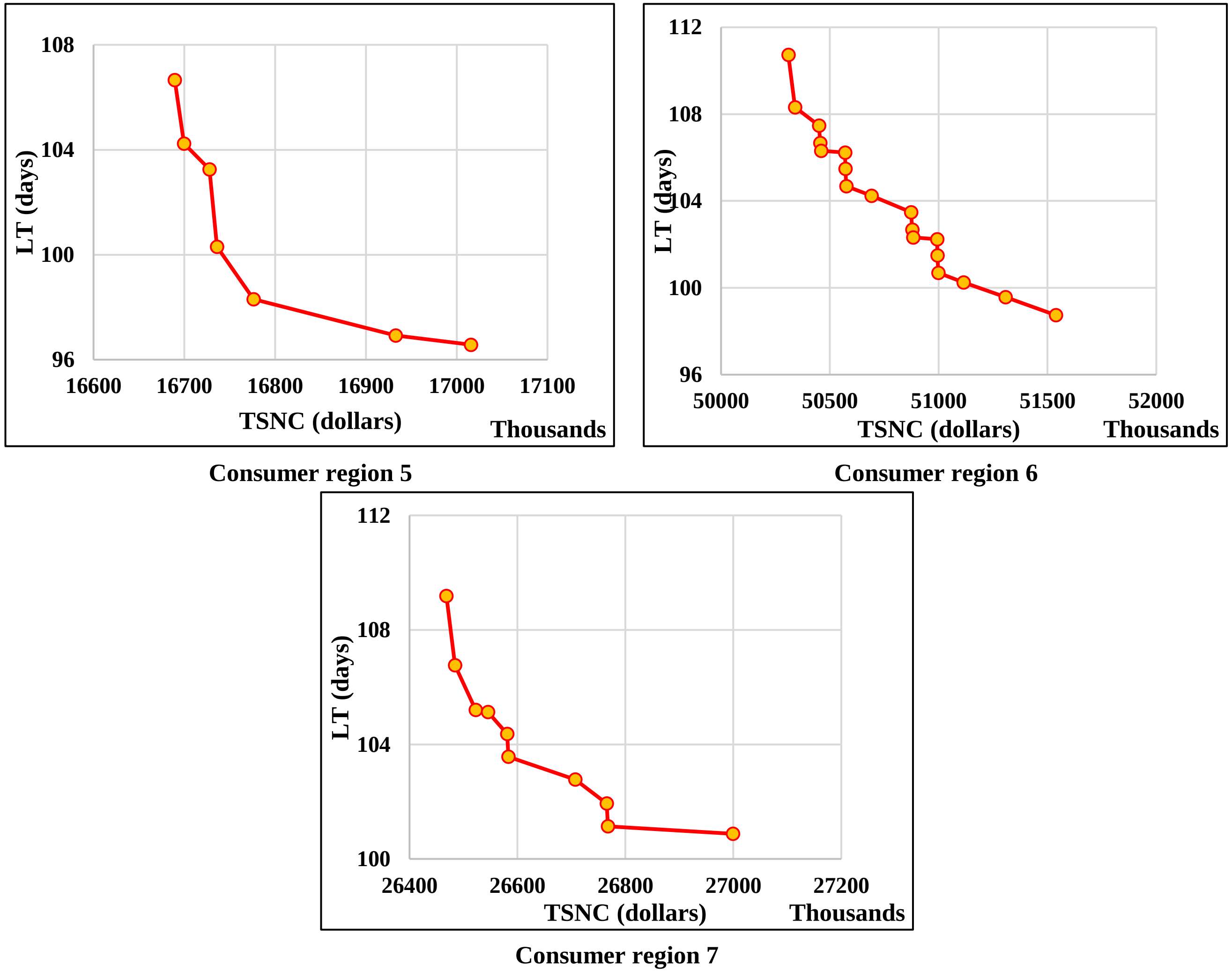


Figure 5.7: Illustration of Pareto front generated by OPT agent for product-market profile in consumer region 5, 6 and 7

Under these conditions, the average computational time taken by a core i7-9700, 3.0 GHz computer to generate a set of Pareto optimal SNCs for a given product-market profile is 45 seconds. It has been reported in the literature that with the other SNC models using ACO, GA and dynamic programming consumed much longer time than that of the proposed MAOM (Moncayo-Martı´nez & Zhang 2011; Huang et al., 2005). For example, Moncayo-Martı´nez and Zhang (2011) have employed ACO to solve a SN with an estimated half of the problem size used in this study (i.e., 1.26×10^6 number of possible solutions) using a 2.4 GHz computer which has taken nearly 40 seconds to solve the problem.

Out of the SNCs generated in 100 iterations, the set of Pareto-optimal SNCs generated in the first 20 iterations for the product-market profile in consumer region 1 is plotted in Figure 5.8. The graph indicates that NSGA-II converges to a Pareto-front even though reverse-auctioning starts with a different set of reserve values. Measuring the quality of the Pareto-front ensures how good the generated solution is in terms of closeness to Pareto-optimality and spread of solutions for the problem considered. In the literature, three key quality measures have been used, namely, convergence metric, spread metric and spacing metric (Ramesh, Kannan & Baskar 2012; Coello, Lamont & Van Veldhuizen 2007; Deb 2001). The convergence matric finds an average distance between non-dominated solutions and the actual Pareto optimal front, which is useful for evaluating the closeness to the true Pareto-front. Having a smaller value for this metric indicates that there is better convergence. The spread metric evaluates the diversity among the non-dominated solutions with respect to the objectives concerned.

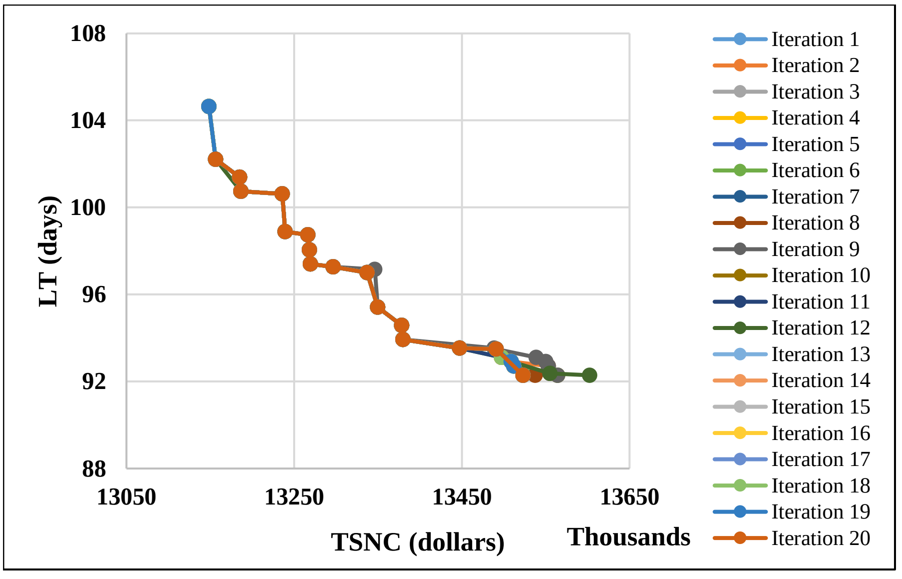


Figure 5.8: Pareto-optimal SNCs generated in the first 20 auctioning iterations for product-market profile in consumer region 1

Having a smaller value for this metric indicates that there is better diversity. The spacing matric considers the distance between non-dominated solutions measuring the standard deviation of distances between solutions. Similar to the other measures, having a smaller spacing is better which indicates that the solutions are uniformly distributed. In this study, the aforementioned quality measures were calculated for the solutions (i.e., SNCs) generated by NSGA-II in the baseline model. The corresponding values for the convergence metric, spread metric and spacing metric are 0.21, 0.13 and 0.03. As stated in a wide range of literature (e.g., Ramesh, Kannan & Baskar 2012; Deb 2001), having a value less than one indicates that NSGA-II generates a good set of Pareto solutions.

Table 5.4 presents the Pareto-optimal SNCs which have the lowest average SN performance (in terms of per-unit TSNC and LT) obtained by repeating the reverse-auctioning for 100 iterations. The key attributes of the Pareto-optimal SNCs of the selected Pareto front include: the average SN performance (i.e., the average of the minimum and maximum values of SNCs) in terms of per-unit TSNC and LT; the range of SN performance (i.e., the minimum and maximum values of SNCs); and the number of Pareto-optimal SNCs in the selected Pareto-front. The results show that out of the product-market profiles for all consumer regions, the lowest and highest average per-unit TSNC (in dollars) and LT (in days) are 887 and 894, and 96 and 106 respectively. These results indicate that the cost of delivering a single refrigerator in many consumer regions is about the same, but the lead-times are quite different.

Furthermore, the number of SNCs in a Pareto-front varies from seven (in consumer region 5) to 24 (in consumer region 1), which means consumer region 1 has a higher number of alternative ways to cater for the respective

Table 5.4: Simulation results of the baseline model

$\boldsymbol{l}$	Product – market profile ($\boldsymbol{V_l}$, $\boldsymbol{LT_l}$, $\boldsymbol{P_l}$)	Average		Range		No. of Pareto optimal SNCs
		TSNC (dollars)	LT (days)	TSNC [min, max]	LT [min, max]	
1	(15000,80,1200)	890	99	[877, 902]	[93,105]	24
2	(30000,150,1300)	894	104	[883,904]	[98,110]	19
3	(35000,120,1200)	893	103	[883,902]	[99,107]	13
4	(12000,100,1200)	893	96	[877,908]	[91,101]	14
5	(19000,110,1200)	888	102	[879,896]	[97,107]	7
6	(57000,250,1300)	894	105	[883,905]	[99,111]	18
7	(30000,160,1100)	887	106	[883,890]	[101,110]	10

product-market profile. Out of all Pareto-optimal SNCs in the Pareto front, a SNC for a given product-market profile was selected based on the energy consumption for the relevant SN operations and transportation between SN entities. Accordingly, the IDs of SN entities in the selected Pareto-optimal SNC are listed in Table 5.5. The results show that there is a set of SN entities common to all product-market profiles. These SN entities are raw material suppliers representing node 1, 2 and 3 with ID 119, 126 and 136. Additionally, there are certain SN entities common to many product-market profiles representing node 4, 5, 6, 7, 9 and 10, namely ID 142, ID 255, ID 262, ID 277, ID 288, ID 297, ID 3106. At node 11 (i.e., distribution node), energy-efficient SN entities are different for each consumer region. The energy consumption of the most energy-efficient SNC varies from 190 kJ (in consumer region 4) to 217 kJ (consumer region 7).

Table 5.5: Indices of SN entities in the most energy-efficient SNC for the product-market profile of each consumer region

l	**SN nodes**											**EC (kJ)**
	N_{11}	**N_{12}**	**N_{13}**	**N_{14}**	**N_{25}**	**N_{26}**	**N_{27}**	**N_{28}**	**N_{29}**	**$N_{3(10)}$**	**$N_{4(11)}$**	
1	119	126	136	142	251	262	278	284	297	3106	4112	195
2	119	126	136	146	255	262	277	288	298	3106	4126	200
3	119	126	136	142	255	262	277	288	297	3106	4131	215
4	119	126	136	142	252	264	278	284	297	3106	4126	190
5	119	126	136	142	255	262	275	288	294	3105	4129	207
6	119	126	136	142	255	262	277	288	297	3106	4126	198
7	119	126	136	142	254	262	277	288	294	3105	4131	217

Note: EC – energy consumption

5.3.4 Scenario analysis

As mentioned in Section 4.3.4, the scenario analysis aims to test the robustness of the proposed MAOM, while examining the impact of SN uncertainties and dynamics on SN performance. The exploratory scenario approach was adopted considering possible future situations where SNs are subject to change due to uncertainties and dynamics. Such changing SN conditions in relation to the supply, production and distribution stages, as well as the consumer demand (Shishebori & Babadi 2018; Salem & Haouari 2017; Dai & Li 2017; Peidro et al. 2009) have already been discussed in the literature review chapter of this thesis. As this study models the entire SN (i.e., all three stages of upstream, midstream and downstream), testing all possible scenarios with respect to the changing attributes, behavior and relationships of SN entities are practically impossible, particularly as the number of scenarios exponentially increase with the increasing number of variables involved (Silvente, Papageorgiou & Dua 2019). Hence, a finite number of scenarios have been developed paying attention to the major issues highlighted in the SN literature and their relevance to SNC decisions, as set out in this study. Accordingly, this study has accounted for the effects of the geographical location of SN entities, variations in the capacity of SN entities (Wu, Blackhurst & Chidambaram 2006; Christopher 2002) and the impact of possible SN disruptions (assuming that these disruptions occur in different regions). Additionally, SN performance was tested against changing product-market profiles. Accordingly, seven scenarios were developed by considering, (1) changing operations cost (PC_{ijk}) and operations time (PT_{ijk}) of upstream SN entities; (2) changing operations cost (PC_{ijk}) and operations time (PT_{ijk}) of midstream SN entities; (3) changing operations cost (PC_{ijk}) and operations time (PT_{ijk}) of downstream SN entities; (4) disrupted upstream SN entities; (5) disrupted midstream SN entities; (6) disrupted downstream SN entities; and (7) changing product-market profiles.

Simulation experiments for the scenario analysis were carried out in the simulation environment with the same settings as mentioned in Section 5.3.1, except for the attributes of SN entities which follow the normal distribution as per the given scenario. For example, in scenario 1, attributes (PC_{ijk} and PT_{ijk}) of upstream SN entities are assumed to follow the normal distribution and attributes of SN entities in other stages assumed to be deterministic. In the literature, log-normal and normal distribution have been used in modelling stochastic economic parameters (Kamath & Pakkala 2002; Johnson & Kotz 1970). In this set of scenario analyses, Pareto-optimal SNCs were generated for the product-market profile of each consumer region, repeating the reverse-auctioning process for 100 iterations. The reported results of the above seven scenario analyses include the average SN performance of 100 iterations and corresponding ranges of per-unit TSNC and LT, the percentage difference between the SN performance of the baseline model and the scenario analysis case performed, and the average number of Pareto-optimal SNCs. The average per-unit TSNC of 100 iterations was calculated by first taking the average per-unit TSNC (i.e., the average of the maximum and minimum TSNC of the Pareto-optimal front in the given iteration) individually and then again taking the average of those values. This average SN performance value was calculated for the purpose of taking a single representative value for SN performance in the face of changing attributes of SN entities and to use that value for comparison with the baseline performance. The range of SN performance (for both per-unit TSNC and LT) was taken as the averaged maximum and minimum of 100 iterations. The percentage difference was calculated by subtracting the SN performance of the scenario analysis from the SN performance of the baseline model. If the percentage difference is positive, values of SN performance measures are higher (i.e., increased per unit TSNC or LT) than the baseline model performance, a negative means values of SN performance measures are lower than baseline model performance. From the SN point of view, positive and negative differences indicate losses and savings, respectively. For example, if SN performance of the scenario analysis resulted in a higher per-unit TSNC that will make a loss to the entire SN and therefore, it is indicated by a negative sign.

5.3.4.1 Scenario analysis 1: changing operations time and cost of upstream SN entities

In this scenario, the impact of uncertainties related to the attributes PC_{ijk} and PT_{ijk}, of upstream SN entities (i.e., tier 1 and tier 2 suppliers) on SN performance was analysed. This scenario represents real-world SN conditions where there may be increased/decreased price of raw material or components, operational delays due to issues such as raw material depletion, industrial actions, and economic downturns. These uncertainties related to attributes of SN entities were modelled, assuming that the attributes follow the normal distribution having values within one standard deviation of the mean.

The reverse-auctioning was repeated for 100 iterations and out of those 100 iterations, the set of Pareto-optimal SNCs generated in the first ten iterations is shown in Figure 5.9. Table 5.6 presents the results of the Pareto-

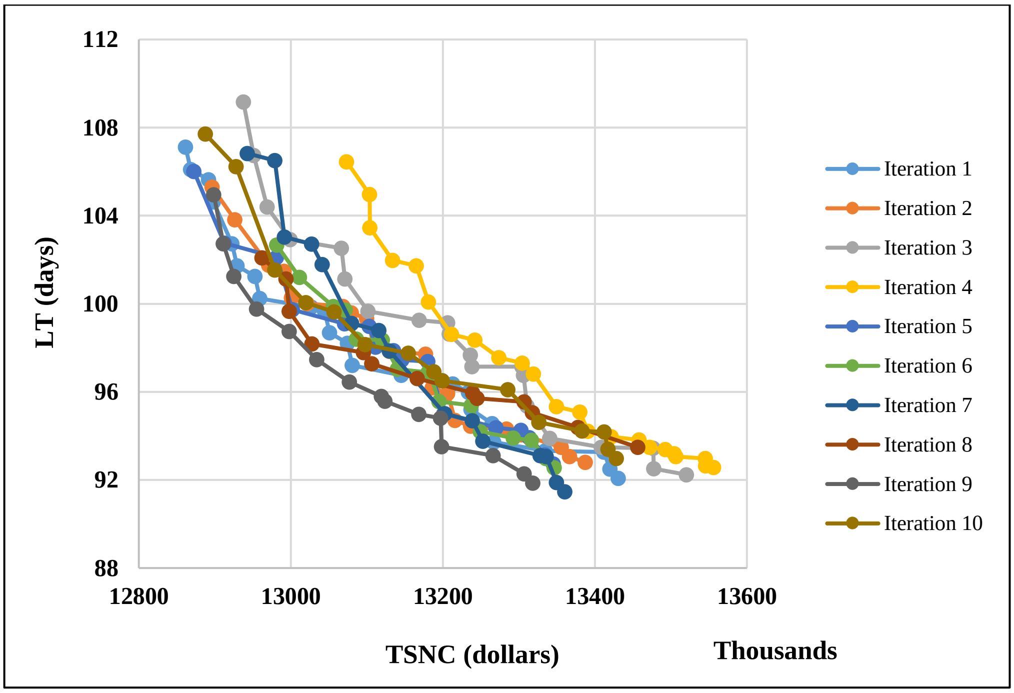


Figure 5.9: Pareto-optimal SNCs generated in the first ten reverse-auctioning iterations – senario analysis 1

optimal SNCs of all 100 iterations using the format of reporting results, as stated at the beginning of the Section 5.3.4. The percentage differences of per-unit TSNC and LT of all product-market profiles indicate that per-unit TSNC is less than the baseline model performance; however, four of them record an increased LT.

The percentage difference of per-unit TSNC varies from +1.1 to +2.4 and LT varies from -3.6 to +1.0. Among all consumer regions, consumer region 4 reported as the region with the highest reduction of per-unit TSNC and the region that requires the highest LT in comparison to baseline conditions. Accordingly, the above results indicate that the changing PC_{ijk} and PT_{ijk} have made a relatively significant impact on SN performance, compared to the baseline conditions. Among them, consumer region 7 is scored as the one having the lowest number of Pareto-optimal SNCs under given SN conditions.

Table 5.6: Simulation experiment results - scenario analysis 1

l	Product – market profile (V_l, LT_l, P_l)	Baseline model (average & range)		Scenario analysis 1 (average & range)		% difference		No. of Pareto-optimal SNCs
		TSNC (dollars)	LT (days)	TSNC (dollars)	LT (days)	TSNC	LT	
1	(15000,80,1200)	890 [877,902]	99 [93,105]	879 [868,890]	100 [94,105]	+1.2	-0.5	14
2	(30000,150,1300)	894 [883,904]	104 [98,110]	881 [864,898]	103 [97,109]	+1.4	+1.0	18
3	(35000,120,1200)	893 [883,902]	103 [99,107]	883 [868,897]	105 [99,111]	+1.1	-1.9	23
4	(12000,100,1200)	893 [877,908]	96 [91,101]	871 [861,881]	100 [95,104]	+2.4	-3.6	8
5	(19000,110,1200)	888 [879,896]	102 [97,107]	885 [861,885]	104 [97,110]	+1.6	-1.5	17
6	(57000,250,1300)	894 [883,905]	105 [99,111]	888 [864,888]	104 [99,109]	+2.0	+1.0	10
7	(30000,160,1100)	887 [883,890]	106 [101,110]	878 [870,878]	105 [103,107]	+1.4	+0.5	4

5.3.4.2 Scenario analysis 2: changing operations time and cost of midstream SN entities

In this scenario, the impact of uncertainties related to the attributes PC_{ijk} and PT_{ijk}, of midstream SN entities (i.e., manufacturers) on SN performance was analysed. This scenario represents SN conditions where PC_{ijk} and PT_{ijk} of manufacturer are changed due to the introduction of new technologies, tariff reduction, workforce issues, machine break downs etc. These uncertainties in the attributes of SN entities were modelled, assuming that the attributes follow the normal distribution having values within one standard deviation of the mean. Following the format of reporting results as stated at the beginning of the Section 5.3.4, Table 5.7 presents the results of scenario analysis 2.

The percentage differences of TSNC and LT of all product-market profiles show that all product-market profiles had reduced TSNC except for consumer region 7. This means uncertainties of midstream SN entities have not made an adverse impact on SN performance compared to the uncertainties of upstream SN entities. Also, except for consumer regions 4 and 6, there is a reduction in LT in other consumer regions, as well. The percentage difference of per-unit TSNC varies from -0.2 to +1.3 and LT varies from -0.5 to +2.0. Among all consumer regions, region 4 (similar to scenario analysis 1) reported as the region with the highest reduction in per-unit TSNC and also the highest increment in LT. The highest reduction in LT is reported in consumer region 2. Additionally, for consumer regions 1, 2 and 3 there is a reduction in both per-unit TSNC and LT. With respect to the number of Pareto-optimal SNCs for each product-market profile, many consumer regions have a smaller number of Pareto-optimal SNCs, compared to the baseline model under given SN conditions.

Table 5.7: Simulation experiment results - Scenario analysis 2

l	Product – market profile (V_l, LT_l, P_l)	Baseline model (average & range)		Scenario analysis 2 (average & range)		% difference		No. of Pareto-optimal SNCs
		TSNC (dollars)	LT (days)	TSNC (dollars)	LT (days)	TSNC	LT	
1	(15000,80,1200)	890 [877,902]	99 [93,105]	881 [873,888]	99 [94,104]	+1.1	0	13
2	(30000,150,1300)	894 [883,904]	104 [98,110]	887 [881,893]	103 [98,107]	+0.8	+1.4	10
3	(35000,120,1200)	893 [883,902]	103 [99,107]	890 [885,895]	103 [97,108]	+0.3	+0.5	10
4	(12000,100,1200)	893 [877,908]	96 [91,101]	882 [874,889]	97 [91,102]	+1.3	-0.5	12
5	(19000,110,1200)	888 [879,896]	102 [97,107]	887 [877,897]	100 [96,104]	+0.1	+2.0	15
6	(57000,250,1300)	894 [883,905]	105 [99,111]	888 [882,893]	106 [100,111]	+0.7	-0.5	6
7	(30000,160,1100)	887 [883,890]	106 [101,110]	889 [885,892]	106 [103,108]	-0.2	+0.5	6

5.3.4.3 Scenario analysis 3: changing operations time and cost of downstream SN entities

In this scenario, the impact of uncertainties related to the attributes PC_{ijk} and PT_{ijk}, of downstream SN entities (i.e., distributors) on SN performance was analysed. This scenario represents changing SN conditions such as varying inventory and warehousing costs due to tariff variations, and disturbed transportation due to natural disasters and increased fuel costs etc. These uncertainties related to SN entity attributes were modelled assuming that the attributes follow the normal distribution having values within one standard deviation of the mean. Table 5.8 presents the results of scenario analysis 3, using the format of reporting results as stated at the beginning of the Section 5.3.4.

The percentage differences of per-unit TSNC and LT of all consumer regions show that there is a reduction in terms of per-unit TSNC except for consumer region 5. However, except consumer region 1, 2 and 6, all other consumer regions require higher LTs. The percentage difference of per-unit TSNC varies from -0.1 to +1.1, and LT varies from -4.7 to +1.4. Among all consumer regions, the highest saving of per-unit TSNC is reported from consumer region 4 (similar to scenario analyses 1 and 2), which is also the region which needs the highest extra LT. There is a saving in both per-unit TSNC and LT in consumer region 1 and 2. With respect to the number of Pareto-optimal SNCs for each product-market profile, many consumer regions have a lesser number of Pareto-optimal SNCs, compared to the baseline model.

Table 5.8: Simulation experiment results - Scenario analysis 3

l	Product – market profile (V_l, LT_l, P_l)	Baseline model (average & range)		Scenario analysis 3 (average & range)		% difference		No. of Pareto-optimal SNCs
		TSNC (dollars)	LT (days)	TSNC (dollars)	LT (days)	TSNC	LT	
1	(15000,80,1200)	890 [877,902]	99 [93,105]	888 [875,901]	99 [92,105]	+0.2	+0.5	19
2	(30000,150,1300)	894 [883,904]	104 [98,110]	891 [881,901]	104 [98,110]	+0.3	0	13
3	(35000,120,1200)	893 [883,902]	103 [99,107]	891 [881,901]	104 [99,109]	+0.2	-1.0	18
4	(12000,100,1200)	893 [877,908]	96 [91,101]	883 [876,890]	101 [95,106]	+1.1	-4.7	11
5	(19000,110,1200)	888 [879,896]	102 [97,107]	889 [879,898]	104 [97,111]	-0.1	-2.0	9
6	(57000,250,1300)	894 [883,905]	105 [99,111]	893 [883,902]	104 [96,111]	+0.2	+1.4	18
7	(30000,160,1100)	887 [883,890]	106 [101,110]	884 [882,885]	107 [103,111]	+0.4	-0.9	6

5.3.4.4 Scenario analysis 4: disrupted upstream SN entities

SNs are subject to a number of structural changes due to existing entities leaving the network and new entities joining the network, or the merging and acquisitions of SN entities etc. Scenario analysis 4 considers such changing SN conditions where upstream SN entities are disrupted due to natural calamities and financial downturns etc. These disruptions could occur to an SN entity at any time holding up their operations temporally or permanently, which in turn, could possibly make an impact on SN performance. The disrupted SN entities subjected to this analysis were selected considering their contribution to overall SN performance, referring to the baseline model results. For demonstration purposes, the results of the scenario analysis related to the product-market profile of consumer region 1 are presented in Table 5.9. Six disrupted instances were analysed assuming those selected SN entities were not available for the continued functioning of the SN. Results presented in Table 5.9 includes the average SN performance and corresponding ranges of per-unit TSNC and LT, the percentage difference between the SN performance of scenario analysis 4 and the baseline model, and the number of SNCs in the optimal Pareto front.

The presented results indicate that all the given disrupted instances incur an increased per-unit TSNC and LT over the baseline model conditions. However, LT is similar to the baseline model in a few instances. The increment of

Table 5.9: Simulation experiment results - Scenario analysis 4

Instance	Disrupted SN entities	Baseline model (average & range)		Scenario analysis 4 (average & range)		% difference		No. of Pareto-optimal SNCs
		TSNC (dollars)	LT (days)	TSNC (dollars)	LT (days)	TSNC	LT	
1	119	890 [877,902]	99 [93,105]	893 [880,905]	99 [93,105]	-0.3	0	20
2	126			891 [879,902]	101 [93,109]	-0.1	-2.0	18
3	253			890 [877,902]	99 [93,105]	0	0	22
4	262			892 [881,902]	100 [93,106]	-0.2	-0.5	18
5	119, 126			894 [882,905]	101 [93,109]	-0.4	-2.0	15
6	255, 262			892 [881,902]	100 [93,106]	-0.2	-0.5	18

per-unit TSNC varies from -0.1 to -0.4 and LT varies from -0.5 to -2.0. Results of Table 5.9 further indicate that there is no impact on SN performance with the absence of SN entity ID 253. However, other disrupted SN entities make an impact on SN performance. Among them, the absence of SN entity ID 126 makes the highest impact, followed by SN entity ID 262 and 191. The average number of Pareto-optimal SNCs are also lower than in the baseline model.

Table 5.10 lists the most energy-efficient SNC in these disruptive SN contexts for the product-market profile of consumer region 1. In the baseline model, the total energy consumption of the most energy-efficient SNC for the product-market profile in consumer region 1 is 195 kJ. However, the energy consumption of the new energy-efficient SNC s in disrupted instances are higher than for the baseline model in all instances.

Table 5.10: Indices of SN entities in the most energy-efficient SNC for the product-market profile of each consumer region (scenario analysis 4)

Instance	SN node											EC (kJ)
	N_{11}	N_{12}	N_{13}	N_{14}	N_{25}	N_{26}	N_{27}	N_{28}	N_{29}	$N_{3(10)}$	$N_{4(11)}$	
Baseline model	119	126	136	142	251	262	278	284	297	3106	4112	195
1	1110	126	136	142	251	262	278	288	294	3105	4112	200
2	119	128	136	142	252	267	278	288	297	3102	4112	206
3	119	128	136	142	252	267	278	284	297	3102	4112	198
4	119	126	135	142	252	267	278	288	294	3104	4112	202
5	1110	128	136	142	252	267	278	288	297	3102	4112	202
6	1110	126	136	146	252	267	278	288	297	3106	4112	200

Note: EC – total energy consumption

5.3.4.5 Scenario analysis 5: disrupted midstream SN entities

In this scenario analysis, simulation experiments were run to analyse the SN performance in the presence of disrupted midstream SN entities (i.e., manufacturers). Two disrupted instances were considered as given in Table 5.11 assuming that Agent ID 3105 and 3106 cease their production in the current planning period. As per the results reported in Table 5.11, average per-unit TSNC and LT of the given scenarios are similar or higher than that of the baseline model.

According to the results of the baseline model, Agent ID 3106 is the one that satisfies all SN performance criteria; hence, the absence of SN entity ID 3106 made an adverse impact on SN performance. Nevertheless, the absence of ID 3105 has not made any difference to SN performance which indicates that it is not such a critical SN entity. Additionally, the average number of Pareto-optimal SNCs in consumer region 1 is less than that of the baseline model. As reported in Table 5.12, the energy consumption of the new SNCs is higher than for the baseline model.

Table 5.11: Simulation experiment results - Scenario analysis 5

Instance	Disrupted SN entities	Baseline model (average & range)		Scenario analysis 5 (average & range)		% difference		No. of Pareto-optimal SNCs
		TSNC (dollars)	LT (days)	TSNC (dollars)	LT (days)	TSNC	LT	
1	3105	890 [877,902]	99 [93,105]	890 [877,902]	99 [93,105]	0	0	18
2	3106			891 [879,902]	100 [93,106]	-0.1	-1.0	18

Table 5.12: Indices of SN entities in the most energy-efficient SNC for the product-market profile of each consumer region (scenario analysis 5)

Instance	SN nodes											EC (kJ)
	N_{11}	N_{12}	N_{13}	N_{14}	N_{25}	N_{26}	N_{27}	N_{28}	N_{29}	$N_{3(10)}$	$N_{4(11)}$	
Baseline model	119	126	136	142	251	262	278	284	297	3106	4112	195
1	119	128	136	146	252	267	278	284	297	3102	4112	199
2	119	126	136	146	251	267	278	288	294	3102	4112	203

Note: EC – energy consumption

5.3.4.6 Scenario analysis 6: disrupted downstream SN entities

In this scenario analysis, SN performance was examined for the product-market profile in consumer region 1 in the presence of disrupted downstream SN entities. Two disruptive instances were tested as given in Table 5.13, assuming agent ID 4112 and 4126 cease their operations during the current planning period. As the results reported in Table 5.13, losing ID 4112 resulted in a reduced per-unit TSNC, however, needed extra LT. Conversely, losing ID 4126 made no difference to SN performance, and gives the same results as the baseline model. SN entities in the most energy-efficient SNC in this scenario are presented in Table 5.14. It shows that the energy consumption of the new energy-efficient SNC in disrupted instance 1 is higher than that of the baseline model

Table 5.13: Simulation experiment results - Scenario analysis 6

Instance	Disrupted SN entities	Baseline model (average & range)		Scenario analysis 6 (average & range)		% difference		No. of Pareto-optimal SNCs
		TSNC (dollars)	LT (days)	TSNC (dollars)	LT (days)	TSNC	LT	
1	4112	890 [877,902]	99 [93,105]	889 [877,900]	100 [94,105]	+0.2	-0.5	15
2	4126			890 [877,902]	99 [93,105]	0	0	23

Table 5.14: Indices of SN entities in the most energy-efficient SNC in different disruptive instances of downstream SC (scenario analysis 6)

Instance	SN nodes											EC (kJ)
	N_{11}	N_{12}	N_{13}	N_{14}	N_{25}	N_{26}	N_{27}	N_{28}	N_{29}	$N_{3(10)}$	$N_{4(11)}$	
Baseline model	119	126	136	142	251	262	278	284	297	3106	4112	195
1	119	126	136	142	252	267	278	284	297	3102	4131	212
2	119	128	136	142	252	267	278	284	297	3106	4112	195

Note: EC – energy consumption

5.3.4.7 Scenario 7: Changing product-market profiles

In this scenario analysis, SN performance was tested with the presence of uncertainties related to the attributes of the product-market profile. Changing product-market profiles were modelled, assuming each attribute of the product-market profile of the given consumer region follows the normal distribution with the mean and standard deviation as given in Table 5.2. For demonstration purposes, five different instances of product-market profile in consumer region 1 were tested as presented in Table 5.15. In two instances, the volume of the new product-market profile is higher than the volume of the product-market profile in the baseline model. In those instances, consumer region 1 resulted in increased per-unit TSNC and LT. In instances 3 and 4, where the product-market profiles have a lower number of units than the baseline model, the analysis reports either a reduced per-unit TSNC or LT.

5.3.4.8 Summary of the scenario analysis results

Scenario analysis was performed to test the robustness of the proposed MAOM and examine the impact of SN uncertainties and SN dynamics on SN performance. Seven scenarios were considered by changing the SN

Table 5.15: Simulation experiment results - Scenario analysis 7

Instance	Product-market profile	Scenario analysis 7 (average & range)		% difference		No. of Pareto-optimal SNCs
		TSNC (dollars)	LT (days)	TSNC	LT	
Baseline	(15000,80,1200)	890 [877,902]	99 [93,105]	-	-	24
1	(15111,81,1249)	894 [883,904]	104 [98,110]	-0.4	-5.1	20
2	(15136,82,1230)	893 [883,902]	103 [99,107]	-0.3	-4.0	18
3	(14820,84,1176)	893 [877,908]	96 [91,101]	-0.3	+3.0	18
4	(14510,86,1187)	888 [879,896]	102 [97,107]	+0.3	-3.0	19
5	(15337,74,1174)	894 [883,905]	105 [99,111]	-0.4	-6.1	16

conditions, including both SN uncertainties and SN dynamics. The first three analyses were performed by changing the operations cost and operations time of SN entities in each SN stage, i.e., the upstream, midstream or downstream stages. The results of these analyses indicate that depending on the increased/decreased operations cost and operations time of SN entities, the resultant SN performance score has decreased in per-unit TSNC/LT or increased per-unit TSNC/LT. Nevertheless, the variations in SN performance in uncertain SN contexts (for the first three scenarios) do not exceed 5% compared to the baseline model results, which means the proposed MAOM remains robust against changing SN conditions. When these three scenarios were individually analysed, the results indicate that compared to baseline SN performance, an upstream SN stage has a higher impact on SN performance than the downstream or midstream SN stages. Among all consumer regions, region 2 and 4 indicate a similar trend in their performance in all three scenarios. Consumer region 2 reports a reduced per-unit TSNC and LT, whereas consumer region 4 reports reduced per-unit TSNC and increased LT.

The next three experiments focused on SN dynamics considering disrupted SN entities in three SN stages. These analyses were performed only for the product-market profile of consumer region 1. Results of those analyses indicate that when the disrupted SN entity(ies) are among the most prominent/popular SN entities (i.e. the SN entities that are common across multiple SNCs in the network) as per the baseline results, the new SN performance shows an increased per-unit TSNC and LT, while also having a higher total energy consumption than for the baseline model. However, the change in SN performance is less than 2% in all the disrupted instances which means the MAOM also remains robust in these disrupted instances.

In the last scenario, the product-market profile of consumer region 1 was analysed subject to changing product-market profile attributes. In instances where the volume attribute of the new product-market profile is higher than that of the baseline model, it results in increased per-unit TSNC and LT. In all seven scenarios, the number of Pareto-optimal SNCs are less than that of the baseline model and also the total energy consumption is higher than that of the baseline model. However, variations in SN performance did not exceed 5% compared to the baseline SN performance. These results indicate the robustness of the proposed MAOM in the face of SN uncertainties and SN dynamics.

5.3.5 Sensitivity analysis

Sensitivity analysis was performed in this study to estimate the extent to which the SN-level performance is vulnerable to the changes in SN characteristics. The first three sensitivity analyses listed below were performed to estimate the extent to which the SN-level performance is vulnerable to the changes in the attributes of SN entities collectively in each stage. Accordingly, experiments were conducted by changing both the operations cost (PC_{ijk}) and operations time (PT_{ijk}) of all SN entities by 10% in the upstream, midstream and downstream, respectively. The last experiment was performed to estimate the extent to which the SN-level performance is vulnerable to the changes in the attributes of SN entities individually. Accordingly, the experiment was conducted by changing both operations cost (PC_{ijk}) and operations time (PT_{ijk}) of selected SN entities by 10%. The selected SN entities for the sensitivity analysis are from all three stages (i.e., upstream, midstream and downstream).

(1) Increasing the operations cost and time of all upstream SN entities by +10%

(2) Increasing the operations cost and time of all midstream SN entities by +10%

(3) Increasing the operations cost and time of all downstream SN entities by +10%

(4) Increasing the operations cost and time of selected SN entities by + 10%

The reported results of the sensitivity analysis include: for the selected Pareto-optimal SNCs, the average SN performance (i.e., the average of minimum and maximum values of per-unit TSNC and LT), and the range of SN performance (i.e., the minimum and maximum values of SN performance); and the number of Pareto-optimal

SNCs in the selected front. The percentage difference is calculated by subtracting the SN performance of the sensitivity analysis experiment from that of the baseline model. For example, if the difference in per-unit TSNC is positive, then there is a saving/reduction in per-unit TSNC, otherwise, the new SNC requires extra/ increased per-unit TSNC.

5.3.5.1 Sensitivity analysis 1: increasing the operations cost and operations time of all upstream SN entities by 10%

In this experiment, a sensitivity analysis was performed by increasing both the PC_{ijk} and PT_{ijk} of all upstream SN entities by 10%. The purpose of this sensitivity analysis is to find the impact of changing attributes of upstream SN entities on the overall SN performance. Pareto-optimal SNCs were generated for the product-market profile of each consumer region, repeating the reverse-auctioning process 100 times (i.e., iterations). Out of these 100 iterations, the set of Pareto-optimal SNCs generated in the first ten iterations is shown in Figure 5.10. Table 5.16 presents the results of the Pareto-optimal SNCs, which have the lowest average SN performance (in terms of per-unit TSNC and LT) found when repeating the reverse-auctioning for 100 iterations. The results of the baseline model are also listed for the purpose of comparison.

The reported results indicate that increased operations costs and operations time of upstream SN entities gave higher per-unit TSNC and LT in all consumer regions compared to the baseline model conditions. Across, all

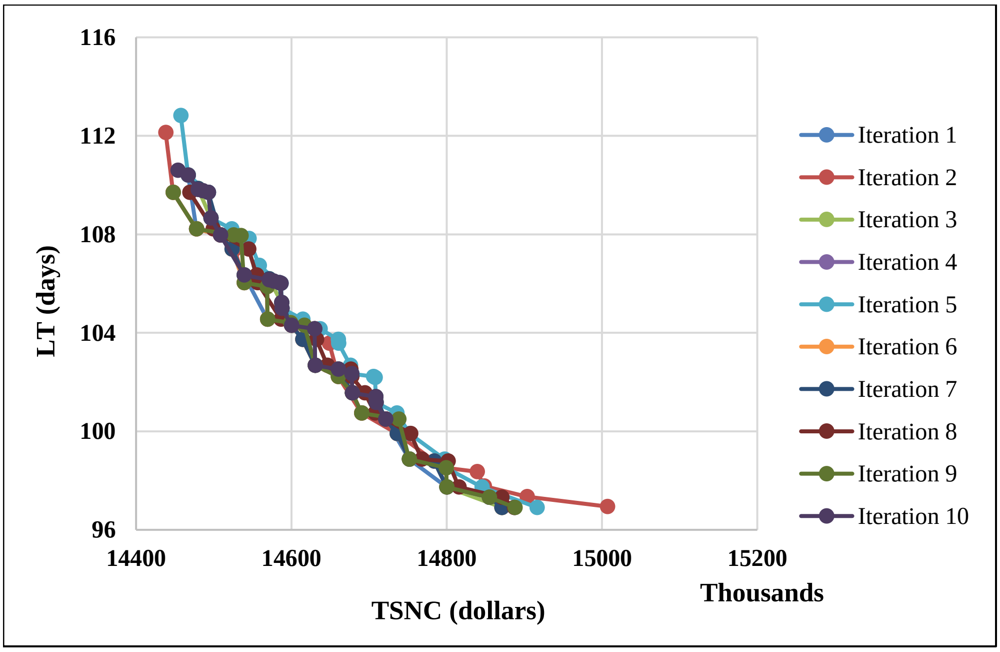


Figure 5.10: Pareto-optimal SNCs generated in the first ten reverse-auctioning iterations – sensitivity analysis 1

consumer regions, the 10% increment of operations cost and time of SN entities resulted in increased per-unit TSNC in the range of 9.2% to 11.1% and increased LT in the range of 2.9% to 7.8%. This further indicates that increasing the operations costs of SN entities has nearly the same level of impact on all consumer regions; however, increasing the operations time of SN entities resulted in varying levels of impact on consumer regions.

Among all the consumer regions, region 5 reports the highest increment in per-unit TSNC and region 3 reports the highest increment in LT. Additionally, both per-unit TSNC and LT have considerably increased in consumer regions 1 to 4, whereas other regions only resulted in increased per-unit TSNC. Accordingly, these results indicate that a 10% increment of operations cost and time of SN entities on average resulted in 10.17% increment of per-unit TSNC and 5.7% increment of LT.

Table 5.16: Simulation experiment results - sensitivity analysis 1

l	Product – market profile (V_l, LT_l, P_l)	Baseline model (average & range)		Sensitivity analysis 1 (average & range)		% difference	
		TSNC (dollars)	LT (days)	TSNC (dollars)	LT (days)	TSNC	LT
1	(15000,80,1200)	890 [877,902]	99 [93,105]	972 [964,982]	106 [101,111]	-9.2	-7.1
2	(30000,150,1300)	894 [883,904]	104 [98,110]	989 [970,1007]	111 [104,118]	-10.6	-6.7
3	(35000,120,1200)	893 [883,902]	103 [99,107]	990 [969,1012]	111 [104,117]	-10.9	-7.8
4	(12000,100,1200)	893 [877,908]	96 [91,101]	977 [962,992]	103 [95,111]	-9.4	-7.3
5	(19000,110,1200)	888 [879,896]	102 [97,107]	987 [966,1009]	107 [102,112]	-11.1	-4.9
6	(57000,250,1300)	894 [883,905]	105 [99,111]	982 [970,994]	108 [104, 117]	-9.8	-2.9
7	(30000,160,1100)	887 [883,890]	106 [101,110]	978 [970,986]	110 [104,115]	-10.2	-3.8

5.3.5.2 Sensitivity analysis 2: increasing operations cost and operations time of all midstream SN entities by 10%

In this experiment, a sensitivity analysis was performed by increasing both PC_{ijk} and PT_{ijk} of midstream SN entities by 10%. The purpose of this experiment was to find the impact to the overall SN performance of changing attributes of the midstream SN entities. Table 5.17 presents the results of the Pareto-optimal SNCs with the average SN performance repeating the auctioning for 100 iterations. The results of the baseline model are also listed for the purpose of comparison. These results indicate that increased operations cost and operations time of midstream SN entities reported mixed (both increases and decreases compared to the baseline model conditions) changes of per-unit TSNC across different consumer regions. In contrast, LT is increased in all consumer regions. Across, all consumer regions, the 10% increase in operations cost and operations time of SN entities resulted in changes to TSNC in the range of -0.2% to +0.4% and increased LT in the range of +1.5% to +2.9%.

This further indicates that the 10% increment of operations cost of SN entities makes less than 0.4 % impact on the SN performance, and a 10% increment of operations time of SN entities makes less than 3% impact on the SN performance. Among all the consumer regions, region 3 reports the highest differences in per-unit TSNC and LT. Additionally, compared to sensitivity analysis 1, the 10% increment of operations cost and time of SN entities

Table 5.17: Simulation experiment results - Sensitivity analysis 2

l	Product – market profile (V_l, LT_l, P_l)	Baseline model (average & range)		Sensitivity analysis 2 (average & range)		% difference	
		TSNC (dollars)	LT (days)	TSNC (dollars)	LT (days)	TSNC	LT
1	(15000,80,1200)	890 [877,902]	99 [93,105]	891 [878,903]	101 [94,107]	-0.1	-1.5
2	(30000,150,1300)	894 [883,904]	104 [98,110]	894 [884,904]	107 [101,112]	-0.1	-2.4
3	(35000,120,1200)	893 [883,902]	103 [99,107]	894 [884,904]	106 [101,111]	-0.2	-2.9
4	(12000,100,1200)	893 [877,908]	96 [91,101]	889 [877,901]	99 [92,105]	+0.4	-2.6
5	(19000,110,1200)	888 [879,896]	102 [97,107]	889 [880,897]	104 [98,109]	-0.1	-1.5
6	(57000,250,1300)	894 [883,905]	105 [99,111]	894 [884,904]	108 [102,113]	0	-2.4
7	(30000,160,1100)	887 [883,890]	106 [101,110]	886 [884,888]	109 [106,111]	+0.1	-2.8

make a higher impact on LT than on the per-unit TSNC. Accordingly, these results indicate that 10% increment of operations cost and time of SN entities resulted on average, in a 0.13% increment of per-unit TSNC and a 2.3% increment of LT.

5.3.5.3 Sensitivity analysis 3: increasing operations cost and operations time of all downstream SN entities by 10%

In this experiment, sensitivity analysis is performed by changing both PC_{ijk} and PT_{ijk} of downstream SN entities by 10%. The purpose of this experiment is to find the impact of downstream SN entities to the overall SN performance. Table 5.18 presents the results of the Pareto-optimal SNCs with the average SN performance repeating the auctioning for 100 iterations. The results of the baseline model are also listed for the purpose of comparison.

These results indicate that increased operations cost and operations time of downstream SN entities gave increased per-unit TSNC and LT in all consumer regions compared to the baseline model conditions. Across all consumer regions, the 10% increment of operations cost and operations time of SN entities resulted in increased TSNC in the range of 0.1% to 0.3% and increased LT in the range of 1.0% to 3.1%. This indicates that with reference to

Table 5.18: Simulation experiment results - sensitivity analysis 3

l	Product – market profile (V_l, LT_l, P_l)	Baseline model (average & range)		Sensitivity analysis 3 (average & range)		% difference	
		TSNC (dollars)	LT (days)	TSNC (dollars)	LT (days)	TSNC	LT
1	(15000,80,1200)	890 [877,902]	99 [93,105]	891 [878,903]	100 [94,105]	-0.1	-1.0
2	(30000,150,1300)	894 [883,904]	104 [98,110]	896 [884,907]	105 [100,110]	-0.2	-1.0
3	(35000,120,1200)	893 [883,902]	103 [99,107]	894 [884,903]	103 [99,107]	-0.1	0
4	(12000,100,1200)	893 [877,908]	96 [91,101]	894 [878,909]	99 [93,104]	-0.1	-3.1
5	(19000,110,1200)	888 [879,896]	102 [97,107]	889 [880,897]	103 [98,107]	-0.1	-1.0
6	(57000,250,1300)	894 [883,905]	105 [99,111]	896 [884,907]	107 [101,112]	-0.2	-2.0
7	(30000,160,1100)	887 [883,890]	106 [101,110]	890 [883,897]	106 [102,110]	-0.3	0

the baseline conditions: a 10% increase of operations cost of SN entities makes less than 0.3% impact, and increases in operations time make less than 3.1% impact. Among all the consumer regions, region 7 reports the highest increment in per-unit TSNC and region 4 reports the highest increment in LT.

Additionally, compared to sensitivity analysis 1, the 10% increment of operations cost and time of downstream SN entities make a higher impact on LT than on the per-unit TSNC. Accordingly, these results indicate that 10% increase of operations cost and operations time of SN entities resulted in a 0.16% increase of per-unit TSNC and a 1.62% increase of LT on average.

5.3.5.4 Sensitivity analysis 4: increasing the operations cost and operations time of selected SN entities

In this experiment, a sensitivity analysis was performed by increasing both PC_{ijk} and PT_{ijk} of selected SN entities by 10%. The purpose of this experiment is to find the impact of individual SN entities on the overall SN performance. As mentioned above, SN entities subject to this analysis were the most promising ones in the baseline model. For demonstration purposes, the product-market profile of consumer region 1 was considered in this analysis.

Table 5.19 presents the results of the sensitivity analysis performed by increasing the operations cost and operations time of selected SN entities. The reported results indicate that the increased PC_{ijk} and PT_{ijk} of 2nd tier, SN entities in the supply stage resulted in the highest increment in per-unit TSNC and LT. However, the percentage difference in SN performance (both per-unit TSNC and LT) is less than 2%. When the SN entities are ranked considering the percentage difference in SN performance, Agent ID 142 is the highest, then Agent ID 128, followed by Agent IDs 267, 4112 and 119. All other SN entities make a less than 0.1% difference in per-unit TSNC and less than 1% difference in LT.

5.3.5.5 Summary of the sensitivity analysis results

Four sensitivity analysis experiments were performed in order to identify the to which SN characteristics the overall SN performance is more sensitive. The first three sensitivity analysis experiments were performed to estimate the impact of SN stage(s) and the fourth to estimate the impact of SN entity(ies) on overall SN performance.

The impact of SN stage was identified by increasing the operations cost and operations time of all SN entities by 10% in each stage. The results of those sensitivity analyses indicate that the overall SN performance is more sensitive to the upstream SN stage (i.e., supply stage), than the midstream (i.e., the manufacturing stage) and the downstream (i.e., the distribution stage). The 10% increment of operations cost of SN entities in supply, manufacturing and distribution stage resulted in 10.17%, 0.13% and 0.16% increment in per-unit TSNC respectively. The 10% increment of operations time of SN entities in supply, manufacturing and distribution stage resulted in 5.7%, 2.3% and 1.62% increment in LT respectively. The results of the fourth sensitivity analysis indicate that the overall SN performance is more sensitive to SN entities in the 2nd tier supply stage, followed by SN entities in 1st tier supply stage and the distribution stage. However, the percentage difference in SN performance against the baseline model is less than 2%.

Table 5.19: Simulation experiment results - Sensitivity analysis 4

Instance	Selected SN entities	Baseline model (average & range)		Sensitivity analysis 4 (average & range)		% difference		No. of Pareto-optimal SNCs
		TSNC (dollars)	LT (days)	TSNC (dollars)	LT (days)	TSNC	LT	
1	119	890 [877,902]	99 [93,105]	900 [887,913]	98 [93,103]	-1.1	+1.0	17
2	128			899 [884,914]	101 [95,106]	-1.0	-1.5	19
3	142			900 [885,914]	101 [95,106]	-1.1	-1.5	24
4	252			890 [877,902]	100 [94,105]	+0.1	-0.5	22
5	267			892 [877,906]	101 [96,105]	-0.2	-1.5	15
6	278			891 [879,903]	98 [93,103]	-0.1	+1.0	19
7	288			891 [878,903]	99 [93,105]	-0.1	0	20
8	294			891 [878,903]	99 [93,105]	-0.1	0	16
9	3106			890 [878,902]	100 [93,107]	0	-1.0	16
10	4112			889 [878,900]	101 [94,107]	+0.1	-1.5	14

5.4 Chapter summary

This chapter presented a detailed description of the case study of the refrigerator SN used to test the proposed MAOM. An array of simulation experiments (i.e., verification, scenario analysis and sensitivity analysis) were carried out: first, to verify the model, and then to test the robustness of the model in the face of uncertainties and dynamics, and finally to identify the changes in which SN characteristics, the overall SN performance is more sensitive.

The proposed MAOM was verified using the 'debug mode' of the MATLAB 2016b, and the behaviour of the agents was examined by plotting and examining the output of the decisions of the AU agent, physical agents, and the OPT agent. Seven scenario analysis experiments were carried out to test the robustness of the MAOM. While the first three scenario analyses focused on SN uncertainties, the next four analyses focused on SN dynamics. The impacts of SN uncertainties and SN dynamics on SN performance were found to be less than 5% and 2% respectively, thus confirming the robustness of the proposed MAOM. When the three scenarios related to SN uncertainties were individually analysed, results indicate that the upstream SN stage has a higher impact on SN performance compared to the baseline SN, followed by the downstream stage and finally the midstream stage. The next three experiments focused on SN dynamics considering disrupted SN entities. Results of those experiments indicate that when the disrupted SN entity(ies) are among the best SN entities as per the baseline results, the new, disrupted, SN performances have an increased per-unit TSNC and LT, and also, the total energy consumption is higher than the baseline model. However, the change in SN performance is less than 2% in all the disrupted instances. Finally, the analysis of uncertainties related to product-market profile attributes indicates that the product-market profile with an increased volume (compared with the baseline model), resulted in increased per-unit TSNC and LT. Collectively, these scenario analyses confirmed that the proposed MAOM is sufficiently robust in the face of SN uncertainties and SN dynamics.

Four sensitivity analysis experiments were conducted, changing the attributes of the SN entities, to identify to which SN stage(s) and SN entity(ies), the SN performance is more sensitive. Results reveal that the most sensitive SN stage is the upstream stage, followed by the midstream stage and finally, the downstream stage. The fourth sensitivity analysis performed on the product-market profile in consumer region 1 and results indicate that SN entities in the 2nd tier upstream stage make a higher impact on SN performance, followed by SN entities in 1st tier upstream stage and the distribution stage.

CHAPTER 6: DISCUSSION

6.1 Introduction

This chapter presents the discussion of the findings of this study, including an account of how these findings relate to those of the comparable previous studies. The review of SN literature, as presented in Section 2.4, identified the need for considering SNC decision-making, mainly, in order to overcome the limitations of current SN design research that does not adequately address a number of challenges associated with dynamic and evolving SNs. Furthermore, there is a crucial need to leverage the complementary strengths of SN entities while addressing the challenges of aligning strategic goals, process integration, information sharing, and effective coordination and communication across the SC, which are critical to delivering customer value. Aptly responding to changing SN conditions such as market turbulence and shifting product-market profiles remains a major challenge for many organisations.

Despite the potential of SNC decisions to provide effective solutions to such practical problems, the research devoted to supporting SNC decisions is quite limited, particularly compared to the extent of available literature on SN design. As it has been presented in Chapter 2, the majority of previous SNC studies have modelled SNs as highly abstract problems and assumed deterministic and static SN contexts. Nonetheless, a few studies have dealt with SNC decisions at a reasonable level of detail, while also accounting for changing SN conditions; the findings of these studies will be further discussed in this chapter.

This chapter is arranged as follows: with the aim of providing the context for the discussion of the findings of the study, Section 6.2 presents a discussion of the simulation results and key findings. In Section 6.3, the key aspects of the methodological approach employed in this study are evaluated against those of the extant literature. In Section 6.4, the significance of the modelling approaches and solution methodologies used in this study is discussed and compared with those used in the extant literature in terms of the comprehensiveness of the incorporated SN characteristics (i.e. structural, spatial and temporal), and considering the types and range of SNC decisions, the number of SNC objectives modelled, and the modelling approaches and solution methodologies used. Finally, the chapter summary is presented in Section 6.5.

6.2 Discussion of the simulation results and key findings

The proposed MAOM considered a multi-stage, multi-echelon SN consisting of geographically dispersed and distinct SN entities catering to different product-market profiles. Intelligent auctioning and bidding strategies were employed to enable SN entities to make competitive bids (in terms of operations cost and operations time) based on the knowledge gained through their past bidding experience. These bids were then considered in generating alternative optimal SNCs for each product-market profile using NSGA-II. The proposed MAOM was tested using a case study of a refrigerator SN which consisted of three stages, five echelons, 18 nodes and 120 SN entities. As presented in Chapter 5, three types of simulation experiments were carried out to generate SNCs for different product-market profiles under different organisational and environmental conditions. First, a baseline model was run under static and deterministic SN conditions, which represented the conditions reflected in the majority of extant literature. Then both scenario analysis and sensitivity analysis were performed to examine the deviations from the baseline model, in the behaviour of SNCs under uncertain and dynamic conditions. An another set of scenario analysis experiments were carried out to test the robustness of the MAOM; and sensitivity analyses were performed to estimate the extent to which the SN-level performance is vulnerable to the changes in the attributes of SN entities collectively in each stage and individually as entities of the SN.

Simulation results show that under static and deterministic SN conditions, the unit SN cost for delivering refrigerators to many consumer regions is about the same, but the lead-times are quite different. These results explain that SN entities in the existing SN are geographically located optimally to satisfy the product-market profiles of different regions. Additionally, the operations cost and operations time attributed to these SN entities are comparable with respect to achieving the same SN-level performance for each product-market profile. Results further show that the number of optimal SNCs (in the optimal Pareto-front) to cater for a given product-market profile varies from region to region. This could happen due to having a comparatively higher number of capable SN entities available to choose from in certain regions. Out of such optimal SNCs, the most suitable SNC to cater for the respective region was selected considering energy consumption as an additional target criterion, representing the SN sustainability perspective. Results showed that three SN entities representing sourcing nodes 1, 2 and 3 were common to all the product-market profiles and other nodes had more than one SN entity serving the relevant product-market profile. This indicates that the attributes of those selected SN entities, in terms of operations cost, operations time, and energy consumption, are better than those of the remaining SN entities. All the above findings indicate that under static and deterministic conditions, the selected SN entities are located optimally with the required capacities in terms of operations cost and operations time, to cater for each product-market profile.

Scenario analysis and sensitivity analysis experiments were conducted to examine the extent to which the uncertainties and dynamics in the SN environment make an impact on SN-level performance. A set of experiments was designed, giving particular attention to the different SN stages, to examine the impact of uncertainties and dynamics in each stage on the overall SN-level performance. This analysis is mainly driven by the notion that the performance of every stage is equally important as a failure in one stage or one SN entity will make an adverse impact on the overall SN performance (Flynn, Huo & Zhao 2010; Ballou, RH 2001). Furthermore, a range of issues has been cited in the SN risk management and SN performance related literature as possible factors that could affect SN performance. These issues include inefficient logistic network designs, coordination issues, unreliable and uncertain suppliers/service providers, disruptions and inefficient logistics planning (Esmizadeh & Parast 2020; Namdar, Sawhney & Pradhan 2018; Prajogo, Oke & J Olhager 2016). To address these issues, a number of strategies (e.g. multiple sourcing and outsourcing, back-up supplier contracts) pertaining to logistics network design, analytical and numerical modelling and the development of algorithms to account for uncertainties, have been proposed in the literature (Govindan, Fattahi & Keyvanshokooh 2017; Snyder et al. 2016; Li & Barnes 2008). SNC decisions can be considered as a holistic approach to deal with many of the above problems. However, as uncertainties and disruptions still could make an impact on SNC decisions, they were also examined using scenario analysis and sensitivity analysis. Findings of these experiments can provide useful insights in relation to contingency planning or the development of risk mitigation strategies under such conditions.

In scenario analysis, the uncertainties associated with SN entity attributes due to factors such as differences in tariff and the introduction of new technologies may be measured by the variation of operations cost and operations time. When the three scenarios related to SN uncertainties were individually analysed, the results indicated that the upstream SN stage makes a higher impact on SN-level performance, followed by the downstream SN stage and finally the midstream SN stage. These results could be explained in two different ways: the one is, depending on the number of SN entities that make up the respective SN stage, their resultant cumulative impact could be higher than the baseline conditions; and the other is, the higher variability associated with the attributes of certain SN entities could create a higher impact. This type of uncertain situation has been dealt with in the SN literature by adopting risk mitigation strategies, including contingency plans (Knight, Pfeiffer & Scott 2015). For instance, the upstream SN stage can be strengthened in terms of: having close relationships with prominent suppliers involving longer-term contracts or agreements to avoid price fluctuations; initiating relationships with new SN entities to expand the supply base; and closely monitoring the performance of existing SN entities (Arunachalam, Kumar & Kawalek 2018; Li & Barnes 2008; Hingley 2001).

SN dynamics were tested assuming the absence (loss) of the most prominent/popular SN entities (i.e. the SN entities that are common across multiple SNCs in the network) for a given planning period. Results indicate that when the disrupted SN entity(ies) is among the prominent SN entities, the overall SN-level performance is reduced. The impact that could occur in similar instances has been widely discussed in the SN risk management literature with various strategies being proposed to mitigate the risks associated with such disruptions (Hingley 2001). The analysis indicates that considerable attention needs to be placed on prominent SN entities to avoid potential losses. Those SN entities could be treated on a priority basis depending on the impact that they could make on SN performance. Additionally, SN entities can be analysed with respect to their attributes (e.g., location) and relevant environmental factors (e.g., economic, political). For example, for a particular SN entity, the probability of being disrupted might be high due to region-specific environmental factors such as political and economic conditions. Accordingly, in such situations, appropriate risk mitigation strategies such as seeking new SN entities from different regions or selecting SN entities from the current pool with similar capacities can be pursued (Namdar et al. 2018).

Sensitivity analysis estimated the extent to which the SN-level performance is vulnerable to changes in the attributes of SN entities collectively in each stage and/or individually as entities of the SN. It was revealed that the SN performance was most vulnerable to changes in the upstream SN stage, followed by the midstream SN stage and finally, the downstream SN stage. Additionally, SN entities in the 2nd tier upstream stage make a higher impact on SN performance, followed by SN entities in the 1st tier upstream stage and the downstream stage. Analysis of these results identified two potential reasons: first, the number of SN entities that make up the respective SN stage, and second, a higher operations cost and operations time associated with certain SN entities, could have a higher impact on TSNC/LT. To mitigate the impact of risk associated with susceptible SN entities in these instances, new competitive SN entities and new locations/regions for respective suppliers can be investigated considering raw material cost or labour cost (Li & Barnes 2008; Hingley 2001).

The results of the simulation experiments of this study confirmed that SN performance can vary due to factors such as the number of SN entities that make up the different stages of a particular SN, their attributes such as location, operations cost, operations time and their changes over time. These factors represent the structural, spatial and temporal dimensions of a SN. Additionally, these experiments further showed that configuring the SN under static and deterministic conditions alone would not address the challenges faced by SN decision-makers in a real-world business context. Hence, investigating the SN performance in changing SN conditions using scenario analysis and sensitivity analysis was found to be useful.

By comparison, none of the studies in the extant SNC literature has tested the SNC configuration problem considering all three dimensions, i.e., structural, spatial, and temporal concurrently, and at the level of detail that has been tested in this study. Therefore, there is limited opportunity for direct comparison of the results of this study against those of the studies referred to above. As such, a concerted effort was made to compare both the approaches used, as well as the results obtained against those of the comparative studies, subject to the said constraints.

6.3 Evaluation of the methodological approach employed

This section evaluates the key aspects of the overall methodological approach employed in this study against those of the extant literature.

When the methodological approach used in this study is compared to those of similar/comparable studies in the extant literature, attention is drawn to two sets of studies. The one set of studies developed SNC models in a static and deterministic SN context and with comparatively the same level of SN complexity used in this study; i.e., with similar numbers of nodes (around 40) and SN entities (around 100). The other set of studies dealt with different forms of changing SN conditions, including the attributes and behaviour of SN entities, however, the proposed models were tested with comparatively simple SNs to those used in this study; i.e., with less than five nodes and less than 20 SN entities.

In the first set of studies, apart from having the above-mentioned common characteristics such as rather complex SNs, and a static and deterministic SN context, those models acted as centralised decision-making units optimising one or two objectives. These models were solved or SNC(s) generated using different meta-heuristics algorithms. For example, Moncayo-Martı´nez and Zhang (2011) developed a multi-objective (i.e., TSNC and LT) SNC model, which was tested on a bulldozer assembly SC consists of three products (wheel loader, track loader, and track-type tractor) where many assembled components are common to all three products with 38 SN nodes and 105 SN entities in the SN. The proposed model was solved using ACO comparing the algorithmic solutions generated by a single pheromone matrix (i.e., having a single matrix for both cost and time) and multi-pheromone matrix (i.e., having two matrices, both cost and time). They compared the solution quality in terms of SN-level performance and convergence rate and concluded that the performance of the algorithms under both algorithmic settings are similar. They found that SNs which handle a family of products can be effectively configured using meta-heuristics. Moncayo–Mart´ınez, Ram´ırez–L´opez and Recio (2016) developed a multi-objective SNC model which was tested on a brake and clutch assembly SN with 29 SN nodes and 75 SN entities. The proposed model was solved using both IWD and ACO, each running for 15 times. A number of simulations were performed to get the best algorithmic parameter settings, and both algorithms were terminated with a set of defined criteria to arrive at trade-off solutions. They concluded that IWD outperformed in terms of solution quality with better non-dominated solutions than the ACO. Mastrocinque et al. (2013) developed a multi-objective SNC model that was solved using Bees algorithm. This model was tested on a similar case study to what was proposed by Moncayo-Martı´nez and Zhang (2011). They performed eight experiments to find optimum parameters for bees algorithm, and then the solution obtained using those algorithmic parameter settings were compared with the solution of ACO in Moncayo-Martı´nez and Zhang (2011). The comparison showed that the bees algorithm is a more powerful tool for finding a Pareto-optimal solution. This set of studies found that the performance of meta-heuristics algorithms are different to each other, however, they are capable of dealing with the structural dimension of SNs. Even though these studies dealt with static SN contexts, the importance of accommodating the uncertainties to find more robust SC designs have been identified.

The other set of studies has dealt with a different form of changing SN conditions testing the models on rather simple SNs. Apart from that those models acted as distributed decision-making units optimising a single objective. For example, Akanle and Zhang (2008) modelled SN in the form of a MAS, while incorporating changing production capacity levels of SN entities within a dynamics SN context. The best combination of SN entities for each customer order was identified through a coordinated iterative bidding process supported by GA. They tested the proposed model on a laptop assembly SN which has 16 nodes and 33 SN entities. First, they configured the SN for 30 orders individually and then a clustering algorithm was used to find a common set of SN entities to cater to any order. Accordingly, this study found their proposed approach is capable of finding a common SNC which is stable and reliable to deliver customer orders at the lowest possible cost while dealing with SN dynamics.

Sheremetov and Rocha-Mier (2008) also modelled a SN in the form of a MAS evaluating SN-entity level decisions at SN-level using RL algorithms. The developed model represented a small SN consisting of four nodes and nine SN entities. Wang and Shu (2007) modelled the SNC problem in a context that each SN node has multiple SN entities that differ in terms of their operations costs and lead times. They have accounted for uncertainty in relation to lead times of SN entities and the consumer demand using a fuzzy set modelling approach. GA approach was used to determine the SC configuration. The proposed approach was tested on the case study of notebook computer SN proposed by Graves and William (2005), which has also been used by many other authors for testing their models. An index was used to characterise the risk attitude of the decision-maker, in relation to calculating the lead-time. Experiments were carried out to examine the effects of varying risk attitude indices on the SC configuration and inventory policies. Risk attitude index, which is called "optimism-pessimism index" was varied from 0.3 to 1.0 representing "risk-taking" to "risk-averse" decision-makers. For each value, GA was run five times, and the results indicated that TSNC increases with the risk attitude index. Accordingly, a decision-maker can select a SNC performing trade-off analysis between lead-time, cost and investment in inventory. They found that the most optimistic decision-maker ended-up selecting low-cost SNCs, whereas others selected high-cost SNCs. Greco et al. (2013) adopted Bayesian decision networks and modelled the SN as a tree using MAS where agents represent SN entities. The entire SN was configured by the successful creation of sub-chains (which consist of upstream SN entities) by each SN entity considering both the reputation and selling price for the product. The reputation of SN entity was determined by analysing the previous experience of collaborations with trading partners. Selling price was determined by each agent based on both the expected minimum profit and the past experience in bidding. Depending on the success or failure of the previous bid, the agent increased (subject to the number of previous successful bids) or decreased (subject to the cost of production) the selling price. The proposed model was tested on a SN, which has five SN nodes and 21 SN entities. A simulation was run for 100 times letting agents learn through negotiation and select a SNC. They found that through the learning process, SN entities make better SNC decisions. The model developed by Ruiqing, Tang and Matsukawa (2014) was the only study to account for SN disruptions in the context of making SNC decisions. In their approach, first, the SNC was developed in a static context, and then the impact of SN disruptions to SNC decisions was tested using scenario analysis with a given probability of holding the functioning of SN entities at each stage. Three methods were used in generating SNCs, namely, the minimum unit manufacturing cost heuristic, the minimum lead-time heuristic and global optimisation method. They considered two scenarios of SN disruptions; the one with safety stock and the other without safety stock. They presented the results of one simulation experiment by setting a 5% disruption probability for stage 5 of the SC. In the first scenario, TSNC was increased by 0.8%, and in the second scenario, TSNC was increased by 3.58%. They found that testing the model for multiple scenarios helps make SNC decisions that align with organisational goals. Even though these studies have considered SN uncertainties and modelled them in different ways to arrive at more realistic SNC solutions, those models were still not tested for structurally complex networks.

The previous studies mentioned above were found to have certain practical limitations in relation to their application in a real business context due to not addressing the structural, spatial and temporal dimensions at an adequate level. This observation is further verified by their simulation experiment results, recommendations and future research directions, as stated in the relevant publications. When comparing the simulation experiments of this study with those of the existing studies, it was further confirmed that incorporating structural, temporal and spatial dimensions into SNC models led to more realistic SNC(s) thus resulting in practical and useful solutions. This study further focused on examining how the above factors were incorporated into modelling SNCs towards achieving optimal SN-level performance when individual SN entities were still aiming to satisfy their local goals, such as organisation-specific competitive priorities. This was achieved by implementing intelligent auctioning and bidding strategies to make competitive bids by SN entities which, in turn, lead to improved SNC decisions, thereby enhancing SN-level performance.

6.4 Significance of the modelling approaches and algorithms used

This section articulates the significance of the modelling approaches and solution methodologies used in this study, in light of those used in the extant literature. To this end, the overall methodological approach adopted in this study is first discussed in terms of the comprehensiveness of coverage in this study (in terms of both the breadth and depth) with regards to the:

(i) SN characteristics (i.e. structural, spatial and temporal) incorporated;

(ii) SNC decisions modelled;

(iii) SNC objectives considered; and

(iv) modelling approaches and solution methodologies.

By covering the above factors when modelling the SNC decisions, the study endeavoured to enhance the applicability and usefulness of the proposed MAOM, as well as the rigour of the solution approaches derived, in relation to the real-world SN contexts. The level of comprehensiveness with respect to the above aspects determines the extent to which the developed models: represent the real-world problem contexts and SNC decisions, meet the modelling objectives and the choice of modelling methods, and provide solution methodologies to generate practical solutions.

Modelling SN characteristics: This study considered a conjoined SN structure having multiple echelons in both upstream and downstream of the SN, while accounting for the geographical locations of SN entities. Most of the structures used in the existing SNC models have considered either convergent (e.g. Jiao, You and Kumar 2006) or conjoined (e.g. Moncayo–Martínez & Mastrocinque 2016) structures. Even though such structures consider multiple echelons in the upstream, downstream entities are not dealt with to the same extent. The only study that has considered a multi-echelon downstream SN is Truong and Azadivar (2005), where distributors and retailers have been incorporated into intermediate echelons.

Modelling the spatial dimension in the context of SNC decisions is one of the contributions of this study. This was achieved in three ways: i.e., (i) incorporating geographical factors in deciding SN entity attributes; (ii) generating distinct product-market profiles to represent the market conditions and customer preferences associated with different geographical regions; and (iii) accommodating transportation-related cost and time by considering the distance between SN entities. This study has modelled the SN entity attributes (i.e., operations cost and operations time) with respect to the social, environmental and economic conditions of the geographical region in which they are located. For example, labour cost of a country was used as a proxy to estimate the operations cost, and the competitive index and annual growth rate of high technology usage were used to estimate the operations time. Additionally, the distance between respective upstream/downstream SN entities is considered as a decision making parameter when selecting SN entities for a particular product-market profile. Even though the SN literature has identified that having developed SNC models to accommodate the spatial dimension is one of the most important aspects, the spatial dimension has not been incorporated into SNC models explicitly at the level of detail (i.e., determining SN entity attributes, estimating the product-market profiles, accounting transportation cost and time between SN entities) they have been dealt with in this study. Some SNC models have not considered the spatial dimension at all. They have assumed that transportation cost and time between SN stages are fixed, regardless of which immediate downstream SN entity is selected by the upstream SN entity (Akanle & Zhang

2008). Another cluster of SN literature accommodates the spatial dimension in finding facility location, considering one or few aspects, including transportation cost and time between SN entities, location-specific characteristics such as risk involved, low manufacturing cost, tariff and concessions (Meixell & Gargeya 2005). Nevertheless, studies that have developed product-market profiles taking the geographical characteristics into consideration were non-existent.

Most of the studies have configured SNs based on two attributes of SN entities (i.e. operations cost and operations time), and these attributes have been assumed to remain the same over time. Additionally, SN dynamics have hardly incorporated into modelling. These limitations indicate the lack of attention to the temporal dimension regardless of importance in accomodating into decision-making. This study has adopted a few strategies to model the temporal dimension into SNC decision-making. Given that the type of SNC decisions modelled in this study are considered at strategic and tactical planning levels (which typically spans between 1 to 5 years), the modelling approach used a series of static simulation runs to mimic the evolution (i.e. change of state) of SN entities across these planning periods. As per this approach, the varied product-market profiles are first created to account for the changed market conditions at different strategic planning periods. These profiles are then used for setting up separate simulations to configure the corresponding SN. Accordingly, each SN entity reviews their production capacity levels at the end of each period when bidding for the relevant product-market profile.

Modelling SNC decisions: This study holistically addressed SNC decisions, including supplier selection and facility location, at both midstream and downstream having considered multiple echelons. A similar attempt has been made in the existing SNC models, however, they did not consider downstream with multiple echelons as is observed in practice. The choice of transport mode (limited to the downstream) is another SNC decision considered in the existing literature, however, this was not incorporated in this study; mainly because the unit transportation cost/time of available transportation modes for this type of good is not substantially different (Kiesmüller, De Kok & Fransoo 2005). Instead, the distance between SN entities (which was not accounted for in the SNC literature at all) was considered in this study as it contributed significant time/cost to overall SN-level performance (Akanle & Zhang 2008).

SNC objectives: This study considered cost, lead-time and selected sustainability metrics as SN-level performance measures. The majority of SNC models proposed in the existing literature have focused on a single objective (i.e. SN cost), except for a few studies that have considered lead time along with cost, while formulating the SNC problem as of a multi-objective optimisation type.

Modelling approaches and solution methodologies used: This study incorporated both individual SN entity decisions and SN-level decisions in a way that modelled the decisions of the SN entities and evaluated the impact of those decisions at the SN-level. This was achieved using a MAS-based optimisation approach in combination with intelligent auctioning and bidding strategies. As reported in Chapter 2, the vast majority of the existing SNC models fall short of comprehensively capturing industry requirements such as SN characteristics, dealing with the changing SN conditions, and accounting for multiple SN-level performance measures that reflect diverse consumer needs (Fiedler, Sackmann & Haasis 2019; Shukla & Patel 2019). The majority of the SNC models proposed in the literature have addressed decision-making at the SN-level with no attention to the individual decisions of SN entities. Accordingly, many studies have formulated the SNC problem as a combinatorial optimisation problem (adopting a centralised decision-making approach) assuming that one (dominant) decision-maker acts to select the best set of SN entities (from all SN nodes) to achieve the expected SN-level performance. This way of modelling only partially addresses the SNC problem with little or no recognition of the real-world situation that SNs are formed as a result of multiple organisational entities collaborating to deliver an end product and/or service. Among the limited body of SNC literature, a few studies have attempted to address these needs from several different perspectives.

Akanle and Zhang (2008) have holistically addressed the SNC decisions involved across the SC. In their study, a typical SN was modelled in the form of a MAS, and incorporating changing production capacity levels of the SN entities within a dynamic SN context. The best combination of SN entities for each customer order was identified through a coordinated iterative bidding process. A set of reserve values (i.e. virtual prices for each node and a minimum virtual profit level for each SN entity), referred to as control parameters, were generated using a GA, upon which SN entities presented their bids given the condition that each SN entity maintained the minimum desired profit level. The chromosome used in the GA was a vector (i.e. a set of genes), which consisted of a full set of virtual prices for each SN node and a minimum virtual profit level for each SN entity. If a SN entity had the required production capacity, then operations cost and operations time were determined, and bids were presented for the invitation. Out of all winning bids, a combination of SN entities was formed, and then the combined performance was evaluated in terms of the total SN cost and lead-time. After evaluating the SN performance as to whether the due date has been met or the total SN cost is lower than the threshold, the bidding process continued by adjusting the virtual prices and minimum virtual profits for a given number of iterations in order to find an optimal set of SN entities.

By comparison, alternative bidding strategies have been employed by a number of studies including Wang et al. (2009); Jiao, You & Kumar (2006) and Lou, Chen & Ai (2004). These studies have used negotiation protocols such as argumentation-based negotiation (Wang et al. 2009), CNP with negotiation (Jiao, You & Kumar 2006) and case-based reasoning with CNP (Lou, Chen & Ai 2004). These protocols have their distinct advantages and limitations. Jiao, You and Kumar (2006) proposed an improved version of CNP by introducing a multi-contract negotiation process with multiple agents to negotiate with multiple SN entities. In their study, SN entities were selected based on their utility, which is a measure of goodness of the bid with respect to customer order requirements. If any of the selected SN entities was not compatible with the other SN entities in meeting the customer requirements, then the negotiation occurred iteratively until the consumer requirements were met. This multi-contract negotiation strategy expedites the decision-making process, thereby configuring the SN within a relatively short time. Furthermore, through the communication between negotiation agents, the proposed approach could enhance SN-level performance as well. Lou, Chen and Ai (2004) used case-based reasoning with CNP in order to enhance coordination efficiency. This method maintained a database (i.e., information on SN entities fulfilling a given order) of past fulfilled orders, referred to as cases. Once a new order was received, the requirements of that order were first compared against those of the cases in the database. Then depending on the availability of similar cases in the database, the same set of SN entities were used for the new order; otherwise, the steps of the general CNP were followed to find a set of suitable alternative SN entities. The compatibility of these SN entities across the SN was tested using an index for the coalition (which is calculated considering the payoff to the agent and cost of operations) subject to a set of constraints related to lead-time, cost and resource availability.

The main difference between the study of Akanle and Zhang (2008) and the other three studies referred to above is the way the bidding process was executed. Akanle and Zhang (2008) adopted a holistic approach to executing the bidding process with the participation of all SN entities simultaneously. The primary intention of this type of parallel bidding was to achieve SN-level optimisation. In contrast, the other studies adopted a cascading/tree-like structure, continuing the bidding process until the downstream SN entity had met the requirements of the upstream SN entities in terms of their local goals (e.g. profits). Through the cascading bidding process, a SN entity gets an opportunity to optimise its local goals without paying attention to achieving SN-level goals. There are a few other aspects worth considering in the models that adopted a cascading/tree-like bidding structure. For example, the study of Greco et al. (2013) used Bayesian network modelling to model the adaptive behaviour of SN entities in a way that incorporates the past bidding experience in subsequent bidding decisions. In comparison to other SNC models, using past experience in making bidding decision informs the way of accommodating the learnt knowledge in decision making.

By comparison, Sheremetov and Rocha-Mier (2008) did not use a bidding mechanism in selecting SN entities. Instead, they employed collective intelligence theory in evaluating the effects of adaptive behaviours of SN entities at the SN-level performance. A RL algorithm was used to model the decisions of SN entities with a local utility function and a Q-value, which contained perceived information about the environment. A generalised version of the Q-neutral algorithm was used for optimising SN-level performance. This is the only study found in the literature, which made an attempt to evaluate SN entity decisions at the SN-level.

The comprehensive approach used to develop the proposed MAOM in this study was inspired by the study of Akanle and Zhang (2008) and Sheremetov and Rocha-Mier (2008). The intelligent reverse-auctioning and bidding process was employed in this study; adapting the mechanism used by Akanle and Zhang (2008) with certain modifications in relation to the learning through the previous bidding and following multiple strategies to make situational bidding decisions. Instead of using the “virtual profit”, as determined by the central system, the proposed approach in this study allowed each SN entity to decide its own profit margins using its previous knowledge to calculate the bids, this enabled a more realistic representation of the autonomous behaviour of individual SN entities. This study only used a set of reserve values generated using GA as a means of selecting potential SN entities through the auctioning processes. Additionally, multiple strategies were followed as indicated in Figure 4.5 in making the bidding decisions. This reverse-auctioning process was continued, with learning through the bidding process, until the termination criteria were met. Q-learning, one of the RL algorithms, was used to make the bidding process-related decisions taking into consideration the non-deterministic nature of the SNC problem and the variability associated with the behaviour of SN entities. The Q-learning has a value iteration process by updating the Q-function in the Q-table using the reward gained from the selected action at a given state. The Q-function helps in predicting the best action in a given state to maximise the cumulative reward. In this study, the Q-table (as given in Table 4.1) was defined in the form of a matrix to store capacity levels and profit ranges (i.e., state-action). Although this study was inspired by the Q-learning used in Sheremetov and Rocha-Mier (2008), it adopted a more comprehensive approach, which includes parameters, conditions and constraints to simulate real-time decision-making. While Q-learning helps to achieve the goals of SN entities through making bidding decisions, those decisions were evaluated at the SN-level generating optimal alternative SNCs in order to meet the target product-market profile requirements.

From a mathematical point of view, the problem of finding optimal alternative SNCs belongs to the combinatorial optimisation type, which cannot be solved with an exhaustive search approach in polynomial time. Sheremetov and Rocha-Mier (2008) used a Q-neutral algorithm to configure the SN minimising the TSNC; a number of other studies (as mentioned in Section 6.2) used different meta-heuristic/evolutionary algorithms. This study employed NSGA-II (as outlined in Figure 4.16), one of the most popular multi-objective optimisation algorithms (Deb et al. 2001) and also proven to outperform other algorithms in computational efficiency and the solution quality (Godinez, Espinosa & Montes 2010; Niyomubyey et al. 2020).

6.5 Chapter Summary

This chapter has presented the discussion of the findings of this study, including an account of how these findings relate to those of the comparable previous studies. The key findings of this study can be summarised as follows:

- SN-level performance varies with SN characteristics in terms of structural, spatial and temporal dimensions, which were also found to be important to consider in making the SNC decisions
- SNC decisions under static and deterministic conditions alone do not address the challenges faced by SN decision-makers in a real-world business context
- Individual SN entities are adaptive, aiming to satisfy their local goals, which in turn leads to differences in SN-level performance
- Intelligent auctioning and bidding strategies enable SN entities to make competitive bids under changing SN conditions, which in turn, lead to improved SNC decisions, thus enhancing SN-level performance without having to share commercially sensitive information among all entities across the SN
- SNC decisions are different under static and dynamic conditions; hence, to configure the SN optimally, SNC decisions need to be tested under changing SN conditions

Overall, the study found that incorporating structural, spatial and temporal SN dimensions is important in making SNC decisions. None of the studies in the extant SNC literature has tested the SNC configuration problem considering all three dimensions concurrently, and at the level of detail that has been tested in this study. Accordingly, this study focused on examining how the above factors were incorporated into modelling SNCs towards achieving optimal SN-level performance, when individual SN entities were still aiming to satisfy their local goals, such as organisation-specific competitive priorities. This was achieved by implementing intelligent auctioning and bidding strategies for SN entities to make competitive bids, which in turn, lead to improved SNC decisions, and thereby enhance SN-level performance without having to share commercially sensitive information among all entities across the SN.

CHAPTER 7: CONCLUSIONS

7.1 Introduction

This study developed a comprehensive approach to support SNC decisions that enhance SN-level performance in catering for different product-market profiles under changing SN conditions. This chapter concludes the thesis, summarising the research effort and findings, and providing some concluding remarks on the research questions addressed, followed by an account of the contributions and limitations of this study, as well as with future research directions.

7.2 Summary of the research effort

SNs evolve in structural, spatial and temporal dimensions due to factors such as advancements in technology and information systems, shifting consumer needs, and changing environmental conditions. In the face of these changes, the effectiveness of SN design decisions, as represented in current practices, has been increasingly challenged, particularly in terms of achieving the desired SN-level performance (Oliveira, Lima & Montevechi 2016; Gerschberger et al. 2012; Choi, Dooley & Rungtusanatham 2001). In response to the limitations of the existing approaches to SN design, researchers have proposed numerous alternatives, including the notion of SNC. It is acknowledged in the literature that a well-configured SN can not only leverage the complementary strengths of SN partners to deliver better value, but also can utilise their combined capacity towards mitigating risks, guarding against disruptions and sustaining performance in dynamic environments. As such, the capacity of a SN to deliver superior customer value is largely determined by the way that SN is configured to deal with the challenges associated with changing conditions.

The majority of previous research on SNC has highlighted the potential of well-configured SNCs to leverage the complementary strengths of SN entities by virtue of the presence of alternative SN entity options in static and deterministic SN contexts. The review of SNC literature undertaken as part of this study revealed that the structural aspect of SNs had been incorporated into existing SNC models to a certain extent, however, limited attention was paid to spatial and temporal dimensions. Lack of a comprehensive and realistic representation of SN characteristics in current SNC models was another major drawback reported in the literature, which from a practice point of view limits the relevance of such models. In comparison, this study examined SNC decisions more holistically, focusing on both changing SN conditions (i.e., new products, uncertainties and dynamics) and leveraging the complementary strengths of SN entities to cater for different product-market profiles in stochastic and dynamic SN contexts.

To address the research problem as stated in Section 1.2, two research questions were set as given below:

(i) What are the key factors that underpin SNC decisions?

(ii) How can SNC decisions be supported through the identification of SNs that are optimally configured for different product-market profiles, under changing SN conditions?

Limitations in the extant SNC literature were addressed in this study by capturing the more realistic SN characteristics to model a multi-stage, multi-echelon SN, consisting of geographically dispersed and autonomous SN entities catering for distinct product-market profiles. Thus, the importance of capturing structural, spatial and temporal dimensions in modelling SNs to represent real-world contexts was identified and addressed in this study. Accordingly, the aim of this study was to take the above factors into account in the development of a comprehensive approach, with the selection of appropriate modelling and solution methodologies, to generate alternative optimal SNCs for varied product-market profiles to achieve the expected SN-level performance. This aim was achieved through developing the proposed MAOM, which is a MAS-based optimisation approach combining intelligent auctioning and bidding strategies. Consequently, the efficacy of the proposed approach was tested by assessing its capacity to account for more realistic SN contexts while accommodating the adaptive behaviour of SN entities in light of changing SN conditions. The proposed approach was also examined for its capacity for evaluating the impact of the decisions made at SN entity level on SN-level performance; i.e., in relation to generating alternative optimal SNCs that achieve the expected SN-level performance.

More specifically, the proposed MAOM was tested using a refrigerator SN case study drawn from the literature. Three types of simulation experiments were carried out. First, a baseline model was run under static and deterministic SN conditions, which represented the conditions reflected in the majority of extant literature. Then both scenario analysis and sensitivity analysis were performed to examine the deviations (from the baseline model) in the behaviour of SNCs under uncertain and dynamic conditions. Additionally, a further set of scenario analysis experiments was carried out to test the robustness of the MAOM; and further sensitivity analyses were performed to estimate the extent to which the SN-level performance is vulnerable to the changes in the attributes of SN entities collectively in each stage and individually as entities of the SN.

7.3 Summary of findings and conclusions on the research questions

Even though the importance of SNC decisions in light of the continuous evolution of SNs has been acknowledged in the literature, the existing analytics tools were found to be inadequate in terms of providing holistic solutions or practical guidance to aid SNC decision-making.

In relation to the two research questions stated above, it was found that accounting for structural, spatial and temporal dimensions is critical to making effective SNC decisions. The study further examined how the above three aspects were incorporated into modelling of SNCs towards achieving optimal SN-level performance, when individual SN entities are still aiming to satisfy their local goals such as organisation-specific competitive priorities. Additionally, attention was paid to SNC decision-making with minimal information sharing among SN entities, which recognised the real-world situation of organisations' reluctance to disclose commercially sensitive information. These modelling requirements were facilitated by the intelligent auctioning and bidding strategies, which enable the SN entities to make competitive bids under changing SN conditions; these, in turn, lead to improved SNC decisions, and the enhancement of SN-level performance. Taking the above conditions into account, this study demonstrated the value of the proposed modelling approach in terms of facilitating SNC decisions to sustain the competitiveness of SNs in a dynamic business environment, which is characterised by changing consumer requirements, as well as the variability associated with SN entity attributes and disruptions.

7.4 Contributions to knowledge and managerial implications

The importance of SNC decisions has been widely recognised in the SN literature in relation to building SN capacity to be responsive, robust and resilient in the face of changing SN conditions while dealing with the inherent complexities of evolving SNs with respect to structural, spatial and temporal dimensions. The review of more recent research also revealed opportunities for improving existing SNC models in terms of both their rigour and relevance.

One of the most significant research gaps reported in the literature was the lack of relevance of existing SNC models or their limited capacity to represent real-world SNC contexts. As such, this study made an attempt to model SNs in a more realistic problem context, while addressing multiple factors covering the structural, spatial, and temporal dimensions. Accordingly, a multi-stage, multi-echelon SN was modelled that considered the autonomous decision-making and spatial distribution of SN entities and incorporated changing SN conditions. The majority of the existing literature had assumed that SNs are formed as a result of centralised decision-making, which in turn has influenced the modelling and solution approaches employed to solve the SNC problem. The vast majority of previous studies have solved the SNC problem using combinatorial optimisation approaches, aimed at finding optimal SNC(s) based on the desired SN entity attributes. The primary limitation of those optimisation techniques is not incorporating individual (i.e. SN entity-level) decision-making which is essential to practitioners in terms of ensuring the relevance of any models developed. It is widely recognised that attributes, goals and strategies of SN entities, as well as the attributes of product-market profiles, continue to change, in dynamic business environments. This means the decisions of SN entities should be responsive to shifting product-market profiles and take into account the changing organisational and environmental conditions. In response to the above practical needs, the novelty of the proposed approach in this study comes from its capacity to account for the product-market profile, and the variability and disparities between individual entities, and have a comprehensive representation of SN characteristics, by the diligent selection and application of 'state-of-the-art' knowledge and technology.

In addressing the first research question, this study made a valuable contribution to theory, particularly by synthesising the state-of-the-art information on the topic of SNC modelling and then identifying the key factors that drive SNC decisions. In addition to this primary contribution, a number of theoretical insights were also drawn through the suite of experiments conducted as part of the study. These insights include: a deeper understanding of the relationships among SN entity level decisions, contextual factors and SN-level performance; a deeper appreciation of the role and significance of the input parameters used in modelling SNC decisions, thus being able to address the current limitations such as lack of information sharing between SC partners; and a range of other benefits that can be derived from the application of MASs, including how to optimise SNC decisions in environments where there is limited historical data available to be used.

In terms of contribution to practice, the proposed comprehensive approach allows for aligning relevant product-market profile attributes with the expected SN-level performance metrics by way of incorporating that requirement in selecting potential SN entities. Furthermore, while accounting for structural, temporal, and spatial dimensions in modelling SNCs to better reflect the real-world SN contexts, the proposed comprehensive approach demonstrated the relationship between SN entity-level decisions, changing SN conditions and SN-level performance. As such, the use of this model will help increase the understanding of SN dynamics at a fundamental level and help assess alternative scenarios by determining the sensitivity of model outcomes to certain parameters that represent the features of real-world SNs.

Potentially, this model can be used to enhance SNC decisions by any SN entity, as well as other parties such as SC analysts or consultants. The primary purpose of the proposed MAOM is to support SC managers with the necessary analytical support (insights) needed to holistically deal with multiple decisions (e.g., determining the most appropriate sourcing options and delivery lead times) which are capable of generating alternative optimal SNCs for a given product-market profile, including the attributes of volume, delivery lead-time, and WTP price. In addition to the above primary use, the proposed MAOM can be used as a tool to analyse the capacity of existing SN entities. For example, certain SN entities are capable of contributing to multiple product-market profiles, whereas other SN entities may not have that capability, depending on the state of their infrastructure, operations cost and operations time. Apart from identifying the competitiveness of SN entities as above, the proposed MAOM can be used to perform sensitivity analysis and thereby, estimate the extent to which the SN-level performance is vulnerable to changes in the attributes of SN entities collectively in each stage(s) or individually as entities of the SN. This enables risk mitigation strategies to be adopted as discussed in Section 6.2 and to be competitive in the business context.

Additionally, the proposed MAOM can be used to test the robustness of the SNC(s) generated under the initial baseline conditions by analysing a number of scenarios (i.e., possible future situations). Depending on the outcome of the scenario analysis, favourable (i.e., instances which make a low impact on SN performance) or unfavourable (i.e., instances which make a high impact on SN performance) SN contexts can be identified, which then could lead to appropriate managerial responses. In favourable scenarios, opportunities created to initiate and maintain suitable relationships with preferred SN entities, whereas, in unfavourable scenarios, mitigating actions can be taken such as identifying new SN entities to cope with such situations or negotiating with existing SN entities to deal with the new situations. Similarly, depending on the case at hand, a decision-maker can determine whether a simple strategy is adequate to address the problem or more specific strategies are required.

Furthermore, the proposed MAOM can be used to support SN design decisions such as capacity planning of existing facilities, identifying potential locations for new facilities and introducing new technologies to overcome inefficiencies in the current system. In this regard, the capacity of the proposed model to evaluate alternative SNCs can be invaluable. Moreover, the proposed MAOM can be used in designing a SN for the first time, for example, when introducing a new product, the extent to which existing SN can be used or decisions made such as prefered SN entity locations and their other attributes, including capacity, lead time and operations cost.

Compared to the existing models, the proposed MAOM effectively helps decision-making to be responsive, robust and resilient in the face of changing SN conditions, which is a significant contribution to practice. Accordingly, there is a distinct advantage in applying this type of decision support tool to enhance SNC decision-making.

7.5 Limitations and future research directions

This study addressed a number of significant research gaps identified through the review of extant SNC literature. As outlined in Section 7.4, there are noteworthy contributions to knowledge. However, a number of limitations of this study are also acknowledged. Addressing these limitations and accommodating certain other extensions could be considered in future studies.

A few limitations of this study can be considered in relation to modelling the behaviour of SN entities, implementing structural characteristics of SNs, as well as SN conditions and accounting for the constraints associated with SNC decisions. Some of those limitations are underpinned by the assumptions used in simulation modelling; i.e., assuming the same profit ranges and capacity levels for all SN entities; not incorporating some current practices such as outsourcing and overtime work; not splitting the customer demand between SN entities; and not testing the proposed model on multiple products or BOM. Many of these limitations can be addressed with minimal additional effort in future studies.

A major limitation of this study is that the proposed model was not validated using empirical data directly drawn from the industry, nor was it implemented in an industrial setting. Although adequate measures were taken to test the veracity of the model through other means such as sensitivity analysis and scenario analysis, it would be worthwhile to implement the model in the context of a real-world SN to more comprehensively test its efficacy. Further opportunities exist for extending and expanding this research to investigate the merits or otherwise of alternative modelling approaches and algorithms such as Real options/Game Theory (Trigeorgis & Tsekrekos 2018), Dynamic Metaheuristics (Yang, Jiang & Nguyen 2012) and improved Bayesian frameworks (Imani, Ghoreishi & Braga-Neto 2018) against those used in the proposed model.

Additionally, this study did not account for supplier switching costs in the proposed MAOM. In the context of strategic supply management, supplier switching is the phenomenon of a buyer choosing a new supplier to replace an existing supplier, with full or partial allocation of orders to the new supplier (Wagner & Friedl 2007; Burnham, Frels & Mahajan 2003). The primary motivations for supplier switching are the need for reducing costs and improving on other aspects of performance such as quality, delivery, flexibility or service (Uluskan, Godfrey & Joines 2017; Gosling, Purvis & Naim 2010). However, the literature also cites other reasons such as breakdown of relationships with existing suppliers, renewal of the existing supplier base and changes in the technologies, product architecture or materials used in relation to the product(s) concerned (Yen, Wang & Horng 2011; Lin, Lo & Sung 2006). These factors may still be directly or indirectly related to the primary reasons referred to above in that they would serve as underlying factors, given that the ultimate goal of an organisation is to sustain its success against a set of performance metrics.

The costs associated with switching suppliers are considered to be multi-dimensional, and may include those related to supplier evaluation and selection, building relationships with the new supplier and other investments required for accommodating a new supplier such as updating coordination, communication or transaction protocols and training of employees (Burnham, Frels & Mahajan 2003; Fornell 1992). Even though switching costs incur only once when the suppliers are changed, the literature suggests that these costs could be substantial given the opportunity costs involved, potential entry barriers they could create, and more broadly, the strategic significance of effective long-term relationships with suppliers (Yen, Wang & Horng 2011; Yi & He 2011). Additionally, switching costs may vary from organisation to organisation depending on the industry sector concerned and the stage of the SN they are part of, as well as the bargaining power that could be exercised by the buyer organisation (Uluskan, Godfrey & Joines 2017; Zhang, Tang & Hu 2015). Given their multidimensional and situational nature, capturing and quantifying switching costs can be quite challenging. In SN modelling literature, switching costs have been accounted for in terms of the difference between the savings achieved through switching and the fixed costs incurred in switching (Burnham, Frels & Mahajan 2003). The amount saved depends on the quantity purchased, unit price difference and benefits gained through distinct competitive strategies (Uluskan, Godfrey & Joines 2017). According to the classification of Burnham, Frels and Mahajan (2003), the fixed switching costs are expressed as a function of procedural switching costs, financial switching costs and relational switching costs. Procedural switching costs (the cost of time and effort) consist of economic risk, evaluation, learning, and setup costs. Financial switching costs include the loss of financially quantifiable resources such as benefit loss costs and monetary loss costs. Relational switching costs, involving psychological or emotional discomfort due to the loss of identity and the breaking of bonds such as personal relationship loss costs, brand relationship loss costs.

Having considered the significance of switching costs, as reported in SCM literature and the way they have been dealt with in SC modelling literature, this study chose not to incorporate switching costs explicitly into the proposed MAOM model. The reasoning behind this choice is briefly outlined below. First, in the context of this study, supplier switching occurs when the existing supply network configuration is no longer able to cater to the current market needs in term of responding to the changes in the product-market profile or delivering on the relevant competitive priorities. As such, the two options available to be considered are investing into the development of existing suppliers so that they could satisfy the expected performance levels or incurring the fixed costs associated with engaging a new supplier that is capable of meeting the desired performance levels. Given the difficulties associated with capturing all cost components associated with these two options at the level of detail and accuracy required to compute the net effect, it was assumed that the difference between the two options is minimal. Any differentials in production costs achieved by supplier switching are implicitly dealt with and evaluated through the bidding process. Nonetheless, there are two further opportunities to address the aspect of switching costs in future studies. In cases where empirical data is available on the components of switching costs, the proposed MAOM could be amended to incorporate switching costs as appropriate. Alternatively, switching costs could be considered in a more subjective and/or case-by-case basis as part of selecting the scenario-based Pareto-optimal SNCs.

The lack of information sharing across the SN remains a fundamental problem in relation to optimising SN-level performance, and the proposed MAOM has been developed to deal with this situation. In order to configure a SN holistically, there are a number of SNC decisions that need to be addressed. Such decisions include determining the location and capacity of the various SN facilities concerned, selection of suitable transport modes and the deployment of technologies across the SN. To make well-informed SNC decisions with respect to each of these aspects, the decision-maker will need to access relevant information such as the product-market profile of target markets, location-specific details, capacity levels of facilities, processing costs, processing times and the capabilities of individual SN entities involved. The role and impact of information in the context of SNC decisions can be considered from two key perspectives. First, the situation where there is incomplete information or imprecise information. This situation gives rise to poor SNC decisions at the individual entity level in terms of identifying and supporting relevant competitive priorities, which will in turn, result in poor SN-level performance, as well. Researchers have attempted to address this limitation through approaches involving some form of stochastic or fuzzy models. The second situation is where the required information may be available at the individual entity level, but not widely shared across the SN. Often, organisations are reluctant to share commercially sensitive information with those other than their immediate upstream and downstream SN partners. In such situations, even though the individual SN entities may be in a position to make effective decisions in relation to achieving their own goals, the resultant SN-level performance may still be sub-optimal. Numerous attempts have been made by researchers to address this issue through process integration, deployment of information and communication technologies and other broad-based initiatives such as collaborative planning, forecasting and replenishment. Despite these efforts, the lack of information sharing across the SN remains a fundamental problem in relation to optimising SN-level performance. As explained in Section 4.3.1 of this thesis, the proposed MAOM was designed to address this issue through a rather unique way. That is, the bidding strategy used in the MAOM allows the globally optimal SNs to be generated without having to share commercially sensitive information among all entities across the supply chain. The only information required to be released by the entities participating in the bidding process is the bidding price and promised lead time, which is consistent with the common industry practice. The other types of information required to run the model, such as the product architecture, product-market profile and transportation costs can all be derived from industry-based data or publicly available information. However, in cases where empirical data representing these parameters are readily available and can be shared across the SN, then it will only make the global optimisation effort more convenient and the outcomes of that process more refined and realistic. There are two key ways in which the information can be utilised. For example, information regarding product-market profile, processing times and processing/transportation costs can be used as direct inputs to the proposed MAOM (rather than having to derive those using other sources). Second, any additional data related to energy consumption, carbon footprint or socially responsible practices can be considered when evaluating the alternative Pareto-optimal SNCs.

Depending on the generic competitive strategy pursued, an organisation may choose to focus on excelling at certain aspects of its operations over the other aspects, in terms of out-performing their competitors. Accordingly, the attributes that the customers are looking for in their final purchasing decision become order-winning attributes while the other attributes that allow a product to go into a customer's shortlist are considered to be order-qualifying attributes. This means, even though the customers' final purchasing decision is driven by the order-winning attributes of a product or service offering, they also expect that product or service to perform at a threshold (i.e., an acceptable) level against order-qualifying attributes. To illustrate the efficacy of the proposed MAOM, operations costs and processing times at the SN entity level have been treated as order-winning attributes of the product, considering their relevance to the product-market profile concerned in term of supporting the individual SN entity-level goals. The other attributes such as quality, delivery, flexibility and service, are assumed to be at an acceptable level for all eligible SN entities. From a practical procurement perspective, this situation could be analogous to soliciting bids using a preferred supplier base.

Accordingly, in future studies, a number of extensions can be implemented with minimal modifications to the existing model. As presented in Figure 3.1, the three key steps of this proposed comprehensive approach can be implemented in alternative ways using state-of-the-art technology. In this study, customer requirements were captured in terms of three attributes using AHP method and using other approximations, however, in future studies, product-market profiles can be generated using demographic and historical data using data mining algorithms. Furthermore, in future studies, the proposed MAOM can be implemented on a cloud-based platform, using advanced technologies (e.g., Industry 4.0 and Logistics 4.0) and used in an industrial context. This can be further supported by more advanced machine learning tools to help with the decisions of individual SN entities. Accommodating the above alternative methods supported by the latest technologies could deliver a data-driven IoT-based decision support tool.

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APPENDIX 1: ESTIMATING PRODUCT-MARKET PROFILE ATTRIBUTES

Steps involve in AHP problem-solving approach to estimate the volume attribute

Step 1: Identify the goal, criteria, sub-criteria and alternatives

Goal: The goal of this problem is to estimate volume attribute of the product-market profile.

Criteria: per captia income, energy consumption and price level index

Alternatives: 10 demand regions (Manchester, Zaragoza, Milan, Munich, Hannover, Nuremberg, Oslo, Palermo, Paris, Prague)

Step 2: Find the rating between each criterion based on subjective opinion using Table A1.1 to construct the matrix estimating the relative importance of each criterion.

Table A1.1: Rating for each subjective judgment of preference

Subjective judgment of preference	**Numerical rating**
Extremely preferred	9
Very strong to extremely preferred	8
Very strongly preferred	7
Strongly preferred	6
Moderate to strongly preferred	5
Moderately preferred	3
Equally to moderately preferred	2
Equally preferred	1

Step 3: Conduct pairwise comparison between each criterion based on the value derived from subjective opinion.

The square matrix (see Table A1.2) is constructed comparing the rating of the criterion in row and column, respectively. It is calculated by dividing the row value by the column value. The elements in the diagonal of the matrix become one, and the elements in the lower triangle of the matrix are derived, taking the reciprocal of upper triangle elements. The weight of each criterion is defined as $w_{i,}$ which is determined to derive the normalized eigenvector (see Table A1.2 to A1.5) which is then checked for consistency. The elements in the normalized eigenvector is relevant weights of each criterion.

Table A1.2: Relative importance of each criterion

	Per capita income($)-country based	Energy consumption(per capita) kwh	PLI (Price level indices)for household appliances
Per capita income($)-country based	1.00	6.00	8.00
Energy consumption(per capita) kwh	0.17	1.00	5.00
PLI(Price level indices)for household appliances	0.13	0.20	1.00

Table A1.3: Step 1 of deriving the normalized eigenvector for criteria

	Per capita income($)-country based	Energy consumption(per capita) kwh	PLI(Price level indices)for household appliances
Per capita income($)-country based	1.00	6.00	8.00
Energy consumption(per capita) kwh	0.17	1.00	5.00
PLI(Price level indices)for household appliances	0.13	0.20	1.00
	1.29	7.20	14.00

Table A1.4: Step 2 of deriving the normalized eigenvector

	Per capita income($)-country based	Energy consumption(per capita) kwh	PLI(Price level indices)for household appliances
Per capita income($)-country based	0.77	0.83	0.57
Energy consumption(per capita) kwh	0.13	0.14	0.36
PLI(Price level indices)for household appliances	0.10	0.03	0.07

Table A1.5: Step 3 of deriving the normalized eigenvector

	Per capita income($)-country based	Energy consumption(per capita) kwh	PLI(Price level indices)for household appliances	Total
Per capita income($)-country based	0.77	0.83	0.57	2.18
Energy consumption(per capita) kwh	0.13	0.14	0.36	0.63
PLI(Price level indices)for household appliances	0.10	0.03	0.07	0.20

Step 4: Collect statistical data to construct the matrix for each criterion with respect to each alternative (i.e., consumer region).

Table A1.6: Statistical value of each criterion with respect to each alternative

l	Consumer region	Population	Per capita income	Energy consumption (per capita)	Price level index (PLI)
1	Zaragoza	674317	30278	5573	95
2	Milan	1251000	35823	5398	102
3	Munich	1388000	47590	7270	98
4	Hannover	532163	47590	7270	98
5	Nuremberg	509005	47590	7270	98
6	Paris	2244000	44538	7344	103
7	Prague	1247000	19563	6305	80

Step 5: Conduct pairwise comparison between alternatives (i.e., regions) for each criterion.

The square matrix is constructed comparing the value of the alternative of each criterion in row and column, respectively. It is calculated by dividing the row value and the column value. The elements in the diagonal of the matrix become one, and the elements in the lower triangle of the matrix are derived, taking the reciprocal of upper triangle elements. For the given criterion *i*, compare *k* number of alternatives and construct the square matrix and then find normalized eigenvector. The elements in the normalized eigenvector is relevant weights of each alternative (w_{ik}) of a given criterion.

Table A1.7: Relative importance of percapita income with respect to each alternative

		C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
		45,653	30,278	35,823	47,590	47,590	47,590	97,013
C1	30,278	1.0	0.8	0.6	0.6	0.6	0.7	1.5
C2	35,823	1.2	1.0	0.8	0.8	0.8	0.8	1.8
C3	47,590	1.6	1.3	1.0	1.0	1.0	1.1	2.4
C4	47,590	1.6	1.3	1.0	1.0	1.0	1.1	2.4
C5	47,590	1.6	1.3	1.0	1.0	1.0	1.1	2.4
C6	44,538	1.5	1.2	0.9	0.9	0.9	1.0	2.3
C7	19,563	0.6	0.5	0.4	0.4	0.4	0.4	1.0

Table A1.8: Step 1 of deriving the normalized eigenvector for each alternative

		C1	C2	C3	C4	C5	C6	C7
		45,653	30,278	35,823	47,590	47,590	47,590	97,013
C1	30,278	1.0	0.8	0.6	0.6	0.6	0.7	1.5
C2	35,823	1.2	1.0	0.8	0.8	0.8	0.8	1.8
C3	47,590	1.6	1.3	1.0	1.0	1.0	1.1	2.4
C4	47,590	1.6	1.3	1.0	1.0	1.0	1.1	2.4
C5	47,590	1.6	1.3	1.0	1.0	1.0	1.1	2.4
C6	44,538	1.5	1.2	0.9	0.9	0.9	1.0	2.3
C7	19,563	0.6	0.5	0.4	0.4	0.4	0.4	1.0
		14.9	12.6	9.5	9.5	9.5	10.1	23.1

Table A1.10: Relative importance of energy consumption with respect to each alternative

		C1	C2	C3	C4	C5	C6	C7
		5573	5398	7270	7270	7270	7344	6305
C1	5573	1.0	1.0	0.8	0.8	0.8	0.8	0.9
C2	5398	1.0	1.0	0.7	0.7	0.7	0.7	0.9
C3	7270	1.3	1.3	1.0	1.0	1.0	1.0	1.2
C4	7270	1.3	1.3	1.0	1.0	1.0	1.0	1.2
C5	7270	8.5	8.8	6.5	6.5	6.5	6.5	7.5
C6	7344	1.3	1.4	1.0	1.0	1.0	1.0	1.2
C7	6305	1.1	1.2	0.9	0.9	0.9	0.9	1.0

Table A1.11: Step 1 of deriving the normalized eigenvector for each alternative

		C1	C2	C3	C4	C5	C6	C7
		5573	5398	7270	7270	7270	7344	6305
C1	5573	1.0	1.0	0.8	0.8	0.8	0.8	0.9
C2	5398	1.0	1.0	0.7	0.7	0.7	0.7	0.9
C3	7270	1.3	1.3	1.0	1.0	1.0	1.0	1.2
C4	7270	1.3	1.3	1.0	1.0	1.0	1.0	1.2
C5	7270	8.5	8.8	6.5	6.5	6.5	6.5	7.5
C6	7344	1.3	1.4	1.0	1.0	1.0	1.0	1.2
C7	6305	1.1	1.2	0.9	0.9	0.9	0.9	1.0
		21.8	22.5	16.7	16.7	16.7	16.5	19.2

Table A1.12: Step 2 of deriving the normalized eigenvector for each alternative

		C1	C2	C3	C4	C5	C6	C7	
		5573	5398	7270	7270	7270	7344	6305	
C1	5573	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.48
C2	5398	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.47
C3	7270	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.63
C4	7270	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.63
C5	7270	0.4	0.4	0.4	0.4	0.4	0.4	0.4	3.62
C6	7344	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.64
C7	6305	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.55

Table A1.13: Relative importance of PLI with respect to each alternative

		C1	C2	C3	C4	C5	C6	C7
		95	102	98	98	98	103	80
C1	95	1.0	1.0	0.8	0.8	0.8	0.8	0.9
C2	102	1.0	1.0	0.7	0.7	0.7	0.7	0.9
C3	98	1.3	1.3	1.0	1.0	1.0	1.0	1.2
C4	98	1.3	1.3	1.0	1.0	1.0	1.0	1.2
C5	98	8.5	8.8	6.5	6.5	6.5	6.5	7.5
C6	103	1.3	1.4	1.0	1.0	1.0	1.0	1.2
C7	80	1.1	1.2	0.9	0.9	0.9	0.9	1.0

Table A1.14: Step 1 of deriving the normalized eigenvector for each alternative

		C1	C2	C3	C4	C5	C6	C7
		95	102	98	98	98	103	80
C1	95	1.0	0.9	1.0	1.0	1.0	0.9	1.2
C2	102	1.1	1.0	1.0	1.0	1.0	1.0	1.3
C3	98	1.0	1.0	1.0	1.0	1.0	1.0	1.2
C4	98	1.0	1.0	1.0	1.0	1.0	1.0	1.2
C5	98	1.0	1.0	1.0	1.0	1.0	1.0	1.2
C6	103	1.1	1.0	1.1	1.1	1.1	1.0	1.3
C7	80	0.8	0.8	0.8	0.8	0.8	0.8	1.0
		10.7	10.0	10.4	10.4	10.4	9.9	12.7

Table A1.15: Step 2 of deriving the normalized eigenvector for each alternative

		C1	C2	C3	C4	C5	C6	C7	
		95	102	98	98	98	103	80	
C1	95	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.94
C2	102	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1.00
C3	98	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.97
C4	98	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.97
C5	98	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.97
C6	103	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1.01
C7	80	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.79

Table A1.16: Relative importance of population with respect to each alternative

		C1	C2	C3	C4	C5	C6	C7
		674317	1251000	1388000	532163	509005	2244000	1247000
C1	674317	1.0	0.5	0.5	1.3	1.3	0.3	0.5
C2	1251000	1.9	1.0	0.9	2.4	2.5	0.6	1.0
C3	1388000	2.1	1.1	1.0	2.6	2.7	0.6	1.1
C4	532163	0.8	0.4	0.4	1.0	1.0	0.2	0.4
C5	509005	0.8	0.4	0.4	1.0	1.0	0.2	0.4
C6	2244000	3.3	1.8	1.6	4.2	4.4	1.0	1.8
C7	1247000	1.8	1.0	0.9	2.3	2.4	0.6	1.0

Table A1.17: Step 1 of deriving the normalized eigenvector for each alternative

		C1	C2	C3	C4	C5	C6	C7
		674317	1251000	1388000	532163	509005	2244000	1247000
C1	674317	1.0	0.5	0.5	1.3	1.3	0.3	0.5
C2	1251000	1.9	1.0	0.9	2.4	2.5	0.6	1.0
C3	1388000	2.1	1.1	1.0	2.6	2.7	0.6	1.1
C4	532163	0.8	0.4	0.4	1.0	1.0	0.2	0.4
C5	509005	0.8	0.4	0.4	1.0	1.0	0.2	0.4
C6	2244000	3.3	1.8	1.6	4.2	4.4	1.0	1.8
C7	1247000	1.8	1.0	0.9	2.3	2.4	0.6	1.0
		14.3	7.7	6.9	18.1	18.9	4.3	7.7

Table A1.18: Step 2 of deriving the normalized eigenvector for each alternative

		C1	C2	C3	C4	C5	C6	C7	
		674317	1251000	1388000	532163	509005	2244000	1247000	
C1	674317	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.70
C2	1251000	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1.30
C3	1388000	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1.44
C4	532163	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.55
C5	509005	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.53
C6	2244000	0.2	0.2	0.2	0.2	0.2	0.2	0.2	2.33
C7	1247000	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1.29

Step 5: Calculate the rating for each alternative.

The derived weights (w_{ik}) for each alternative for each criteria is multiplied by the weight of the respective criteria w_i and aggregate it to get the total weight. The total weight of the alternative k, W_k; $W_k = w_{1k}w_1 + w_{2k}w_2 + \ldots + w_{Ik}w_I$

Table A1.19: Normalised eigenvector for each criterion

l	City	Per capita income($)-country based	Energy consumption (per capita) kwh	PLI(Price level indices) for household appliances	Population
1	Zaragoza	0.67	0.48	0.94	0.70
2	Milan	0.79	0.47	1.00	1.30
3	Munich	1.05	0.63	0.97	1.44
4	Hannover	1.05	0.63	0.97	0.55
5	Nuremberg	1.05	3.62	0.97	0.53
6	Paris	0.99	0.64	1.01	2.33
7	Prague	0.43	0.55	0.79	1.29

Table A1.20: The derived weight for each alternative

l	City	Per capita income($)-country based	Energy consumption (per capita) kwh	PLI(Price level indices) for household appliances	Population	
		0.42	0.23	0.79	2.55	
1	Zaragoza	0.67	0.48	0.94	0.70	1.44
2	Milan	0.79	0.47	1.00	1.30	2.96
3	Munich	1.05	0.63	0.97	1.44	3.50
4	Hannover	1.05	0.63	0.97	0.55	1.23
5	Nuremberg	1.05	3.62	0.97	0.53	1.88
6	Paris	0.99	0.64	1.01	2.33	5.70
7	Prague	0.43	0.55	0.79	1.29	2.99

APPENDIX 2: REFRIGERATOR SUPPLY NETWORK

Table A2.1: Parameter values of refrigerator components

No	Component	Material	Weight (g)	Price (yen)	Mfg. cost (yen)	Mfg. energy (kWh)
1	Cabinet frame	Fe	23606	18000	5313	72.9
2	Cabinet	Plastic	29313	78800	24313	147.7
3	Cabinet pipe	Cu	326	2000	558	1.0
4	Duct	Plastic	1028	4000	1265	5.2
5	Fan motor	Fe	483	2600	851	1.5
6	Evaporator case	Plastic	897	6000	1940	4.5
7	Accumulator	Fe	177	1400	461	0.6
8	Evaporator	Al	532	5000	1401	1.6
9	Back grill	Fe	986	2700	867	3.0
10	Compressor	Fe	7985	8000	2401	24.7
11	sideboard	Fe	980	4200	1367	3.0
12	radiator	Fe	2669	4000	1244	8.2
13	duct	Plastic	633	1700	525	3.2
14	Base	Fe	1240	2600	825	3.8
15	Door1	Fe	2693	6000	1910	8.3
16	Door2	Fe	669	2000	644	2.1
17	Door3	Fe	1838	2500	772	5.6
18	Door4	Fe	1834	2500	772	5.6
19	Gasket	Plastic	100	1500	493	0.5
20	Door plastic	Plastic	6709	15500	4719	33.8
21	SPCB	Plastic	3113	14700	4693	15.7
22	MPCB	Fe	1564	18500	6115	1.1
23	Heater	Al	112	4200	1344	0.35
24	Tank	Plastic	1412	10300	3339	4.4
25	Dryer	Cu	111	1300	396	0.3

Source: Umeda et al. (2000)

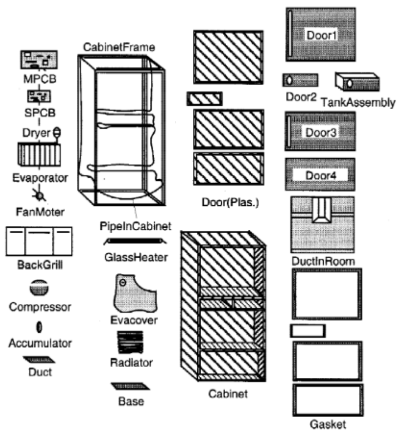

Figure A2.1: Physical appearance of components manufacture in 1st tier supply stage

Table A2.2: Operations cost of each node of refrigerator SN

Tier 2 supply stage node		Tier 1 supply stage node			Manufacturing SN node		Distribution SN node	
Type	OP cost ($)	Type	OP cost ($) Individual	OP cost ($) Total	Type	OP cost ($)	Type	OP cost ($)
Fe	49	Cabinet frame	53.13		Product assembly	10	Storing and dispatching	5
Plastic	88	Door1	19.1					
Cu	5	Door2	6.44					
Al	15	Door3	7.72					
		Door4	7.72					
		Base	8.25					
		Sideboard	13.67					
		Back grill	8.67					
		mpcb	61.15					
				185.85				
		Compressor	24.01					
		Radiator	12.44					
		fan motor	8.51					
		Accumulator	4.61					
				49.57				
		Cabinet	243.13					
		Duct	12.65					
		Evaporator case	19.4					
		Duct	5.25					
		Gasket	4.93					
		Door plastic	47.19					
		SPCB	46.93					
		Tank	33.39					
				412.87				
		Cabinet pipe	5.58					
		Dryer	3.96					
				9.54				
		Evaporator	14.01					
		Heater	13.44					
				27.45				

Table A2.3: Operations time of each node of refrigerator SN

Tier 2 supply stage node		Tier 1 supply stage node			Manufacturing SN node		Distribution SN node	
Type	OP time (min)	Type	OP time (min) Individual	OP time (min) Total	Type	OP time (min)	Type	OP time (min)
Fe	30	Cabinet frame	30		Product assembly	45	Storing and dispatching	5
Plastic	50	Door1	20					
Cu	10	Door2	20					
Al	20	Door3	20					
		Door4	20					
		Base	15					
		Sideboard	12					
		Back grill	10					
		mpcb	10					
				157				
		Compressor	60					
		Radiator	30					
		fan motor	20					
		Accumulator	15					
				125				
		Cabinet	15					
		Duct	13					
		Evaporator case	12					
		Duct	10					
		Gasket	10					
		Door plastic	7					
		SPCB	7					
		Tank	3					
				77				
		Cabinet pipe	7					
		Dryer	3					
				10				
		Evaporator	7					
		Heater	8					
				15				

Table A2.4: Energy consumption of each node of refrigerator SN

Tier 2 supply stage node		Tier 1 supply stage node			Manufacturing SN node		Distribution SN node	
Type	OP energy (Kwh)	Type	OP energy (Kwh) Individual	OP energy (Kwh) Total	Type	OP energy (Kwh)	Type	OP energy (Kwh)
Fe	340.26825	Cabinet frame	73		Product assembly	0.15	Storing and dispatching	0.05
Plastic	1319.963	Door1	8.3					
Cu	17.360625	Door2	2.1					
Al	94.99734	Door3	5.6					
		Door4	5.6					
		Base	3.8					
		Sideboard	3					
		Back grill	3					
		mpcb	1.1					
				105.5				
		Compressor	24.7					
		Radiator	8.2					
		fan motor	1.5					
		Accumulator	0.6					
				35				
		Cabinet	1					
		Duct	3.2					
		Evaporator case	1.6					
		Duct	5.2					
		Gasket	0.5					
		Door plastic	33.8					
		SPCB	15.7					
		Tank	4.4					
				65.4				
		Cabinet pipe	1					
		Dryer	0.3					
				1.3				
		Evaporator	1.6					
		Heater	0.4					
				2				

Table A2.5: List of SN entity attributes

Node	City	SN entity index	PC_{ijk} (\$)	PT_{ijk} (mins)	AC_{ijk} (in units)	λ^1_{ijk}	λ^2_{ijk}	EC_{ijk} (KJ)
1	Madrid	111	60	39	9000	0.3	0.2	20
	Lyon	112	71	36	12600	0.4	0.3	30
	Nice	113	69	37	14400	0.5	0.4	25
	Naples	114	63	40	15120	0.1	0	22
	Berlin	115	67	30	16920	0.2	0.1	23
	Stuttgart	116	68	31	16560	0	0.1	21
	Essen	117	65	30	15120	0.11	0.2	20
	Krakow	118	50	35	14400	0.15	0.23	15
	Kharkiv	119	47	43	13320	0.22	0.14	17
	Odessa	1110	48	45	14040	0.32	0.15	13
2	Barcelona	121	95	64	21600	12	0.25	5
	Sevilla	122	94	63	14400	10	0.15	3
	Nantes	123	109	60	23400	15	0.02	2
	Zurich	124	92	57	25200	17	0.001	3
	Lausanne	125	91	56	22680	10	0.001	4
	Winterthur	126	90	55	25920	12	0.02	6
	Milan	127	103	65	21600	15	1.5	1
	Dortmund	128	107	50	19800	14	0.5	2
	Istanbul	129	100	75	20520	10	0.55	3
	Izmir	1210	102	76	21600	20	1	2
3	Lisbon	131	9	10	10800	15	2	2
	Amadora	132	8	11	16200	10	1	3
	Coimbra	133	7	9	12600	12	1.5	2
	Szeged	134	6	14	14400	17	3	1
	Plovdiv	135	5	14	15120	15	1	1
	Varna	136	4	15	13320	20	2.5	3
	Burgas	137	5	14	18000	25	1	5
	Vienna	138	10	12	16200	22	1.5	2
	Linz	139	11	12	14400	21	2	4
4	Valencia	141	16	20	16200	0.3	0.4	17
	Paris	142	15	23	12600	0.4	0.3	20
	Bucharest	143	18	15	14400	0.5	0.2	15
	Craiova	144	17	20	18000	0.2	0	18
	Kiev	145	30	25	18720	0.1	0.1	20
	Athens	146	15	21	18000	0	0.2	21
	Heraklion	147	18	19	16200	0	0.3	23
	Volos	148	16	20	16920	0.4	0.1	20

Node	**City**	**SN entity index**	PC_{ijk} **($)**	PT_{ijk} **(mins)**	AC_{ijk} **(in units)**	λ_{ijk}^{1}	λ_{ijk}^{2}	EC_{ijk} **(KJ)**
5	Almada	251	186	160	7200	0.3	0.4	20
	Zaragoza	252	188	156	18000	0.4	0.3	22
	Marseille	253	195	154	5400	0.5	0.2	23
	Basel	254	187	150	9000	0.3	0	19
	Turin	255	189	158	10800	0.2	0.1	18
	Munich	256	191	147	8640	0.1	0.2	20
	Amsterda m	257	192	153	7200	0.4	0.15	21
	Groningen	258	193	154	9000	0	0	22
6	Presov	261	52	145	7200	0.3	0.4	40
	Trnava	262	53	144	9000	0.4	0.3	42
	Martin	263	52	145	10800	0.1	0.2	40
	Dnipro	264	49	147	12600	0.2	0.1	35
	Larissa	265	54	143	7200	0	0	30
	Jonava	266	51	146	8640	0.2	0	32
	Ankara	267	56	135	7200	0.3	0.2	40
7	Antwerp	271	425	17	21600	0.3	0.4	10
	Brussels	272	424	15	9000	0.4	0.3	12
	Geneva	273	415	20	7920	0.5	0.2	10
	Rotterdam	274	422	25	19800	0.1	0	12
	Katowicw	275	413	21	22320	0.2	0	15
	Ostrava	276	414	20	21600	0	0.2	20
	Budapest	277	412	23	20520	0	0.3	17
	Alytus	278	412	25	19800	0.1	0.15	20
	Salzburg	279	421	27	20000	0	0.2	15
	Bursa	2710	417	20	19000	0	0.1	16
8	Porto	281	13	14	14400	0.3	0.4	9
	Braga	282	12	15	16200	0.4	0.3	7
	Ghent	283	20	12	15480	0.5	0.2	6
	Bruges	284	19	13	25200	0.5	0.2	5
	Eindhoven	285	16	10	12600	0.2	0.1	10
	Bratislava	286	11	20	15120	0.15	0.15	12
	Nitra	287	10	19	13500	0.1	0	11
	Sofia	288	8	21	14000	0.4	0.3	13
	Ruse	289	9	22	14500	0.2	0	10
	Innsbruck	2810	15	18	15000	0	0.1	9
9	Murcia	291	32	18	16200	0.3	0.4	9
	Toulouse	292	40	16	19800	0.4	0.3	5
	Rome	293	33	20	18000	0.2	0	10

Node	City	SN entity index	PC_{ijk} ($)	PT_{ijk} (mins)	AC_{ijk} (in units)	λ^1_{ijk}	λ^2_{ijk}	EC_{ijk} (KJ)
	Lublin	294	28	15	18720	0.1	0.15	12
	Prague	295	32	16	16200	0.15	0.2	15
	Olomouc	296	31	17	16920	0.2	0.3	10
	Košice	297	30	27	18000	0	0.15	9
	Iași	298	28	21	18000	0.2	0.2	10
	Donetsk	299	27	25	17500	0.1	0.1	12
	Patras	2910	33	25	16000	0.3	0.15	11
	Graz	2911	35	26	15000	0	0.25	15
10	Namur	3101	25	50	18000	0.3	0.4	10
	Bern	3102	18	48	19800	0.4	0.3	12
	Palermo	3103	22	51	21600	0.3	0.4	9
	Hamburg	3104	24	45	18000	0	0	15
	Warsaw	3105	12	49	16200	0.2	0	12
	Oradea	3106	10	52	16920	0.3	0.15	14
	Kaunas	3107	11	60	15120	0.5	0.6	13
11	Funchal	4111	9	23	9000	0.3	0.4	20
	Palma	4112	10	19	12600	0.4	0.3	15
	Bilbao	4113	10	18	14400	0.4	0.3	25
	Strasbourg	4114	16	16	15120	0.2	0	20
	Lille	4115	15	17	14400	0.5	0.2	25
	Leuven	4116	17	20	12600	0.3	0	30
	Genoa	4117	11	21	10800	0.1	0.15	32
	Bologna	4118	11	22	9000	0.3	0.4	20
	Dresden	4119	12	21	12600	0.4	0.3	15
	Bremen	4120	14	10	14400	0.4	0.3	25
	Utrecht	4121	14	15	15120	0.2	0	20
	Poznan	4122	7	14	14400	0.5	0.2	25
	Brno	4123	8	17	12600	0.3	0	30
	Liberec	4124	8	16	10800	0.1	0.15	32
	Debrecen	4125	7	28	9000	0.3	0.4	20
	Arad	4126	6	20	12600	0.4	0.3	15
	Zaporizhia	4127	5	21	14400	0.4	0.3	25
	loannina	4128	5	22	15120	0.2	0	20
	Pleven	4129	4	28	14400	0.5	0.2	25
	Rhodes	4130	4	27	12600	0.3	0	30
	Klagenfurt	4131	4	26	10800	0.1	0.15	32
	Vilnius	4132	7	25	12500	0	0.1	25
	Bregenz	4133	6	25	10000	0	0.2	20

Table A2.6: Country-specific details

Country	labour cost (hourly)	Manufacturing Competitiveness Index	Investment on high-tech industries (in Euro millions)
Belgium	39.6	48.3	830
Bulgaria	4.9	43.2	93
Czech Republic	11.3	55.3	316
Denmark	42.5	74.2	507
Germany	34.1	93.9	4914
Greece	14.5	10	53
Spain	21.2	50.6	504
France	36.0	55.5	2047
Italy	28.2	46.5	1273
Lithuania	8.0	12.1	18
Hungary	9.1	13.5	462
Netherlands	34.8	55.7	confidential
Austria	34.1	58.9	625
Poland	9.4	59.1	266
Portugal	14.1	37.9	105
Romania	6.3	42.8	229
Slovakia	11.1	32.5	102
Switzerland	58.4	63.6	3059
Ukrain	32.2	53.6	not available
Turkey	35.6	46.2	not available