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A Hybrid Approach for The Design of Facility Location and Supply Chain Network Under Supply and Demand Uncertainty: A Systematic Review

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A Hybrid Approach for The Design of Facility Location and Supply
Chain Network Under Supply and Demand Uncertainty:
A Systematic Review

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ABSTRACT

In today's extremely competitive marketplace, firms are facing the need to meet or exceed increasing customer expectations while cutting costs to stay competitive in a global market. To develop competitive advantage in this business climate, companies must make informed decisions regarding their supply chain.

In recent years, supply chain networks have received increasing attention among companies. The decision makers confront the network design problem in different situations. In order to make decisions, especially in strategic supply chain management, decision makers must have a holistic view of all the components. Supply chain network design, particular facility location problems, is one of the most complex strategic decision problems in supply chain management

The aim of this dissertation is to make an inquiry about the facility location problems and related issues in supply chain and logistics management, and the use of modelling approaches to solve these problems.

The methodology is to construct a review protocol by forming a review panel, and developing a detailed search strategy with clear inclusion and exclusion criteria. In addition, the measurement for evaluating the quality of studies is presented with a strategy for extracting data and synthesising the methodologies.

The search results show the background of the facility location problems, the importance and the basic questions of these problems. The taxonomy of facility location problems with eighteen factors is presented. The basic static and deterministic problems in facility location including the covering, centre, median and fixed charge problems are discussed. Also, the extension of facility location problems comprises of location-allocation, multi-objective, hierarchical, hub, undesirable and competitive problems. In terms of uncertainty, dynamic, stochastic and robust facility location problems are presented.

Finally, strengths and weaknesses of different modelling approaches are discussed; importantly, gaps from the review process are indentified. Recommendations of future research are described; and the facility location problem to be addressed by the proposed research is shown. In addition, contributions of the proposed facility location problem are illustrated.

Keywords:

Facility Location Problem; Logistics and Supply Chain; Optimisation; Simulation; Hybrid Approach

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1 Introduction

1.1 Aim of the review

The aim of the review is to make an inquiry about the facility location problems and related issues in supply chain and logistics management, and the use of modelling approaches to solve these problems. The review is conducted using the systematic review approach (Tranfield, Denyer, & Smart, 2003). This begins with a scoping study to provide a broad view. Next, the methodology is constructed and applied in order to make sure that essential resources are not overlooked during the review. Finally, findings are reported with critical discussion, particularly strengths, weaknesses and gaps in literatures.

1.2 Structure of the review

The review comprised of the following structure:

Chapter 1 is this introduction chapter.

Chapter 2 describes the scoping for this study. This chapter presents study background including the answers for important questions: Why is facilities location a key issue?, What are the alternative approaches for facility location problems?, and What are the benefit of modelling over other approaches? Ontology and epistemology as primarily perspective of this review are described. Then, research and review questions are posted. Finally, the prospective research contribution is also illustrated.

Chapter 3 details the methodology behind the systematic review. It outlines the review process including the setting up the consultation panel, search strategy, selection criteria, quality appraisal, data extraction, and data synthesis, respectively. This chapter attempts to explain the primary processes of performing a systematic review which enables it to perform in a “systematic, transparent and reproducible” manner.

Chapter 4 presents a statistical summary of the search results. The evidence is analysed by theme, year, type of book/journal and geographical location.

Chapter 5 describes and synthesises the evidence found from the literature search. First, the theoretical background, the problem-solving process, and modelling approaches are reviewed. Then, a complexity analysis is presented to explain why the interesting problems are difficult to solve. Next, a synthesised taxonomy of facility location problems is described; and various types of facility problems – static, deterministic, dynamic, extended and uncertain problems – are depicted. Finally, strengths, weaknesses and gaps in the literature are indentified.

Chapter 6 discusses and summaries the review. The major topics of the review are also considered critically in light of the review questions. This chapter discusses strengths and weaknesses of different modelling approaches. Then, the gaps from the review process are indentified. Next, recommendations of future research are described; and the facility location problem to be addressed by the proposed research is shown. Finally, contributions of the proposed facility location problem are illustrated.

2 Scoping Study

2.1 Study background

In today's extremely competitive marketplace, firms are facing the need to meet or exceed increasing customer expectations while cutting costs to stay competitive in a vicious global market. To develop competitive advantage in this business climate, companies must make informed decisions regarding their supply chain.

Decisions in the supply chain can be classified into three categories: strategic, tactical and operational decisions (Simchi-Levi, Kaminsky, & Simchi-Levi., 2008). The strategic decisions involve determining the number and location of facilities such as manufacturing plants, warehouses and distribution centres. They take several years to construct and have a long lasting impact on the supply chain. The tactical decisions are concerned with production and distribution networks, often related to the flows of goods between existing facilities, and stock location and quantity decisions, which may be evaluated monthly to quarterly. The operational decisions involve production planning and scheduling and are usually reviewed daily to weekly.

Typically when facilities are located and capacity allocated the overall objectives are to maximize the overall profit, or to minimize their total cost while ensuring they offer customers an appropriate service level. Managers always face many trade-offs during the design of supply chain network. For instance, many warehouses enable local markets to be served which can reduce transportation costs. This improves the response time to customers; however, this tends to increase the facilities and holding costs incurred by a company.

The decision makers confront the network design problem in different situations. First, they must make a decision on location issues where facilities are set up, then, the capacities that will be allocated to each facility. Finally, they must assign current demand to the available facilities and identify channels, modes, and routes which their merchandise will be transported.

According to Chopra and Meindl (2005), the following information is ideally available in making the design decision at least on an annual basis:

- Location of supply sources and markets
- Location of potential facility sites
- Demand forecast by market
- Facility, labour and material costs by site
- Transportation costs between each pair of sites
- Inventory costs by site and as a function of quantity
- Sale price of product in different regions
- Taxes and tariffs

- Desired response time and other service factors

In order to make decisions, especially in strategic supply chain management, decision makers must have a holistic view of all the components that represent the supply chain network and must be able to understand, plan and evaluate their supply chain performance.

2.1.1 Why is facilities location a key issue?

The facility location problem was first addressed by Weber who said *"The question of the location of industries is part of the general problem of the local distribution of economic activities. In each economic organisation and in each stage of technical and economic evolution there must be a "somewhere" as well as a "somehow" of production, distribution, and consumption"* (Weber & Friedrich, 1929a).

Brandeau and Chiu (1989) surveyed over 50 representative problems and defined location problem as *"a spatial resource allocation problem. In the general location paradigm, one or more service facilities ('servers') serve a spatially distributed set of demands ('customers'). The spatial topology being modelled may be a general network, or a specialized network (e.g., a tree). The objective is to locate facilities (and perhaps allocate customers to servers) to optimise an explicit or implicit spatially dependent objective."*

Facility location problems are central to the concern of a number of researchers and practitioners in many areas, as is evident by the articles in professional journals, such as Management Science, European Journal of Operation Research, International Journal of Production Research, Logistics and Transportation Review, Journal of Farm Economics, Geographical Analysis, Econometrics, Transportation Science, etc. Facility location problems are also critically important topic in logistics and supply chain management (Guedes, 1994).

Location of a facility determines the distribution pattern and associated characteristics such as cost, time and service. Placement of one or more facilities, each in optimum locations and assigning the customers to them in the best possible manner, not only improves flow of material and services offered by the facility to customers, also utilises the facilities in an optimum manner, thereby reducing a need for multiple redundant facilities.

The basic question may be to decide how to choose from the known feasible locations or from an infinite number of locations, in which to place a facility and how to assign the customers to this facility. In terms of facilities and customers, the meanings are defined according to the nature of the problem. For instance, in determining suitable locations for industrial plants in order to serve the demands from various regions in the country, the plants are the facilities, and the product users are the customers. In transportation services, location of a hub is important to determine how to serve different districts. Other examples include location of fire stations, hospitals, electric power plants, and even equipment in machine shops.

Several businesses face these problems in the real-world: for example, the automotive industry (Nozick & Turnquist, 2001), the hardware/electronic industry (Sabri & Beamon, 2000), the chemical industry (Jung, Blau, Pekny, Reklaitis, & Eversdyk, 2004; Altiparmak, Gen, Lin, & Karaoglan, 2009), food industry (Leven & Segerstedt, 2004), the forestry and agriculture industry (Troncoso & Garrido, 2005; Piewthongngam, Pathumnakul, & Setthanan, 2009), and the military (Cusick, 2004; Overholts Ii, Bell, & Arostegui, 2009).

2.1.2 What are the alternative approaches for facility location problems?

There are many approaches to the facility location problem. A primary concern for facility location is to analyse the main factors influencing a decision. According to Sule (2001), site selection is a collective decision. The analysis team including executives, managers, and engineers consider the important factors which include:

- Transportation facilities
- Labour supply
- Availability of land
- Nearness to markets
- Availability of suitable utilities
- Proximity to raw materials
- Geographic and weather characteristics
- Taxes and other laws
- Community attitudes
- National security
- Proximity to the company's existing plants

While several companies think about location analysis factors in such aspects, many multinational corporations add more considerations, e.g. political, social, and local factors in their investment decision. Some of these characteristics are interrelated.

A traditional procedure is to weight these factors and to rank each site in order to accomplish a decision-making process. The main advantage of the rating method is simplicity for its application. One can use personal judgement and the knowledge of the problem for each decision. However, it is obvious that the ranking obtained by this method is largely subjective (Sule, 2001). When the factors are evaluated, decision makers express an analyst's feelings that are measured in terms of assigned weights. It is possible that different analysts might choose varying weights for the same site conditions, leading to wholly diverse site selections.

A useful alternative method is an analytic hierarchy process (AHP), which was developed by Thomas L. Saaty (1980). It is a multi-criteria decision-making method using hierarchic structures to represent a decision problem and developing priorities for alternatives based on the decision maker's judgements. It is able to evaluate both subjective and objective criteria with the rank order of the alternatives, or the relative standing measured on a ratio scale. There are a number of studies developed by AHP in different areas, and it has been well established as one of the most powerful and capable decision-making tools available today (Sule, 2001). The AHP can break down the problem into hierarchy and helps simplify the difficulty to a large extent. It uses pair comparisons of the decision elements which can help the decision-makers focus only on the two factors under consideration; therefore, the judgements are considered more consistent and objective. The subjective factors effecting a decision can be merged with the objective ones. Another advantage of the AHP is its ability to underline the inconsistencies in the rating procedure, if there are any. Other extension methods include, for example, a multi criteria approach proposed by Tabari, Kaboli, Aryanezhad, Shahanaghi and Siadat (2008) which offered a hybrid fuzzy AHP considering objective, critical and subjective factor in their model.

Modelling techniques are one of the most popular methods to tackle facility location problems. Models can be a formal representation of theory or formal account of empirical observation. They can be mathematical or non-mathematical. Non-mathematical models include physical three-dimensional building models, conceptual models (e.g. Porter's five-force model), and organisational models. This study focuses on mathematical models which include financial models, optimisation models, and simulation models.

2.1.3 What are the benefits of modelling over other approaches?

In the previous section alternative methods to modelling, for facility location problems, were discussed. These techniques have their limitations, for instance they are largely influenced by subjective and personal opinions, therefore, may not always result in an optimum solution. In addition, they cannot answer more complicated and important questions, i.e. capacity allocation "How much capacity should be allocated to each facility?", market allocation "What markets should each facility serve?", and supply allocation "Which supply sources should feed each facility?".

A mathematical model is usually an abstract representation of a real system, but the model is simpler than the real system. In general management science, several studies apply the modelling approaches; inventory control, transportation and network problems are typical instances of such applications (Littlechild & Shutler, 1991). Benefits of using mathematical modelling approaches are given in the following list (Fishman, 1978).

- Enables an investigator to organise his/her theoretical beliefs and empirical observations about a system and to deduce the logical implications of this organisation.
- Leads to improved system understanding.
- Brings into perspective the need for detail and relevance.
- Expedites the speed with which an analysis can be accomplished.
- Provides a framework for testing the desirability of system modifications.
- Is easier to manipulate than the system is.

- Permits control over more sources of variation than direct study of a system would allow.
- Is generally less costly.

A modelling approach, particularly using a mathematical model, allows all the sites to be considered for more objective evaluation and be able to answer such questions. An optimisation model attempts to find an optimum solution by two major methods, exact approaches and heuristic approaches. On the one hand, mathematical programming with its family of approaches – a linear programming (LP), an integer programming (IP), and a mix-integer programming (MIP) – are commonly used to construct the model of the problem, whereas the heuristic models – genetic algorithms, and swarm intelligence, etc. – provide the near optimum or optimum result. On the other hand, simulation models are frequently applied to imitate systems. Most of them are performed in complex systems, which are closely-related to the real-world situation (Robinson, 2004).

Facility location decision problem and supply chain network design have been well established as a research area in operation research and management science (OR/MS). A good example was Procter & Gamble (P&G) improving their effectiveness overall global supply chain, as their following statement.

> *'In 1993, Procter & Gamble (P&G) began an effort entitled strengthening global effectiveness (SGE) to streamline work processes, drive out non-value-added costs, and eliminate duplication. A principal component of SGE was the North American product supply study, designed to re-examine and reengineer P&G's product-sourcing and distribution system for its North American operations. The methodology developed to solve this problem drew on OR/MS and information technology, merging integer programming, network optimisation models, and a geographical information system (GIS). As a result of this study, P&G is reducing the number of North American Plants by almost 20 percent, saving over $200 million in pre-tax costs per year and renewing its focus on OR/MS approaches …'* (Camm, Chorman, Dill, Evans, Sweeney, & Wegryn, 1997).

This statement provides evidence that the application of OR/MS methods, specifically mathematical programming, applied to a facility location problem in a supply chain network can produce a significant benefit to a company.

According to Napolitano (1997), a network study was motivated by two primarily purposes: to reduce costs and/or to improve customer service. He also said that *"studies have shown that optimising network designs have resulted in savings of logistics costs from 5 percent to as much as 15 percent."*

Hamedi, Zanjirani Farahani, Husseini, and Esmaeilian (2009) use a mixed integer programming model applied to a natural gas supply chain in Iran in order to minimise direct or indirect distribution costs. They simplify the supply chain in a mathematical model using the relations among the components of transmission and distribution network. They develop an algorithm to solve their model in sensible time. In contrast to implemented plan in reality, the outputs illustrate 19.84% improvement in objective function.

More tangible benefit can be found in a study by Piewthongngam et al. (2009). They apply a mathematical model to a real-world problem in sugar industry in Thailand in order to maximise overall sugar production. They deal with the problem in the sugar production chain so as to match the difference between mill and cane growers. They propose a framework to support decision-makers in choosing cultivar, and planting and harvest periods. In their framework, a cane growth model is developed to forecast cane yield, and a mathematical programming is formulated to determine planting periods, cultivar and harvesting time. As a result, it is possible to boost sugar production by 23% when compared to the current process.

2.2 Ontology and epistemology

In logistics and supply chain contexts, many studies deal with the effectiveness of the supply chain. In this sense, the ontology (assumptions made regarding the nature of reality) is positivist, by which reality exists and reacts to what is happening around them as tangible perception, for instance, reduction of total cost, lessening of lead time and increase in per cent order correction.

In this study, objectivist epistemology is assumed so that the effectiveness can be examined as a measureable value. It is based in principal on the values of reason, truth and validity. In my project, the same ontology is applied in which the view of social reality is the holistic view of the whole system. The objective of the study is to minimise the total cost of the whole items in the supply chain.

This research's theoretical and philosophical approach is decision theory under conditions of uncertainty. The research paradigm is classical positivist. This view is focused on effective management based on the ability to make rational decisions. Decision theory approaches led to the development of a number of quantitative methods and model building (Easterby-Smith, Thorpe, & Lowe, 2008). In this research, mathematical modelling is proposed as a tool for decision-making; it offers an optimum solution for a rational decision.

First, the research design and methods lead to the construction of a hybrid theory, in which the combination of optimisation and simulation is proposed. It is a quantitative method in which a mathematical model will be built.

Then, the next step is a testing model with data from an archive of firms in the supply chain. It is variance data as static point of view in which the data is in a point of the study horizon year, e.g. customer demand, operation cost, facility capacity, and so on. Figure 2.1 (Adapted from Blaikie, 2007), shows the various choices of theoretical and philosophical approaches, while Figure 2.2 (Adapted from Partington, 2002) illustrates four fundamental elements of my research.

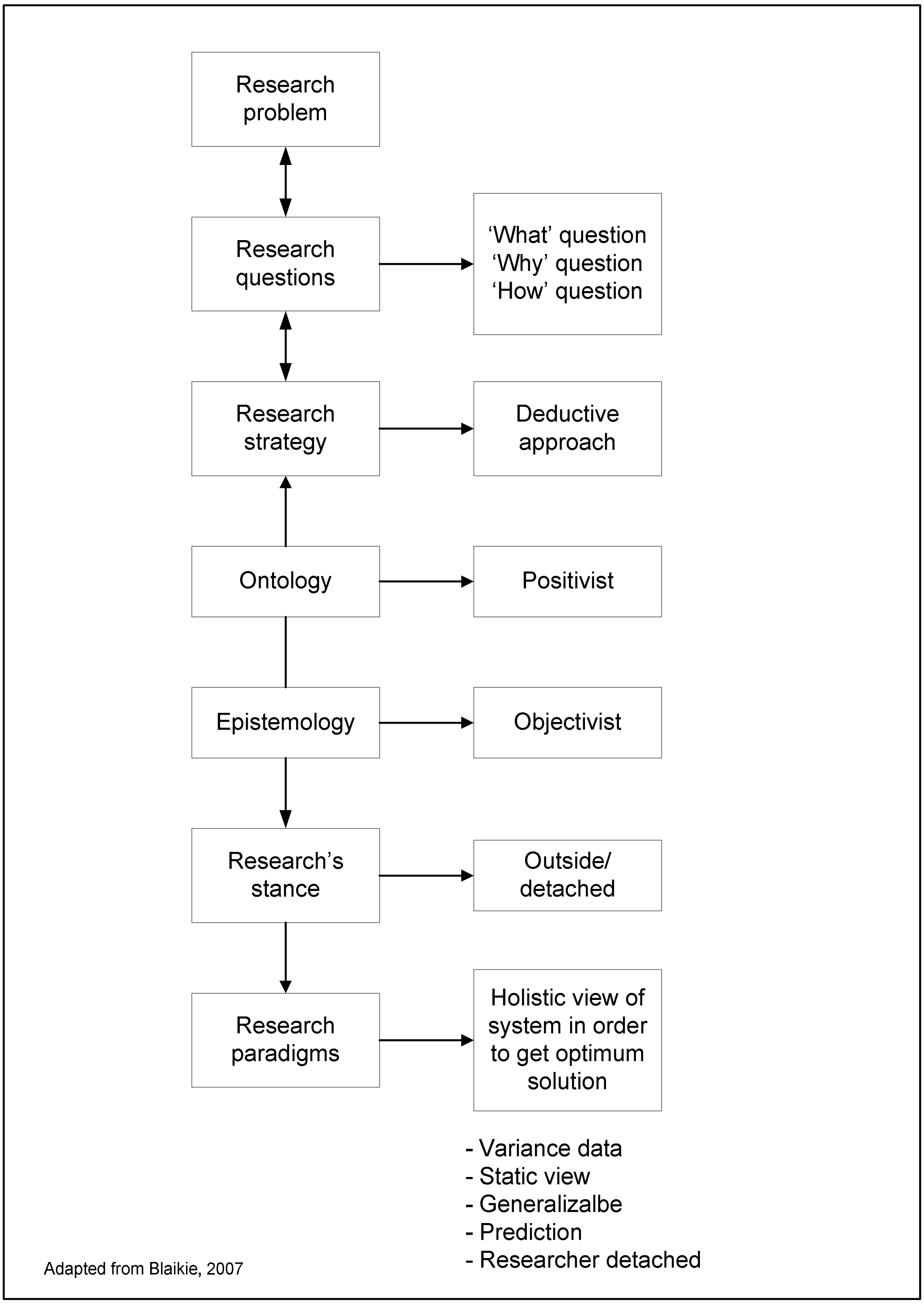


Figure 2.1 Diagram shows the theoretical and philosophical approach

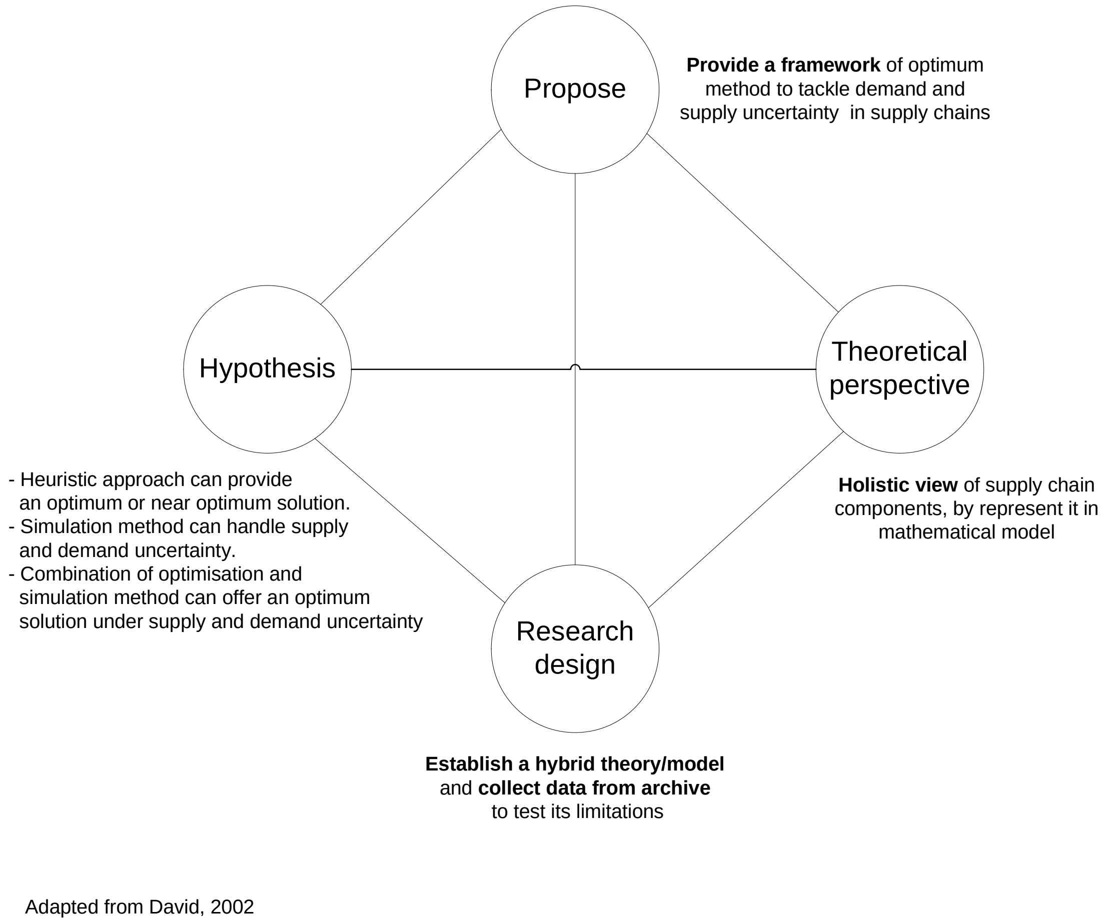


Figure 2.2 Diagram illustrates four fundamental elements of my research

2.3 Mapping the field

This research will focus on supply chain management, the facility location problem, and their analysis and solving techniques, as can be seen in Figure 2.3

First of all, supply chain management is a broad area concerning several stakeholders namely suppliers of suppliers, suppliers, manufacturers, distribution centres, through to end customers. According to the Council of Supply Chain Management Professionals, supply chain management was defined as *"encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third party service providers, and customers. In essence, supply chain management integrates supply and demand management within and across companies".*

The Council of Supply Chain Management Professionals also describe logistics management as *"part of the supply chain which plans, implements and controls the efficient, effective forward and reverse flow and storage of goods, services and related* *information between the point of origin and the point of consumption in order to meet customers' requirements".* Thus, supply chain management usually deals with other parts not only the facility location problem. It concerns with, for example, supplier selection, customer relationship, product services, and so forth.

Secondly, the focus problem is defined as a facility location problem as described in the previous section. Facility location problems are a broad area, e.g., network design, warehouse location, competitive facility location, fire box coverage and emergency service vehicles/facilities (Brandeau & Chiu, 1989). In general, the facility location problem relates to several fields not only supply chain management. Its implementation was applied to, for instance, water treatment networks (Karuppiah & Grossmann, 2008), emergency service vehicles/facilities (Valenzuela, Goldberg, Keeley, & Criss, 1990), and defence installations (Dasarathy & White, 1980).

Finally this problem will focus on modelling approaches. These modelling techniques should provide an answer that represents an optimum solution. To find such a result, a set of mathematical programming techniques could be used including linear, integer, and mix-integer programming, whereas heuristic approaches give a near optimum or optimum solution. Simulation models are a fundamental tool to deal with the complexity arising from uncertainty.

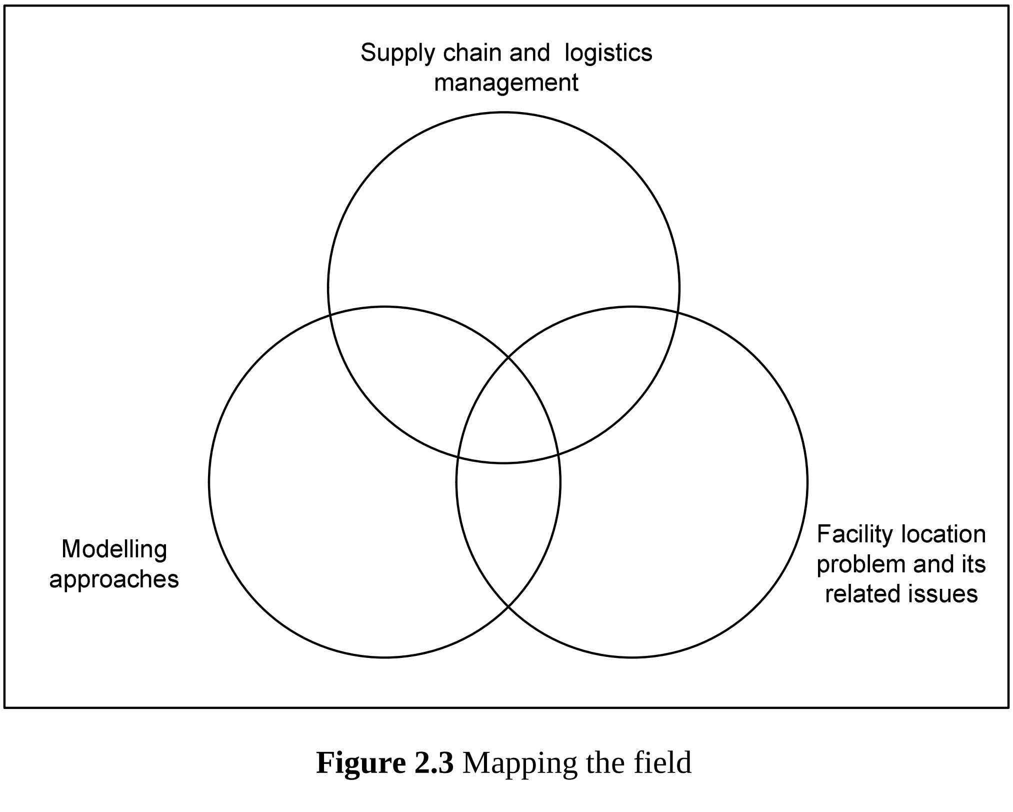


Figure 2.3 Mapping the field

2.4 Research question

The core concept of this research is to provide a framework for the optimisation of supply chains. Therefore, it will focus on the development of methods/techniques, specifically mathematical modelling approaches, which combine simulation and optimisation. Research questions consists of the main and sub questions demonstrated below:

- What kinds of methods/techniques have been used to address facility location problem in supply chains with uncertainty?
- What are the strengths, weaknesses and limitations of the different modelling approaches?
- How can simulation and optimisation be used in combination for facility location problems to provide 'improvements' (or benefits) over other modelling approaches?

2.5 Planned research contribution

This research will examine the combination of simulation and optimisation approaches in order to provide a tool/technique to tackle the facility location problem in a supply chain context with uncertainty conditions. This technique may provide significant improvements or benefits compared to existing techniques in terms of considering complex situations with features such as a multi-objective function and/or multiple uncertain variables.

2.6 Review question

To produce a systematic review, it is vitally important to examine all linked sources. The aims of the systematic review are as follows:

- What are the facility location problems in supply chains and the modelling approaches used to address them?
- How are these modelling approaches being applied?
- What are their strengths, weaknesses and limitations?

3 Methodology

3.1 Objective

The objective of this section is to construct a review protocol by forming a review panel, and developing a detailed search strategy with clear inclusion and exclusion criteria. In addition, the measurement for evaluating the quality of studies is presented with a strategy for extracting data and synthesising studies. In a systematic review, the process is performed in a "systematic, transparent and reproducible" manner, to ensure that the results will minimise bias and error (Tranfield et al., 2003).

3.2 Review process

The systematic review process is presented in five stages: planning the review, identifying and evaluating studies, extracting and synthesising data, reporting, and utilising the findings, as can be seen in Table 3.1. This chapter presents the first stage – planning the review – of the review process.

Table 3.1 Systematic review process

Stage I – Planning the Review
Step 1 – Forming a review panel
Step 2 – Mapping the field of study
Step 3 – Producing a review protocol
Stage II – Identifying and evaluating studies
Step 4 – Conducting a systematic search
Step 5 – Evaluating studies
Stage III – Extracting and synthesising data
Step 6 – Conducting data extraction
Step 7 – Conducting data synthesis
Stage IV – Reporting
Step 8 – Reporting the findings
Stage V – Utilising the findings
Step 9 – Informing research
Step 10 – Informing practice

Source: Cranfield School of Management web portal, 12 August 2009

3.3 The consultation panel

The following table shows the consultation panel, which comprised of my supervisors, logistics and supply chain advisor, modelling advisor for both optimisation and simulation, supply chain cost advisor, and literature search advisor.

Table 3.2 Illustrates the consultation panel

Person	Organisation	Role
Dr. Heather Skipworth	Cranfield School of Management	Supervisor
Dr. Andrew Palmer	Cranfield School of Management	Supervisor
Dr. John Towriss	Cranfield School of Management	Logistics/supply chain and transport advisor
Dr. Nicola Yates	Cranfield School of Management	Optimisation and simulation modelling advisor
Dr. Partha Priya Datta	School of Applied Sciences, Cranfield University	Simulation modelling advisor
Simon Templar	Cranfield School of Management	Supply chain cost advisor
Heather Woodfield	Social sciences information specialist	Literature search advisor

3.4 Search strategy

A high-quality and robust search strategy can help to discover the relevant and essential literature. To guarantee that an important source of data is not overlooked during the search, a sound and powerful search strategy is required. The following sections describe the process of developing a sensible search strategy. Figure 3.1 Search flow chart shows a flow chart that summarise search process.

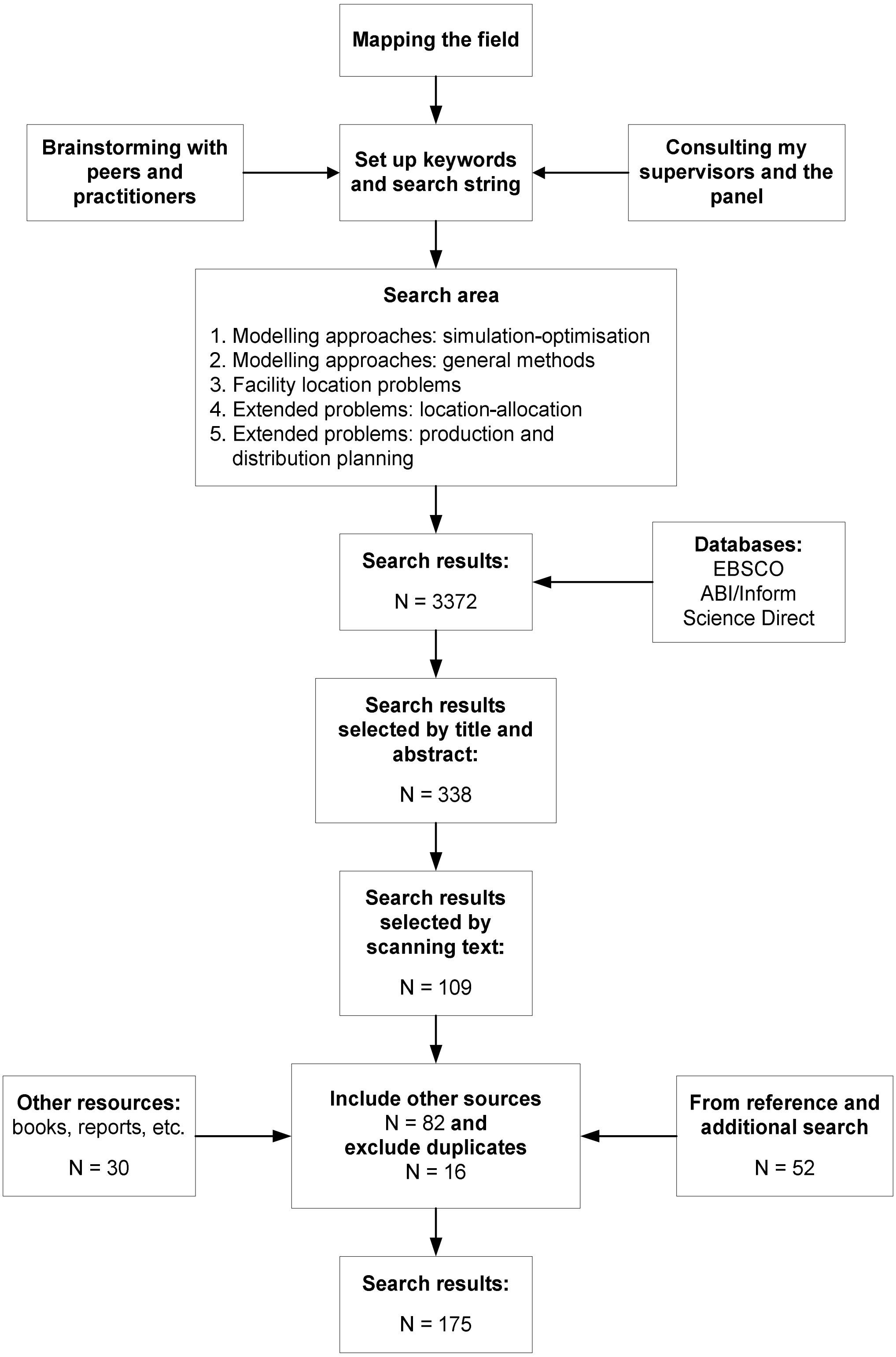


Figure 3.1 Search flow chart

3.4.1 Keyword search

The keywords for constructing search strings were primarily derived from (1) mapping the field and (2) brainstorming with peers and practitioners and (3) consulting my supervisors and the panel. Keyword searches were generally confined to title, abstract and keywords of documents being searched.

As discussed previously in the scoping study chapter, the field of interest can be defined in three major areas: (a) supply chain and logistics management (b) facility location problems and related issues, and (c) modelling approaches. The intersection of three areas can be defined in the following statement *"facility location problems, and related issues in supply chain and logistics management, solved by modelling approaches"*. After pilot searching in the scoping study stage, the outputs showed a large number of papers according to broad areas of such problems. The search strategy has been re-examined several times; finally, the refined search method can be described as follows:

To begin with, modelling approaches are a significant part due to a large number of papers using these techniques. Optimisation with the exact approach is a fundamental technique. Mathematical programming modelling such as linear programming, integer programming, and mixed-integer programming is a typical model for this approach (Melo, Nickel, & Saldanha-da-Gama, 2009). However, heuristics approaches are also popular among the optimisation techniques (Melo et al., 2009). Simulation is another tool that is often applied to lots of studies, especially dealing with uncertainty (Almeder, Preusser, & Hartl, 2009). In addition, the search strategy also considers a hybrid approach, combining simulation and optimisation methods in supply chain and logistics management as can be seen in Table 3.3

Furthermore, the interesting area is concerned with the facility location problems within supply chain and logistics disciplines. After the pilot search, the keywords have been listed and investigated; then, it was found that there were a number of keywords related to the facility location problems. Particularly, the location-allocation, production and distribution planning were often found in the keywords of search results, for instance, some papers by Lee and Kim (2002), Zhou and Liu (2003), and Ko, Ko and Kim (2006). Thus, as can be seen in Table 3.3, the extended facility location problems were primarily established according to keywords of the pilot search results.

Table 3.3 Keywords and search string

Area	Keywords	Search String
Modelling approaches: general approaches for facility location problems	Facility location problems, location analysis, optimisation, simulation, heuristic, hybrid	("facilit* locat* problem*" OR "locat* analys*") AND (optimi?ation OR simulation OR heuristic OR hybrid)
Modelling approaches: simulation-optimisation for supply chains	Supply chain, logistics, simulation, optimisation	("supply chain*" OR logistics) AND (simulation AND optimi?ation)
Facility location problems only (modelling approaches excluded)	Facility location problems, location analysis	("facilit* locat* problem*" OR "locat* analys*") AND NOT (optimi?ation OR simulation OR heuristic OR hybrid)
Extended facility location problems: location-allocation	Supply chain, logistics, location-allocation	("supply chain*" OR logistics) AND ("locat* allocat*")
Extended facility location problems: production and distribution planning	Supply chain, logistics, production distribution, distribution planning	("supply chain*" OR logistics) AND (("product* distribut*") OR ("distribut* plan*"))

3.4.2 Other search strategy

Although the search strategy was constructed rigorously, some specific problems may be overlooked because of various reasons such as too specific problems, and missing important keywords as defined by the authors. Therefore the 'branching' strategy has also been used where relevant papers are selected from the reference list in papers satisfying the selection criteria. Further, additional search strings have been included for further information, i.e. competitive location, hierarchical facility location, hub location, undesirable facilities, and multi-objective function. This method has been used, particularly during the problem review and taxonomy of problems.

3.5 Resources

To produce a systematic review, it is vitally important to examine all related sources including reports, practitioner journals, books and theses as well as academic journals. After pilot search results, it was found that the selected results often contained duplicates. Thus, the three chosen databases will be applied on the basis of the publication coverage, as can be seen in Table 3.4.

First, EBSCO – Business Source Complete is the main resource in the supply chain and logistics management discipline in which it is the world's largest scholarly business database.

Next, ABI/Inform global / Trade & industry (Proquest) is selected as the key resource providing top journals, periodicals in management science, computing, transportation from the highest-quality sources of information, and major publishers: working paper, business case, annual report, dissertation, etc.

Finally, while both EBSCO and ABI/Inform provide mostly information about problems and relevant business area, Science Direct is the key database in the area of modelling techniques. According to the pilot search, the results found that a number of papers relate to analysis and problem-solving techniques.

Furthermore, for reports, books, theses and practitioner journals, the main resources are from Cranfield library and The Chartered Institute of Logistics and Transport (CILT).

Table 3.4 Databases

Databases	Key area	Description
EBSCO – Business Source Complete	Supply chain and logistics management	The world's largest scholarly business database provides the leading collection. Offers more than 2,800 scholarly business journals, including full text for more than 900 peer-reviewed business publications. Coverage includes virtually all subject areas linked to business.
ABI/Inform global / Trade & industry (Proquest)	Facility location problem and its related issues	Provides top journals, periodicals in deep business, management science, computing, transportation from the highest-quality sources of information, and major publishers: working paper, business case, annual report, dissertation, etc. nearly 3000 worldwide business periodicals.
Science Direct	Analysis and problem-solving technique	More than 2,500 journals and over nine million full-text articles are available in Science Direct.

3.6 Selection criteria

As can be seen in Figure 3.1, when the search strings are applied, a large number of papers are listed. To identify those papers that are relevant to this review the inclusion and exclusion criteria (Table 3.5 and Table 3.6, respectively) were applied first through reading the title and abstract and then through a full read (as shown in the search strategy, Figure 3.1). The inclusion and exclusion criteria minimise bias and the rationale for each criterion is given in the respective tables.

Table 3.5 Inclusion criteria

Criteria	Rationale for inclusion
All sources, i.e., academic papers, journals, conference proceedings, books, and so on	Acquire information as much as possible, not limit to data sources
Technical approaches possibly connected to the problem, even though in closed fields (e.g. the combination of simulation and optimisation in production planning)	The modelling approach maybe applied to the focusing problems
No restriction regarding industries	Supply chain and logistics are broad disciplines, that apply to many different industries and across suppliers, manufacturers and customers
No restriction regarding timeframe	The papers will not be limited to a specific time period, since many developments of methodology provide significant information

Table 3.6 Exclusion criteria

Criteria	Rationale for exclusion
Technical: exclude approaches to specific supply chain configuration (e.g. supplier selection)	The review focuses only on the facility location and capacity allocation problem, not on a particular technical application
Technical: exclude approaches to specific operation management (e.g. inventory management)	The review focuses only on the facility location and capacity allocation problem, not on a particular technical application
Other problems, which are not facility location problems or related areas (e.g. vehicle routing problem)	The review focuses only on the facility location and capacity allocation problem, not on other problems
All information or publications in any other language except English	Researcher can acquire information on this language

3.7 Quality appraisal

Papers that satisfied the selected criteria were subject to a quality appraisal covering a number of assessment criteria: theoretical background, literature review, methodology, outcome, contribution and their limitations (as described in Table 3.7). If papers were evaluated with low quality or not applicable in any criterion, they were excluded from the review process.

Table 3.7 Quality Appraisal

Criteria	Low	Medium	High	Not Applicable
Theoretical background	Little or no description of theoretical background	Moderate description of theoretical background, basic definition of the concepts	Well-articulated theory, concepts are clearly defined, major ideas are original	N/A
Literature review	Poorly cites the relevant literature, no discussion or discussion incomplete and inaccurate	Fairly cite and discuss the relevant literature	Appropriately cites the literature, good discussion of the relevant literature	N/A
Methodology	Inconsistence in the research question and the linked theory, feeble methodology	Fairly consistent in the research question and the linked theory, limited methodology	Clear link between the research question and the related theory, justified methodology	N/A
Outcomes	Weak results of the model, or no information to asses this criteria	Reasonable output of the tested model	Excellent output of the proposed method, clearly states their performances	N/A
Contribution to knowledge	Little or no theoretical or empirical contribution	Justified theoretical or empirical contribution	Significant contribution to either theoretical or empirical knowledge	N/A
Limitations	No information to asses this criteria	Limitation is not relevant to knowledge, future research are not stated	Clearly defined the limitation and understanding in directly relevant background, the future research are evidently stated	N/A

3.8 Data extraction

To retrieve and manage data easily, it is important to gather reviewed papers and relevant information in as systematic a format as possible. Table 3.8 shows the data extraction form comprising citation information, methodology, supply chain structure, supply chain decision, study background, and their quality assessment.

Table 3.8 Data extraction

Citation information	
Items	
Title	
Author(s)	
Publication	
Month and year of publication	
Volume	
Issue	
Page number	
Key words	
Link to file	
Study Methodology	
Methods	
Results	
Uncertainty variables	
Specific tools	
Supply chain structure	
Multi-echelon	
Multi-commodities	
Multi-periods	

Table 3.8 Data extraction (Cont.)

Stochastic	
Objective function	
Supply chain decision (decision variables)	
Capacity	
Inventory	
Procurement	
Production	
Routing	
Location facility	
Distribution	
Transport mode	
Reverse logistics	
Other aspects	
Study background	
Industry	
Type of data	
Level of management	
Limitations/comments	
Quality assessment	
Theoretical background	
Literature review	
Methodology	
Outcomes	
Contribution to knowledge	
Limitations	

3.9 Data synthesis

One of the essential parts of a systematic review is the data synthesis. The aim of this part is to bring together information found from the reviews into a logical composition. To illustrate that the imperative evidence is acknowledged and all relevant information is regarded, the report must be organised coherently, together with well informative details.

The data will be described in statistic view point so as to comprehend the overview of the acquired data in the next chapter. The findings will be primarily presented in terms of a basic process of problem-solving, modelling approaches, and facility location problems with their extension problems in line with discussions in Chapter 5 and 6.

4 Classification of evidence

This chapter provides an analysis of the evidence identified through the literature search detailed in Chapter 3. The evidence can be classified by theme, year, type of book/journal and geographical location, respectively.

4.1 Evidence by theme

The theme of the search strategy comprises of (a) the different modelling approaches used for the facility location problem in the supply chain context, i.e. exact optimisation; heuristic optimisation; simulation; and hybrid approaches (b) the various type of facility location problems.

As can be seen in Table 4.1 and Figure 4.1, many documents which approximate two thirds are related to several various kinds of facility location problems (will be described in the next chapter). All most all of them, approximately 90 per cent, are academic documents, while the rest are practitioner's documents. The main theme of the facility location problem is evidenced by a variety of problems (97 papers), while the extended problems: location-allocation and production-distribution are found in 11 and 3 papers, respectively.

In terms of the modelling approaches, the most popular approach from search result is the heuristic approach (nearly half of them, 31 of 64 documents). The second popular method, about a quarter (15 of 64 papers), is exact approach. Only a small proportion focus on hybrid and other approaches, 5 and 7 papers respectively, about 10% of papers for each category.

In addition, by observing the percentage of academic documents among different approaches, the figure shows that the optimisation method, i.e. exact (80%); and heuristic (94%) approaches are employed significantly more than the hybrid (60%) and simulation (67%) approaches. In other words, in practitioner's application the hybrid and simulation approaches are more popular than the heuristic and exact approaches. The search result show that the hybrid approach, combining simulation and optimisation, has not received much attention from either academics or practitioners thus far.

Table 4.1 Evidence by theme and academic/practitioner's documents

Theme	Academic documents		Practitioner's documents		Total	
Modelling approaches						
- Exact approaches	12	(80%)	3	(20%)	15	(100%)
- Heuristic approaches	29	(94%)	2	(6%)	31	(100%)
- Simulation approaches	4	(67%)	2	(33%)	6	(100%)
- Hybrid approaches: simulation-optimisation	3	(60%)	2	(40%)	5	(100%)
- Other approaches	7	(100%)		(0%)	7	(100%)
Total modelling approaches	55	(86%)	9	(14%)	64	(100%)
Problems						
- General problems	89	(92%)	8	(8%)	97	(100%)
- Location-allocation	10	(91%)	1	(9%)	11	(100%)
- Production-distribution	2	(67%)	1	(33%)	3	(100%)
Total problems	101	(91%)	10	(9%)	111	(100%)
Grand total	**156**	**(89%)**	**19**	**(11%)**	**175**	**(100%)**

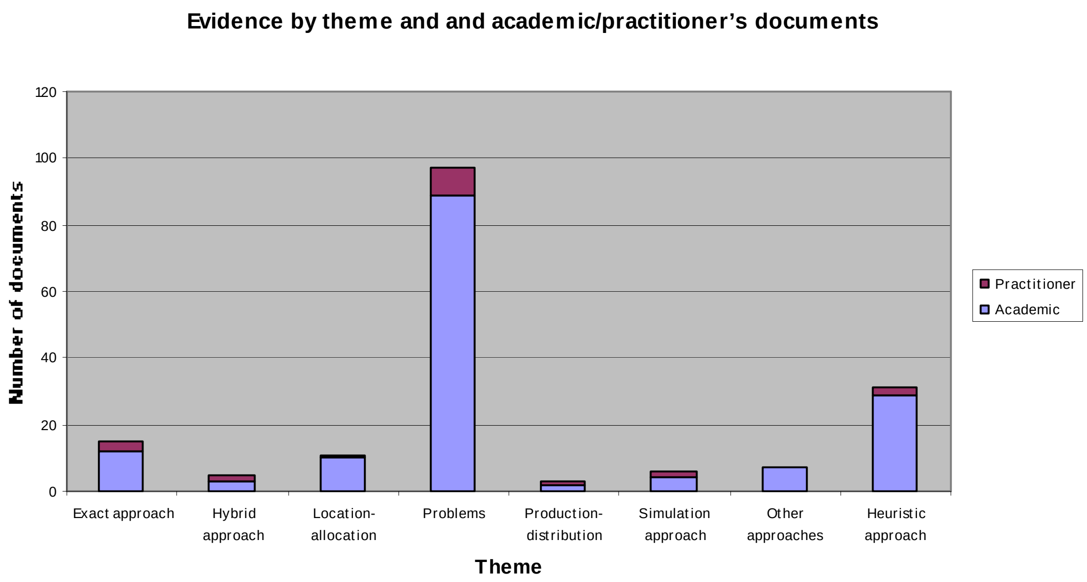


Figure 4.1 Evidence by theme and academic/practitioner's documents

4.2 Evidence by date

This section presents evidence classified by date in Figure 4.2. From historic information, the results show an interesting trend since the beginning of location study by Weber in 1909 (Weber & Friedrich, 1929b). In 1964, Hakimi (1964) triggered the current era of facility location study. After that, the result shows an increase that leads to the number of papers approximately double every decade as can be seen in Figure 4.2. The figure shows an increasing number of published papers before 1960, and last five decades are 2, 5, 11, 23, 45 and 89, respectively.

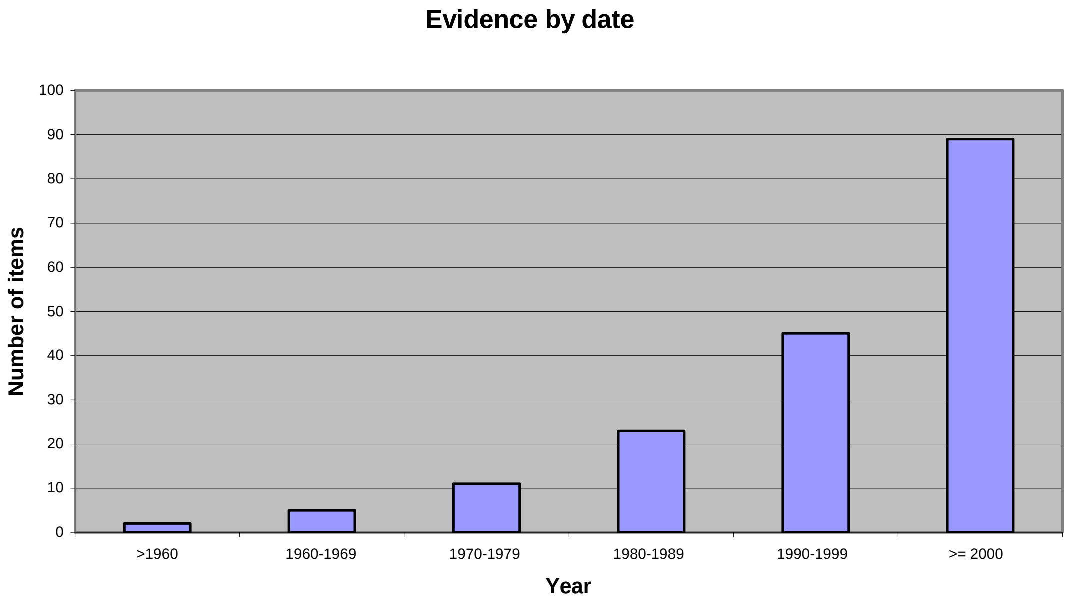


Figure 4.2 Evidence by date

More specifically, Table 4.2 presents the year of document by the search theme in details. An interesting figure is, first, hybrid approaches have just been presented in review papers since 2000s, while exact and heuristic approaches have been applied since 1960s and 1970s, respectively. Similarly, general facility location problems have been known since Weber paper in 1909 and progressively more interested by researchers until this decade, but other extended problems in supply chain: location-allocation and production-distribution problems have just been interested increasingly since 1970s and 2000s, respectively.

Table 4.2 Evidence by decade and theme

Theme	Decade						Total
	<1960	1960s	1970s	1980s	1990s	2000s	
Modelling approaches							
- Exact approaches			2	1	3	9	15
- Heuristic approaches		1		4	8	18	31
- Simulation approaches			1			5	6
- Hybrid approaches: simulation-optimisation						5	5
- Other approaches			1	1		5	7
Total modelling approaches	0	1	4	6	11	42	64
Problems							
- Location-allocation			2	3	1	5	11
- General problems	2	4	5	14	33	39	97
- Production-distribution						3	3
Total problems	2	4	7	17	34	47	111
Grand total	**2**	**5**	**11**	**23**	**45**	**89**	**175**

4.3 Evidence by journal

The evidence classifies the variety of sources of book/journal into 52 groups as can be seen in Table 4.3. They are mainly from the European Journal of Operational Research, books or theses, and the journal Computers & Operations Research. In addition, the range of journals falls in several type of discipline, e.g. operational research, transportation, computer science, economics, environment, health, marketing, logistics and supply chain management. In terms of type of document, the majority of documents are journals and the others are books/thesis (Figure 4.3).

Table 4.3 Evidence by books / journal distribution

Sources	Items
European Journal of Operational Research	39
Book/Thesis	30
Computers & Operations Research	17
Transportation Research	8
Location Science	6
Operations Research	6
Computers & Industrial Engineering	5
Computers & Chemical Engineering	4
Management Science	4
Annals of Operations Research	3
Environment and Planning	3
Journal of Regional Science	3

Table 4.3 Evidence by books / journal distribution (cont.)

Sources	Items
Omega	3
Interfaces	2
International Journal of Production Economics	2
Journal of Retailing	2
Naval Research Logistics	2
Socio-Economic Planning Sciences	2
Applied Mathematical Modelling	1
Annals of Emergency Medicine	1
Administrative Science Quarterly	1
Agricultural Systems	1
Applied Mathematics and Computation	1
British Journal of Management	1
Computers & Mathematics with Applications	1
Computers, Environment and Urban Systems	1
Decision Sciences	1
Econometrica	1
The Economic Journal	1
Energy Policy	1
Engineering Applications of Artificial Intelligence	1
Forest Policy and Economics	1
IIE Transactions	1
INFORMS Journal on Computing	1
International Transactions in Operational Research	1
Journal of Business Logistics	1
Journal of Marketing Research	1
Journal of Operations Management	1
Journal of Retailing and Consumer Services	1
Journal of Transport Geography	1
Journal - Operational Research Society	1
Mathematical and Computer Modelling	1
Mathematical Modelling	1
Networks	1
Networks and Spatial Economics	1
Operational Research Quarterly	1
OR Spectrum	1
Papers in Regional Science	1
Public Health	1
SIAM Journal on Discrete Mathematics	1
Supply Chain Management	1
Transportation Science	1
Total	**175**

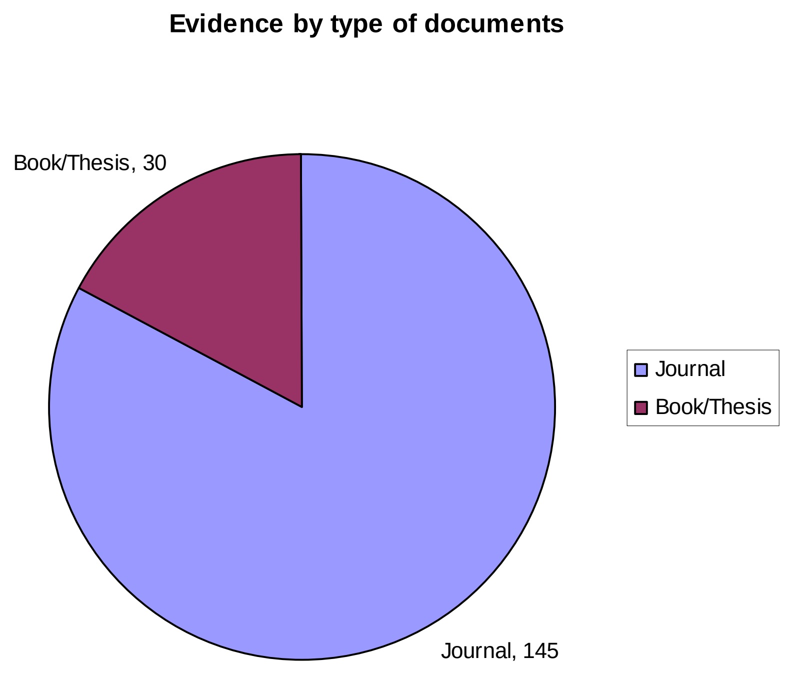


Figure 4.3 Evidence by type of documents

4.4 Evidence by geographic location

In terms of geographic location, most papers, more than half of all papers, can be found in North America, especially the United States of America. The second most common source is in Europe, particularly the United Kingdom, Germany and Spain. Asia is the third most important location that the selected papers originated from. Table 4.4 presents the article by countries, while Figure 4.4 illustrates the results by continents.

Table 4.4 Evidence by geographic location

Country	Items
USA	97
UK	10
Germany	8
Spain	7
Japan	5
Belgium	4
South Korea	4
Austria	3
Canada	3
Chile	3
France	3
Italy	3
Netherlands	3
Singapore	3
Australia	2
China	2
Iran	2
Israel	2
Portugal	2
Turkey	2
Brazil	1
Denmark	1
New Zealand	1
Sweden	1
Switzerland	1
Taiwan	1
Thailand	1
Total	**175**

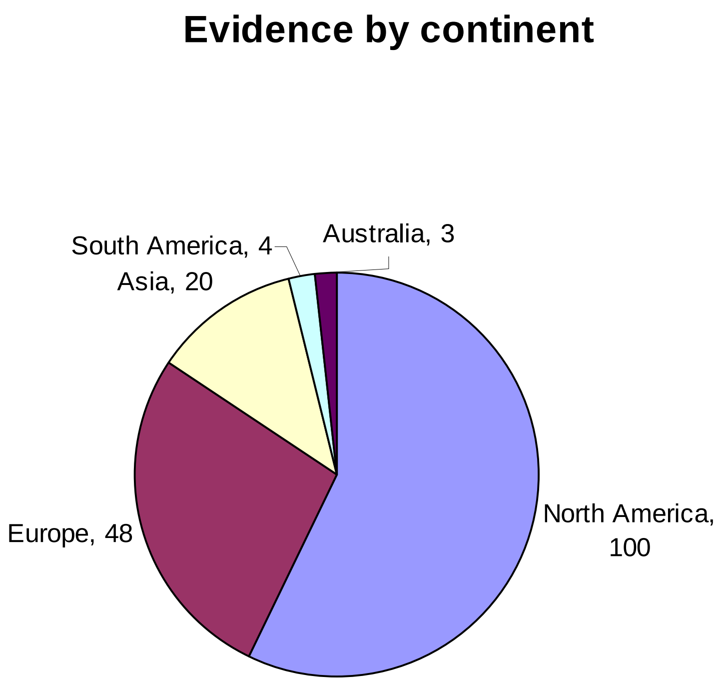


Figure 4.4 Evidence by geographic location

4.5 Summary

To summarise first, in the facility location context the number of publications has dramatically increased in recent years. Secondly, there are a number of publications in a range of journals in many disciplines in several countries around the world. Thirdly, the simulation approach and hybrid approach, combining simulation and optimisation, have not received much attention. However, evidence shows that interest has grown during since 2000.

The steady interest in facility location problems is driven by a number of factors (Current, Min, & Schilling, 1990). First of all, decisions of facility location are everywhere: individual, family, company and government. Next, the location decisions are inherently strategic. The result of strategic decision involves a large number of resources such as a vast sum of money and requires a long period of time. Then, the problems are difficult to solve optimally; they commonly represent an *NP-hard* problem (Garey & Johnson, 1979). Finally, location problems are uniquely defined; applications vary upon their objectives and constraints.

The implication of these trends in conjunction with the market globalisation in supply chain (Thomas & Griffin, 1996) may cause more and more interested in the facility location problems. As the evolution of computer technology, algorithm, software capabilities, data development and management tools continues (Geoffrion & Powers, 1995), new modelling approaches are likely to be developed.

5 Findings

5.1 Overview

In recent years, supply chain networks have received increasing attention among companies due to growing competitiveness, which stemmed from market globalisation (Thomas & Griffin, 1996). Companies are forced to reduce costs and maintain profit as well as delivering satisfactory customer service. Conventionally, manufacturing, marketing, distribution and finance operated separately along the supply chain. Each stage of the supply chain notices its operation locally and is not able to distinguish the effect of its action on other units. Each department has its own objectives which are often conflicting (Walton & Dutton, 1969). This is one of the most important issues in supply chain problems.

Specifically, marketing departments usually state their goals in terms of sales, market share and product portfolio expansion, which are enhanced by responsiveness to customer demands for services, such as fast delivery, right quality, or customised product design. In contrast, a manufacturing unit typically sets objectives around production efficiency, capacity utilisation, or productivity and these are commonly in conflict with the marketing objectives. Further, while marketing and production departments may find it necessary to increase inventory holdings to maintain customer service, financial departments will only be concerned with minimising inventory and the associated holding costs.

A mechanism to integrate these different functions is necessary. In general, *Supply chain management (SCM)* is a strategy to tackle this difficulty (Ballou, 2004; Chopra & Meindl, 2005). Supply chain network design, particular facility location problems, is one of the most comprehensive strategic decision problems in supply chain management (Owen & Daskin, 1998).

In supply chain management, decisions can be distinguished -- depending on the time horizon -- between, strategic, tactical and operational decisions (Simchi-Levi et al., 2008). Simchi-Levi et al. also stated that "the strategic level deals with decisions that have a long-lasting effect on the firm. These include decisions regarding the number, location and capacities of warehouses and manufacturing plants, or the flow of material through the logistics network". This explanation clearly connects between the facility location problem and strategic level planning in supply chain management. Decisions about facility location are a strategic issue for almost every company (Klose & Drexl, 2005).

This chapter substantially describes findings from review papers. Figure 5.1 provides a schematic diagram to illustrate the structure of the chapter. To begin with, the problem-solving process is explained to provide a basic understanding of the interrelation among real-world situations, formulated problems, and developed models.

The next section describes an overview of complexity analysis to understand the complication of such problems. Then, modelling approaches are presented with a discussion. Next, the background to the facility location problem is described followed by a taxonomy of facility location problems. Finally, the last four sections discuss various problems on facility location together with: static and deterministic, extended, dynamic, and uncertain facility location problems.

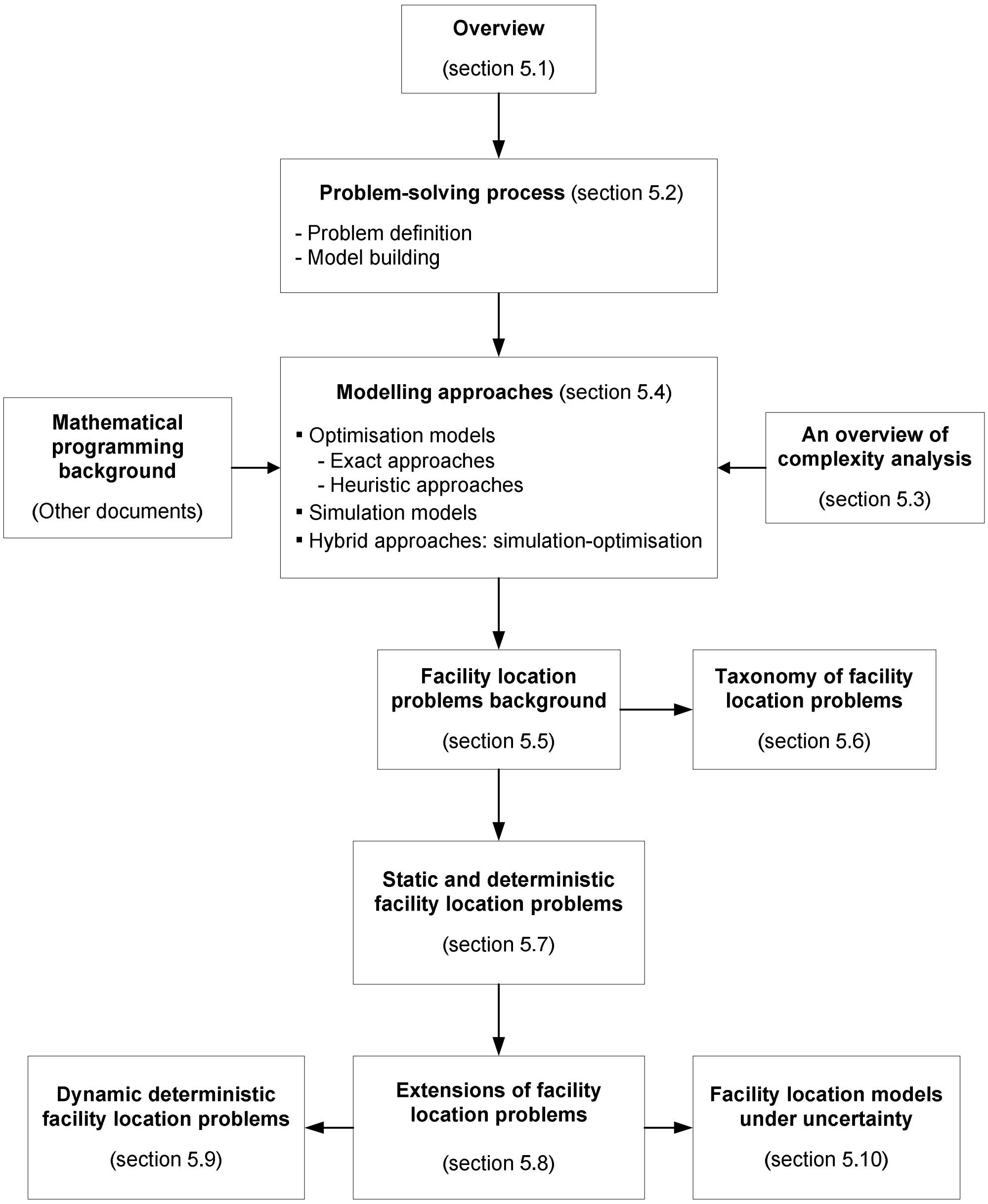


Figure 5.1 The schematic diagram illustrates the structure of findings

5.2 Problem-solving process

Jensen and Bard (2003) describe the decision making process generally beginning with (1) a situation in which a dilemma is recognized, which may be actual or abstract, as can be seen in Figure 5.2. When the situation is portrayed, it is shown with a vague and irregular outline since most difficulties are weakly defined in their original notion. Historical data describe that it may be present in a variety of forms.

A subsequent step is to (2) formulate the problem. At this stage, objectives, constraints, assumptions, descriptions of processes, data requirements, and options of action are introduced. The boundaries of the system must be indentified because it represents an interest of the decision makers.

Next, (3) a model is constructed. The problem is translated from verbal, qualitative terms to explicitly quantitative terms. Then, (4) the solution is provided by various methods such as statistical analysis, optimisation, simulation, and others.

The testing step (5), is concerned with the validity and reliability of the model. Once a procedure has been established, the analyst may face new problems, leaving the procedure to handle the required tasks. It is important (6) to establish control procedures that can distinguish an altering situation and indicate the requirement to adjust or update the solution.

Finally, (7) an implementation of the solution and (8) an implementation of the procedure are the last stage of the problem-solving process. The implementation of the solution is concerned with an application of this solution to the problem, while that of procedure applies more generally to other situations.

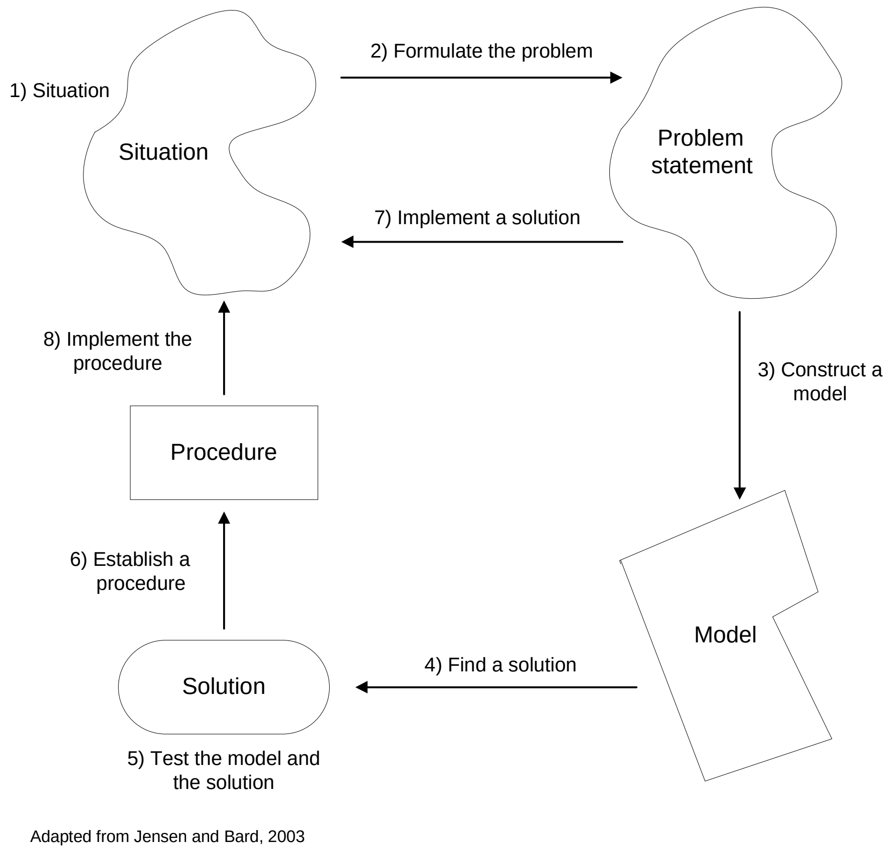


Figure 5.2 Problem-solving process

One of the objectives of management science, decision science, and operations management is to provide a framework for constructing models of decision-making in order to find the best solutions with respect to given situations. It is important to simplify the real-world situation into a suitable problem in order to be handled by appropriate methods, in technical terms namely a model.

From a real-world situation, the general procedure is to formulate a problem, to construct a model, and to provide a method for establishing a solution as shown in Figure 5.2.

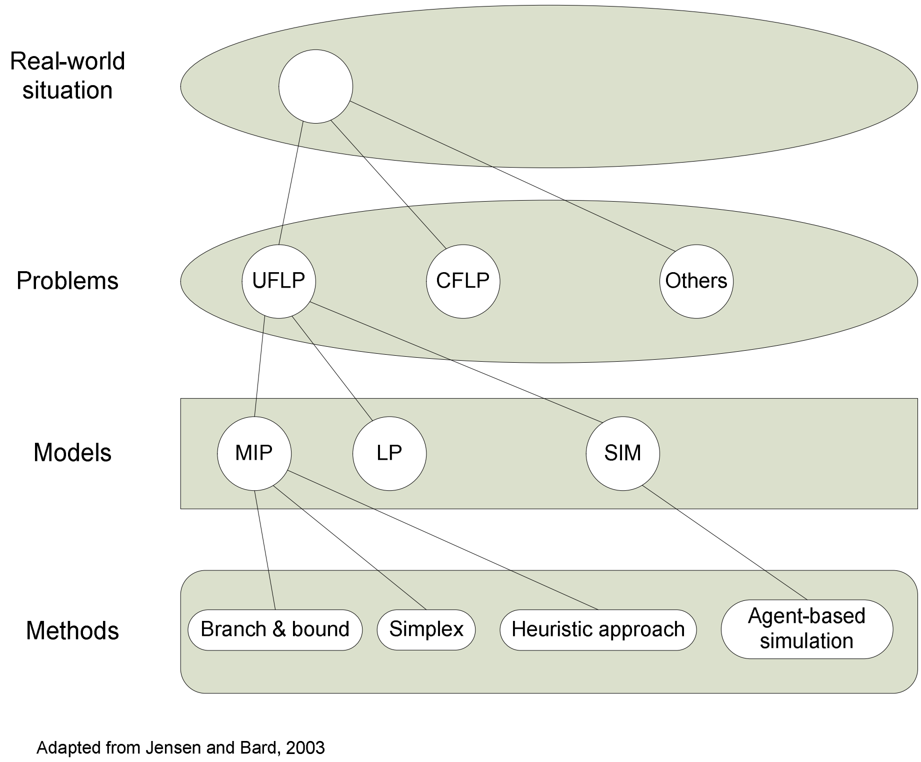


Figure 5.3 Problems, models and methods

The top level in Figure 5.3 indicates a circumstance taking place from the real-world situation, whilst the second top level illustrates a simplified situation. Many problems fit elements of them depending on which parts of the situation are eliminated or modified through abstraction. There are several problems for each circumstance, for example, the vehicle routing problem for finding the best route in order to transport goods to their customers and back to the depot. In this study, the problem is defined as a facility location problem with various conditions such as capacitated or uncapacitated environment.

In terms of model building, researchers can simplify the problems through their models. Some parts of the process require a large number of judgements constrained by a set of resources. This may suggest that the problem could be modelled as a linear programming problem, an integer programming problem or a mixture of the two. Some models are constructed by imitating the entire system or part of it. These are called simulation models.

In addition, the lowest level in Figure 5.3 is a tool/technique to solve the models in the upper level. The linear and integer programming problems can be solved by simplex, branch-and-bound techniques, or heuristic approaches, whereas the simulation models, especially in the supply chain context, can be implemented with discrete simulation techniques such as agent-based simulation.

5.2.1 Problem definition

The term "facility location problems" refers to the modelling, formulation, and solution of a class of problems that can best be described as locating facilities in some given spaces. The facility location problem has received attention from academia and practitioners (Klose & Drexl, 2005). According to the American Mathematical Society, this problem has been defined with a specific code, 90B80, *"a discrete location and assignment"*. Among the area of logistics and supply chain management, facility location problems play a critical role in the strategic planning for a broad area of both public and private sectors (Owen & Daskin, 1998).

In facility location problems, candidate locations are restricted to a finite set of facilities. The facility location problem (FLP) covers the components of distribution system design. The FLP in which an arbitrary number of customers can be connected to a facility is called an uncapacitated facility location problem (UCFLP). If each facility has a limit on the number of customers it can serve it is called a capacitated facility location problem (CFLP). Both UCFLP and CFLP are *NP-hard* problems, which mean in practice it is difficult to find the best solution (more details about *NP-hard* will be described in Section 5.3).

An exampler of the defined facility location problems can be seen in papers by Brandeau and Chiu (1989), Klose and Drexl (2005), ReVelle and Eiselt (2005), and Melo, Nickel, and Saldanha-da-Gama (2009). They reviewed several studies and classified the facility location problems by their significant characteristics such as a single-period/multiple planning horizon, a single/multiple product, and deterministic/stochastic parameter. They discussed the variety of major facility location problems as follows:

> *"Multi-period location problems have been proposed to approach situations in which parameters change over time in a predictable way… Another important extension regards the inclusion of stochastic components in facility location models… Another aspect driven by real-life applications, and that has raised much attention, regards the necessity to cope with multi-commodity problems…"* (Melo et al., 2009).

5.2.2 Model building

In the stage of model building, the set of optimisation models attempts to find an optimal solution by two major methods, exact approaches and heuristic approaches (Church & Murray, 2009). First, the mathematical programming approaches – linear programming, integer programming, and mixed-integer programming – are commonly used to construct the model of the problems. Secondly, the heuristic models – genetic algorithms, and swarm intelligence, etc. – provide the near optimal or optimal result.

Instead of providing an optimal solution, simulation models are frequently applied to imitate systems (Robinson, 2004). In supply chains, simulation is generally applied for a supply chain network design, for operational decision, particularly distribution, transportation and inventory planning (Terzi & Cavalieri, 2004).

5.3 An overview of complexity analysis

This section will illustrate why the facility location problems are very difficult to solve. To comprehend the tough exercise, the computational science term -- complexity theory -- often depicts this complication.

5.3.1 Why is complexity theory important?

In the development of algorithms, one is often interested in the effectiveness of the algorithm. A variety of ways have been developed to evaluate this; for example, the algorithms are executed on a set of data and the execution time is recorded. That is an approach which considers how long an implementation of the algorithm takes to solve one particular instance of the problem on a particular machine.

An alternative approach is to develop a complexity theory, in which the execution time is given as a function of the size of the problem (Garey & Johnson, 1979). In other words, to illustrate the efficiency of the algorithm, the number of steps that has to be taken to solve an instance of the problem is measured, which is obviously independent from any specific computer or machine.

More specifically, complexity theory defines, first, clearly what solving a problem efficiently means and, secondly, categorises problems into those that can be solved efficiently and those that cannot, and finally estimates the amount of time needed to solve these problems (Daskin, 1995).

5.3.2 What is complexity theory?

The most common approach is to compare the growth rates of the two runtimes, each viewed as a function of the instance size (Martin, 2002). Term 'big-*O*' is used to measure time and space complexity of a problem. It gives information about complexity of algorithms in respect to steps to resolve the problem.

Constant time, or $O(1)$ time, denotes the computation time of a problem when the time needed to solve that problem does not depend on the size of the data. For instance, to access any single element in an array, the computational time is constant as only one operation is required.

An algorithm in linear time, or $O(n)$ time, refers to the running time growing linearly with the size of input data. An example is to find the maximal value in an random order array which takes $O(n)$ time since all elements in array must be examined.

In computational complexity theory, polynomial time refers to the execution period of a problem where the run time, $m(n)$ is no greater than a polynomial function of the problem size, n. The mathematical big-O notation can demonstrates that $m(n) = O(n^c)$ where c is a constant that may depend on the problem.

Finally, exponential time is the computation time of a problem where the time to complete the computation, $m(n)$, is bounded by an exponential function of the problem size, n. Simply put, as the size of the problem increases linearly, the time to solve the problem soars exponentially. Written mathematically with, big-O notation: $m(n) = O(c^n)$ where c is a constant and $c > 1$.

To demonstrate the big-O notation in the process of estimating the computational time of an algorithm, Dijkstra's algorithm (Ahuja, Magnanti, & Orlin, 1994), which is frequently used to find a shortest path, is described as follows:

Given: A graph with nonnegative link distance or cost c_{ij} associated with link (i, j); n is the number of nodes.

Find: The shortest path tree at node K.

Note: Nodes will be labelled with a two-part label. So, the label for node j would be $[V_j, P_j]$, where V_j gives the minimum cost way of getting to node j, while P_j specifies the predecessor node to node j on the path from K to j.

Step 1:	Initialisation	
	(a) Label node K[0, -]	$O(1)$
	(b) Label all other nodes[∞, -]	$O(n)$
	(c) Set node K *as* scanned	$O(1)$
Step 2:	Label updates	
	(a) Call the last scanned node, node m	$O(1)$
	(b) For all links (m, j), compute	$O(n)$
	(b.1) $T_j = V_m + c_{mj}$	$O(1)$
	(b.2) If $T_j < V_j$, relabel node j with [T_j, m]	$O(1)$
Step 3:	Scan a node	
	(a) Find the unscanned node with smallest label V_j	$O(n)$
	(b) Scan this node	$O(1)$
Step 4:	Termination check	
	(a) All are nodes scanned?	$O(1)$
	(a.1) Yes → stop	$O(1)$
	(a.2) No → go to step 2	$O(1)$

In sum, the first step takes approximately $O(n)$ times. Then, the second step takes $O(n)$ time each time it is executed. Step 2, 3 and 4 will be executed a total of $n-1$ times (until all nodes are scanned); this means that they will be executed *O(n-1)* times. So, the entire algorithm therefore has complexity *O(n(n-1))* or $O(n^2-n)$. However, the dominant terms are only concerned in computing the complexity. In fact, the n^2 term dominates the term *n* for large values of *n*. Thus, the whole process can be said to have complexity of $O(n^2)$.

5.3.3 Why does exponential time indicate such a high complexity?

The focus of complexity is on the worst scenario performance of an algorithm. An algorithm is said to be a *polynomial* time algorithm if *f(n)* is a polynomial function of n. More specifically, n, n^2, and n^3 are all polynomial function of n as well as *n.log (n)*, n^2*.log (n)* and so forth. In contrast, other algorithms whose time complexity function cannot be so bounded such as 2^n, e^n, 3^n, and *n!* are *exponential* time algorithms for which *f(n)* grows exponentially with *n*.

While polynomial time algorithms are considered efficient, exponential time algorithms are the opposite. Garey and Johnson (1979) illustrate the difference between these two kinds of algorithm with Table 5.1. It assumes the computation time for a set of algorithm can be executed in 10^6 operations per second and the constant multiplying the function of the problem size *n* equal to 1. Therefore, it assumes that a linear time [*O(n)*] algorithm will require exactly n operations, while other functions are increased dramatically.

Table 5.1 Growth in solution times as a function of problem size

Complexity	*n* = 10	*n* = 20	*n* = 40
O(n)	10^{-5} sec	2 x 10^{-5} sec	4 x 10^{-5} sec
$O(n^2)$	10^{-4} sec	4 x 10^{-4} sec	0.0016 sec
$O(n^3)$	10^{-3} sec	8 x 10^{-3} sec	0.064 sec
$O(2^n)$	10^{-3} sec	1.05 sec	12.7 days
$O(e^n)$	0.022 sec	8.08 min	74.6 centuries !!

Computers and Intractability: A guide to the Theory of NP-Completeness by Garey and Johnson, 1979

As can be seen from Table 5.1, a linear time [*O(n)*] algorithm is faster than a quadratic [$O(n^2)$] and cubic [$O(n^3)$] algorithm, respectively. Since computers are growing faster everyday, it seems that the issue of the speed of an algorithm need not concern us too much. As demonstrated in Table 5.2, if the complexity is linear time [*O(n)*], the efficiency of algorithm increases as much as speed of computer. If the algorithm is polynomial, the size of the problem that can be solved grows multiplicatively with that of the speed. Nevertheless, when the algorithms are exponential, the size of problem grows only additively with the speed. Considering a problem with N_4 nodes using an $O(2^n)$ algorithm, by using a computer is 1000 times faster, it can only solve a problem with N_4 + 10 nodes in the same amount of time.

Table 5.2 Growth in size of problems that can be solved in same time as a function of speed of computer and complexity

Complexity	Speed = 1	Speed = 10	Speed = 100	Speed = 1000
$O(n)$	N_1	$10N_1$	$100N_1$	$1000N_1$
$O(n^2)$	N_2	$3.16N_2$	$10N_2$	$31.6N_2$
$O(n^3)$	N_3	$2.15N_3$	$4.64N_3$	$10N_3$
$O(2^n)$	N_4	$N_4 + 3.32$	$N_4 + 6.64$	$N_4 + 9.97$
$O(e^n)$	N_5	$N_5 + 2.30$	$N_5 + 4.61$	$N_5 + 6.91$

Computers and Intractability: A guide to the Theory of NP-Completeness by Garey and Johnson, 1979

5.3.4 Complexity classes

Complexity theory categorises problems into those that can be solved efficiently and those that cannot be solved efficiently. Problems that can be solved efficiently are those for which a polynomial time algorithm exists. Such problem are said to be in the class *P* (Garey & Johnson, 1979).

There are many problems for which no efficient algorithm is known (Mehlhorn & Sanders, 2008), for instance, the travelling salesman problem, the knapsack problem and a graph colouring problem. The fact is that an efficient algorithm for these problems does not exist yet. In general, it is very hard to prove that a problem cannot be solved in a given time period, but most researchers believe that such problems have no efficient solution (Mehlhorn & Sanders, 2008). Such problems are defined as *NP-complete problems.* Here, *NP* is an abbreviation for "nondeterministic polynomial time".

In addition, sometimes researchers speak of problems that they find difficult to solve as *NP-hard*. The term *NP-hard* is often used to describe the optimisation versions of the decision problems that are *NP-complete.*

In addition, Garey and Johnson (1979) illustrate a list of problems that fall into the class of *NP-complete*; unsurprisingly, facility location problems are *NP-hard*.

5.3.5 Reduction

A reduction is a way of converting one problem into another problem in such a way that, if the second problem is solved, it can be used to solve the first problem (Sipser, 1996). It is widely believed that *P* is a proper subset of *NP* (Mehlhorn & Sanders, 2008). All *NP-complete* problems have a common destiny. If anybody should find a polynomial time algorithm for one of them, then $NP = P$.

Daskin (1995) points out that it is likely to be possible to transform problems that are difficult to solve into manageable problems. In other words, many *NP* problems can possibly be transformed into *P* problems as can be seen below:

> *"However, many location problems fall into a class of problems for which no polynomial time algorithm exists (as yet) and it is believed that no such algorithm will ever exist (though this has not been proven either). We do know, however, that if a polynomial time algorithm can be found for any such problem (in the class of problems that are called NP-complete), then a polynomial time algorithm must exist for all such problems."* (Daskin, 1995)

In short, it is likely to be possible to develop an efficient algorithm to reduce the complexity of *NP* problems in to the problems in the *P* class. In order words, the *NP* problems can possibly be solved.

5.4 Modelling Approaches

The complexity of the network problems was described in the section 5.3. However, it is possible to lessen the *NP*-hard problems into polynomial time solvable problems (Daskin, 1995). In this section, the fundamental modelling approaches to deal with that complexity will be discussed. First, the optimisation approach will be described including an exact method and a heuristic method. Then, a simulation modelling approach will be examined. Finally, a hybrid modelling approach, the combination of optimisation and simulation, will be considered.

A number of methods capably solve complicated and/or large problem instances. To illustrate, Table 5.3 summarises different methods that have been taken to solve a *P*-median problem (this will be described in section 5.7.3).

Table 5.3 Select research focused on solution of the *P*-median problem

Solution	Approach	Description
Exact (model reformulation), with solution by general purpose optimization software	Hybrid: Smaller model formulation, helping to solve larger problems	A model that combines two forms of allocation constraints
	COBRA: A model that reduces needed variables and constraints by taking advantage of spatial structure	A model that combines variables and constraints based on spatial properties
	BEAMR: A model that can be used in two modes, exact or approximate, reducing problem size	A model that eliminates variables and associated constraints that do impact the identification of the optimal solution
Exact	Lagrangian relaxation with subgradient optimization embedded into a branch and bound algorithm	Based on solving a dual model generated by the relaxation of one or more model constraints. The procedure searches for optimal values of Lagrange prices, and guarantees optimal results because it is embedded in a branch and bound algorithm
Heuristic	Vertex substitution (or neighbourhood search)	A substitution-based algorithm, like interchange
	Lagrangian relaxation with subgradient optimization	A Lagrangian based process without a branch and bound algorithm
	Tabu search	A substitution-like approach that always makes a change, regardless of improvement, keeping track of the progression of changes and avoiding "tabu" moves
	Variable neighbourhood search	A substitution heuristic that involves a search neighbourhood that varies in size
	Heuristic concentration	Based on using a heuristic to identify core and concentration sites, then using the hybrid exact model to select from the concentration set
	Simulated annealing	Based on an analogy to tempering glass or metal, where configuration perturbations are tested and compared to a Boltzman distribution
	Genetic algorithm	Based on a genetic encoding and biological inspired operators, such as mating and mutation

Business Site Selection, Location Analysis and GIS by Church and Murray, 2009

When a discrete optimisation problem is in the polynomially solvable category in complexity, it is normally clear how to work with an efficient algorithm. In *NP*-hard problems, Rardin (2001) suggests a more careful selection methods by offering a very approximate guideline in Figure 5.4. It based on two significant features: (a) the number of binary decision, and (b) the error of the best available relaxation bound.

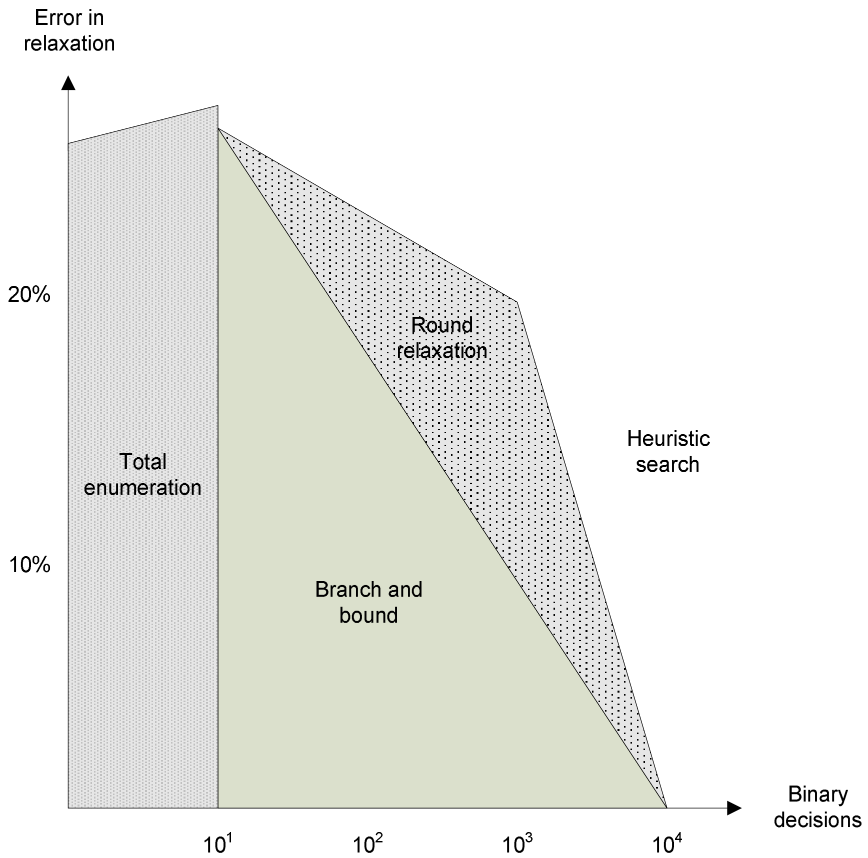


Figure 5.4 Guideline for *NP-hard* problems

5.4.1 Optimisation models

An aim of optimisation models is to find a best solution. In general, there are two principal approaches to achieve this goal: exact approaches, and heuristic approaches (Church & Murray, 2009). On the one hand, exact approaches provided an optimum solution. On the other hand, heuristic approaches, which may be considered as approximated approaches, offer a near optimum or optimum solution.

5.4.1.1 Exact approaches

Exact approaches refer to the method with an ability to assure either a mathematically optimum solution to the problem, or at least a solution of known accuracy (Ballou, 2004). Examples of some well-known exact methods are Dijkstra's shortest path algorithm, spanning tree algorithm, and mathematical programming methods such as linear programming with the simplex algorithm, and integer programming with the branch and bound method.

To find the optimum solution, a number of methods are offered. The popular methods applied in these approaches are simplex method for linear programming, branch-and-bound method for integer and mix-integer programming, while other methods are provided for particular purpose, for example, branch-and-cut, Lagrangian relaxation, column generation, and decomposition methods (Daskin, 1995).

Several models for the supply chain problem have been developed based on optimisation model with deterministic variables, in which all parameters are assumed to have fixed values. For example, Geoffrion and Graves (1974) established a multi-commodity capacitated single-period of an optimal location design in distribution problems for food company. They formulated the problem as a mixed integer linear programming using solving technique based on Benders decomposition method.

Camm, Chorman, Dill, Evans, Sweeney, and Wegryn (1997) examined Procter & Gamble (P&G) supply chain in order to improve product-sourcing and distribution system. They developed the methodology based on an integer programming method using a transportation model and an uncapacitated facility location model. To solve this model, they employed standard mathematical programming software namely LINDO, which the solver based on branch and bound opimisation method.

The strength of these approaches is to provide the best or optimum solution. However, in terms of limitations, the problem size is generally very limited and massive memory is required (Almeder et al., 2009). This method results in long computer run-times. Indeed to solve a dynamic facility location problem in polynomial time is not possible since this problem fall into the class of *NP*-hard problems (Krarup & Pruzan, 1983).

5.4.1.2 Heuristic approaches

When a supply network is complex probably because of more than one facility layer and many constraints, the number of variables is massive. So, this leads to unacceptably long computer run-times and enormous memory requirements. As a result, the best solution cannot be solved by exact approaches. This difficulty can sometimes be solved by an alternative method, namely *heuristic* approaches. In some cases exact approaches cannot solve the problem in polynomial time. In most of these cases most of these cases heuristics have been successfully used (Ko et al., 2006).

According to Church and Murray (2009), a heuristic method is defined as *"a technique, or algorithm, that gives a solution to the model, but cannot prove or verify anything about the quality of the solution."* Typically, heuristics are designed to produce feasible solutions and are finite in operation. However, the heuristic approaches are not certain that the result is a global optimum; it may be a local or near optimum. In other words, an identified solution using a heuristic may be optimal, but this cannot regularly be proven, or it may merely be of deficient quality (Church & Murray, 2009).

A common characteristic of a heuristic is that it is able to solve a problem quickly, and may be easy to implement (Church & Murray, 2009). Specific algorithms with heuristics are the most fashionable techniques (Melo et al., 2009). Among heuristics approaches, *evolutionary algorithms* (EAs) can frequently outperform optimisation methods when applied to complicated real-world problems (Gen, Cheng, & Lin, 2008).

EAs mostly involve heuristic optimisation algorithms such as *genetic algorithms* (Goldberg, 1989; Holland, 1992), *evolutionary programming* (Fogel, Owens, & Walsh, 1966), *evolution strategy* (Schwefel, 1995), *genetic programming* (Koza, 1992; 1994), *ant colony optimisation* (Dorigo & Stützle, 2004), and *particle swarm optimisation* (Kennedy, Eberhart, & Shi, 2001). Among such algorithms, *genetic algorithms* are the most commonly known algorithms used today (Gen et al., 2008).

An application using heuristic approaches can be found in a large number of studies. For instance, Nozick (2001) developed a fixed charge facility location model with coverage restrictions. The objective was to minimise cost while a service level was maintained appropriately. They offered two Lagrangian relaxation-based heuristics: a greedy adding algorithm to find upper bounds and subgradient optimization to calculate lower bounds.

Imai et al. (2005) addressed the berth allocation problem, with a heuristic for both discrete and continuous location problems. A wide variety of experiments were conducted and the results showed that the heuristic works well from a practical point of view.

One of the papers related to computational complexity was published by Erlenkotter (1981). He compared several approaches for dynamic location problems by examining a dynamic, fixed charge, capacitated, cost minimisation problem with discrete time intervals. His study suggested that combining heuristic approaches in a multiple phase solution process may prove the computational performance more effective.

Silva et al. (2009) introduced a heuristic method namely ant colony optimisation for distribution in supply chain management. Ant colony optimisation algorithm is a type of multi-agent optimisation which uses a pheromone matrix to keep an information record during the optimisation process. They claimed that the results showed this to be more efficient than a simple decentralised methodology. Nevertheless, they did not compare the results using testing instance with other popular algorithms such as genetic algorithms.

Although optimisation methods, exact and heuristic approaches, attempt to provide a best solution, it is difficult to capture uncertain features. Rarely can it easily perform a range of testing policies for making a decision.

5.4.2 Simulation models

In general, a *simulation* can be defined as 'an imitation of a system' (Robinson, 2004). In many industries, simulation has been primarily used as an important support for decision making. In the supply chain context, it is mainly applied for designing a supply chain network, for verifying strategic models and management; in addition, most of the implemented simulations involves distribution, transportation and inventory planning (Terzi & Cavalieri, 2004).

While exact approaches provide an optimum solution and heuristic approaches offer a near optimum, simulation approaches predict the performance of a modelled system under a specific set of inputs. In other words, the purpose of simulation approaches is not to provide the optimal solution; on the contrary, it focuses on an imitation of a considered system in order to test a decision-maker policy, or predict a system performance.

Simulation allows us to evaluate operation performance prior to the implementation because of many reasons (Terzi & Cavalieri, 2004). First, it can perform powerful 'what-if' analyses in order to inform better planning decisions. Second, it allows comparing several operational scenarios without interrupting the real situation. Finally, it can simplify the long time horizon into short periods so that the policy based on time decision can be performed.

To examine such performances or policies, an experimental approach in modelling is applied by a 'what-if' analysis technique. That is model assumptions or input data is altered and re-optimisation is performed so as to observe the change by comparison with a 'base' or 'reference' case (Geoffrion & Powers, 1980). Generally, modellers input a scenario, predict a result, and explore alternative scenarios until they gain understanding how to improve its actual system.

Simulation approaches can be classified primarily as *discrete*, *continuous*, and *agent-based* simulation. Discrete or discrete-event system simulation is the modelling of systems in which the state variable changes at a discrete set of points in time. An example of the discrete-event is a queuing service at bank: a customer arrives, a customer starts receiving service, and then a next customer receives service.

However, many systems e.g. chemical plants and oil refineries, the state of the system changes continuously through time. In this situation the system is to be analysed as a continuous simulation system. In some systems e.g. digital computers cannot model as a continuous state change. The continuous simulation can be approximated by accounting for small discrete time-steps. *System dynamics* is a specific form of the continuous simulation that represents a system as a set of stocks and flows (Robinson, 2004).

An agent-based simulation is relatively a new simulation approach that is introduced. Instead of interesting in an event or time, agents are represented in order to model the systems. The major characteristic of agents comprises of autonomy, interacting, responsiveness, pro-activeness, adaptability, mobility, veracity and rationality (Paolucci

& Sacile, 2005). More specifically, agents can interact autonomous among other agents proactively. They have an ability to adapt themselves in order to response to changing environment and to an enhanced knowledge about problem-solving capability. Computational advances enable an increasing number of agent-based application across many fields (Macal & North, 2005).

The conventional simulation methods usually refer to discrete and continuous simulation. The difference between agent-based simulation and conventional simulation model can be concluded by the following issues (Paolucci & Sacile, 2005) and Table 5.4:

- Part of the system entities is associated with agents.
- The entities that are simulated as agents are able to communicate with each other, perceive changes in the circumstance and show a proactive behaviour.
- The system model is intrinsically distributed since agents behave autonomously.
- The model make possibly to study the emergent behaviour of a system, i.e., the outcome of the simulation at the macro level derives from the evolution of the interaction of single or groups of agents at the micro level.

Table 5.4 Differences among system dynamics, discrete and agent-based simulations

	System dynamics simulation	**Discrete simulation**	**Agent-based simulation**
Developed year	1950s / 1960s		1990s
Perspective	Top-down		Bottom-up
Focused	Aggregated (stocks, flow, etc)	Process (Sequence of operations, entities, resources)	Individual behaviour of objects (people, departments, companies, etc)

The main advantage of simulation modelling is to be able to model variability and its effects. Most of simulation are performed in complex systems, which are closely-related to the real-world situation (Terzi & Cavalieri, 2004). Other models cannot, or can be adapted to account for variability, but this normally raises their complexity; furthermore, simulation modelling requires few assumptions to simplify the model compared to other modelling approaches (Robinson, 2004). Queuing theory, for example, often presume certain distributions; however, for many processes these distributions are not suitable; on the contrary, for simulation modelling any distributions are able to be chosen (Robinson, 2004).

A number of studies employ the simulation approach. For example, Geoffrion and Powers (1980) presented the framework of a comprehensive distribution planning system by addressing the sensitivity and flexibility in terms of adaptive 'what-if' questions. Carson, Manivannan, Brazier, and E. Ratlift (1997) and Banks, Buckley, Jain, Lendermann, and Manivannan (2002) presented a panel session in the Winter Simulation Conference where they discussed the opportunities for simulation modelling in supply chain. Iannoni and Morabito (2006) applied simulation techniques to analyse an agro supply chain by studying the process from harvesting, transportation, to plants processing and investigating alternative configurations as well as operational policies testing. In addition, instead of using an analytic model alone to capture a system dynamic and uncertainties of a supply chain network, simulation approaches are able to provide an alternative method (Ko et al., 2006).

Considering the hybrid simulation approaches in the supply chain context, Lee and Kim (2002) introduced a combination of analytic and simulation approaches in the case of integrated production-distribution planning. They used simulation to check the capacity assumptions for a linear model in order to update the capacity parameters and used an analytic approach to optimise the whole production-distribution. The authors claimed that the proposed method provided realistically optimal operation times and production-distribution plan. However, the main disadvantage of this method was the rigidity of the assumption of analytic model and the verification of the analytic solution to the real system.

Datta (2007) developed an agent-based simulation model for studying and improving the resilience of production and distribution networks. His study addressed the tactical level in supply chain management by investigating the internal decision making, rules and control procedures through an agent-based model. This study presented a simulation approach to tackle the problem for their supply chain management. However, it performed the simulation model in order to imitating the systems. The purposes did not include a search for the optimum solution.

In chemical industry, Pitty, Li, Adhitya, Srinivasan, and Karimi (2008) proposed a dynamic simulation model of integrated refinery supply chains. Their proposed model included the various supply chain activities, for example, transportation, procurement planning, scheduling and operation management, and many players such as crude oil supply, 3rd party logistic providers, shippers jetty operator, and customers. Discrete supply chain activities were integrated along with stochastic variations in distribution, yields and prices. In case studies, they also presented the effects of varying different parameters and policies. The authors claimed that their model allowed users to modify parameters, change testing policies and decision-making algorithms easily through graphical user interface. However, their model was a pure simulation model, and they did not provide the optimal results but a good result still based upon the classical 'what-if' analysis.

5.4.3 Hybrid approaches: simulation-optimisation

This section will describe hybrid approaches in terms of the combination of simulation and optimisation methods. As noted in the scoping study section, the intersection of three circles from mapping the field will be the focus of this section. Several studies have employed this methodology as the following reviews:

Jung et al. (2004) proposed a simulation-based optimisation approach to an operation management in chemical industry. In routine operation, the deterministic planning and scheduling models including safety stock levels as a tool to cope with demand uncertainty were proposed in their study. In the stage of planning and scheduling, "*rolling horizon mode*" was usually applied to accommodate demand and other uncertainty. The rolling horizon mode involves dividing the operation time into a certain number of planning periods, then solving each period was solved using appropriate deterministic demand projections, finally the results of a couple of first year were input as fixed data into scheduling models which output depicted time-based production and consecutive solutions. Their study intended to propose a means to set up safety stock levels using such rolling horizon planning and scheduling method as described above. The advantage of their approach, first, they attempted to take the uncertain characteristic of the customer satisfaction level into account. Second, they simplified a stochastic nature into a set of slice deterministic data, which it eased to manage than original one. However, the weakness of this method was iteration between simulation and optimisation may cause computational time. In addition, the distribution pattern must be known in order to create the simulation model.

Not only are applications found in manufacturing and the supply chain analysis, but also in the military. Cusick (2004) analysed the complexity activities occurring at a military airfield in order to improve the airfield performance. Existing airfield systems used by the Air Force were extremely complex in nature. Since the airfield comprised of several activities and various resources to be managed and controlled, the diverse variety of such resources must interrelate each other. He recognized the shortcoming of an existing simulation model that it did not accurately capture the capacity of the airfields used in the global system when dynamic loads were required. Because the system contained both continuous and discrete dynamics, it cannot be optimised using traditional optimisation methods. A hybrid composition method was used to enhance the performance of such complexity in the airfields. In his purposed composition method, the enormous hybrid system was decomposed into lesser subsystems which were able to actively modelled and optimised by proven methods. The strength of his method was able to categorise the different type of resources into groups according to continuous or discrete data, then optimise each sub-module using a proven heuristic or exact method. However, the weakness was, as often found in most real world problems, how to define a cost function which was extremely difficult. He described in his case that many of the cost functions can be defined in terms of delay time perceived by users and resource utilisation.

Ko et al. (2006) developed a hybrid optimisation/simulation modelling approach for taking into account dynamics of clients and uncertain demands. The optimisation module by a genetic-based heuristic was utilised to establish the distribution structure; furthermore, the simulation model was employed to capture the uncertainty in clients' demands, order-picking time and service time. In the optimisation model, they formulated a multi-period, two-echelon, multi-commodity, capacitated location model in order to find an appropriate period for the closing and opening of warehouses. The model framework set up a recursive procedure between optimisation and simulation. To combine simulation and optimisation was an advantage in which it used an automatic generated distribution pattern form simulation module and found a good solution in optimisation module. However, the weakness of this method was iteration between simulation and optimisation may cause more computational run-time. Besides, to model a simulation, the probability distribution must be known before modelling process.

In the transportation business, Fink and Reiners (2006) address short-term car rental problems involving the optimisation of fleet utilisation by minimising cost network flow. They proposed a decision making framework for tactical and operational management. Their model incorporated significant practical features such as multi-period planning, a national network, fleeting data, and different vehicle sets. The model experiments were conducted on real-world data by apply a simulation model to assess optimisation results for various scenarios. Because the network flow model did not represent all facets, the core optimisation module was enhanced by pre- and post-optimisation stages. More specifically, the planning process may comprise of various sets of data that were estimated by the simulation method. The core optimisation was calculated by an exact brand-and-bound simplex method. The advantage of the study was, first, an attempt to apply management science/operation research to a real-world problem. Second, the scenarios with pre- and post-process were constructed to assess the weakness of the main optimisation module. The drawback of their study was also similar to most simulation approaches in that it intended to simplify the system yet did not to offer a best solution. In addition, the probability distribution must be known.

Ding, Benyoucef, and Xie (2006) developed a toolbox to assist decision makers for the assessment, design and improvement of supply chain networks. The toolbox integrated all level of strategic, tactical and operational management. The architecture of proposed toolbox comprised of (a) network module, (b) optimisation module, (c) statistical data miner, and (d) simulation module. They employed a simulation-based optimisation approach which Genetic algorithm was used to determine the candidate solution and a simulation model was carried out performance evaluation. Finally, two case studies in automotive and textile industries are presented. The advantage of this toolbox is a representation of the supply chain in a holistic approach with a continuous visual sight on the entire network and integrating different parts of various supply chain into a whole network. Because the toolbox is too general purposes without specific function, it is considered as a main drawback. According to review papers, most of studies focus on one level of management. More specifically, facility location problems often are inherent in strategic nature (Owen & Daskin, 1998). Furthermore, as the test cases were implemented, the dynamic of a system including a large number of autonomous performing self-controlled entities is barely to forecast and appraise in an actual operation.

Koo, Adhitya, Srinivasan, and Karimi (2008) extended the study on a dynamic simulation by Pitty et al. (2008) in which they offered a decision support for optimal refinery supply chain design and operation based upon a simulation-optimisation framework. The framework was a linkage between simulator and optimiser module, which optimisation was performed using a non-dominated sorting genetic algorithm and implementing in a parallel computing environment. They asserted that the technique using a parallel computation was a major advantage in computational efficiency. The objective of simulation-optimisation was to maximise profit margin and customer satisfaction index of the refinery. Profit margin was clearly distinct as total revenue minus overall cost, while customer satisfaction was defined as the expected value of the ability to meet the product needs of a customer. The benefit of their study was that it took customer satisfaction into account; however, to measure customer satisfaction was complicated and questionable for different perspectives, it can often employ in operational decision only but not in strategy or tactical decision.

In agricultural sector, Piewthongngam et al. (2009) applied a crop growth simulation and optimisation model in order to maximise overall production. This study drew its data form sugar industry in Thailand. They dealt with the problem in sugar production chain so as to harmonise the dissonance between mill and cane growers. They proposed a framework to support decision-makers in choosing cultivar, and planting and harvest periods. In their framework, a cane growth model was developed to forecast cane yield, and a mathematical programming was formulated to determine planting periods, cultivar and harvesting time. The benefit of this study was an attempt to apply a combination between simulation and optimisation into real world problem. In addition, the modelling framework was simply implementation, due to the linear relation between simulation and optimisation model. The drawback of this study was that it did not integrate the entire chain or more related players in the chain of sugar industry; however, the author claimed that because of complex linkages across the chain, and being able to manage some portions of the chain individually. The stochastic parameters were applied only in the crop growth model, while the optimisation model took only deterministic inputs into account e.g. fix capacity, no a variation in planting, cultivar and harvesting date.

In terms of tools, Vamanan, Wang, Batta, and Szczerba (2004) presented the integration of two commercial, off-the-shelf software packages: CPLEX and ARENA. They described the need for integration and the methods how to integrate them. They explained the limitation of using them in the case of mixed integer programming that computational time was too long, because time requirement increased exponentially with problem size.

The advantage of combination of simulation and optimisation is that using strength of both methods. Simulation is able to model variability and perform in complex systems, whereas optimisation provides a best or optimal solution. This approach can perform an automatic generated distribution pattern form simulation module and find a good solution in optimisation module.

5.5 Facility location problem background

The mathematical science of facility location problem has attracted much attention from many academia and practitioners (Klose & Drexl, 2005). The study of location theory began formally in 1909 when Alfred Weber deliberated how to locate a single warehouse in order to minimise the total distance between warehouse and several customers. Since this first examination, a few applications were introduced. Hakimi (1964) proposed the way to locate centres in a communications network and police stations on a highway network. Facility location problems are also critically important topic in logistics and supply chain management (Guedes, 1994).

Facility location models are used in a variety of applications in real-world situations: for example, the automotive industry (Nozick & Turnquist, 2001), the hardware/electronic industry (Sabri & Beamon, 2000), the chemical industry (Jung et al., 2004; Altiparmak et al., 2009), food industry (Leven & Segerstedt, 2004), the forestry and agriculture industry (Troncoso & Garrido, 2005; Piewthongngam et al., 2009), and the military (Cusick, 2004; Overholts Ii et al., 2009).

The basic question may be to decide how to choose from the known feasible locations or from an infinite number of locations, in which to place a facility and how to assign the customers to this facility. In terms of facilities and customers, the meanings are defined according to the nature of the problem. For instance, in determining suitable locations for industrial plants in order to serve the demands from various regions in the country, the plants are the facilities, and the product users are the customers. In determining the emergency territories to assign to each service centre, the territories are customers and the latter are facilities. In transportation services, location of a hub is important to determine how to serve different districts. Other examples include location of fire stations, hospitals, electric power plants, and even equipment in machine shops.

More specifically, mathematical models for facility location problems are designed to address a set of questions including:

- To what extent facilities should be built?
- At what locations should each facility be built?
- What sizes should they be?
- How should demand be allocated to the facilities?

To answer these questions, it depends on the context that the problem is being solved and on the objectives underlying. For example, a fire station should be located as near as possible to the demand sites; however, a waste collection plant should be sited as far as possible from the residential area. The number of facilities to be established and the dimension of them are often trade-offs between cost and service. The last question is also important to facility location problems; it is concerned with the allocation of demand to each facility.

5.6 Taxonomy of facility location problems

Facility location problems can be categorized in a number of different ways; its classification regularly bases on different inputs and environment. To help identify these problems from Brandeau and Chiu (1989), Daskin (1995), Klose and Drexl (2005), ReVelle and Eiselt (2005), Melo et al. (2009) and the author's reviews, a classification scheme for facility location problems and models can be described by eighteen factors described below.

5.6.1 Planar versus network versus discrete location models

In the classification of facility location models, one of the main variations among these models is how demands and each facility location are represented. In *planar or continuous location models*, demands and facilities are able to take place wherever sites are on a plane, in which demands and any facilities can be located only on nodes and links of their networks. *Discrete location models* are more flexible, in which modellers can apply arbitrary distances between nodes. By removing the restriction that the distances between nodes are obtained from an underlying network, the more general class of discrete location models permits a wider range of problems to be simulated (Daskin, 1995).

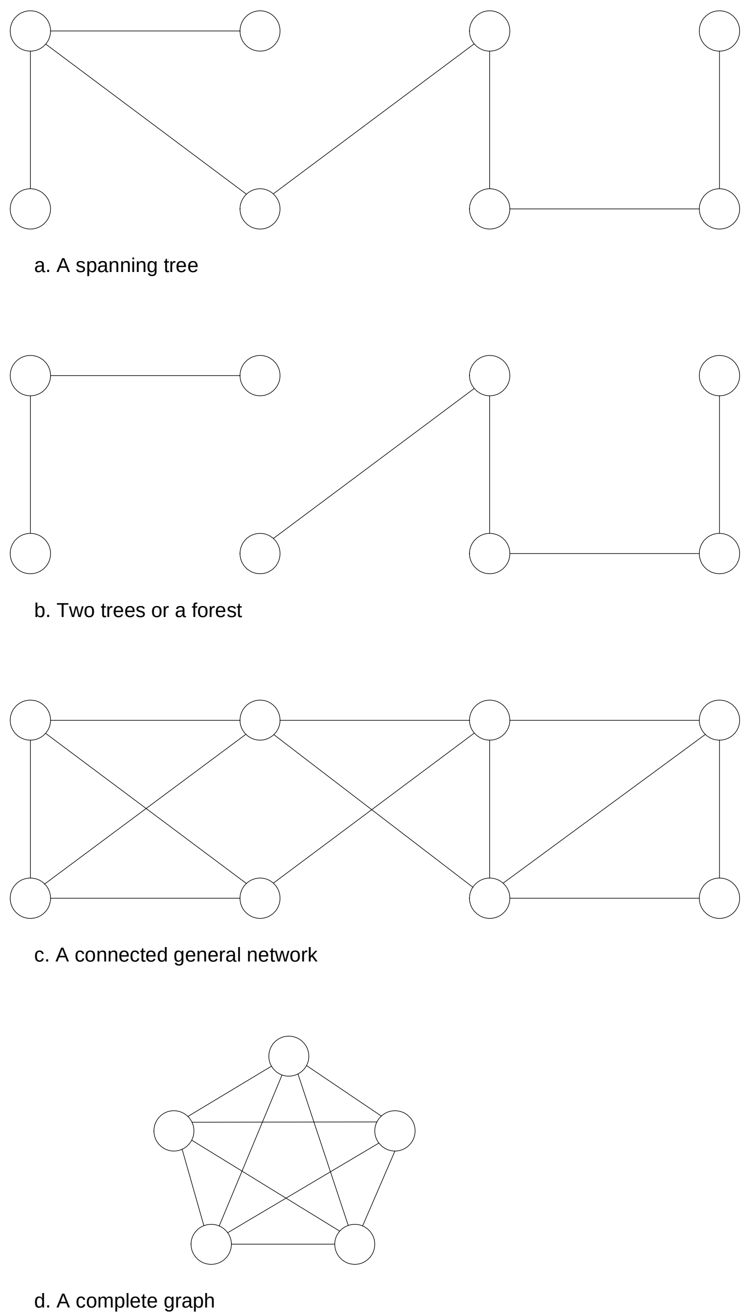
Most formulation in facility location model allows facilities to be located at a finite set of potential site, which they represent as nodes on a network. Hakimi (1964) demonstrates that for any number of facilities *P*, at least one optimal solution to the *P*-median problem has been located only at nodes. As a result, the simplified version of the representative problem can include only nodes as potential facility sites.

The standard method to tackling location problems is to model candidate locations and demands as discrete entities. One of main attributes considering the employment of continuous location models is whether the solution space is continuous. That is it is feasible to locate facilities on every point on the plane (Klose & Drexl, 2005). In some practical problems, they are concerned with dense demands and uncertainties of the cost and sites of the potential locations. Murat, Verter, and Laporte (2009) insist that it is usually inappropriate to model such problems using the discrete method. They present an alternative method to simulate these problems as a continuous density function and solve them by means of calculus techniques.

5.6.2 Tree versus general graph problems

A graph is a set of points, called nodes or vertices, and a set of curves or lines, called links or arcs that connect certain pair of nodes. A tree is a subset of graphs in which there is at most one path from any node to any other node. Figure 5.5 illustrates an example of graphs and trees.

In the set of network location models, a network can be represented in *tree* or in *graph* form. The distinction between tree and general graph relates to facility location modelling resulting from two concerns (Daskin, 1995). First, many problems can easily be represented as trees, for instance, major parts of telecommunication network or power transmission. Secondly, a mathematical model can simply be worked out on a tree; in contrast, it is difficult to be solved on a general graph.



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Mark S. Daskin, 1995

Figure 5.5 Example trees and graphs

5.6.3 Distance Metrics

The technique of measuring distances can be the one of factors to classify the location models. In network location models, the shortest distance metric can be calculated by a shortest path algorithm such as a popular Dijkstra's algorithm (Ahuja et al., 1994). In planar models are different; one of three distance metrics is generally applied (Daskin, 1995).

1. Manhattan or right-angle distance metric

$$d\left[(x_i,\, y_i);\ (x_j,\, y_j)\right] = \left|x_i - x_j\right| + \left|y_i - y_j\right| \qquad [5.1]$$

2. Euclidean or straight-line distance metric

$$d\left[(x_i,\, y_i);\ (x_j,\, y_j)\right] = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad [5.2]$$

3. l_p distance metric

$$d\left[(x_i,\, y_i);\ (x_j,\, y_j)\right] = \sqrt[p]{\left(\left|x_i - x_j\right|\right)^p + \left(\left|y_i - y_j\right|\right)^p} \qquad [5.3]$$

$(x_i,\, y_i)$ is the coordinates of the point *i*, and $d\left[(x_i,\, y_i);\ (x_j,\, y_j)\right]$ is the distance between the point *i* and point *j*.

5.6.4 Number of facilities

Another means of describing facility location problems is by the number of facilities to be set up. In some problems, e.g. *p*-median, *p*-centre and maximum covering problem, the number of facilities to establish is *exogenously* specified, while other cases, e.g. the set covering problem and the fixed charge facility location problem, the model output is *endogenous*. *Single-facility* location problems are first simple problems and are solved markedly less complicated than *multi-facility* location problems (Owen & Daskin, 1998). In the supply chains context, Melo et al. (2009) found few studies concerned with the *multi-echelon* facility location problems.

5.6.5 Strategic versus tactical versus operational decisions

In supply chain management, according to Talluri and Baker (2002) and Simchi-Levi et al. (2008), a planning stage mainly consists of three planning levels: strategic, tactical, and operational planning level.

- Strategic planning level involves supply chain network design, which determines the location, size, and optimal numbers of facilities to be employed in the network. This planning level is long-range planning and is typically performed every few years, when firms need to expand their capabilities.

- The tactical planning level basically includes supply planning, which primarily involves the optimisation of flow of goods and services through a given supply chain network design. This also includes purchasing and production decisions, inventory policies, and transportation strategies, including the frequency with which customers are visited. Tactical planning level is medium range planning, in which is typically performed on a monthly basis.
- The operational planning level is short-range planning that refer to an hour-to-hour or day-to-day decision such as production scheduling, lead time quotations, routing, and truck loading.

Often inherit facility location problems the strategic decision (Owen & Daskin, 1998). Nevertheless, Dasci and Verter (2001) observe a trend of the integration of strategic and tactical decisions.

5.6.6 Static versus dynamic location problems

Static models in this field mean the inputs do not depend on time. In practice, the models represent a single set of in puts, and solve the problem for a single representative period. On the contrary, for *dynamic* models, the inputs depend on time (Owen & Daskin, 1998). Different periods may be to capture the patterns of demands on weekdays and weekends, or to reflect hourly differences in the number of demands, or to account for variation of demand or supply over a period of years.

Much of the research on location problems focuses on static facility location due to their complexity of problems (Owen & Daskin, 1998). Besides, it does not capture some aspects of real-world problems, in particular, future uncertainty. Thus, dynamic models must be applied in this case.

5.6.7 Deterministic versus uncertain models

Deterministic models mean that the parameters of the model are certainly known; in contrast, *uncertain* models refer to those where parameter of the model are uncertainly known. It is simple to assume almost all parameters to be deterministic, because the computational method is not complicated. Nevertheless, dealing with several location problems, many of the inputs are likely to be uncertain such as customer demands, and transit time (Snyder, 2006).

To capture the real-world problems, decision-maker or modeller must trade-off between an accuracy of assumptions and computational time. In this issue, the more uncertain parameters input into the model, the more time and memory required.

5.6.8 Single versus multiple product models

Several models deal with a *single homogenous product*; yet, products are distinguished in many cases. For example, a single set of transhipment facilities or distribution centres may be used by a distributor in shipping goods from several suppliers to several dealers or customers. At such points, goods may be loaded from different suppliers to consolidate and transit to customers. If products are not homogenous, multiple product models must be applied to analyse the impact of the distribution system.

According to the paper by Melo et al. (2009), approximately 40 per cent of their review papers involve the feature of multiple products. In fact, this aspect is driven by real-life situations and raises much attention, for instance, the growth of distribution centres in modern trade.

5.6.9 Private versus public sector problems

Revelle, Marks, and Liebman (1970) were among the first to distinguish between *public* and *private sector* location problems. In private sector problems, the costs and benefits are regularly considered in monetary units; on the other hand, in public sector location problems, many aspects are measured including nonmonetary costs and benefits (Daskin, 1995). However, the costs and benefits commonly insist on supply chains (Melo et al., 2009).

Each problem must clearly define its objective which may often be either of a *minsum* or a *minmax* type. On one hand, the minsum objectives are to minimise average distances; on the other hand, the minmax models are designed to minimise maximum distances. For the most part, minsum models focus on facility location problems of private firms, whereas minmax models embrace such problems in public sectors (Klose & Drexl, 2005).

5.6.10 Single versus multiple objective problems

Most location models represent a *single objective* function. Recently reviews by Melo et al. (2009) for facility location problems in supply chains, the result shows that majority of objective function is a cost minimisation. Such objective function indicates as a single objective through the summation of all cost components in supply chain. Even though, traditionally minimisation of total cost is a principal objective function, other criteria may also influence the final decision (Current et al., 1990).

Many problems are inherently *multi-objective* (Daskin, 1995; Klose & Drexl, 2005). There are no tasks that are merely single objective problems; the design / planning / scheduling projects always concern with trade-offs among goal incompatibilities (Gen et al., 2008). A large body of literature focuses on single objective function, while the work which has been perform multi objective problems is very limited (Klose & Drexl, 2005).

5.6.11 Elastic versus inelastic demand

For most models in facility location, demands are treated as independent of the level of service. This makes an implicit assumption that demand is fixed and independent from customer service, namely *inelastic demand*. Demands in many cases depend on the level of service offered. In fact, *inelastic* or *elastic* demand depends on whether goods or provided service are necessary or unnecessary. Ho and Perl (1995) have examined some of the implications of elastic demand on warehouse location decision. Santos-Peñate et al. (2007) presented a type of location models, the *leader–follower location model*, in several scenarios. The results were derived from both inelastic and elastic demands.

5.6.12 Capacitated versus uncapacitated facilities

Several models in the facility location context deal with facilities of unlimited capacity. *Standard set covering, maximum covering, P-median, and P-centre* models are merely uncapacitated models due to their assumptions. On the contrary, other models impose explicit capacity limits on facilities. In some cases the size of a facility is an output of the models. In some implementations, it is essential to limit capacity in order to reflect the reality of the capability of the facility. If there are capacity constraints, demands must be assigned to candidate sites carefully. Sridharan (1995) examines various techniques for capacitated plant location problems. Most of the techniques are heuristic approaches because it is difficult to solve an exact solution for instances of practical size of problems (Klose & Drexl, 2005).

5.6.13 Competitive versus non-competitive facilities

Most location models assume that the facility is a unique service and is a single player in the market. In the recent modelling development, some models address *competitive facility location problems*, in which they allow the other facilities to compete with them for their market share. Many survey papers about competitive facility location are in print, such as Eiselt and Laporte (1989), Drezner and Zemel (1992), Shiode and Drezner (2003), Plastria (2001), and Fernández et al. (2007).

Plastria (2001) describes the competitive location problem to be a *static* competitive problem as long as the competitors have already presented in the market, and the characteristics of competitors are known in advance and are assumed to be fixed. On the contrary, if the competitive environment changes, in which it reacts to the competing actors, the models are called *dynamic* competitive models.

5.6.14 Nearest facility versus general demand allocation models

Demand allocation type may be one of the factors in classification of facility location models. Normally, Demands are allocated to the nearest facility on condition that facility has the capacity to serve. For many basic models such as *p*-median, *p*-centre and covering problems, demands are assigned to the nearest facility. In capacitated facility models, the demand may be split into other facilities not only the closet site. However, in other cases, models must recognize that a portion of the demand at a site will be fulfilled by the nearest facility and the rest of the demand will be served by more remote facilities when the nearest facility is not available (Daskin, 1995).

5.6.15 Hierarchical versus single-level models

Many systems are inherently hierarchical in nature; for example, the health care systems consist of health centres, hospitals, and medical centres. A health centre offers essential health care; a hospital provides services in addition to those provided by a health centre; a medical centre offers more services than at either a hospital or a health centre. Narula (1986) named this system a *successively inclusive facility hierarchy*. Another hierarchical system, for instance, is a production and distribution system called *successively exclusive facility hierarchy*. In this case, the finished goods from the factory are stored in a warehouse. After that, they are shipped to a distribution centre and are distributed to customers.

Considering the examples above, facilities are not able to locate autonomously at each level. It is important to recognise the nature of problems so as to represent the real-life problems, particularly it inherits hierarchical behaviour.

5.6.16 Forward versus reverse models

Gungor and Gupta (1999) reviewed more than 300 documents on manufacturing and product recovery. They focused on product recovery in terms of an environmentally conscious perspective. Both regulatory and opinion pressure, by government and consumers, are mentioned. Examples of such '*reverse*' streams of products range from end-of-life mobile phone to returned goods in superstore, from reusable packaging to defective equipment requiring rework (Fleischmann, Krikke, Dekker, & Flapper, 2000).

Therefore, supply chain management no longer is confined to one-way product flows from raw materials to end users, but also it is increasingly necessary to deal with opposite flows (Fleischmann, Bloemhof-Ruwaard, Dekker, van der Laan, van Nunen, & Van Wassenhove, 1997).

5.6.17 Combined routing versus classical models

For classical models, the demand allocation is independently measured for supply and demand points. If demands explicitly depend on their delivery so as not to work out for overall operational costs for each pair of demand and supply points separately. In this case, the decisions on location and routing are obviously related. Thus, the combination of location and routing models are required inevitably.

Unfortunately, as noted by Klose and Drexl (2005), the solution of routing location models is very difficult to solve due to many reasons. A first reason is that optimisation formulation is extremely complicated. Second, the planning periods in both problems are poles apart. Finally, facility location problem requires a macro level, i.e. aggregate demand; on the contrary, routing problem needs more micro level, i.e. individual demand.

5.6.18 Desirable versus undesirable facilities

In most cases of location problems, the facilities are desirable, such as distribution centre and customers in order to improve service level, or emergence service and incident sites to minimise time to access an incident event. Some facilities, however, are considered undesirable, e.g. garbage dumps, chemical plants, and prison. In such instances, a model which maximises distance may be more suitable. This problem can be distinguished as *Noxious* (hazardous to health) and *Obnoxious* (nuisance to lifestyle) facilities problems, and both are regarded as *Undesirable*.

A detailed review of such problems can be seen in works of Erkut and Neuman (1989), Tamir (1991) Plastria and Carrizosa (1999) and Fernández et al. (2000). More discussion of this problem can be seen in section 5.8.5.

5.7 Static and deterministic facility location problems

Since the 1960s, after a publication by Hakimi (1964), an interest in location theory has been scrutinised dramatically. Most of the studies have focused on static and deterministic characteristics of parameters (Owen & Daskin, 1998). In terms of '*static'*, the meaning can be explained that input parameters do not depend on time period. In other words, the solution will be worked out in one period of time. A *'deterministic'* expression means that the parameters of the model are certainly known. In this section, the principal static and deterministic location problems will be described. (Note that throughout this document, travel time and distance will be used interchangeably in order to represent the "generalised cost" of travelling.)

Considering applications, Schilling, Jayaraman and Barkhi (1993) reviewed a nearly hundred papers dealing with the covering models as applied to facility location problems. A large number of applications, in many industries, adopt covering models. For example, in military, Overholts Ii, et al. (2009) used a two-stage maximal covering model to develop Inter continental ballistic missile maintenance schedules for the US Air Force. Murawski and Church (2009) applied the maximal covering model to improve an accessibility to health facility in a certain district of Ghana. In emergency medical service, Rajagopalan, Saydam, and Xiao (2008) employed a multi-period set covering location model for dynamic redeployment of ambulances. Erdemir, Batta, Spielman, Rogerson, Blatt and Flanigan (2008) developed an improved covering model and presented a case study for locating cellular base stations in Erie County, New York State, USA.

Sankaran and Raghavan (1997) extend the classical capacitated fixed charged model to incorporate the endogenous selection of candidate sites for importing LPG in south India. Legües et al. (2007) formulate a combination of a plant location problem and a fixed charge network flow problem dealing with two main difficulties in forest harvesting: first, selecting the locations for the machinery to haul logs, and second, designing the access road network.

5.7.1 Covering problems

In many location problems, service to customers depends on the distance or travel time between the customer and the facility to which the customer is assigned. For example, emergency service such as ambulance locations or fire stations could be minimise response time, e.g. under 4 minutes. In other words, this objective is to minimise the number of emergency services needed so that all demand nodes are within a given number of minutes of the nearest emergency service. Such problem is known as *set covering problem* (Owen & Daskin, 1998).

In the set covering problem, the mathematical formulation of this problem can be represented by the following integer programming:

Inputs:
i = index of demand node

j = index of candidate facility site

c_j = fixed cost of locating a facility at node j

S = maximum acceptable service distance or travel time

N_i = set of facility sites j within acceptable distance or travel time of node i
(i.e., $N_i = \{ j \mid d_{ij} \le S \}$)

Decision variables:
X_j = 1 if site j is located, 0 if not

Minimise $$\sum_j c_j X_j \qquad [5.4]$$

Subject to: $$\sum_{j \in N_i} X_j \ge 1 \qquad \forall i \qquad [5.5]$$

$$X_j \in \{0, 1\} \qquad \forall j \qquad [5.6]$$

The objective function [5.4] is to minimise the cost of facilities. Constraint [5.5] requires that all demand i have at least one facility located within the acceptable distance or time. Constraints [5.6] forced the variables to be integer 0 or 1 only.

The set covering problem examines the extent to which facilities are needed. In some practical application, there are not enough allocated resources to construct the facilities according to the desired level of coverage. This condition leads to consider fixing the number of facilities that are to be located and maximising the number of covered demands. This new objective results in this problem namely *maximise covering problem*.

This model originally proposed by Church and ReVelle (1974) as the following formulation:

Inputs:
h_i = demand at node i

P = number of facilities to locate

Decision variables:
Z_i = 1 if node i is covered, 0 if not

Maximise $\sum_{i} h_i Z_i$ [5.7]

Subject to: $Z_i \leq \sum_{j \in N_i} X_j \quad \forall\, i$ [5.8]

$\sum_{j} X_j \leq P$ [5.9]

$X_j \in \{0, 1\} \quad \forall\, j$ [5.10]

$Z_i \in \{0, 1\} \quad \forall\, i$ [5.11]

The objective function [5.7] maximises the number of covered demands. Constraints [5.8] establish which demand nodes are covered within the acceptable distance. Constraint [5.9] stipulates the number of facilities to be located no more than P facilities. Finally, constraints [5.10] and [5.11] are integrality constraints.

In terms of methods for the solution of set covering models, row and column reduction techniques are used to tackle such models. These techniques often result in complete solution. Nevertheless, if they cannot, the linear programming relaxation of the resulting integer programming problem is adopted. Provided that the solution is an integer, the problem is able to be solved. However, if it is not all integers, branch-and-bound techniques are employed instead.

The crucial issue of this problem is *"coverage"*. That is demands or customers must be covered within a specific period of time. An important assumption of the basic covering model is uncapacitated; several models make use of this assumption. Nevertheless, some studies by Current & Storbeck (1988), Pirkul and Schilling (1989), Carnes and Shmoys (2008) developed a model and algorithm including a capacitated assumption. Other limitations of set covering models are that the model often requires more facilities than given budgets. Moreover, all demand points are recognised equally; as a result, the model cannot distinguish high demand or low demand nodes. To tackle these limitations, the maximum covering models are formulated in which the objective is to assign a certain number of services to maximise the quantity of demands that are enclosed.

For the maximum covering location problems, three broad methods can handle including: a greedy adding and substitution heuristic, a heuristic based on Lagrangian relaxation, and branch and bound technique (Daskin, 1995). Among these approaches, the greedy adding and substitution heuristic is the simple method to comprehend and to work out. However, other information how different from an optimal solution does not provide. On the contrary, the Lagrangian relaxation heuristic offers a lower bound for the outcome and its result is very close to optimum solution (Daskin, 1995).

5.7.2 Centre problems

Instead of using an exogenously specified coverage distance and asking the model to minimise the number of facilities needed to cover all demands, *P-centre problems* minimise the coverage distance such that each demand point is covered within the endogenously determined distance by one of the facilities (Owen & Daskin, 1998). The *P*-centre problem is known as a *minimax problem*, which it seeks to minimise the maximum distance between a demand and the nearest facility to demand. If facilities can be located anywhere on the network, the problems are known as *absolute centre problems*. On the contrary, problems which the facilities can only be located on the nodes of the network are known as *vertex centre problems*.

In the vertex *P*-centre problem, the mathematical formulation of this problem can be represented by the following:

Inputs:
d_{ij} = distance from demand node i to candidate facility site j

h_i = demand at node i

P = number of facilities to be located

Decision variables:
X_j = 1 if candidate site j is located, 0 if not

Y_{ij} = fraction of demand at node i that is served by a facility at node j

D = maximum distance between a demand node and the nearest facility

Minimise D [5.12]

Subject to: $\sum_j X_j = P$ [5.13]

$\sum_j Y_{ij} = 1 \quad \forall\, i$ [5.14]

$Y_{ij} - X_j \leq 0 \quad \forall\, i, j$ [5.15]

$$D \geq \sum_j d_{ij} Y_{ij} \qquad \forall\, i \qquad [5.16]$$

$$X_j \in \{0, 1\} \qquad \forall\, j \qquad [5.17]$$

$$Y_{ij} \geq 0 \qquad \forall\, i,\, j \qquad [5.18]$$

The objective function [5.12] is basically to minimise the maximum distance between a demand node and the closest facility to the node. Constraint [5.13] requires that all of the demand at node *i* must be assigned to a facility at some node *j* for all nodes *i*. Constraint [5.14] imposes that *P* facilities be located. Constraints [5.15] declare that demands at node *i* cannot be assigned to a facility at node *j* unless a facility is located at node *j*. Constraint [5.16] identifies the maximum distance between demand node *i* and the closest facility *j*. Constraints [5.17] and [5.18] are the integrality and nonnegativity constraints, respectively.

In some practical cases, the demand-weighted distance is considered. So, the constraint [5.16] can be replaced by

$$D \geq h_i \sum_j d_{ij} Y_{ij} \qquad \forall\, i \qquad [5.19]$$

Note that constraint [5.18] can be allowed to be fractional in order that one demand point may be served by multiple facilities.

Martinich (1988) proposes a vertex closing heuristic for solving the vertex centre problem. A vertex closing algorithm begins with facilities located at all candidate locations and proceeds to close facilities. Daskin (1995) provides a polynomial time algorithms for solving the unweighted and weighted absolute 1-centre and the absolute 2-centre, and the vertex 1-centre problems on trees. For more general graphs, he recommends a method that guesstimate a value of the solution and then solving a set covering model instead. Mladenović, Labbé, and Hansen (2003) propose a basic variable neighbourhood search and two tabu search heuristics for the *p*-centre problem using the 1-interchange or vertex substitution neighbourhood structure. Elloumi, Labbé, and Pochet (2004) offer a new integer linear programming for this problem with a polynomial number of variables and constraints, and illustrate how to obtain tight bounds on the optimal solution. Chen and Chen (2009) offer a new relaxation algorithms for the uncapacitated continuous and discrete *P*-centre problems.

Whenever the number of facilities to be located is fixed, both the vertex and absolute centre problems are able to be worked out within polynomially solvable time. For the vertex centre problem, a polynomial algorithm can be found, while the absolute centre problem is able to devise an improved network so that its result will be on a subset of the original nodes and amplified points. On condition that the number of facilities is variable, both vertex and absolute type of problems are *NP*-completeness (Owen & Daskin, 1998).

5.7.3 Median problems

The *P-median problem,* firstly introduced by Hakimi (1964), is to find the location of *P* facilities on a network so that the total cost is minimised. This problem can be formulated using the following notation:

Inputs:
h_i = demand at node *i*
d_{ij} = distance from demand node *i* to candidate facility site *j*
P = number of facilities to be located

Decision variables:
X_j = 1 if candidate site *j* is located, 0 if not
Y_{ij} = 1 if demands at node *i* are served by a facility at node *j*, 0 if not

With this notation, the *P*-median problem can be formulated as follows:

Minimise $$\sum_i \sum_j h_i d_{ij} Y_{ij} \qquad [5.20]$$

Subject to: $$\sum_j X_j = P \qquad [5.21]$$

$$\sum_j Y_{ij} = 1 \qquad \forall\ i \qquad [5.22]$$

$$Y_{ij} - X_j \leq 0 \qquad \forall\ i,\ j \qquad [5.23]$$

$$X_j \in \{0, 1\} \qquad \forall\ j \qquad [5.24]$$

$$Y_{ij} \in \{0, 1\} \qquad \forall\ i,\ j \qquad [5.25]$$

The objective function [5.20] minimises the total demand-weighted distance between each demand node and the closest facility. Constraint [5.21] requires that exactly *P* facilities are to be located. Constraint [5.22] states each demand node *i* to be assigned to exactly one facility *j*, while constraints [5.23] allow to assign only the site at which facilities have been located. Finally, constraints [5.24] and [5.25] are standard integrality conditions.

On a tree network, the solution can be found in polynomial time algorithm. However, in general graph the problem become *NP*-hard. Owen and Daskin (1998) present that the limitation of potential location is able to lessen the number of feasible location to:

$$\binom{N}{P} = \frac{N!}{P!(N-P)!} \qquad [5.26]$$

Where N represents the number of nodes and P represent the number of facilities to be located. Therefore, the P-median problem can be solved in polynomial time.

The technique as described above can achieve an optimal solution for moderately sized problems in a practical period of time (Owen & Daskin, 1998). However, for more sized problems, Daskin (1995) suggested heuristic approaches are essential. He presents two improvement algorithms, an exchange algorithm, a neighbourhood search algorithm, and two Lagrangian relaxations of the integer programming. Rosing and Hodgson (2002) proposed a common (1-opt) interchange heuristic and heuristic concentration. Furthermore, Domínguez and Muñoz (2008) presented a competitive recurrent neural network technique for P-median problem.

An extended P-median problem was offered by ReVelle (1986) for an establishment of retail site in the competing environment. The goal of this extension was to maximise the retailer's market share. In the standard P-median, an important assumption is that each demand site is served by closest facility; nevertheless, demand is separated among the facilities in some cases. Customers may choose their preferred facility, where is not the nearest one. Drezner and Drezner (2007) presented a gravity P-median problem, which it was assumed that customers split among the facilities according to the proportion of an attractiveness of the facility and to a decreasing function of the distance to the facility. Moreover, Church (2008) offered a new model formulation for the P-median problem including an exact and approximate approach. He also presented a methodological framework indicating that can not only extend the application frontier using general-purpose software, but presented good performance for several instance problems.

5.7.4 Fixed charge facility location problems

The *fixed charge facility location problems* include an explicit cost associated with locating at candidate locations. The basic model in this set is the *uncapacitated fixed charge facility location problems*. It assumes that the facilities are not restricted by their capacities. To formalise the problem, the sum of facility location, operational costs are minimised by adding a fixed cost to the objective function of P-median and removing the constraint that controls the number of facilities to be placed. The problem is defined in the following notation:

Inputs:
c_j = fixed cost of locating at candidate site j

h_i = demand at node i

d_{ij} = distance from demand node i to candidate facility site j

α = cost per unit of distance per unit of demand

Decision variables:
X_j = 1 if candidate site j is located, 0 if not

Y_{ij} = fraction of demand at node i that is served by a facility at node j

The uncapacitated fixed charge facility location problems can be formulated as follows:

Minimise $$\sum_j c_j X_j + \alpha \sum_i \sum_j h_i d_{ij} Y_{ij} \qquad [5.27]$$

Subject to: $$\sum_j Y_{ij} = 1 \qquad \forall\ i \qquad [5.28]$$

$$Y_{ij} - X_j \leq 0 \qquad \forall\ i,\ j \qquad [5.29]$$

$$X_j \in \{0, 1\} \qquad \forall\ j \qquad [5.30]$$

$$Y_{ij} \geq 0 \qquad \forall\ i,\ j \qquad [5.31]$$

Similar to the *P*-median problem, the objective function [5.27] minimises the total cost which is the sum of the fixed facility costs and the total demand-weighted distance multiplied by the cost per unit of distance per unit of demand. Constraint [5.28] stipulates that each demand node *i* is served, while constraints [5.29] allocate assignment only to site at which facilities have been located. Finally, constraints [5.30] and [5.31] are binary integrality and nonnegativity conditions, respectively.

In many situations, capacities of facility are considered to be important, e.g. the capacity of production plant, warehouse, service centre, and so on. In this case, the problem is called a *capacitated fixed charge facility location problem*; accordingly, the capacity notation is defined as following input variable:

k_j = capacity of a facility at candidate site *j* if a facility is located

Besides, the additional constraints [5.32] have been included so as to ensure that demands at node *i* are not assigned to a facility at candidate site *j* if candidate location *j* has not been selected.

$$k_j X_j - \sum_i h_i Y_{ij} \geq 0 \qquad \forall\ j \qquad [5.32]$$

For a solution of the uncapacitated facility location problem, Erlenkotter (1978) introduced a dual-based approach that consider to be remarkably effective in solving this facility location problem. It based on a linear programming dual construction. A basic ascent and adjustment process commonly created optimal dual solutions, which in turn frequently related exactly to optimal integer primitive results. If not, a branch-and-bound practice was carries out the solution process.

Daskin (1995) presented two heuristic construction algorithms for the solution of the uncapacitated fixed charge facility location problem. The ‘add’ heuristic consecutively added facilities greedily until addition of the next facility would result in a cost improve. The ‘drop’ heuristic started with facilities assigned at all of the candidate sites. Then in sequence, it eliminated facilities until the exclusion of the next facility would lead to am improvement in the total cost. In addition, neighbourhood and exchange improvement heuristics, and a Lagrangian relaxation algorithm were described.

In terms of a solution for the capacitated facility location problem, Van Roy (1986) presented an approach that merged Bender's decomposition and Lagrangian relaxation into a predominantly effective approach. Daskin (1995) presented two alternative relaxations. First, the relaxing of the capacity constraints was presented. The second approach involved the relaxing of demand constraints. Then, he presented the application of Bender's decomposition method.

In the variation of fixed charge facility location problems, Sankaran and Raghavan (1997) extended the classical capacitated fixed charged model to incorporate the endogenous selection of candidate sites. Nozick and Turnquist (1998) integrated an inventory cost within a fixed charge facility location model. Nozick (2001) developed a fixed charge facility location model with coverage restrictions that incorporates both cost and customer responsiveness considerations in identifying locations. Legües et al. (2007) formulated a combination of a plant location problem and a fixed charge network flow problem and present a tabu search approach for solving their model.

5.8 Extensions of static and deterministic facility location problems

5.8.1 Location-allocation problems

One of the key questions addressed by location models is the extent to which demand for the facilities' services is allocated to the facilities. The set of *location-allocation problems* or alternative name *production/distribution system design problems* construct a fundamental problem to simultaneously located facilities and assign demands to facilities (Dasci & Verter, 2001). These problems include a standard transportation problem, a problem for allocating flow among facilities, with location problems. In some environment, multiple products are concerned instead of single product.

In a typical supply chain, products are moved from plant either directly to markets or to warehouse and from there to customers. The primarily questions are: (a) how many warehouses to set up, (b) where to locate them, and (c) how the products should flow through the supply chains.

The location-allocation problems apply to many implementations. For instance, Yeh and Chow (1996) presented the integration of the location-allocation model and GIS for public facilities planning by using open space planning in Hong Kong as an example. They also offered decision makers a better view of the problem and how to experiment different scenarios by varying the objectives, constraints, and parameters of the models.

Smallman-Raynor, Muir, and Smith (1998) presented a location-allocation modelling by which the accessibility criterion can be used to determine the optimal number, location and capacity of units for a given cancer site. Their study drew data from the important primary source of Trent Health Authority Region, UK.

Rahman and Smith (2000) reviewed the use of location-allocation models in health service development planning in the developing nations. The purpose of this review was to examine the role of location-allocation models in planning health care systems and to consider their relevance to overall development problems in such countries.

Melkote & Daskin (2001) present an integrated model of classical plant location problem and transportation network design. The fundamental resource allocation is investigated with a set of sensitivity analysis. The details provide insight into helping decision makers in budgeting and planning decisions.

Imai, Sun, Nishimura, and Papadimitriou (2005) applied location-allocation model by addressing the berth allocation problem in a multi-user container terminal. A heuristic for the berth allocation problem in continuous locations was provided. A wide variety of experiments were conducted and the results showed that the heuristic works practically well.

Aboolian, Sun, and Koehler (2009) examined a location-allocation problem for a web service provider in a competitive market. Demands for services of these servers were available at each point of a network, and a subset of points was to be selected to assign one or more servers in each. The objective was to maximize the provider's profit. An exact solution approach with efficient result is provided.

Bischoff and Dächert (2009) studied a generalised class of location-allocation problems. They compared various methods i.e. multi-start, neighbourhood search, tabu search, simulated annealing, an evolutionary algorithm, and an ant colony optimisation. Results showed the most heuristics were able to combine a diversified search over the search solution and gave a solution near the best-known result.

5.8.2 Multi-objective problems

Strategic facility location decisions are inherently long term and likely to be many possibly conflicting or competing objective (Walton & Dutton, 1969; Owen & Daskin, 1998; Plastria, 2001); therefore, it need to be considered carefully. For example, in locating warehouses, decision makers may need to balance the average distance between customers and the nearest warehouse and the extent of demand coverage. In goods delivery, to compete with competitors, companies may trade-off between minimising the total demand-weighted distance and maximising the number of customers.

Current et al. (1990) reviewed the broad and multidisciplinary literature of location analysis and examine the multi-objective aspects in 45 papers around 20 journals. Four broad categories of objectives have been presented. First of all, the largest category was cost minimisation (also an interchange term, distance). The second most popular group was demand-oriented objectives including demand coverage and demand assignment. Thirdly, profit maximisation was found, and finally environmental concern objective was revealed. The last two groups were found only ten per cent of the review articles.

Giannikos (1998) presented a multi-objective model for locating disposal or treatment facilities and transporting hazardous waste. He developed a goal programming model to represent the problem. Four objectives were examined: (a) minimisation of total operating cost, (b) minimisation of total perceived risk, (c) equitable distribution of risk among population centres and (d) equitable distribution of the disutility caused by the operation of the treatment facilities.

Melachrinoudis and Min (2000) examined a relocation and phase-out decision in order to adapt to dynamic changes in supply chains including changes in supplier and customer, distribution networks, corporate re-engineering, business climate, and government legislation. To manage the effective change strategy, they applied a multiple objective mix-integer programming by weighting and re-scale each objective function.

Sabri and Beamon (2000) developed an integrated multi-objective supply chain model for use in simultaneous strategic and operational supply chain planning. They adopted the multi-objective decision analysis allowing to measure cost, customer service level (fill rates), and volume/delivery flexibility with the ε-constraint method to determine the optimal supply chain performance.

Fernández and Puerto (2003) investigated the multiple objective uncapacitated facility location problem. Both approximate and exact approaches were proposed in their study. A dynamic programming method and an enumerative approach were developed so as to set up the set of non-dominated, namely pareto-optimal, solutions.

Du and Evans (2008) developed a bi-objective mix-integer programming optimisation model for the reverse logistic network problem. A heuristic algorithm, scatter search, was used to deal with the discrete variables, while the dual simplex method was adopted to obtain the solution for continuous variables.

5.8.3 Hierarchical facility location models

The typical models described in section 5.7 assume that there is only one type of facility being located. In several cases, the facilities interact in one or more probable ways; facilities often are hierarchical in terms of the types of services being offered (Narula, 1986). For example, postal services represent the hierarchical facility location problems. Customers may only drop mail at post boxes, which are lowest level. At branch offices, postal customers may deposit mail, get stamps, and obtain a limited range of other services. Customers also are able to access all kinds of service at main post offices.

Daskin and Stern (1981) adopted a hierarchical and multi-objective programming in a public decision making. To locate emergency medical service vehicles, they set up a hierarchical objective function which first minimises the number of vehicles needed to satisfy the service demand and then assigned the vehicles to maximise the several coverage of demand sites.

Current and Pirkul (1991) examined a hierarchical network design problem with transhipment facilities, which the objective was identified a least cost and two-level network. The network contained a main path from a pre-specified origin point to a pre-specified destination point. All points not on the main path must be connected to that path via secondary links. In addition, transhipment facilities were necessary at the intersections of the two network levels. To answer this problem, they introduced two efficient heuristics based on a Lagrangian relaxation.

Recently paper, Sahin and Süral (2007) have reviewed a number of hierarchical facility location models. They classified these problems according to the features of systems based on: (a) flow pattern, (b) service availability at each level of the hierarchy, (c) spatial configuration of services, and (d) the goal to set up facilities. The basic applications range in many industries both public and private sectors, e.g. health-care systems, solid waste management systems, production-distribution systems, education systems, emergency medical service systems and telecommunication networks. Two fundamental distinct mixed-integer programming models were presented in their literature: flow-based and (path) assignment-based formulations. The former demand flows from facilities at one-level to the next-level of the hierarchy; the latter allocates demand to facilities at each hierarchical level.

5.8.4 Hub location problems

In all of the models discuss previous, services are normally performed by or at a facility. Each origin/destination pair represents a different service that needs to be provided. Hub location problems arise when a direct pair of these demands cannot be realised. An operational cost among networks may extremely be high. An alternative practical solution is called hub-and-spoke network where the hubs perform as consolidation, transfer, or break-bulk place (O'Kelly & Miller, 1994). In other words, hub facilities serve as switching and consolidation point for an origin-destination flows. Hub-and-spoke configurations reduce and simplify network construction costs, centralize commodity handling and sorting, and allow carriers to take advantage of scale economies through consolidation of flows (O'Kelly & Miller, 1994; Meyer, Ernst, & Krishnamoorthy, 2009).

O'Kelly and Miller (1994) surveyed the increasing in network hub location design and focus on the topological alternatives available in hub networks. More review were presented by Klincewicz (1998) on the design of hub networks and the location of hub nodes in telecommunications.

Sasaki, Suzuki, and Drezner (1999) formulated the 1-stop multiple allocation p-hub median problem and proposed a branch-and-bound algorithm and a greedy-type heuristic algorithm. They examined the models with airline passenger interactions between 25 US cities in 1970 evaluated by the Civil Aeronautics Board.

Mayer and Wagner (2002) offered an new exact branch-and-bound solution method for uncapacitated multiple allocation hub location problem. Computational experiments showed that optimal solutions for problems with up to 40 nodes can be found in a reasonable amount of time.

Wasner and Zäpfel (2004) presented an integrated multi-depot hub-location vehicle routing model for network planning of parcel service. They developed a heuristic approach in order to solve this problem. Decision makers can simultaneously decide the number, locations, service areas and routes from demand points to depots as well as the number and locations of hubs and the routes of depot-hub and hub-hub transports.

Jeong et al. (2007) addressed a hub-and-spoke network problem for railway freight. They formulated a linear integer programming model with objective function included not only the typical operational cost, but also cost by the transit time. They developed heuristic algorithms to solve large scale instances occurring in rail freight systems in France plus Italy; Germany; and a 10-country European network.

Recently paper by Alumur and Kara (2008) surveyed network hub location models and classified. In addition, they provide some recent trends on hub location problems.

5.8.5 Undesirable facility location models

Most of models above focus on locating facilities in order to access to their customers or services. On the other hand, several real-world problems deal with establishing facilities which are undesirable to nearby people or communities. For example, to locate a waste disposal plant, it is usually unwanted by any communities. Problems which address these situations include the *anti-median problem*, which assigns a service facility to maximise average distance between demand point and its service facility; the *anti-centre problem*, which maximises the minimum distance between demand point and its service facility; and the *P-dispersion problem*, which locates facilities to maximise the minimum distance between any pair of facilities. This problems can be notable as *Noxious* (hazardous to health) and *Obnoxious* (nuisance to lifestyle) facilities problems, and both are regarded as *Undesirable*.

Current and Ratick (1995) proposed a multi-objective model to locate hazardous material locations and to provide a routing of these material to the facilities. Risks and equity were spatially determined and were adopted both a macro level, with minisum objectives, and at the micro level, with minimax objectives.

Yapicioglu, Smith, and Dozier (2007) introduced a model for the semi-obnoxious facility location problem, in which comprised of a weighted minisum function to represent the transportation costs and a distance-based piecewise function to represent the obnoxious effects of the facility. They also proposed a single-objective particle swarm optimizer (PSO) and a bi-objective PSO so as to tackle this problem.

Alçada-Almeida, Coutinho-Rodrigues, and Current (2009) examined a problem to locate hazardous material incineration facilities. They presented a mixed-integer, multi-objective programming method, in which incorporated a Gaussian dispersion model and a multi-objective optimisation model in a GIS-based interactive decision support system. The proposed method is examined with a case study in central Portugal.

5.8.6 Competitive facility location problems

In the previous section, the majority of facility location problems concerns with the assumption that the companies are only an actor in the market. That is they do not compete with each other. In fact, they compete with other firms in some manners. For instance, when a firm sets up a new facility e.g. plant, warehouse or distribution centre, this activity affects somewhat the relevant market area either competitors or alliances. This often triggers some forms of response from existing companies or a new comer in the related business and leads to the studies with more concerning about competitors.

To apply the competitive facility location models, first, a new facility will be calculated based on market share maximisation. Second, an impact of change in existing facilities on the market share needs to be analysed. For further analysis, decision makers are able to carry out a "what-if analysis" and predict the effect on their facilities.

The first modern study on competitive facility location was Hotelling's paper on duopoly in a linear market (Hotelling, 1929). He considered the location of two competing facilities on a market. If one facility was located with no competition, all customers patronised the existing facility. Nevertheless, when another competing facility was introduced, the customers would patronise the closest facility.

An extension of Hotelling's model is the case of location-allocation model, in which the selection of sites will be served by a spatially dispersed population. In location-allocation model, the facility location and the allocation of customers to them are determined simultaneously. For instance, Goodchild (1984) introduced the location-allocation market share model in retail site selection.

The assumption that customers patronise the closest facility means that each facility is equally attractive. One of the methods for solving this plane is a Voronoi diagram (Okabe & Suzuki, 1997). The disadvantage of this closest assumption is an "all or nothing" property, which all demands at a point will be assigned to a single facility.

When the consideration facilities are not equally attractive, the proximity premise for allocating demands is no longer valid. Drezner (1994) introduced a utility model to account for variations in facility attractiveness. Based on aggregated utility values for existing facilities and a utility function for a new facility, the best location was found. The optimal location for the new facility was sensitive to its attractiveness.

An alternative approach for competing facilities is based on the gravity model (Drezner, 1998). In gravity model, customers are assigned according to the attractiveness of facilities e.g. retail floor area, parking space. In addition, the negative factor such as the extent to which distance from demand points to facilities are taken into account as an inverse proportion to such distance.

In supply chain context, Meng, Huang, and Cheu (2009) addressed a competitive model for a firm intends to enter an existing decentralised supply chain which was comprised of three tiers: manufacturers, retailers and consumers.

Zhang (2008) proposed a multi-site location-allocation model for selecting locations in competitive service systems. Algorithms and essential spatial data were discussed; the model was analysed in locating bank branches.

5.8.7 Other application of facility location problems

Not only are the typical and extended problems described in previous section, but also other diversity of them. For instance, Current and Weber (1994) present vendor selection problems by formulate a mathematical constructs of facility location modelling. Some of problems are inherit in more features that illustrate before. Table 5.5 represents various classes of location model.

Table 5.5 Representative location model class

Model class	**Definition**
Median	Locate one or multiple facilities in order to minimize weighted distance
Line-based facility	Locate a route or corridor across a terrain or along a network
Covering	Maximize coverage given *p*-facilities or minimize cost in order to completely cover all demand
Area-based facility	Acquire land for same intended use
Obnoxious facility location	Locate one or more facilities in order to disperse them from each other or from demand
Fixed-charge location	Locate one of more facilities in order to minimize facility and interaction costs
Centre	Locate one or multiple facilities in order to minimize the maximum distance that any user is from their closest facility
Tree-based facility	Locate a tree structure (continuous space or network) to maximally connect and minimize cost
Hub and spoke	Locate one or more hub facilities along with connections so as to optimize transport or travel between a number of origin-destination pairs
Competitive	Locate one or more facilities in order to marginalize competitors market share, knowing that they are attempting to do the same
Resilient design	Locate facilities so that risk of disruption is taken into account
Hierarchical	Locate a facility system that has defined levels that are interrelated (e.g., clinics and hospitals; elementary, middle and high schools; etc.)
Flow capturing	Locate facilities in order to capture customer flow, where flow is based on travel patterns of potential customers
Combined route and access point models	Locate a route (e.g., public transit bus), along with access sites along the route (e.g., bus stops) to optimize service
Combined network design and facility location	Expand a network as well as locate facilities so that the combined system is as efficient as possible
Reserve design	Select sites in order to protect endangered species, as well as to reduce the risk of species loss

Business Site Selection, Location Analysis and GIS by Church and Murray, 2009

5.9 Dynamic deterministic facility location problems

In the previous section, *static* models mean the inputs do not depend on time; in other words, the models represent a single set of inputs, and are solved the problem for a single representative period. In contrast, this section presents *dynamic* or *multi-period* models, which the inputs depend on time (Owen & Daskin, 1998).

Most of the models assume that the facilities will be disposed of at the end of the life time horizon since remote expected circumstances can't be predicted accurately (Kelly & Marucheck, 1984). This difficulty results in optimal for only one hypothesized post horizon facility configuration and often become non-optimal under a changed circumstance. Many pragmatic situations, the demands rarely remain constant over period of time. For example, the need of fire brigade service in an area varies over time as the community change.

The issues dealing with the uncertainties inherent in facility location will be discussed in this and next section. The uncertainties related to planning for future conditions, namely *dynamic deterministic facility location models*, will be discussed in this section, whereas uncertainty cases due to limited knowledge of model input parameters will be discussed in the section 5.10.

A early paper attempted to distinguish the limitation of static and deterministic location models was published by Ballou (1968). He made an effort to locate a single warehouse in order to maximise profit over a given planning period. He applied a dynamic programming technique to solve this problem. For each stage of the particular period, a series of static deterministic good result was set up.

Tapiero (1971) extended the location-allocation problems by considering potential facility capacities and transportation cost. Wesolowsky and Truscott (1975) also added the multi-period location-allocation problem by offering a dynamic model to trade off among present values of static distribution costs in each period and costs of relocating facilities.

For a set covering model, Chrissis, Davis, and Miller (1982), and Gunawardane (1982) introduced a dynamic characteristic of this model for facility location problems in the public sector. The problem was regarded as binary cover coefficients that may vary value from one period of time to the next horizon.

Chand (1988) presented a number of decision/forecast horizon results for a single facility dynamic location problem, which results were helpful in finding optimal preliminary decisions for the infinite horizon problem by using information only for a finite horizon.

Drezner and Wesolowsky (1991) addressed both the minisum Weber problem and minimax facility location in altering city with predictable population movement, i.e. demands vary among a given set of demand points in a deterministic way. In this study, not only did they attempt to locate the facilities, but also found the appropriate period when changes would happen.

For a median location problem, Galvão and Santibañez-Gonzalez (1992) proposed a Lagrangean heuristic for the *pk*-median dynamic location problem. In the proposed model, customers had to be assigned from *p* facilities in period *k* with the minimisation of installation and transportation costs. Furthermore, Drezner (1995) formulated a progressive *P*-median problem, offered a special algorithm and solved by a standard mathematical programming; similarly, Hribar and Daskin (1997) presented a heuristic algorithm to restrict the size of the set of dynamic programming solution by an extension of the greedy adding algorithm.

Current, Ratick, and ReVelle (1998) proposed two approaches for analyzing these types of dynamic location problems, focusing on situations where the total number of facilities to be located in uncertain. They analyzed this problem using two well-established decision criteria: the minimization of expected opportunity loss, and the minimization of maximum regret.

In supply chain context, Melo, Nickel, and Saldanha da Gama (2006) addressed the strategic design of supply chain networks with some aspects: dynamic planning horizon, generic supply chain network structure, external supply of materials, inventory opportunities for goods, distribution of commodities, facility configuration, availability of capital for investments, and storage limitations. They concerned the changing of relocation of facilities over the planning horizon. The practical insights on the effect of various features on network configuration decisions are offered.

More recently, Hinojosa, Kalcsics, Nickel, Puerto, and Velten (2008) have extended the dynamic supply chain design problem with considering inventory in warehouses between consecutive periods. Thanh, Bostel, and Péton (2008) have addressed the design and planning of a production-distribution system focusing on a dynamic characteristic in strategic and tactical decisions: opening, closing or enlargement of facilities, supplier selection, flows along the supply chain.

Not only does the concept of extended facility location problems as described in section 5.8 apply to the dynamic problems, but it can adapt to the problems dealing with uncertainty. Consequently, the variety of problems occurs from the mutation of that characteristic.

5.10 Facility location models under uncertainty

On the one hand, the dynamic location models, which locate facilities over a specified time period, are described in the previous section. These models have an important assumption that input parameters are known and vary deterministically over time. On the other hand, the uncertainties caused by limited knowledge of input parameters will be addressed in this section.

Rosenhead, Elton and Gupta (1972) classified decision-making environment into three categories: certainty, risk and uncertainty. In *certainty*, all parameter are assumed to be known; in other words, it is deterministic. In *risk* situations, uncertain parameters are represented by probability distributions that are assumed to be acknowledged by the decision maker. In *uncertainty* situations, parameters are uncertain, and there is obviously no information about its probabilities. On the one hand, problem in risk situations are known as *stochastic location problems*. On the other hand, problems under uncertainty without information of probability distribution are acknowledged as *robust location problems*. A common goal of stochastic location models is to optimise the expected value of some objective functions, whereas that of robust location models is an attempt to optimise the worst-case scenario.

5.10.1 Stochastic facility location problems

In this section, the stochastic location models will be discussed. Most of common objective functions of these models are to minimise the expected cost or to maximise the expected profit of the system.

In terms of modelling approaches, these problems can be classified into two main approaches: *a probabilistic approach* and *a scenario planning approach*. The former treats the variables by using the probability distributions, whereas the latter considers a generated array of possible future quantity of the input parameter.

5.10.1.1 Probabilistic approaches

One of the earliest paper considering stochastic was published by Manne (1961). He addressed the capacity expansion over an infinite horizon. The objective of his model was to minimise the discounted installation cost so as to choose extended range of facilities. The demands were treated probabilistically, in which a discount rate was modified to capture the magnitude of uncertainty.

Cooper (1978) examined a stochastic model by addressed a continuous transportation-location problem. He considered predetermined points as random variables with a specific probability distribution. He also developed an exact method of solution for small problems and a heuristic algorithm for large scale problems.

Ermoliev and Leonardi (1982) considered both demand for facilities and trip pattern of customers as stochastic features to formulate their model. Non-differential optimisation techniques were applied in their paper.

Logendran and Terrell (1988) presented an uncapacitated plant location-allocation problem on maximizing the expected net profits in price sensitive stochastic demands. The relationships between price and demand quantity were accounted in the model. The patterns of demand were regarded as both normal and uniform distributions.

As an increasing in a significance of global marketplace, Min and Melachrinoudis (1996) addressed a location strategy shifting from domestic to international. They insisted that the international and domestic location problem were dissimilar in many manner, e.g. political conditions, expropriation risks, trade regulations, currency exchange rates, cultural differences, and global distribution channel structures. They proposed a stochastic location model with multiple-period, multiple-plant and multiple-objective so as to help the multinational firm formulate the international location problem.

Ricciardi, Tadei and Grosso (2002) considered the optimal location and size of facilities where the total costs were random. The generalised transportation costs were defined as the sum of two terms: (a) the transportation cost from the origin to the destination through the facility and (b) the throughput cost of the facility. The former term was recognized as deterministic parameter; however, the latter was stochastic with a Gumbel probability distribution.

In the design of supply chain system, Hwang (2002) proposed a design system by considering the number of warehouse and vehicle routing schedule. He formulated a stochastic set covering problem to determine the minimum number of warehouse in the first step. Then, he constructed a vehicle routing problem using a modified genetic algorithm.

Zhou and Liu (2003) addressed stochastic capacitated location-allocation problem as expected value model, chance-constrained programming and dependent-chance programming according to different criteria. They proposed a hybrid method with a combination of stochastic simulation and genetic algorithm.

In terms of competitive atmosphere, Shiode and Drezner (2003) examined two competitive companies which the assumption of the weight of demand site at the entry time of the follower was stochastic. The objective of each company was to locate its facility in order to maximise the captured buying power after the follower's entry.

Miranda and Garrido (2004) proposed a simultaneous approach to incorporate inventory decisions into location models so as to answer the distribution network design problem. A simultaneous model was developed considering a stochastic demand, modelling also the risk pooling phenomenon.

In the emergency medical services, Beraldi, Bruni and Conforti (2004) addressed the stochastic problem using a stochastic programming model with probabilistic constraints in order to work out both the location and the sizing of the facilities. To achieve a reliable level of service and to minimise the total costs, they concerned the randomness of the system as far as the demand of emergency service.

5.10.1.2 Scenario planning approaches

In scenario planning method, uncertainty pattern is represented by specifying a number of potential expectations. The goal is to identify a set of solutions that considering good solution under all scenarios. A set of scenarios will represent the potential realisation of unknown parameters.

One of the first papers concerning a scenario planning approach to facility location problem was published by Sheppard (1974). He attempted to combine spatial and temporal features into one solution which various possibilities were formulated to integrate them into a model.

Ghosh and McLafferty (1982) presented a multi-criteria decision-making method to locate retail stores under uncertain environments. They set up a series of scenarios characterising future marketing and determined well-performed strategies.

In a competitive environment, Serra, Ratick and ReVelle (1996) extended the maximum capture problem, a problem to maximise market capture, in order to handle an uncertain demand by generating a series of possible scenarios with respect to demand and/or the location of competitors. They proposed a method to locate server facilities where competitors are exist in the market.

Chang, Tseng and Chen (2007) developed a decision-making tool in planning for flood emergency logistics with uncertainty. First, a GIS analysis was used to determine the locations of demand points and the quantity of required equipment. Then, a scenario planning approach was generated a set of different flooding scenarios for setting up a rescue resource distribution system for urban flood disasters.

5.10.2 Robust facility location problems

When no information about probability pattern, the expected cost discussed in section 5.10.1 is no longer valid. This section will present robust facility location problems, which problems are considered under uncertainty without information of probability distribution. While a common objective of stochastic problem is to minimise expected cost, that of robust problem is an attempt to minimise the worst-case scenario, e.g. minimise maximum regret.

With no probability information, there are two common solution to access robustness: the *minimax cost solution*, and the *minimax regret* (Snyder, 2006). The former is to minimise the maximum cost across all scenarios; while the latter is the most common robustness measure. Term '*regret*' can be described as "*sometimes described as opportunity loss: the difference between the quality of a given strategy and the quality of strategy that would have been chosen had one known what the future held*" (Snyder, 2006).

In terms of methodology, because of no information of probability distribution, the probabilistic approach is no longer applied. The scenario-based approach is often applied to this problem as following described.

Schilling (1982) also utilised a scenario-based planning to a problem for locating a number of facilities over time as described in the dynamic location section with robustness (even though not explicitly). Each scenario, which can be recognised as a contingency plan, was used to establish a set of good site configurations.

Mulvey and Vanderbei (1995) introduced a framework for robust optimisation, in which involved (a) solution robustness: the solution is nearly optimal in all scenarios, and (b) model robustness: the solution is nearly feasible in all scenarios. In their framework, uncertainty generally represented by scenarios or intervals, with or without probability distributions.

Killmer, Anandalingam and Malcolm (2001) considered the stochastic capacitated hazardous material location decisions for the Albany, New York region. Production and transportation costs, and demand are uncertain. They applied the robust optimisation framework proposed by Mulvey and Vanderbei (1995) to construct their model. A robust optimisation model as a nonlinear programming was developed with both solution robustness as well as model robustness.

Daskin, Hesse and Revelle (1997) introduced a new worst-case model class namely "α-reliable minimax regret", which the solution was computed only over a subset of reliability scenarios.

For an application in public sector, Serra and Marianov (1998) applied a scenario planning method to locate fire stations in Barcelona. They formulated a *P*-median-like model with uncertainty in demand at nodes, travel time/distance along links. Such demand and travel time vary depending on time of day, day of the week basis. The objective functions are to minimise the maximum average travel time and to minimise the maximum regret.

5.11 Strengths, weaknesses and gaps in the literature

This section will address strengths, weaknesses and gaps in literature, which covers all classifications of facility location problems, as can be seen in Table 5.6. The structure of the table consists of the modelling approach for each study, strengths and weaknesses for each article, and importantly gaps in literature relating to each facility location problem.

The modelling approaches in the table are shown primarily in heuristic, exact and simulation method. The facility location problems are illustrated according to their classifications that are: location-allocation, multi-objective function, hierarchy, hub, undesirable facility, competitor, dynamic deterministic, stochastic, and robust facility problems.

For each group of facility location problems, the gap is described in terms of an absence of some factor(s).

A strength of basic static and deterministic problems (covering, centre, median and fixed charge facility location problems) is that they are simply identified problems. However, their weaknesses are that these problems are assumed to be static and deterministic, which does not represent a real-world situation.

Many extensions of the primary static and deterministic problems, for example, location-allocation, hierarchical, hub, competitive, and dynamic deterministic facility location problems have common gaps in the literature. They only consider a single objective function and several parameters in the models are considered deterministically, while that of the real-world problems is always stochastic.

While considering one variable at that time, the problems tend to ignore other factors. For the stochastic or robust facility location problems, multi-objective function is rarely taken into account. When the models look into the multi-objective function, they often characterise most parameters deterministically.

In terms of modelling approaches, heuristic methods always apply in various models, especially when sizes of variables in the model are enormous. Heuristic methods base on random search, so it may provide a sub optimum solution. The exact methods often utilise a small or medium problem; however, the real-life problem size is questionable.. The simulation hardly ever uses when models need an optimum result; except for representation of a stochastic parameter.

The objective function of most problems is popular total cost. Only a few models take the customer's view point as another key performance index. Not only are the popular objective function, i.e. the total cost, and customer's perspective index considered in the facility location model, but also other factors, e.g. an environment impact, may be considered.

For multi-objective model, the priority weight of each goal was assumed; no scientific basis for determining the weighing of each objective function.

While the planar model frequently assumes for many facility location problems, discrete and network model can better represent the real-network problems, e.g. road network.

After carefully examined each article, the main gaps found in the review are identified. The gaps mean the missing of considering some factors in a study. Concisely, the common gaps found in these literatures consist of: first, most data was not treated stochastically; secondly, the objective functions other than the total cost were not often considered and the multi-objective function was rarely taken into account.

After identify the main gaps, the next step is to further review articles with regard to considering factor according to these gaps. The purpose of the review is to identify a proposed facility location problem (it will be discussed in the next chapter), therefore selected articles focused on the main gaps are examined.

Table 5.7 illustrates the focused articles by describes the method and supply chain structure. The structure of the presented table consists of: the modelling approaches including heuristic, exact and simulation methods; the supply chain structure including number of echelons, number of commodities, whether it is dynamic model, uncertainty variables, number and the description of objective function, and the level of management of the models.

Table 5.8 shows strengths, weaknesses and comment of gap of the same focused papers as in Table 5.7.

Table 5.6 Strengths, weaknesses and comments of gap in literatures

Type of facility location problems with Citations	**Modelling approaches**			**Strengths**	**Weaknesses**	**Comments of gap in literature**
	Heuristic (H)	**Exact (E)**	**Simulation (S)**			
Static and deterministic facility location problems and their extensions ***Location-allocation problems***						
An integrated GIS and location-allocation approach to public facilities planning -- An example of open space planning (1996) A. G.-O. Yeh and M. H. Chow	✓			The model included GIS in facility location problem. Heuristic approach was able to handle large data sets.	Heuristic method in this model based on random search, it may provide a sub optimum solution.	Objective functions other than total cost were not considered Most input data was not treated stochastically.
The geographical assignment of cancer units patient accessibility as an optimal allocation problem (1998) M. R. Smallman-Raynor, K. R. Muir and S. J. Smith		✓		This model applied a classical transportation problem, so it can efficiently solve by optimisation tool.	The objective function of the problem was only total travel cost of patient access to cancer units.	
An integrated model of facility location and transportation network design (2001) S. Melkote and M. S. Daskin		✓		This model attempted to simultaneously optimise facility locations and the design of transportation network.	The solution was demonstrated using a small network. However, the real-life network was questionable.	
A location-allocation problem for a web services provider in a competitive market (2009) R. Aboolian, Y. Sun and G. J. Koehler		✓		The authors introduced a competitive Web Services location problem. They developed an efficient exact methodology to obtain a solution in a reasonable time for small to medium size problems.	A key limitation of their model was that it ignored the competitor’s reaction to their decision.	

Table 5.6 Strengths, weaknesses and comments of gap in literatures (Cont.)

Type of facility location problems with Citations	Modelling approaches			Strengths	Weaknesses	Comments of gap in literature
Multi-objective problems	**H**	**E**	**S**			
A multiobjective programming model for locating treatment sites and routing hazardous wastes (1998) I. Giannikos		✓		This paper tried to involve multi-objective in locating disposal facilities and transporting hazardous waste.	For multi-objective function, the priority weight of each goal was assumed.	No scientific basis for determining the weighting of each objective function. Input data was rarely treated stochastically. Other factors, e.g. environment impact were not taken into account as objective function.
The dynamic relocation and phase-out of a hybrid, two-echelon plant/warehousing facility: A multiple objective approach (2000) E. Melachrinoudis and H. Min		✓		This model was developed to tackle multiple conflicting objectives. They also considered integrating multiple planning horizons.	This model was developed for specify purposes, however, it did not consider some factors, e.g. competitor, stochastic variables.	
A multi-objective approach to simultaneous strategic and operational planning in supply chain design (2000) E. H. Sabri and B. M. Beamon	✓	✓		Strategic and operational considerations have been integrated into a single approach.	When a large number of variables were considered, it may require a large computer run-time and enormous memory. It was likely that the suboptimum solution was found.	
Multiobjective solution of the uncapacitated plant location problem (2003) E. Fernández and J.Puerto	✓	✓		Both approximate and exact approaches were proposed. The set of non-dominated solution was provided.	The model focused on the uncapacitated plant location problem.	
A bi-objective reverse logistics network analysis for post-sale service (2008) F. Du and G. W. Evans	✓	✓		This paper introduced the model for the design of a bi-objective reverse logistics network. Both heuristic and exact approaches were adopted.	The method did not consider stochastic input data. Heuristic method, scatter search, in this model based on random search, it may provide a sub optimum solution.	

Table 5.6 Strengths, weaknesses and comments of gap in literatures (Cont.)

Type of facility location problems with Citations	Modelling approaches			Strengths	Weaknesses	Comments of gap in literature
Hierarchical facility location problems	**H**	**E**	**S**			
A Hierarchical Objective Set Covering Model for Emergency Medical Service Vehicle Deployment (1981) M. S. Daskin and E. H. Stern		✓		This paper performed multi-objective by applying simply hierarchical, two-level, covering problem.	Several parameters were deterministic, while in the real-life situation they could be uncertain.	Most input data was not considered stochastically.
Theory and methodology: The hierarchical network design problem with transhipment facilities (1991) J. Current and H. Pirkul	✓			The hierarchical transhipment facilities model can be efficiently designed by this providing method.	One of the limitations of this paper was network must consist of a predefined starting and ending node. Several parameters were deterministic. In addition, the objective function was only a minimum cost.	
Hub location problems	**H**	**E**	**S**			
On the selection of hub airports for an airline hub-and-spoke system (1999) M. Sasaki, A. Suzuki and Z. Drezner	✓	✓		This paper considered the 1-stop multiple allocation p-hub median problem. They provided efficient algorithm both heuristic and exact approaches.	All parameters were deterministic, facilities were uncapacitated, and the objective function was only a minimum cost.	Most input data was not considered stochastically. Multi-objective function was not taken into account.
HubLocator: an exact solution method for the multiple allocation hub location problem (2002) G. Mayer and B. Wagner		✓		This literature offered a new branch-and-bound procedure for the uncapacitated multiple allocation hub location problem. The optimal solutions can be found in a reasonable amount of time.	All parameters were deterministic, facilities were uncapacitated, and the objective function was only a minimum cost.	
An integrated multi-depot hub-location vehicle routing model for network planning of parcel service (2004) M. Wasner and G. Zapfel	✓			The more complex hub problem including multi-depot and vehicle routing was introduced. Heuristic was offered to tackle this problem.	Since this problem integrated multi-depot and vehicle routing, the global optimum solution was hardly found.	

Table 5.6 Strengths, weaknesses and comments of gap in literatures (Cont.)

Type of facility location problems with Citations	Modelling approaches			Strengths	Weaknesses	Comments of gap in literature
The European freight railway system as a hub-and-spoke network (2007) S.-J. Jeong, C.-G. Lee and J. H. Bookbinder	✓			This paper addressed a hub-and-spoke network problem for railroad freight. Heuristic approach was proposed to handle this problem.	Because this problem concerned with large scale instances, the global optimum solution was hardly found.	
Undesirable facility location problems	**H**	**E**	**S**			
A model to assess risk, equity and efficiency in facility location and transportation of hazardous materials (1995) J. Current and S. Ratick		✓		This paper proposed a multiobjective model to locate hazardous material locations and to provide a routing. Not only was cost provided, but risk and equity were concerned.	This model was efficiently applied to small and medium scale problems, while large scale problems caused massive run-time.	Discrete or network models were not considered. No functionality in the models to identify optimum locations, only able to consider pre-defined candidate locations. Non-linear function was not considered.
Solving the semi-desirable facility location problem using bi-objective particle swarm (2007) H. Yapicioglu, A. E. Smith and G. Dozier	✓			The authors provided a new and more realistic assumption of semi-desirable facility problem using bi-objective function.	A planar facility location and linear distance-based piecewise function were assumed in this model.	
A multiobjective modeling approach to locating incinerators (2009) L. Alcada-Almeida, J. Coutinho-Rodrigues and J. Current		✓		This research developed various techniques: atmospheric dispersion modelling, facility location modelling, geographical information systems (GIS), and multiobjective decision analysis. An interactive decision support system was developed to help decision makers understand, analyze, and explain the complicated decisions.	Since this research had been done to help decision makers to analyze the site selection, candidate sites must be pre-defined before further selection process. In addition, some assumption must be simplified to ease the complicated problem.	

Table 5.6 Strengths, weaknesses and comments of gap in literatures (Cont.)

Type of facility location problems with Citations	**Modelling approaches**			**Strengths**	**Weaknesses**	**Comments of gap in literature**
Competitive facility location problems	**H**	**E**	**S**			
Locational optimization problems solved through Voronoi diagrams (1997) A. Okabe and A. Suzuki		✓		This paper offered a new method to tackle a location optimisation problem through a common geometrical diagram, called the Voronoi diagram.	This method was good for continuous location problem. The main limitation of Voronoi was it closest assumption, which all demands at a point will be assigned to a single facility.	Input data was seldom considered stochastically. Multi-objective function was rarely taken into account.
Locating a single new facility among existing unequally attractive facilities (1994) T. Drezner	✓			The method proposed in this paper can handle the limitation of "all or nothing" assumption in previous models.	The share of a facility based on attractiveness of the facility, which presented in terms of utility function.	
Location of multiple retail facilities with limited budget constraints -- in continuous space (1998) T. Drezner	✓			The model was based on the gravity model, customers were assigned according to attractiveness and an inverse proportion to distance between demand points to facilities.	The parameters in the model were estimated solely under the form of gravity model.	
Competitive facility location on decentralized supply chains (2009) Q. Meng, Y. Huang and R. L. Cheu	✓			The paper attempt to apply competitive feature on supply chains. They considered a supply chain as an equilibrium network.	This model considered that all supply chain have the production capacity constraint. This model was similar to many models in that they considered of a competiveness of node in their network.	
Optimizing the size and locations of facilities in competitive multi-site service systems (2008) L. Zhang and G. Rushton	✓			The model investigated in a competitive condition: queuing problem, budget constraint, exiting facilities.	The continuous location model was assumed in this study. The degree of influence of different customers was treated equally.	

Table 5.6 Strengths, weaknesses and comments of gap in literatures (Cont.)

Type of facility location problems with Citations	Modelling approaches			Strengths	Weaknesses	Comments of gap in literature
Dynamic deterministic facility location problems	**H**	**E**	**S**			
Dynamic Warehouse Location Analysis (1968) R. H. Ballou		✓		This was a early paper attempted to model a facility location over a planning period of time.	The pattern of future conditions must be known deterministically. Only a few factors were in these problems.	Not many parameters were considered stochastically. Multi-objective function was seldom taken into account.
The Multiperiod Location-Allocation Problem With Relocation of Facilities (1975) G. O. Wesolowsky and W. G. Truscott		✓		They provided a good tool for analyzing tradeoffs among present values of static distribution costs in each period and costs of relocating facilities.		
Dynamic versions of set covering type public facility location problems (1982) G. Gunawardane		✓		These problems extended set covering problem by considering a multi-period.		
The dynamic set covering problem (1982) J. W. Chrissis, R. P. Davis and D. M. Miller		✓				
Decision/forecast horizon for a single facility dynamic location/relocation problem (1988) S. Chand		✓		The main advantage of the proposed method was it helped in finding optimal initial decisions for the infinite horizon problem by using information only for a finite horizon.		
Facility location when demand is time dependent (1991) Z. Drezner and G. O. Wesolowsky		✓		This problem extended minisum and minimax problem by considering a multi-period.		

Table 5.6 Strengths, weaknesses and comments of gap in literatures (Cont.)

<table>
<tr><th>Type of facility location problems with Citations</th><th colspan="3">Modelling approaches</th><th>Strengths</th><th>Weaknesses</th><th>Comments of gap in literature</th></tr>
<tr><td>A Lagrangean heuristic for the pk-median dynamic location problem (1992) R. D. Galvao and E. d. R. Santibanez-Gonzalez</td><td>✓</td><td></td><td></td><td rowspan="3">These problems extended p-median problem by considering a multi-period. They provided a heuristic approach to tackle a large size problem.</td><td rowspan="4"></td><td rowspan="6"></td></tr>
<tr><td>Dynamic facility location The progressive p-median problem (1995) Z. Drezner</td><td>✓</td><td></td><td></td></tr>
<tr><td>A dynamic programming heuristic for the P-median problem (1997) M. Hribar and M. S. Daskin</td><td>✓</td><td></td><td></td></tr>
<tr><td>Dynamic facility location when the total number of facilities is uncertain: A decision analysis approach (1998) J. Current, S. Ratick and C. ReVelle</td><td>✓</td><td></td><td></td><td>This paper introduced a new problem in dynamic location analysis, i.e. Identify the locations for an initial set of facilities when the total number of facilities was uncertain.</td></tr>
<tr><td>Dynamic multi-commodity capacitated facility location a mathematical modeling framework for strategic supply chain planning (2006) M. T. Melo, S. Nickel and F. Saldanha da Gama</td><td></td><td>✓</td><td></td><td rowspan="2">The strength of this study was it captured many practical aspects of network design problems in strategic supply chain planning.</td><td rowspan="2">The small and medium size of problems can compute efficiently, but a large size of problem was still questionable.</td></tr>
<tr><td>A dynamic model for facility location in the design of complex supply chains (2008) P. N. Thanh, N. Bostel and O. Peton</td><td></td><td>✓</td><td></td></tr>
</table>

Table 5.6 Strengths, weaknesses and comments of gap in literatures (Cont.)

Type of facility location problems with Citations	**Modelling approaches**			**Strengths**	**Weaknesses**	**Comments of gap in literature**
Dynamic supply chain design with inventory (2008) Y. Hinojosa, J. Kalcsics, S. Nickel, J. Puerto and S. Velten	✓			These studies included a strategic and tactical decision in supply chain, i.e. inventory. They introduced heuristic approaches to handle the complex models.	The objective function of these models considered only a single objective function i.e. total cost. The future condition must be predicted deterministically.	
Stochastic facility location problems *Probabilistic approaches*	**H**	**E**	**S**			
Capacity Expansion and Probabilistic Growth (1961) A. S. Manne	✓			This paper was one of the earliest studies included a stochastic parameter in the model.	Only cost factor was considered in this model.	Multi-objective function was rarely taken into account. Multiple commodity and multiple markets were not considered. More than two competitors were not considered.
The stochastic transportation-location problem (1978) L. Cooper	✓	✓		Both the exact and heuristic solutions were offered.	This method can apply only a continuous location problem. The exact algorithm presented for this problem was limited to problems of very small size.	
Some proposals for stochastic facility location models (1982) Y. M. Ermoliev and G. Leonardi	✓			Numerical stochastic non-differentiable optimisation techniques were applied in this research.	A cost function was solely considered in this model.	
Uncapacitated plant location-allocation problems with price sensitive stochastic demands (1988) R. Logendran and M. P. Terrell	✓			This model assumed the price sensitivity and stochastic demands. The relationships between price and demand quantity were accounted in the model.	This model assumption was an unlimited capacity. In addition, an objective function was only cost in terms of net profit.	
Dynamic location and entry mode selection of multinational manufacturing facilities under uncertainty A chance-constrained goal programming approach (1996) H. Min and E. Melachrinoudis		✓		This paper proposed a model for an international location problem including multiple-period, multiple-plant, multiple-objective, and stochastic environment.	Although several factors were integrated in this model, it was still able to develop in some aspects.	

Table 5.6 Strengths, weaknesses and comments of gap in literatures (Cont.)

Type of facility location problems with Citations	**Modelling approaches**			**Strengths**	**Weaknesses**	**Comments of gap in literature**
Optimal facility location with random throughput costs (2002) N. Ricciardi, R. Tadei and A. Grosso	✓			The strength of the model was the assumption of its cost component which consisted of two terms: deterministic and stochastic part.	The model concerned carefully about the cost term, but it disregarded other factors.	
Design of supply-chain logistics system considering service level (2002) H.-S. Hwang	✓			The research integrated the vehicle routing schedule and supply chain design.	The objective of this model did not include cost, because it concerned with service level only. Thus, it was possible to give a result with poor performance of other factors e.g. high total cost.	
New stochastic models for capacitated location-allocation problem (2003) J. Zhou and B. Liu	✓		✓	This model integrated the network simplex algorithm, stochastic simulations and genetic algorithm to produce a new hybrid intelligent algorithm.	Only a few factors were considered in this model.	
A competitive facility location problem on a tree network with stochastic weights (2003) S. Shiode and Z. Drezner	✓			This model proposed a competitive facility location problem which the assumption of the weight of demand site at the entry time of the follower was stochastic.	The model assumed only two competitive companies in the system and stochastic assumption was only the weight of demand site at the entry time of the follower.	
Incorporating inventory control decisions into a strategic distribution network design model with stochastic demand (2004) P. A. Miranda and R. A. Garrido	✓			This paper introduced a non-linear-mixed-integer model with risk pooling effect.	The model considered a single inventory facility and no information share among between facilities.	
Designing robust emergency medical service via stochastic programming (2004) P. Beraldi, M. E. Bruni and D. Conforti		✓		The study introduced a stochastic programming with probabilistic constraints. The model also trade-off between service and cost.	The exact approach produced a good performance in a small and medium size problem.	

Table 5.6 Strengths, weaknesses and comments of gap in literatures (Cont.)

Type of facility location problems with Citations	Modelling approaches			Strengths	Weaknesses	Comments of gap in literature
Scenario planning approaches	**H**	**E**	**S**			
A conceptual framework for dynamic location - allocation analysis (1974) E. S. Sheppard	✓			This was a early paper addressed a scenario planning approaches.	All scenarios must be predefined to represent the potential realisation of unknown parameters. When it was no information about probability pattern, the expected cost was no longer valid.	Multi-objective function was rarely taken into account.
Location Stores in Uncertain Environments (1982) A. Ghosh and S. L. McLafferty	✓			This study preset a possible future scenario which it narrowed the feasible solutions. The run-time process was shorter than general probabilistic approaches.		
The maximum capture problem with uncertainty (1996) D. Serra, S. Ratick and C. ReVelle	✓			The research included a competitive environment and extended the maximum capture problem. The scenario was generated in order to handle an uncertainty.		
A scenario planning approach for the flood emergency logistics preparation problem under uncertainty (2007) M.-S. Chang, Y.-L. Tseng and J.-W. Chen		✓		The study applied this method for the emergency logistics decision and GIS analysis.		

Table 5.6 Strengths, weaknesses and comments of gap in literatures (Cont.)

Type of facility location problems with Citations	Modelling approaches			Strengths	Weaknesses	Comments of gap in literature
Robust facility location problems	**H**	**E**	**S**			
Strategic Facility Planning The Analysis of Options (1982) David A. Schilling	✓			The study adopted a scenario-based approach to a robust problem.	A set of possible scenarios must be pre-specified.	Multi-objective function was rarely taken into account.
Robust optimization of large-scale systems (1995) S. M. Mulvey and R. J. Vanderbei	✓			In this study, the author introduced a framework for robust optimisation problem.	To resolve this robust model, the high performance computer was needed.	
Siting noxious facilities under uncertainty (2001) K. A. Killmer, G. Anandalingam and S. A. Malcolm	✓			This research applied a robust optimisation framework.		
[alpha]-Reliable p-minimax regret A new model for strategic facility location modeling (1997) M. S. Daskin, S. M. Hesse and C. S. Revelle	✓			Both studies applied the minimax regret concept for the robust problems.	A set of worst case scenarios must be pre-defined.	
The p-median problem in a changing network the case of Barcelona (1998) D. Serra and V. Marianov	✓					

Table 5.7 The modelling approaches and supply chain structure of focused articles

<table>
<tr><th rowspan="2">Items</th><th rowspan="2">Title</th><th colspan="4">Modelling approaches</th><th colspan="7">Supply chain structure</th></tr>
<tr><th>Heuristic</th><th>Exact solution</th><th>Simulation</th><th>Method</th><th>No. of echelons</th><th>No. of products</th><th>Dynamic</th><th>Uncertainty variables</th><th>No. of objective</th><th>Objective function</th><th>Level of management</th></tr>
<tr><td>1</td><td>A simulation-based multi-objective genetic algorithm approach for networked enterprises optimization (2006) Ding, H., Benyoucef, L., & Xie, X.</td><td>✓</td><td>✓</td><td>✓</td><td>Interaction between discrete simulation and optimisation via GA or mathematic programming</td><td>Multiple</td><td>Multiple</td><td>✓</td><td>Transportation times, demand fluctuations, supply disruptions</td><td>2</td><td>1. Total cost
2. The average demand response time, the average customer demand fill-rate, and the on-time delivery rate.</td><td>Strategy and tactic</td></tr>
<tr><td>2</td><td>Decision support for integrated refinery supply chains: part 1 Dynamic simulation (2008) Pitty, S. S., Li, W., Adhitya, A., Srinivasan, R., & Karimi, I. A.</td><td>×</td><td>×</td><td>✓</td><td>Discrete simulation</td><td rowspan="2">Multiple</td><td rowspan="2">Multiple (Crude oil, product oil)</td><td rowspan="2">✓</td><td rowspan="2">Customer’s demands, supply of crudes, prices of crudes and products, raw material and product quality, and production yields</td><td rowspan="2">2</td><td rowspan="2">1. Profit margin
2. Customer satisfaction (in terms of the expected value of the ability to meet the product needs of a customer)</td><td rowspan="2">Tactic and operation</td></tr>
<tr><td>3</td><td>Decision support for integrated refinery supply chains: part 2 Design and operation (2008) Koo, L. Y., Adhitya, A., Srinivasan, R., & Karimi, I. A.</td><td>✓</td><td>×</td><td>✓</td><td>Interaction between discrete simulation and optimisation by NSGA-II</td></tr>
<tr><td>4</td><td>Simulation and optimization of supply chains: alternative or complementary approaches? (2009) Almeder, C., Preusser, M., & Hartl, R.</td><td>×</td><td>✓</td><td>✓</td><td>Discrete simulation and optimisation</td><td>3</td><td>Multiple</td><td>✓</td><td>Demand, transportation time, an amount of product, inventory</td><td>1</td><td>Total cost</td><td>Tactic</td></tr>
</table>

Table 5.7 The modelling approaches and supply chain structure of focused articles (Cont.)

Items	Title	Modelling approaches				Supply chain structure						
		Heuristic	Exact solution	Simulation	Method	No. of echelons	No. of products	Dynamic	Uncertainty variables	No. of objective	Objective function	Level of management
5	A hybrid optimization/simulation approach for a distribution network design of 3PLS (2006) Ko, H. J., Ko, C. S., & Kim, T.	✓	×	✓	GA and discrete simulation	2	Multiple	✓	Demands, order-picking time, travel time	1	Total cost	Strategic and tactic
6	Optimal design methodologies for configuration of supply chains (2005) Truong, T. H., & Azadivar, F.	✓	✓	✓	GA, MIP and discrete simulation	Multiple	Multiple	✓	N/A	1	Total cost	Strategy
7	A simulation based optimization approach to supply chain management under demand uncertainty (2004) Jung, J. Y., Blau, G., Pekny, J. F., Reklaitis, G. V., & Eversdyk, D.	✓	✓	✓	Interaction between discrete simulation and optimisation	Multiple	Multiple	✓	Demand, delivery times, production delays	1	Total cost	Tactic
8	Production-distribution planning in supply chain considering capacity constraints (2002) Lee, Y. H., & Kim, S. H.	✓	×	✓	Iteration between analytic model and discrete simulation	Multiple	Multiple	✓	Operation time	1	Total cost	Tactic

Table 5.7 The modelling approaches and supply chain structure of focused articles (Cont.)

Items	Title	Modelling approaches				Supply chain structure						
		Heuristic	**Exact solution**	**Simulation**	**Method**	**No. of echelons**	**No. of products**	**Dynamic**	**Uncertainty variables**	**No. of objective**	**Objective function**	**Level of management**
9	The dynamic relocation and phase-out of a hybrid, two-echelon plant/warehousing facility: A multiple objective approach (2000) Melachrinoudis, E., & Min, H.	×	✓	×	Multiple objective MIP	2	1	✓	×	3	1. Total profit 2. Total access time from the proposed plant/warehousing facility to its suppliers and customers 3. Aggregated local incentives	Strategy
10	A multi-objective approach to simultaneous strategic and operational planning in supply chain design (2000) Sabri, E. H., & Beamon, B. M.	✓	✓	×	Analytic model and MIP	4	Multiple	✓	Demand, production lead-time, supply lead-time, , cost, flexibility level etc.	2	1.Total cost 2. Volume flexibility: plant and distribution	Strategy and tactic
11	A genetic algorithm approach for multi-objective optimization of supply chain networks (2006) Altiparmak, F., Gen, M., Lin, L., & Paksoy, T.	✓	×	×	GA	Multiple	Multiple	✓	×	3	1. Total cost 2. Total customer demand (in %) that can be delivered within the stipulated access time 3. The equity of the capacity utilization ratio for plants and DCs	Strategy

Table 5.8 Strengths, weaknesses and comments of gap in focused articles

Items	Title	Strengths	Weaknesses	Comment of gap in literature
1	A simulation-based multi-objective genetic algorithm approach for networked enterprises optimization (2006) Ding, H., Benyoucef, L., & Xie, X.	This toolbox comprised of user-friendly concepts related to the modelling, simulation and optimization of modern enterprise networks. Either make-to-stock or make-to-order can be set in this model.	This study provided generally toolbox for supply chain optimisation through simulation-optimisation algorithm. It was not specific to particular problems. The variation of network design problems was limited probably according to existing configuration. Some factors were not taken into account in the model, e.g. competitive supply chain, routing, or hub decision. A set of candidate facilities must be predefined.	Other factors, e.g. environment impact were not taken into account as objective function. An agent-based simulation was not implemented in this model.
2	Decision support for integrated refinery supply chains: part 1 Dynamic simulation (2008) Pitty, S. S., Li, W., Adhitya, A., Srinivasan, R., & Karimi, I. A.	This simulation model included dynamic, information flow both push- and pull-mode in supply chain. In addition, it comprised of mix continuous and discrete events. The parallel computing was adopted.	This model were developed according to an existing supply chain structure, it was not built for the design of supply chain network. This model did not consider some factors, e.g. competitor of its supply chain, location decision of its facility. In terms of uncertainty, stochastic parameters were assumed.	Other factors, e.g. environment impact were not taken into account as objective function. An agent-based simulation was not applied in this model.
3	Decision support for integrated refinery supply chains: part 2 Design and operation (2008) Koo, L. Y., Adhitya, A., Srinivasan, R., & Karimi, I. A.			
4	Simulation and optimization of supply chains: alternative or complementary approaches? (2009) Almeder, C., Preusser, M., & Hartl, R.	The model was introduced a simulation and optimisation interaction. As a result, it successfully tested examples showed that faster results compared to conventional mixed-integer model in a stochastic environment.	They assumed that there was a central planner with perfect information and order-driven only. However, in many situations, operations may apply push and/or pull manner. It solely applied for a tactical decision.	The strategic decision was not included in this model. Other factors, e.g. environment impact were not taken into account as objective function. Agent-based simulation was not implemented in this model.

Table 5.8 Strengths, weaknesses and comments of gap in focused articles (Cont.)

Items	Title	Strengths	Weaknesses	Comment of gap in literature
5	A hybrid optimization/simulation approach for a distribution network design of 3PLS (2006) Ko, H. J., Ko, C. S., & Kim, T.	This study was suitable for the design a distribution network.	This study assumed that the locations of client's markets and the potential warehouses were known. The demands of product were also assumed to be known for the analytic model. An objective function was solely a total cost.	Multi-objective function was not utilised. Agent-based simulation was not implemented in this model.
6	Optimal design methodologies for configuration of supply chains (2005) Truong, T. H., & Azadivar, F.	This study considered qualitative and policy variables in the model, e.g. outsourcing–supplier selection, make-buy decisions, production planning policy.	The objective function was only total cost.	Multi-objective function was not utilised. Agent-based simulation was not implemented in this model.
7	A simulation based optimization approach to supply chain management under demand uncertainty (2004) Jung, J. Y., Blau, G., Pekny, J. F., Reklaitis, G. V., & Eversdyk, D.	This study focused on demand uncertainty for supply chain management, especially inventory.		
8	Production-distribution planning in supply chain considering capacity constraints (2002) Lee, Y. H., & Kim, S. H.	When the different rate between subsequent iteration was close enough, the model stopped running. Then, the model was used to represent the optimum design. That made the model was fast convert to optimum point.	Not only were the stochastic parameters operation time, but also objective function was only total cost.	Most parameters were not treated stochastically. Multi-objective function was not employed. Agent-based simulation was not implemented in this model.

Table 5.8 Strengths, weaknesses and comments of gap in focused articles (Cont.)

Items	Title	Strengths	Weaknesses	Comment of gap in literature
9	The dynamic relocation and phase-out of a hybrid, two-echelon plant/warehousing facility: A multiple objective approach (2000) Melachrinoudis, E., & Min, H.	This paper experimented three objectives in the model. Using standard optimisation software, LINGO, made the model was simply to solve.	All parameters were assumed deterministic.	Most parameters were not treated stochastically. Multi-objective function was not employed. Agent-based simulation was not implemented in this model.
10	A multi-objective approach to simultaneous strategic and operational planning in supply chain design (2000) Sabri, E. H., & Beamon, B. M.	This was one of the first attempts to include strategic and tactical level in the model. It also considered multi-objective in this model.	The weakness of the analytic approach is that it cannot handle a complex supply chain; in addition, the model is too rigid to modify the relation among the supply chain and to adjust some parameters e.g. the distribution pattern.	Other factors, e.g. environment impact were not taken into account as objective function. An agent-based simulation was not implemented in this model.
11	A genetic algorithm approach for multi-objective optimization of supply chain networks (2006) Altiparmak, F., Gen, M., Lin, L., & Paksoy, T.	This paper proposed a new Genetic Algorithm to cope with multi-objective in supply chain networks optimisation.	All parameter were assumed deterministic.	All parameters were not treated stochastically. Other factors, e.g. environment impact were not taken into account as objective function. An agent-based simulation was not implemented in this model.

The gaps in the literature identified in Table 5.7 lead to the identification of an FLP which would address these gaps (as described in detail in chapter 6). A number of papers which are closely related to this proposed FLP (called the 'focussed papers') are reviewed in Table 5.8.

The weaknesses and comments of gaps of these focused papers with regards to the considering factors can be described as following issues.

To begin with the objective functions, about half of all articles concern a total cost as a single objective function, while the rest are bi- or multi-objective functions that can be grouped into, first, an internal organisation performance and, second, a customer perspective index. The internal organisation performance is often represented by a total cost or a profit, whereas the customer perspective index is illustrated by respond time, fill rate, on time delivery, or access time, etc. None of them addresses the environment impact in their models.

Turn to focus on the level of management, the study by Almeder et al. (2009) focuses solely on a tactical decision with a few number of decision variables. A strategic decision, e.g. location, size, number of facilities can provide for further analysis. Many factors can possibly be included in the model, e.g. multi-objective function. Only a few articles combine both a strategic and tactical decision in the model. For example, Sabri and Beamon (2000), Ding et al. (2006), Ko et al. (2006) proposed an integration of strategic and tactical decision, while others often concern with simply strategic or tactical decision.

In terms of modelling approaches, Jung, Blau, Pekny, Reklaitis, and Eversdyk (2004), Truong and Azadivar (2005), Ding et al. (2006), and Almeder et al. (2009) offered an interaction between an optimisation and a discrete simulation. In case of simulation approach, the discrete simulation often applies to represent an uncertain parameter; however, the alternative approach, e.g. agent-based simulation approach, may provide the different perspective and interesting results. According to the review, the agent-based simulation did not apply to the integrated optimisation and simulation models.

Sabri and Beamon (2000) offered a multi-objective approach to simultaneous strategic and tactical planning. This paper addressed the uncertain parameters by an analytic model without a simulation. The weakness of the analytic approach is that it cannot handle a complex supply chain; in addition, the model is too rigid to modify the relation among the supply chain and to adjust some parameters e.g. the distribution pattern.

5.12 Conclusion

This chapter presents all findings from the systematic review process. It is argued that facility location problems are important with significant implications. The problem-solving process is explained to provide a basic understanding of the interrelation among real-world situations, formulated problems, and developed models. It can be concluded that there is a relationship between real-life situations and the formulation into problems. Models are developed to represent such problems and solved by various mathematical techniques. An overview of complexity analysis to understand the complication of facility location problems shows how they usually fall into the class of *NP-hard* problems.

Modelling approaches are reviewed and a number of conclusions are drawn. First of all, optimisation models include exact and heuristic approaches where the former provide the best or optimal solution and the latter offers the near optimal result. The optimisation methods, both exact and heuristic, attempt to provide a best or optimal solution however uncertainty is difficult to capture. In particular, they cannot perform a number of testing policies for making various decisions. Second, simulation predicts the performance of a system in order to test a decision-maker policy, or predict a system performance. The main advantage of simulation modelling is to be able to model variability and its effects. However, the main disadvantage of simulation approaches is that they do not provide an optimal solution. Also, the probability distribution of input variables must be known. Third, the hybrid approaches, the combination of combination of simulation and optimisation are given details. The advantage of this approach is that it combines the strength of both methods. Nevertheless, the limitation of this method is that iterations between simulation and optimisation may cause long computational time. In addition, the distribution pattern must be known.

A taxonomy of facility location problems with eighteen factors is developed and will be used to classify problems throughout the study. Eighteen factors are as following:

- Planar versus network versus discrete location models
- Tree versus general graph problems
- Distance Metrics
- Number of facilities
- Strategic versus tactical versus operational decisions
- Static versus dynamic location problems
- Deterministic versus uncertain models
- Single versus multiple product models
- Private versus public sector problems
- Single versus multiple objective problems
- Elastic versus inelastic demand
- Capacitated versus uncapacitated facilities
- Competitive versus non-competitive facilities
- Nearest facility versus general demand allocation models
- Hierarchical versus single-level models
- Forward versus reverse models
- Combined routing versus classical models
- Desirable versus undesirable facilities

Various problems involving static and deterministic, extended, dynamic, and uncertain facility location problems are reviewed. The static and deterministic problems in facility location include the covering, centre, median and fixed charge problems. These problems can perform an extended feature responding to more real-life problems. The extension of facility location problems involves location-allocation, multi-objective, hierarchical, hub, undesirable and competitive problems. Dynamic or multi-period deterministic facility location problems capture a future uncertainty depending on time horizon with an important assumption that input parameters are known and vary deterministically over time. On the other hand stochastic and robust facility location problems deal with uncertain parameters. The former describes uncertain parameters as probability distributions that are assumed to be acknowledged by the decision maker; the latter assumes no information about uncertain parameters. The probabilistic approaches are usually adopted for the stochastic models only, whereas the scenario planning approaches are often applied to both the stochastic and robust facility location models.

The key weaknesses of these problems can be summarised that heuristic methods base on random search, so it may provide a sub optimum solution. The exact methods demonstrate in the review article often apply to a small or medium problem, however the real-life problem size is doubtful. The objective function of most problems is popular total cost. Only a few models take the customer's view point as another key performance index. Several parameters in the models are considered deterministically, while that of the real-world problems is always stochastic.

Consequently, the common gaps found in these literatures are: most data was not treated stochastically; objective functions other than the total cost were not often considered and multi-objective function was rarely taken into account.

The key gap from the review is no one model covering simultaneously more than two objective functions, stochastic input parameters, and integrate strategic and tactical decision.

Further discussions of identifying the gap in literatures, recommendation of future research, identifying the proposed facility location, and contribution of the proposed problem will be presented in Chapter 6.

6 Discussion

This chapter discusses strengths and weaknesses of different modelling approaches. Then, the gaps from the review process are indentified. Next, recommendations of future researches and the facility location problem to be addressed by the proposed research are shown. Finally, contributions of the proposed problem are illustrated.

6.1 Strengths and weaknesses of different modelling approaches

Generally speaking, each modelling approach can apply to the various facility location problems. The exact method can solve a small or medium size problem, while a large scale problem can be approximated by heuristic or hybrid approaches. The exact approaches can provide the optimum solution, whereas the heuristic methods do not guarantee the optimum solution. The goal of the optimisation model is to offer a best solution, while it is difficult to perform the policy testing and to model uncertainties. On the contrary, the simulation approaches are able to perform the policy testing easily, but they do not provide the optimum or near optimum solution. In addition, the probability distribution of parameters must be known. Table 6.1 summarises the strengths and weaknesses/limitations of optimisation, simulation and hybrid approaches.

Table 6.1 The strength and weakness/limitation of modelling approaches

Modelling approaches	Strength	Weakness/limitation
Optimisation		
- Exact approaches	Provide the optimum solution.	Need long computational time and massive memory, when the problem size is large. It is difficult to model uncertainty and perform the policy testing.
- Heuristic approaches	Reasonable computational time and manageable memory. It can handle a large problem size.	It does not guarantee the optimum solution. It is also difficult to model uncertainty and perform the policy testing.
Simulation	Easy to model uncertainty and perform the policy testing.	Does not provide the optimum or near optimum solution. The probability distribution of parameters must be known.
Hybrid: simulation-optimisation	Able to account for parameter uncertainty and find the optimum or near optimum solution.	The computational time may be long since the interaction between both simulation and optimisation. The probability distribution of parameters must be known.

6.1.1 Optimisation approaches

An aim of optimisation models is to find a best solution. On the one hand, exact approaches provide an optimum solution. On the other hand, heuristic approaches offer a near optimum or optimum solution. Rardin (2001) suggests an approximate guideline in the selection of optimisation methods based on the number of binary decisions, and the error of the best available relaxation bound as described in Section 5.4.

In many aspects, an exact solution approach should be considered the ideal method, as long as the exact approach can provide an optimal solution within reasonable computational time. With an exact approach, as the problem size increases, more computational time and memory is required (Almeder et al., 2009). Therefore for large problems it may be necessary to adopt heuristic approaches as an alternative.

In recent years, there has been an increasing interest in using various evolutionary computation methods to solve *NP-hard* optimisation problems (Gen & Cheng, 1997). Among of these evolutionary methods, genetic algorithms are probably the most well known technique (Syarif, Yun, & Gen, 2002). According to an empirical comparison among four heuristic algorithms: pattern search, simplex, simulated annealing and Genetic algorithm (Lacksonen, 2001), genetic algorithms have shown their ability to solve large problems vigorously and to tackle problems with non-numeric variables.

The optimisation methods, both exact and heuristic, attempt to provide a best or optimal solution however uncertainty is difficult to capture. In particular, they cannot perform a number of testing policies for making various decisions.

6.1.2 Simulation approaches

While optimisation approaches provide an optimum or near optimum solution, the objective of simulation approaches is to predict the performance of a modelled system under a specific set of inputs. In other words, the simulation approach does not provide the optimal solution; on the contrary, it focuses on an imitation of a system so as to test a policy, or predict a system performance (Robinson, 2004; Terzi & Cavalieri, 2004).

The conventional simulation methods usually refer to discrete and continuous simulation. These simulation approaches lack of a capability to link among different levels of decision making, the systems responsible for control (Datta, 2007). Under globalisation today, market atmosphere is changing by lessening product cycle times, and a rising shift from mass production to mass customisation. A new circumstance requires a different approach, particularly supply chain management. In such an extremely dynamic environment, decentralised management has recently been introduced to conquer the limitations of centralised information systems (Paolucci & Sacile, 2005). One of the modelling tools introduced in recent years is an agent-based simulation approach.

Kornienko et al. (2004) stated that because the activity of agents is a result of the group behaviour that is based on different forms of negotiations among agents, the problem solving – decision making, planning – in an agent-based system has essentially more degrees of freedom than in traditional centralised systems. Datta (2007) stated that the interactive agent-based framework becomes more flexible and more resilient to different disturbances in the supply chain network.

Datta (2007) also summarised benefits of agent-based modelling in supply chain network as follows:

- Ability to model more complex systems realistically.
- Achieve increased flexibility and adaptability without losing efficiency or productivity.
- Attain lean and agile enterprise operations.
- Achieve better integration of enterprise functions.
- Results in improve quality of decision making.

The advantages of agent-based simulation model over the discrete simulation are that it can simulate the behaviour of each agent including the ability for adapting or learning by itself. For example, in case of supply chain, the warehouse or distribution centre agent is more intelligent by automatically adjusting the inventory level according to the existing stock level, incoming/outgoing goods, and incoming order.

The main advantage of simulation modelling is to be able to model variability and its effects. Most simulations are performed in complex systems, which are closely-related to real-world situations (Terzi & Cavalieri, 2004). However, the main disadvantage of simulation approaches is that they do not provide an optimal solution. In addition, its limitation is the probability distribution of input variables must be known.

6.1.3 Hybrid approaches: simulation-optimisation

Since real world problems, e.g. an airfield system are often very complex in nature, it may be made up of both continuous and discrete data, applying classical optimisation methods can often not be done in a straightforward fashion (Cusick, 2004). There are some studies that involve the combination of simulation and optimisation; for example, the studies by Ko, Ko and Kim (2006), Ding, Benyoucef and Xie (2006) and Koo, Adhitya, Srinivasan and Karimi (2008).

The advantage of a combination of simulation and optimisation is that this approach combines the strength of both methods. More specifically, this approach can generate probability distribution in performing simulation module; meanwhile it is able to provide a good or optimal solution in optimisation module. Nevertheless, the limitation of this method is that iterations between simulation and optimisation may cause long computational time. In addition, the distribution pattern must be known.

6.2 Identifying the gap in the literature

Two gaps were identified by the literature review:

- Existing facility location problems do not simultaneously use environment impact, internal organisation performance and customer service as objective functions
- Existing modelling approaches do not apply agent-based simulation approach to the hybrid simulation-optimisation models.

According to the literature review, none of facility location models used three objective functions; most of them used a single objective function, typically total cost, while the bi- and multi-objectives often dealt with total cost and some variables representing a customer perspective.

Furthermore, no article applies the agent-based modelling in line with the combination of optimisation and simulation in supply chain context.

6.3 Recommendations for future research

To solve facility location models can be extremely complicated because they fall into the *NP-hard* class of problems (Garey & Johnson, 1979). Thus, it is not surprising that much of the research on facility location focuses on static, deterministic problems, and single objective function. To make the problem more realistic, other factors can be considered e.g. stochastic parameters, multi-objective function.

Melo et al. (2009) also points out that almost all studies are devoted to the uncapacitated facility location problems; however, there are not many papers concerned with capacitated and multi-echelon facility location problems in the supply chain context:

> *"A conclusion that can be drawn from the literature devoted to the uncapacitated facility location problem and its extensions is that this research field has somehow evolved without really taking the supply chain management (SCM) context into account. Features such as multiple facility layers or capacities have been included in the models in a rather general way and specific aspects, that are crucial to SCM, were disregarded"* (Melo et al., 2009).

Melo et al. (2009) noted that many research areas still require intensive study; one of them is uncertainty, particularly due to stochastic effects combined with other aspects such as a multi-echelon structure.

Many models in facility location problems focus on the strategic decisions, while the tactical and operational decisions e.g. inventory, routing, or production are rarely considered. Dasci and Verter (2001) suggest two general trends: (a) integration of strategic and tactical decisions, and (b) including international features in production-distribution system design problems.

Finally, in the reviews of the combination of optimisation and simulation, hardly ever do the studies involve factors such as dynamic, multiple objective, elastic demands, competitive, hierarchical, reverse, routing and undesirable facility models. Future researches may focus on these factors.

In terms of modelling approach, the alternative optimisation approaches may provide a better result e.g. evolutionary optimisation technique, whereas the agent-based simulation model can also deploy as a recent simulation technique.

6.4 The facility location problem to be addressed by the proposed research

This section will describe the proposed facility location problem. Table 6.2 illustrates the summary of proposed problem, which can classify according to the taxonomy as be described in section 5.6.

Table 6.2 The proposed facility location problem

Item	Taxonomy	Proposed problem	Rational for proposed problem
1	Planar vs. network vs. discrete location models	A network location model	The network model can simplified the problem realistically e.g. it can include each road link in a network
2	Tree vs. general graph problems	A graph problem	A road network simply define as a graph problem
3	Distance Metrics	-	Because it is not the planar location
4	Number of facilities	Multi echelons	There are multi echelon in the proposed network model
5	Strategic vs. tactical vs. operational decisions	A combined strategic and tactical decision	The proposed model is an integration of strategic and tactical decision
6	Static vs. dynamic location problems	A static and dynamic location problem	Propose a static model for a strategy sub-module, and a dynamic model at a tactical sub-module
7	Deterministic vs. uncertain models	An uncertain model	Propose demand and supply uncertainty, which can represent more realistic real-world problems
8	Single vs. multiple product models	A multiple product model	There are multiple products in the model
9	Private vs. public sector problems	A private sector problem	Propose a private sector for a test case
10	Single vs. multiple objective problems	A multiple objective problem	Propose multiple objective function in this model

Table 6.2 The proposed facility location problem (Cont.)

Item	Taxonomy	Proposed problem	Rational for proposed problem
11	Elastic vs. inelastic demand	An inelastic demand	Consider demand as inelastic demand
12	Capacitated vs. uncapacitated facilities	A capacitated or uncapacitated facility	Depends on the test case capacity, whether it is limited or unlimited
13	Competitive vs. non-competitive facilities	A non-competitive facility	The proposed model do not include the effect of competitor in a model, so the model is assumed as a single supply chain
14	Nearest facility vs. general demand allocation models	A general demand allocation model	Using a general demand allocation in the model
15	Hierarchical vs. single-level models	A hierarchical model or interactive sub-model	Propose a model as a strategic decision and a tactical decision with the hierarchical or interactive relationship between both decisions
16	Forward vs. reverse models	A forward model	Consider only a forward model
17	Combined routing vs. classical models	A non-combined routing model	The proposed model do not combine a routing decision
18	Desirable vs. undesirable facilities	A desirable facility	The proposed model look into a desirable facility only

The proposed facility location problem focuses on the gaps identified in the literature review and outlined in the previous section. The problem is the design of facility location and supply chain network. The main features of the problem consist of:

- Multi-objective functions
- Multi-echelons
- Multiple products
- Demand and supply uncertainties
- An integration of strategic and tactical decisions

The two key points which distinguish the proposed study from the existing research are: the proposed problem, and the different modelling approach:

- The proposed problem address the multi-objective function consisting of 1) an internal organisation performance, e.g. a total cost or profit, 2) a customer perspective, e.g. respond time, fill rate, or on time delivery, and 3) an environment impact, e.g. CO_2.
- The modelling approach will apply an agent-based simulation approach in the stage of simulation in stead of the discrete simulation.

6.5 Contribution of the proposed facility location problem

The major contribution of the proposed research is to provide a modelling method for improving the decision making process involved in the design of supply networks (involving facility location problem) under supply and demand uncertainty. The improved method will be novel in that it will: integrate strategic and tactical decisions; deal with demand and supply uncertainties; accept multiple products; account for multi-echelons; and use multiple objectives.

In terms of objective functions, in particular an environmental impact will be taken into account simultaneously with an internal organisation performance and a customer perspective index. This will lead to understanding of the relationship among such factors in the facility location problem.

The proposed modelling approach will apply an agent-based simulation approach in the stage of simulation instead of the discrete simulation. By the agent-based simulation, it will provide an autonomous, adaptable, interacting and pro-active tool for complex supply chain. The proposed modelling method can link among different levels of decision making, the systems responsible for control; it can also provide a decentralised management simulation in order to overcome the limitation of the conventional discrete simulation.

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