Chapter 1. Introduction

1.1. Definitions Related to Logistics

Logistics

Logistics is concerned with the organization, movement, and storage of material and people. The term logistics was first used by the military to describe the activities associated with maintaining a fighting force in the field and, in its most narrow sense, describes the housing of troops. The term gradually spread to cover business and service activities. There exist a multitude of formal definitions. The Council of Logistics Management is a large trade association in the United States that promotes the practice and education of logistics. Their definition is probably the most widely used.

Council of Logistics Management (CLM) Definition

"Logistics is the combination of transport, storage, and control of material all the way from the supplier, through the various facilities, to the customer, and the collection of all recyclable materials at each step."

It is worthwhile to expand on some of the characteristics of logistics. Foremost is the fundamental principle that logistics takes a holistic, integrated view of all the activities that belong to its domain. Logistics is a mission-oriented discipline that will encompass and coordinate all the activities necessary to achieve its mission, which can be summarized as providing time and space utility to an organization. A business organization has the goal to incorporate the following values into its products: form and function, time and space, and ownership. The form and function values are generated by its research and design and production activities. Providing the customers with the right product, in the right place, at the right time, generates the time and space values, which is the domain of the logistics activities. Finally, the ownership value is created and enhanced by the marketing activities.

Logistics focuses on three types of flows: material flows, information flows, and monetary flows. The most traditional flow is the physical “material flow”, where the material can range from traditional
products, through services, to livestock, and people. The “flows” can refer to material in motion, indicating the space utility typically associated with transportation, or to material at rest, indicating the time utility typically associated with storage and inventory. The second important flow in logistic activities is the flow of information. The sharing of information on the status of the physical flows across the various organizations executing the logistics functions can dramatically decrease the magnitude of the physical material flows. This has led to the implementation of massive software packages for Enterprise Resource Planning (ERP) that provide such information first within a single organization and now among all the organizations in a supply chain. Finally, the increasingly global nature of trade and logistics has sharpened the focus on monetary flows in logistics. Currency fluctuations and fiscal regulations of trade associations such as the Economic Union (EU) and North American Free Trade Association (NAFTA) can dramatically change the feasibility and efficiency of the physical flows.

**Supply Chain**

Very closely related to the logistics is the concept of a supply chain. A supply chain is a network of functional organizations that through their activities perform the logistics functions. Again many alternative definitions exist.

“A supply chain is a network of organizations that are involved through upstream and downstream linkages in the different processes and activities that produce value in the form of products and services in the hands of the ultimate customer,” Christopher (1998).

The linkages consist of material, information, and financial flows. The supply chain is usually not a single or simple chain but a complex network with many divergent and convergent flows. Because of the current focus of companies on their core competencies, there are typically many different organizations in a supply chain. If all these organizations belong to the same (multinational) corporation, information flows usually are more complete and powerful and decision-making is easier, but the fundamental nature of the supply chain remains unchanged. In other words, there is no difference in the definition of a supply chain depending on the fact if one or more corporations are involved.

For an organization to become part of a supply chain requires this to be a beneficial relationship or win-win situation in the long run for the organization and for the rest of the supply chain.
There exist an enormous variety of supply chain implementations. In the manufacturing industries, examples are the manufacturing and distribution of consumer goods, the assembly of limited-quantity goods such as aircraft and locomotives, or the construction of telephone switching centers. In the service industries, supply chains take the form of hospital and provider networks, functionality and location of banking outlets, and hub-and-spoke networks by major airlines to offer seats on flights. In the defense organizations, supply chains correspond to personnel, equipment, and bases functions and locations. While there exist many different manifestations and configurations, the underlying structure of any supply chain remains a network of capacitated production, storage, and transportation assets to provide customer service by the timely delivery of goods and services to the customers at the lowest possible cost.

Stadtler and Kilger (2000) define supply chain management (SCM) as “the task of integrating organizational units along a supply chain and coordinating materials, information, and financial flows in order to fulfill the demands of the ultimate customer with the aim of improving competitiveness of a supply chain as a whole.”

Computers & Communications

The Internet has had a tremendous impact on the control and information flows in logistic systems. Figure 1.1 illustrates the information presented to an end customer when a package is shipped. The current location and the transportation history of the shipment are reported in detail. This allows the receiver to better plan its activities and provides detailed transactional data to the carrier to optimize its network and operations.
A virtual logistics enterprise temporarily combines various logistics service providers and requesters into a single organization for the execution of a particular logistics mission. After the mission has been completed, the component companies become independent again. A particular company may at the same time be a partner with another company for one logistics mission and a competitor for another mission.

1.2. Logistics Planning and Decisions Support

Three Levels of Logistics Planning

To maximize the value along a supply chain, a large variety of planning decisions has to be made, ranging from the simple warehouse-floor choice which item to pick next to fulfill a customer order to the corporate-level decision to build a new manufacturing plant. Supply chain planning supports the full range of those decisions related to the design and operation of supply chains. The focus of this book is on use of normative models and mathematical solution algorithms to support supply chain planning. Such models and algorithms require the identification and quantitative specification of objectives, constraints, and alternatives.
There exist a vast amount of literature, software packages, decision support tools, and design algorithms that focus on isolated components of the supply chain or isolated planning in the supply chain. Examples are production planning in manufacturing, vehicle dispatching in transportation, and warehouse management systems in distribution operations. However, maximization of the potential for adding value along the supply chain requires an integrated and comprehensive planning approach. The supply chain considered should extend from the suppliers of the raw materials, through the various transformation stages, to the final consumers. In recent years, the recovery and recycling operations and processes of post-consumer products are also included in the supply chain and its planning.

In the last two decades, several companies have developed Enterprise Resource Planning (ERP) systems in response to the need of global corporations to plan their entire supply chain. Two major examples of such software vendors are Baan and SAP. ERP systems integrate the data of one or more principal business functions such as accounting, human resources, production planning, and sales. In their initial implementations, the ERP systems were primarily used for the recording of transactions rather than for the planning of resources on an enterprise-wide scale. Their main advantage was to provide consistent, up-to-date, and accessible data to the enterprise.

In recent years, the original ERP systems have been extended with Advanced Planning Systems (APS). The main function of APS is for the first time the planning of enterprise-wide resources and actions. “The goal of APS is to find feasible, near-optimal plans across the supply chain as whole, while potential bottlenecks are considered explicitly,” Stadtler and Kilger (2000). This implies a coordination of the plans among several organizations and geographically dispersed locations. APS are responsible for planning, while an ERP system is still required as a transaction and execution system. APS use or extract data stored in the ERP to support algorithm-based decision-making and then store the plans back into the ERP. APS do not substitute for ERP but supplement existing ERP systems.

APS typically comprise several planning modules ranging from strategic network planning, through intermediate demand planning and master planning, to operational material requirements planning (MRP), production planning, distribution planning (DRP), and transportation planning. At the current time, the major emphasis in APS is on the operational planning and execution levels. The strategic planning modules are still in their infancy in current implementations. The organization of the various planning modules in supply chain planning and the relations between them are shown in Figure 1.2. More details on the hierarchy of planning tasks and on APS can be found in Stadtler and Kilger (2000).
and Fleischmann and Meyr (2001). Software to plan the supply chain that has been created outside the ERP system many times is called Supply Chain Management (SCM) software.

![Figure 1.2. Organization of Supply Chain Planning Modules](image)

The individual planning tasks in an APS constitute in themselves very difficult planning problems. Sophisticated optimization algorithms, such as mixed integer programming (MIP), constraint programming techniques and heuristic algorithms may be used. Since decisions are made at different times, by different decision makers, and in different locations, no single integrated and comprehensive planning model and corresponding planning algorithm exist. Most often, the overall planning task is solved using hierarchical decomposition or hierarchical planning.

Examples of major software houses offering APS or SCM are Baan, I2, Manugistics, J.D. Edwards, and SAP. Several of these companies also provide the ERP system, while others rely on third-party ERP systems. The modules in these APS, their capabilities and functionalities change continuously and dramatically. Many times, the only available information is based on marketing and promotional materials provided by the software vendors. The detailed assumptions, constraints, and objectives of the strategic models and algorithms are particularly hard to determine.

Anderson Consulting, in cooperation with the Council of Logistics Management (CLM), annually compiles a database of software packages used for the planning and scheduling of logistics operations, see Haverly and Whelan (2000) for a recent edition.
Strategic Planning

The decisions made at the strategic planning level are characterized by their permanence and importance to economic survival of the company. Examples in manufacturing are the construction of a manufacturing plant, the sizing and location of production capacity, the switch from company-owned to third-party logistics, the selection of distribution channels, and the identification and ranking of product-customer pairs. Examples in the service industry are the decision for two banks or hospitals to merge and again the identification of desirable product-customer pairs. Finally, examples in the defense sector are the configuration of the armed forces, the deployment of a new weapon system, and the decisions on location or closure of bases.

A third characteristic is the lack of quantitative and validated data for the full time horizon of the decision. A manufacturing plant typically has a useful life of twenty years are more, while the products manufactured in the facility may have a life cycle of less than a year. Many times the decision has to be based on external data that are forecasted with a huge amount of uncertainty especially for time periods farther and farther into the future. Examples are the population evolution and wages in various areas of the country or the world and the forecasts of acceptance and use of technologies and products. The opportunities for success and the penalties for mistakes can mean the survival or demise for the corporation for several years or even permanently.

Tactical Planning

The decisions made at the tactical planning level typically have a permanence of three months to a year. Examples are the production schedule for the next three months, the long-term contract with a supplier or transportation company, and the determination of the level of customer service. The data on which the tactical decisions are based are typically a mixture of internal and external data. Internal data may comprise sales forecasts based on historical sales and questionnaires. External data may include the overall health of the economy, the exchange rates between various currencies, and the season of the year. An external or corporate forecasting department typically creates the sales forecast in a periodic fashion. The configuration of the supply chain determined at the strategic level now translates into a number of constraints at the tactical level. The consequences of success or failure can have dramatic impact on the share price of the corporation.
Operational Planning

The decisions made at the operational planning level typically have a permanence of a day to a week. Examples are the weekly production schedule, the amount of product to be picked and shipped to a customer, the amount of product purchased from a supplier. The data available to support operational planning is most often internal data known with great detail and accuracy. The more recent use of ERP systems has provided planners with extensive operational data. The savings and penalties associated with operational decisions typically impact the performance measures of a facility or a department in a facility.

Execution

The decisions made at the execution level typically have a permanence of a few minutes to a few hours. Examples are which part to produce next, which part to pick next in a distribution center, or which customer is delivered to next by a vehicle. The impact of a single execution decision is often very small or negligible, but since so many execution decisions are made their aggregate impact determines the cost and resource consumption rates used at the higher planning levels.

1.3. Engineering Design Process

Steps in the Engineering Design Process

Formulate the problem

The more general or wider the problem is formulated, the more solutions and the more diverse the solutions will be.

Collect data and analyze the problem

In the problem analysis there are three phases. The data on the current system must be collected, the constraints for the new system must be identified and the evaluation criteria for the new systems must be defined. In facilities layout it is essential that the major and supporting activities, their interrelationships, and their space requirements are identified.
Generate alternative solutions

The key during this step is to generate as many as possible, high quality, creative solutions.

Evaluate design alternatives

Evaluation of the different alternative solutions by the different criteria. Compute the quality of each alternative with respect to each criteria.

Select the preferred design(s)

The best alternative is selected with the ranking, factoring, or any other method.

Specify the solution

The detailed configuration specification is created.

Evaluate the design in use

Implementation of the Solution. The selected configuration is build. The design process can start all over again by adjusting or redefining the objective.

1.4. Modeling

Introduction

Modeling Definition and Model Usage

A (logistics) model is a simplified representation or abstraction of a real-world (logistics) system. Models are created because they are easier to manipulate than the real-world system or because they provide enhanced insight in the behavior of the real-world system. While there is an obvious cost associated with the development, construction, and maintenance of a model, models of various levels of complexity are used nearly universally in planning and design processes. The validity of using models as decision support aids differs significantly on a case by case basis. For example, one simple model predicts the rise or fall of the Dow Jones industrial stock market index for the coming year depending on the fact if the football team that wins the Super bowl in January of that year belongs to the National or the American Football Conference. This is a very simple model to use, but it is difficult to argue its
validity. At the opposite end of the modeling complexity spectrum, Artnzen et al. (1995) have developed a model for the global supply chain of a specific computer manufacturer that incorporates both spatial and temporal characteristics. Clearly, not all models are equally valid or suitable for logistics systems design and a knowledgeable design engineer must carefully evaluate model use and model recommendations.

Models are primarily used for assistance in making decisions regarding complex systems. Ballou and Masters (1993) surveyed developers and practitioners in the logistics and supply chain industry to determine the most important characteristics of and the state of the art in decision support systems for supply chain design. They found that model features and user friendliness were the most important characteristics of the models and design packages. Ballou and Masters (1999) repeated the survey six years later and observed that advances in computer hardware and software had allowed real-world strategic supply chain systems design projects to be completed using mathematical models that were incorporated in commercial software packages. They reported that specialized and efficient algorithms had been developed to solve the spatial or geographical location aspect of supply chain systems, but that specialized or general-purpose simulation models are used for the temporal aspects such as tactical inventory and production planning. Few models combine or integrate the spatial and temporal aspects of the supply chain. Based on a survey of active models and software packages, they found that the models are becoming more comprehensive and are beginning to include some tactical aspects. Global characteristics such as taxes, duties and tariffs, and exchange rates are included in only a few models. They reported that linear programming (LP), mixed-integer programming (MIP), and heuristics are the most commonly used techniques to find solutions. In the survey the practitioners responded with a large majority that modeling was used to configure their supply chain. In contrast with the 1993 result, in 1999 the practitioners ranked the optimality of the solution as the most important characteristic of the software. According to the practitioners, the best features of the models were their ability to represent the real-world system and to find an effective configuration. The worst features were the difficulty in obtaining the necessary data, the complexity of using the model, and the poor treatment of inventory costs, especially in connection to customer service levels. Finally, the authors observed that a consolidation trend is reducing the number of models and software applications.
Modeling Process and Framework

The building of explicit models for the analysis, design, and management has traditionally been called management science. Most of the management problems are initially observed in the form of symptoms. A model is developed and used to aid in the decision making. Based on the model recommendations, a number of decisions is made and implemented in the real-world system. The definition of a clear and comprehensive problem statement is part of the modeling process. This modeling process is most often not a single pass process but rather an iterative, successive refinement procedure, as illustrated in Figure 1.3. If the decisions suggested by the model do not yield the anticipated results when they are implemented, then the model structure, the model data, or the solution algorithm has to be further refined.

![Figure 1.3. Modeling Framework](image)

Model Validation

It is often infeasible or impractical to validate a model in a scientific way. For example, to validate scientifically that one location for a major new manufacturing plant is better than another location is impossible, since only one plant can be build. Similarly, a frequent validation claim states that an organization saved a certain amount of expenses after having used a model for decision-making. Scientific validation would require the determination of expense reductions if no model had been used. One imperfect way to validate a model is to use the model to predict history. This activity is often called benchmarking. Historical data on parameters and actions for a particular problem instance are inserted into a model. The outcomes of the model are compared to the observed outcomes in the real-
world system. The model is assumed to be valid if it mimics sufficiently close the real-world behavior. Next, the model is allowed to make its own decisions and the two outcomes, with or without the model use, are compared. The yield of the improved decision-making process using the model becomes evidence for the value of the model. One would assume that the model is then used to support decision making for current and future problems. This, of course, assumes that historical validity implies future validity.

**Model Data**

Even if the validity of the model has been established to a sufficient degree, obtaining correct and accurate data for use by the model is a difficult process. The data required by the model usually correspond to some future time period and typically are forecasted based on historical data. Many times the historical data is simply not available or the forecasting methods have not been validated.

Recently warehouse management systems (WMS), manufacturing execution systems (MES), and enterprise resource planning systems (ERP) have started to capture the status, actions, and performance of logistics systems in great detail. For example, a warehouse management system may have collected a detailed order history by individual customer and individual product or stock keeping unit (SKU) for the last few years. Typically, this raw data cannot be used directly in decision support models. A first transformation converts the detailed transaction data into aggregate statistics. For example, individual orders may be aggregated into average weekly demand and a demand distribution for a particular product is determined. The aggregate statistics are then further synthesized into knowledge about the logistics system. For example, Pareto analysis may identify the products that account for the majority of the sales dollars and divide the products into fast, medium, and slow movers and compute the sales dollars for each class.

![Data to Knowledge Transformation](image-url)

**Figure 1.4. Data to Knowledge Transformation**
The same transformation process occurs when modeling transportation systems. Detailed freight bills may have been retained for the transportation charges paid to trucking companies for the past year. This date is transformed into information by aggregating the customer destinations into regions based on their three-digit ZIP codes and by computing the average shipment quantity for each region. For each region the LTL transportation cost is estimated using LTL freight rate tables based on the average shipment quantity for that region. Again Pareto analysis can be used to identify the regions that account for the majority of the outbound transportation charges. The location of each region can be found with help of a geocoding database and the total transportation quantity to the regions can be used to compute the center of gravity to estimate the best location for a distribution center.

The next figures illustrate this transformation process from data, into information, and knowledge. The objective of the project was to design a cost-efficient delivery policy to group of customers in the continental United States. The customer and aggregate product demand data were extracted from a corporate database, which held detailed data on all sales orders for the last year. The data was then inserted into a Microsoft Access relational database, which contained the customer identification, its city, state and ZIP code, and the product demand for the last year.

![Relational Database with Customer Information and Demand](image)

**Figure 1.5. Relational Database with Customer Information and Demand**

The ZIP code of each customer was used to determine their geographical location expressed in longitude and latitude. This process is called geocoding. The customers were then located on a map of the continental United States. This provided graphical information on the dispersion of the customers. It
can be observed in the next figure that most of the customers were located in the Midwestern and the northeastern areas of the country.

**Figure 1.6. Customer Locations**

Further data analysis runs were made to determine the aggregate product demand by state. Finally, combination of the data for this project with logistics domain knowledge that the size of a customer order strongly impacts the delivery cost yielded the average size of a customer order by state.

**Figure 1.7. Total Customer Demand by State**
Figure 1.8. Average Customer Order Size by State

The statistical analysis revealed that the state of California had the largest cumulative demand and that the customers in the state of Arizona placed the largest orders on average. This information was then used to develop the knowledge that for this logistics system a differentiated distribution strategy may be effective. Customers in Arizona and New Mexico are serviced by a different transportation mode since their average order is much larger than the orders from customers in the Midwest.

While the availability of transactional data has clearly enabled the modeling process, collecting, validating, and synthesizing the data is still a resource and time intensive activity that requires specific technical expertise, judgment, and insight in the logistics system.

**Model Terminology and Classification**

The basic function of a model is to transform a number of known input variables into a number of output variables, whose values are sought. The input-output diagram of a model is shown in Figure 1.9.

**Figure 1.9. Model Input-Output Diagram**

*Exogenous* or input variables are determined outside the model. They can be further classified as *parameters*, which are not controllable by the model and the decision maker, and *decision variables*,
which are controllable. *Endogenous* or output variables are determined by the model. They can be further classified as *performance measures*, which quantify the behavior of the system with respect to one or more goals, and *activities*, which describe the configuration of the system being modeled and the intensity of activities in the system.

**Physical, Analog, and Mathematical Models**

Models can physical, analog, or mathematical. The three dimensional scale models of military aircraft, chemical molecules, a manufacturing plant with its machines, or a real estate development with its buildings and roads are just some of the examples of *physical* models. Physical models have the same appearance as the real system being modeled but usually at much smaller or larger scale.

*Analog* systems do not physically resemble the real system they model but exhibit connections between input parameters and output variables proportional to the relationships between the corresponding input parameters and output variables of the real system. A map is common example of an analog system. The location of two points and the distance between them are examples of input parameters and output variables in the analog model and the real system. If the distance on the map between a pair of points is twice as large as between another pair of points, then we expect the distance between the first pair in the real world also to be twice as large as between the second pair. A truck dispatcher may determine the shortest distance path from the port of Dunkerque on the North Sea to Marseilles on the Mediterranean Sea with a map of the interstate road network in France and then route a truck following that path.
A classical example of an analog model used in logistics systems design is the Varignon frame. Weber described in 1909 the use of the model to determine the location of a new facility that minimizes the sum of weighted distances to existing facilities. Holes are drilled in the table at the locations corresponding to the customers. A thread is strung through each hole with a weight on one end and all the threads are tied together in a knot on the other end. The weights are proportional to the number of trips between the facility and its customers. The knot is raised above the table and then let go. The final location of the knot corresponds to the optimal location of the manufacturing facility. The optimal location of the knot and other interesting optimality conditions can be found based on the principles of static forces. This mechanical analog is illustrated in Figure 1.11. It will be discussed in more detail in the chapter on continuous location with Euclidean distances.
Figure 1.11. Varignon Frame as a Mechanical Analog Model

Mathematical or symbolic models incorporate the structural properties and behavior of the real system in mathematical relations. They can be further divided into descriptive and normative models. Descriptive models predict the values or distribution of one or more output variables for a given set of parameters. Normative models determine the value of some decision variables to optimize one or more performance measure or objective function. A widely used descriptive modeling tool in the design of material handling systems is digital simulation combined with animation. Descriptive queuing models are often used to predict the number of people and their expected waiting time in waiting line systems found in post offices, fast food restaurants, and amusement parks. A widely used normative modeling tool in the design of strategic distribution systems is mixed integer programming (MIP).

\[
\begin{align*}
\text{Min} & \quad \sum_i \sum_j c_{ij} x_{ij} \\
\text{s.t.} & \quad \sum_i x_{hi} - \sum_j x_{ij} = b_i \quad \forall i \\
& \quad 0 \leq x_{ij} \leq u_{ij} \quad \forall ij
\end{align*}
\]

Figure 1.12 Minimum Cost Network Flow Formulation as a Normative Mathematical Model

To determine the decision variables in normative models, a solution method is required. This is often called "solving the model" and the solution method is referred to as the solution algorithm. An optimal solution is a decision that gives the best answer to mathematical model, but it may not be the best answer to the original real-world problem.
Deterministic versus Stochastic Models

A model is said to be deterministic if all its relevant data parameters are known with certainty, i.e., they are given as a unique value. For example, when scheduling our day we may assume that we know exactly how long it takes to drive to work in the morning. Of course, we realize the time it takes to drive to work varies from day to day. A model is said to be stochastic or probabilistic if some parameters are not known with certainty. Parameters that are not known with certainty are called random variables and they represent the ignorance and variability in the model. Usually, random variables are represented or modeled with probability distributions. Even though virtually all real-world problems are stochastic, deterministic models are still used very often because they may give an acceptable approximation of reality and they are much easier to construct and to solve than stochastic models.

Deductive versus Inferential Models

A model is said to be deductive if starts from the definition of variables, makes some assumptions, and then defines the relationships between the variables. For example, a simple deductive model to compute the average speed ($v$) with corrugated cardboard boxes can be unloaded from the back of trailer is to divide the total time it takes to unload the trailer ($\Delta T$) by the number of boxes on the trailer ($n$). This represents a top-down approach.

A model is said to be inferential if determines the relationships between various variables by analyzing data from data streams or data warehouses. A typical example is the determination of relationships between variables with regression analysis. For example, you may collect total unloading times and number of boxes unloaded at the truck docks of a receiving department during a year and then run a linear regression model to determine the relationship between those two data items. Based on the results of the regression analysis, you may then decide that those two items are linearly related and that boxes are unloaded at a constant speed.

Modeling Advantages and Disadvantages

Modeling Advantages

Probably the most significant advantage of using models to assist in the decision process of configuring logistics systems results of the execution of the modeling process. Developing a logistics model requires that the organization clearly articulates its business objectives, its standard or allowable
business practices, the structure of the organization, and business operating constraints and relations. This information can then be shared or presented to everybody involved with the logistics system such as employees, vendors, and customers.

The solution of the developed model requires that business parameter values and costs are defined consistently and have a numerical value agreed upon by all stakeholders in the logistics system. Again the process of defining and computing these parameters and costs is most likely more beneficial than their actual use in the model.

Since most models are solved by some form of optimization algorithm, the suggested configurations and activities typically will provide a higher quality solution than a manual decision process. The model results have the added benefit of being systematic and scientific, which may make their implementation more palatable or politically acceptable.

Developing the first logistics model for an organization is a long and tedious process. However, once the model has been validated and gained acceptance, providing answers to the follow up logistics questions becomes much faster, easier, and more accurate than would have been possible without modeling assistance.

**Modeling Disadvantages**

The major time and expenses in a modeling effort are usually associated with defining, collecting, validating, and correcting the model data, such as parameters and costs. Once these data have accepted, they form a very valuable asset to the corporation.

The modeling process still requires specialized knowledge and computer software. The required powerful computer hardware has become less and less expensive. The recent advances in personal computer power and user friendly analysis software, such as spreadsheets and statistical analysis packages, have revolutionized modeling and brought the modeling process much closer to the practitioner and manager. However, this does not mean that the previously required analytical skills, mastery of advanced mathematics, computer programming, and algorithmic thinking are no longer required. Computer power and analysis software empower the knowledgeable modeler so that the modeling process can be performed faster and in greater depth. They do not guarantee by themselves that the appropriate model is applied or that the user understands the modeling assumptions and limitations of the software. Powerful analysis software is not unlike a chainsaw. With a chainsaw a
logger can cut down a tree much faster than with a bow saw, but the use of a chainsaw does not guarantee that the right tree is cut down and significantly increases the risk of injury to an inexperienced logger. More than once a simulation model has been developed with powerful and graphical digital simulation software and then decisions were based on a single model run.

The models for many logistics problems are intrinsically hard to solve, be it either to find a feasible solution or to find the optimal solution. This often leads to very long computation times for the solution algorithms. It would not be unusual for a facilities design program to find a high quality layout in 24 hours on a personal computer for a facility with no more than ten functional areas. The same computer program may then require more than one or two weeks of computing time to prove that this layout is within close range of the best possible layout.

**Model Realism versus Model Solvability**

There always exists a tradeoff between model solvability and model realism. The more realistic the model is, the more resources have to be allocated for model development, data collection, model maintenance, and model solving. Since all models involve some level of abstraction, approximations, and assumptions, the results of the models should always be interpreted with common (engineering) sense. Also, there is no such thing as a unique correct model. Just as two painters may create two vastly different views of the same landscape, different models can be developed to support decision making for a particular logistics problem.

Different models with different levels of detail and realism are appropriate and useful at different stages of the design process. Systematically increasing the level of model complexity for the same problem and evaluating their solutions and their consistency provides a way to validate the models. For example, a normative model based on queuing network analysis and simple travel time models may be used to determine the required number of cranes and aisles in an automated storage and retrieval systems (ASRS) to satisfy throughput requirements. A descriptive simulation model can then be used to verify and validate the performance of the system and investigate the behavior of the system during exceptional events such as crane breakdowns. This successive refinement approach is a primal solution approach, which has the advantage that an approximately feasible solution exists if the solution process has to be terminated prematurely.
Decision Support versus Decision Making

There exist many examples of successful automated decision-making systems for operational decisions where the real world system is sufficiently simple so that it can be accurately represented and solved by a model. A prime example is the routing of a truck to deliver to a set of customers. Other examples are routing of an automated order-picking crane in a warehouse rack or building a stable pallet load with boxes that arrive on a conveyor belt. The more complex the real world system is, the more approximate any model will become. Models used to assist in strategic decision-making are infamous for not capturing many of the real world factors and subjective influences. Such strategic models should only be used as decision support tools for the design engineer. A healthy skepticism with respect to the results of any model is required. Just because a computer model specifies a particular decision, does not imply that this is the best decision for the real world system. Be especially wary of experts that tout the infallibility of their computer models or the optimality of the generated decisions.

Distance Norms Used as Simple Models

One of the most fundamental models used in the design, analysis, and operation of logistics systems is the distance norm used to model the actual distance. An example of actual distance is the over-the-road distance driven by trucks on the interstate highway system in national distribution systems. While recent computer advances have made it possible to use actual over-the-road distances in many models and solution algorithms, approximation of the real distance by a distance norm is still required in some algorithms because the actual distance is too expensive to compute or unknown. For instance, the location problem for which the Varignon frame is a mechanical analog may not place the new facility on the road network and thus any real distances need to be approximated.

The Euclidean, rectilinear, Chebyshev, and ring-radial distance norms are used to compute the distance between points in a plane. The great-circle distance norm is used to compute the distance between points on the globe.

Planar Distance Norms

A planar distance norm is the formula for computing the distance between two points in the plane. Let $d_{ij}$ denote the distance between two points $i$ and $j$ in the plane with coordinates $(x_i, y_i)$ and $(x_j, y_j)$, respectively.
Three norms are frequently used in the appropriate situations: Euclidean, rectilinear, and Chebyshev.

\[ d_{ij}^E = L_2 = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \] (1.2)

\[ d_{ij}^R = L_1 = |x_i - x_j| + |y_i - y_j| \] (1.3)

\[ d_{ij}^C = L_{\infty} = \max\{|x_i - x_j|, |y_i - y_j|\} \] (1.4)

In the above formulas \( E, R \) and \( C \) denote the Euclidean, rectilinear, and Chebyshev norm, respectively. All the above norms are members of the family of \( L^n \) norms, defined as

\[ d_{ij}^n = L_n = \sqrt[n]{|x_i - x_j|^n + |y_i - y_j|^n} \] (1.5)

where \( n \) is equal to 2, 1, and \( \infty \), respectively, for the Euclidean, rectilinear, and Chebyshev norm.

**Euclidean Norm**

The *Euclidean* distance is also called the straight-line travel distance and is frequently used in national distribution problems and for communications problems where straight-line travel is an acceptable approximation. Multiplying the Euclidean distance with an appropriate factor, e.g. 1.2 for continental United States or 1.26 for the South Eastern United States, can then approximate the actual over the road distances. The Euclidean distance is the shortest distance between to points in a plane.
Rectilinear Norm

The *rectilinear* norm is primarily used in manufacturing and warehousing layout where travel occurs along a set of perpendicular aisles and cross aisles, and in cities with an orthogonal grid pattern such as New York. From this it derives its alternative name of Manhattan norm.

![Figure 1.14 . Office Layout with Rectilinear Travel](image)

The rectilinear norm is also called the sequential travel distance for material handling devices that move only along one axis at the time. An example is an order picking truck used by picker to retrieve cartons from a rack and to build a pallet for a customer order. The platform with the order picker can only move up and down while the vehicle is at a standstill.
Chebyshev Norm

Finally, the *Chebyshev* norm is also called the simultaneous travel distance and is used with material handling equipment such as AS/RS and bridge cranes, where travel occurs simultaneously along two axes. In the following bridge crane schematic the bridge crane end truck and cross beam move independently from and simultaneously with the trolley and hoist.

In the following Automated Storage/Retrieval Systems (ASRS) schematic, the crane moves back and forth in the aisles independently from and simultaneously with the movement of the platform up and down the mast of the crane.
Ring-Radial Distance

Other travel norms exist but are much less often used. One example is the ring-radial distance in old medieval cities such as the central districts of Paris and Moscow or the street plan corresponding to the canals in downtown Amsterdam.

The ring-radial distance between two points with polar coordinates \((\rho_i, \theta_i)\) and \((\rho_j, \theta_j)\) is given by:

\[
d_{ij}^{RR} = \min \{ \rho_i, \rho_j \} \min \left( |\theta_i - \theta_j|, 2\pi - |\theta_i - \theta_j| \right) + |\rho_i - \rho_j| \tag{1.6}
\]

The angular coordinate \(\theta\) is expressed in radians.
Great Circle Norm

A great circle of a sphere is defined by a plane cutting through the center of the sphere and the surface of the sphere. Examples of great circles on the earth are the equator and any meridian. The shortest distance between any two points on the surface of a sphere is measured along the great circle passing through them and is the shorter of the two arcs between the points on the great circle. Computing the distance between two points located on the surface of a sphere with the straight-line distance would imply digging a tunnel through the body of the sphere. The additional complexity of the great circle distance compared to the Euclidean distance norm is usually only warranted for intercontinental transportation models. A typical application is the curved routes of airplanes between two continents as seen on airline system maps.

The \textit{great circle} distance norm computes the distance along a great circle on the surface of the earth between two points with latitude and longitude coordinates \((lat_i, lon_i)\) and \((lat_j, lon_j)\) with the following formula, where \(R\) denotes the world radius:

\[
d_{ij}^{gc} = R \cdot \arccos \left( \cos(lat_i) \cos(lat_j) \cos(lon_i - lon_j) + \sin(lat_i) \sin(lat_j) \right)
\]  

(1.7)

The earth radius is approximately 6366.2 kilometers or 3955.8 miles. By convention the Greenwich meridian has a longitude equal to zero and the equator has a latitude equal to zero.

Physical Distance versus Distance Norms

The adjustment factors to go from the Euclidean or great circle distance norm to the actual distance traveled over the road or rail network for developed countries were computed in Ballou (1999, pp. 557) and are summarized in the next table. The value of the adjustment factors depends on the density of the highway or railway network in area covered by the logistics model.

<table>
<thead>
<tr>
<th></th>
<th>Euclidean</th>
<th>Great Circle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Road</td>
<td>1.21</td>
<td>1.17</td>
</tr>
<tr>
<td>Rail</td>
<td>1.24</td>
<td>1.20</td>
</tr>
</tbody>
</table>

Recent advances in computer and database technology have made it possible in the United States to get detailed driving instructions, distance, and estimated driving time between two locations based on their address. This route planning can be obtained from several inexpensive commercial software packages or over the Internet. The distances reported are actual over-the-road driving distances. An example for
the route planned from the Georgia Institute of Technology to the Atlanta International airport is given next.

<table>
<thead>
<tr>
<th>Time</th>
<th>Mile</th>
<th>Instruction</th>
<th>For</th>
</tr>
</thead>
<tbody>
<tr>
<td>5:00 PM</td>
<td>0.3</td>
<td>Depart 765 Ferst Dr NW, Atlanta, GA 30318 on Ferst Dr NW (North)</td>
<td>0.3 mi</td>
</tr>
<tr>
<td>5:01 PM</td>
<td>0.2</td>
<td>Turn LEFT (North) onto Dalney St NW</td>
<td>0.2 mi</td>
</tr>
<tr>
<td>5:02 PM</td>
<td>0.5</td>
<td>Turn RIGHT (East) onto 10th St NW</td>
<td>0.5 mi</td>
</tr>
<tr>
<td>5:03 PM</td>
<td>0.1</td>
<td>Turn RIGHT (South) onto Ramp</td>
<td>0.1 mi</td>
</tr>
<tr>
<td>5:03 PM</td>
<td>6.8</td>
<td>Merge onto I-75 [I-85] (South)</td>
<td>6.8 mi</td>
</tr>
<tr>
<td>5:12 PM</td>
<td>3.6</td>
<td>Continue (South) on I-85</td>
<td>3.6 mi</td>
</tr>
<tr>
<td>5:16 PM</td>
<td>0.4</td>
<td>At I-85 Exit 72, turn off onto Ramp</td>
<td>0.4 mi</td>
</tr>
<tr>
<td>5:17 PM</td>
<td>1.0</td>
<td>Continue (West) on Airport Blvd [S Terminal Pkwy]</td>
<td>1.0 mi</td>
</tr>
<tr>
<td>5:20 PM</td>
<td>0.2</td>
<td>Continue (South-West) on Airport Circle</td>
<td>0.2 mi</td>
</tr>
<tr>
<td>5:21 PM</td>
<td>0.6</td>
<td>Bear RIGHT (East) onto N Terminal Pkwy</td>
<td>0.6 mi</td>
</tr>
<tr>
<td>5:22 PM</td>
<td>0.2</td>
<td>Turn RIGHT (East) onto Local road(s)</td>
<td>0.2 mi</td>
</tr>
<tr>
<td>5:23 PM</td>
<td>13.9</td>
<td>Arrive Hartsfield-Atlanta International Airport</td>
<td>13.9 mi</td>
</tr>
</tbody>
</table>

Figure 1.19. Georgia Tech to Atlanta Airport Driving Instructions

### 1.5. Algorithms

#### Algorithm Definition

To determine the decision variables in normative models, a solution method is required. This is often called "solving the model" and the solution method is referred to as the solution algorithm. An algorithm is a set of rules to determine the system activities and configuration in a normative model. This configuration can then be evaluated and yields a value for one or more performance measures.
Algorithm Characteristics

Efficient versus Effective

An algorithm is said to efficient when it finds a solution in short amount of computing time. More specifically, it is efficient if it runs in a polynomial time, i.e., its running time is not larger than a polynomial function of the size of the problem. The efficiency of an algorithm for large problem instances can be estimated by the order of the running time of an algorithm.

Order of the Running Time of an Algorithm

Suppose \( n \) is a measure of the problem instance size and the number of computational steps required by a certain algorithm is found to be

\[
a_k n^k + a_{k-1} n^{k-1} + \ldots + a_1 n + a_0,
\]

where \( a_k > 0 \). Then we say that the algorithm is “of order of \( n^k \)”, which is written as \( O(n^k) \). The magnitude of the leading coefficient \( a_k \) is usually ignored, since for very large \( n \), i.e. for very large problem instances, a lower order algorithm will always perform faster than a higher order algorithm. The actual performance on smaller problem instances may depend on the value of the different \( a \) coefficients.

The growth of the running time of an algorithm for the different types of algorithms is illustrated in the next table. The first two algorithms are said to be polynomial (P) and their running times grow relatively slowly. The last algorithm is said to be exponential or non-polynomial (NP) and its running time grows quickly to overwhelm the processing speed of any conceivable computer. Further details on the computational complexity of an algorithm can be found in Garey and Johnson (1979).

Table 1.2. Algorithm Running Times

<table>
<thead>
<tr>
<th>Run Time</th>
<th>Problem Size</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10</td>
</tr>
</tbody>
</table>

| \( n \)  | 0.001 seconds | 0.002 seconds | 0.004 seconds | 0.008 seconds |
| \( n^3 \) | 0.001 seconds | 0.008 seconds | 0.064 seconds | 0.512 seconds |
| \( 2^n \) | 0.001 seconds | 1.024 second  | 12.43 days    | 37.43 million millenia |

It is important to recognize during a logistics design project if the algorithm that will be used to solve the model is easy or hard. Easy algorithms have a low polynomial growth of their running times. The most prominent examples are linear programming (LP) solvers. In linear programming the objective
and all the constraints are linear equations and all the decision variables are continuous, which means that they can have fractional values. Very large linear programming models can be solved to optimality by current LP solvers. Many logistics models focus on the flow of materials between facilities and they naturally correspond to a special subset of LP models called network flow models. The LP solvers can exploit the additional structure in the network flow models and solve instances faster or solve even larger problem instances. Hard algorithms typically have exponentially growing running times. This implies that optimal solutions can only be found in a reasonable amount of computing time for small problem instances. Many of the most commonly used models in logistics belong to this class. Examples are vehicle routing, production planning and scheduling, distribution and supply chain system design, manufacturing and warehousing facilities layout, and fleet planning and scheduling. Many times, the problem becomes hard because certain configuration and activity decisions are restricted to have non-negative integer values. For example, a distribution center can be built in a particular location or not, but it cannot be partially built. Similarly, a truck route will run from customer \( a \) to customer \( b \), but it cannot continue half from customer \( a \) to customer \( b \) and half to customer \( c \). These models belong to the class of either pure integer, where all decision variables are discrete, or mixed-integer programming (MIP) models, where there are both continuous and discrete decision variables. Pure and mixed-integer models usually are difficult to solve to optimality because the number of possible design configurations grows exponentially. For example, the number of possible combinations of building or not building \( N \) distribution centers is \( 2^N \). The computation time required to evaluate all these alternatives grows quickly beyond all reason, as illustrated in Table 1.2. Further information on integer and mixed-integer programming can be found in Nemhauser and Wolsey (1988).

In many instances of logistic models, decision variables that are naturally discrete can be approximated with sufficient accuracy by continuous variables. For example, an LP solver may generate an optimal configuration for a logistics system that involves sending 5238.8 intermodal containers per year from Hong Kong to Long Beach, California. The error introduced by rounding the number of containers to 5239 is negligible. However, the effort required from the solver if all transportation flows of containers were restricted to be integer numbers of containers would be very significant.

**Optimal (Exact) versus Heuristic**

If the algorithm produces the mathematically best solution it is called an *optimal or exact* algorithm, if it produces a good, but not necessarily the best solution, is called a *heuristic*. An optimal solution is a set
of configuration and activity decisions that gives the best answer to a performance measure of a mathematical model, but again it should be stressed that this is not necessarily the best configuration for the original real-world problem.

**Worst Case Performance Bound of an Heuristic**

Since a heuristic is not guaranteed to give the best possible configuration, decision-makers may be interested in the performance gap generated by the heuristic configuration compared to the best obtainable configuration. This performance gap can either depend on the particular problem instance or be the worst case bound for any instance. A heuristic algorithm for a minimization objective is said to have a worse case error bound of $K$, if for any problem instance the ratio of the heuristics solution to the optimal solution value is smaller than or equal to $K$ and if there exist an instance for which this ratio is satisfied as an equality, i.e.

$$
\min \ z \Rightarrow \left\{ \begin{array}{l}
\frac{z_{\text{heuristic}}}{z_{\text{optimal}}} \leq K \\
\exists p : \frac{z_{p,\text{heuristic}}}{z_{p,\text{optimal}}} = K
\end{array} \right.
$$

(1.9)

This also called an a-priori performance bound since it does not depend on the execution of the heuristic for a particular problem instance. The asymptotic worst-case error bound of a heuristic is the worst-case error bound for very large problem instance, i.e., when the problem size grows to infinity. The asymptotic worst-case error bound is not larger and is usually strictly better than the worst-case error bound. Both performance bounds usually can only be computed for very simple heuristics and for very simple logistics systems and operations problems and their value may be much worse than the average error bound on the performance of the heuristic. A more useful statistic is the average case error bound but the average case bound is typically even more difficult to compute than the worse case error bound.

The *optimality gap* is the worst-case performance bound of a heuristic solution for a particular instance. This gap is often more of interest to decision makers since it concerns their particular problem. For a minimization problem, the optimality gap is the difference between the solution generated by the heuristic and some lower bound value. Since the optimal solution value must fall between the lower bound and the heuristic solution, the optimality gap gives the maximum difference between the heuristic solution and the optimal solution. An algorithm is said to be *effective* if it produces a high quality solution or, equivalently, a small optimality gap.
Primal versus Dual

A primal algorithm initially creates and then maintains a feasible solution and improves the quality of the solution while it strives to reach optimality. A dual algorithm initially creates and then maintains an optimal solution for either a subset of the decision variables or of the constraints and strives to reach feasibility by adding either decision variables or constraints. The advantage of a primal algorithm is that on premature termination a feasible solution is available for implementation. In addition, the list of the K best configurations found during the execution of the primal algorithm can be retained and considered for implementation based on other factors not included in the performance objective. The advantage of a dual algorithm is that on premature termination a bound on the optimal objective function value is available. Many solution algorithms for the design of complex logistics systems are composite algorithms that have both primal and dual sub-algorithms embedded in them. The composite algorithm terminates when the gap between the solution value of the best-found primal feasible solution and the bound provided by the dual algorithm falls within an acceptable tolerance level.

Construction versus Improvement

A construction algorithm creates a feasible configuration for the logistics system based on the values of the data input parameters. An improvement algorithm requires a feasible solution or configuration in addition to the input parameters and attempts to improve the quality of the solution. Many improvement algorithms belong to the class of local search procedures. One, several, or all feasible solutions in the neighborhood of the current feasible solution are evaluated. A first descend algorithm will choose the first configuration it finds that has a better solution value. A steepest descend algorithm will choose the configuration with best solution value among all the ones it evaluated. The process is repeated until the search algorithm cannot find a feasible solution with a better solution value in the neighborhood. All local search procedures may terminate at locally optimal solutions, i.e., there does not exist a better solution in the neighborhood of the current feasible solution but there may exist better solutions when considering the full solution space. First descend and steepest descend algorithms belong to the class of deterministic algorithms. Deterministic algorithms will always arrive at the same final configuration when they are started from a particular initial configuration. To find a different final configuration, deterministic algorithms must be started from a different initial configuration, which may be difficult or impossible to obtain. To avoid this phenomenon, Kirkpatrick et al (1983) and Vechi and Kirkpatrick (1983) proposed a non-deterministic search algorithm called simulated annealing. This algorithm will
evaluate random neighboring configurations and choose configurations with better solution value but also choose configurations with a worse solution value with a decreasing probability during the execution of the algorithm. The algorithm is called simulated annealing because of its similarities with the behavior of energy levels in metal alloys during the annealing process.

**Alternative Generating versus Alternative Selecting**

An alternative-generating algorithm creates feasible solutions. An alternative-selecting algorithm selects the solution of the highest quality from a set of feasible candidate solutions provided to it as input parameters. A prominent example in the design of logistics systems of an alternative-generating algorithm is the location-allocation problem, where the location of a given number of distribution facilities and the allocation of customers to these distribution facilities is to be determined. The decision space is the continuous area where the customers are located. Several optimal or heuristic algorithms exist that will generate the location of the distribution facilities. However, even the optimal location derived from the model may be infeasible for the real-world system. Typical examples are the location of a distribution center for the southeast region of the United States in the Gulf of Mexico or for the state of Georgia in downtown Atlanta. Because the algorithm has to describe the cost of the configuration in mathematical expressions, exceptions to cost or constraints can be difficult to incorporate. In addition, since the algorithm determines the solution, a method must be developed to evaluate all possible solution configurations. This typically implies that simplified and approximated cost functions will be used. All of these factors combined indicate that the application of alternative generating algorithms is usually reserved for problems that have a simple cost and constraint structure.

On the other hand, alternative selecting algorithms select a solution configuration from among a set of possible and feasible configurations. This implies that there exists an external mechanism to generate feasible configuration and evaluate the cost of these configurations. Typically this is a person or separate algorithm which is an expert for the problem domain. Since the solution algorithm picks a configuration from a set of feasible configurations, the proposed solution will always be feasible. It is assumed that the expert has the capability to recognize and incorporate exceptions and can compute accurate costs. The solution algorithm to select the alternatives can then be of a general-purpose nature. Typically, variants of the set partitioning or the set covering algorithms are used. The prime application area of alternative selecting algorithms is usually for problems that have complex constraints or cost structures.
A second major class of alternative selecting algorithms is simulation. Simulation belongs to the class of descriptive algorithms, since all design and configuration occurs before the simulation is started and the simulation is used to evaluate the design. Almost all simulation applications today use digital Monte Carlo simulation methods, where realizations of input parameters are sampled randomly from prescribed probability distributions. These parameter values are then inserted in the simulation model of the logistics system under investigation and statistics on the performance measures of interest are collected. Simulation models typically have a very high level of detail or fidelity. Modern simulation applications are able to animate the results of simulation runs, which has proven to be very effective in debugging the simulation model and in marketing the proposed design. While simulation is a very powerful tool for the verification and validation of a design, it is limited in its design capabilities. Minor modifications to the configuration such as increasing the number of truck doors in a distribution center or changing the inventory level of a product can be made with little effort. However, a significantly different configuration of the logistics system requires the development of a new simulation model, which again has to be debugged and validated. In addition, simulation is a descriptive algorithm and relies on other programs or designers to generate good design alternatives. These characteristics make simulation algorithms more useful in the later stages of the design, such as verification, validation, final tuning of the design, and acceptance testing, where the number of alternatives is limited but the required model fidelity is very high. Simulation can also be used to study off-line or in real time the effects of certain decisions on an existing logistics system, if the status of the simulation model and parameters is kept synchronized with the status of the real logistics system.
Because many logistics systems have a natural graphical and geometric representation, the combination of best characteristics of human designers and computerized models and algorithms into interactive and graphical design frameworks has proven to be very effective. The designer is responsible for higher-level decisions and the computer algorithms are responsible for the detailed computations. Communications between the designer and the computer algorithms is achieved through a graphical user interface. This user friendly and powerful interaction has now become a necessary requirement for the acceptance and use of logistics models and design algorithms.

**Model Hierarchy and Corresponding Solution Technologies**

**Model Hierarchy and Associated Solution Technologies**

Organizations typically start with simple models for a particular logistics systems design or operations problem. Once the simple models and their configurations gain acceptance, the models are further refined and enhanced. When the models become more comprehensive and powerful, the corresponding solution algorithms become more complex and resource intensive. The first phase usually involves a deterministic and descriptive model. Examples are the computations to determine the cost, the distance, and duration of a vehicle route, or the computations to determine the cost for the warehousing personnel staffing for the next shift. In the next phase, organizations recognize that many parameters are not known with certainty and they develop stochastic descriptive models. The most prominent is digital simulation but queuing analysis is also sometimes used. Examples are the evaluation of the service levels for various levels of inventory in a hierarchical distribution system or estimation of waiting times experienced by truck for a dock at a distribution center. In the next phase, the decision makers attempt to improve the quality of the solution or to reduce the time and effort required to generate a solution by letting the computer models and algorithms make some decisions. The first step is typically a descriptive normative model and solution algorithm. Prominent examples are vehicle routing algorithms to determine the lowest distance or cost routes, or network flow models to minimize transportation costs. Much more demanding applications are the design of distribution and supply chain systems, which typically require mixed-integer programming models. Finally, the stochastic nature of the parameters is added to the models to create stochastic normative models. Examples are supply chain models that find the best inventory levels to achieve a required customer service level or supply chain models that find
the most robust, flexible, and cost-efficient supply chain configuration for a variety of possible demand scenarios.

1.6. Summary and Conclusions

Logistics Systems Modeling and Algorithm Challenges

Strategic Supply Chain Models

At the current time three factors continue to make models for the design of global supply chains complex, very large, and very difficult to solve to optimality. The first factor consists of the complications created by taxation, duties, tariffs, and local content rules and regulations that create a non-homogeneous domain for the supply chain. For example, a realized profit may not have the same value because of different tax rates, or the value of an otherwise identical product may be different depending on its country of origin. Corporations in the short run can only respond to these regulations by varying either the materials flows in the supply chain or by changing the transfer prices. Models for these global supply chains will require more variables to keep track of the products that are now differentiated by their complete production history. Incorporating transfer prices leads to non-linear models that are much harder to solve than the corresponding mixed-integer linear models. The second factor is caused by the increasing velocity of the supply chain and the decreasing life cycle of the products, which have become even more constraining because of the inherent greater length in distance and time of global supply chains. A product may go from introduction, to demand exceeding capacity, to being phased out in a time span of six months. This implies that supply chain models have to incorporate more and more tactical and even operational features. The most important among them is the incorporation of pipeline, cycle, and safety inventory. The third factor is the requirement that global supply chains at the same time should be efficient for the current set of economic conditions but also flexible and robust enough so that the chain can resist sudden shocks and changes and can adapt to constantly changing products, customers, and suppliers.

Models that incorporate all these features will tend to be complex and most likely will no longer have the standard linear mixed-integer structure. Specialized solution algorithms and heuristics will have to be developed to solve these models in a reasonable amount of computing time. At the same time
Corporations have come to realize that small deviations from optimality can result in significant financial consequences and are demanding more and more optimal solutions.

The increasing complexity of the models, the demand for near-optimal solutions, and the complexity of the solution algorithms to achieve acceptable solution times, all require a high level of technical expertise in model development and solution algorithm execution. Even the ever-increasing processing speeds and growing memory capacity of computers will not be sufficient to allow the use of standard non-specialized solution techniques. Very few organizations will have the technical expertise to build and solve their own models, but most will rely on third parties to provide them with this service.

To remain competitive, global corporations need a methodology to evaluate and efficiently configure global logistics systems in a short amount of time. While at the current time, there exist several comprehensive models and solution algorithms for the design of single-country or domestic logistics systems, such methodology does not appear to exist for global logistics systems.

For domestic logistics systems, comprehensive and multi-period design models have been developed. The models are capable of determining the optimal configuration of the logistics system, including which manufacturing lines should be located in which facilities. They can also determine the production and inventory schedule for systems with seasonal demands. Computation times are in the order of tens of minutes for realistically sized problems. The simultaneous decision on facilities, manufacturing lines, production, and inventory schedules can yield significant savings compared to the sequential decision process where first the facilities are located and then the tactical production-distribution-inventory flows are determined.

One of the most significant issues in global logistics systems is the incorporation of taxation, tariffs, and duty relief effects. Since they are within the control of a corporation, determination of the transfer prices between subsidiaries of the global corporation will yield the most immediate benefits with minimal investment cost. Tax authorities have limited the flexibility to set these transfer prices, but at the current time, the prices can still be set within a prescribed interval. Making the decisions on transfer prices and material flows simultaneously may yield significant after-tax profit increases for the corporation when compared to the most sophisticated sequential decision processes.

At the current time, the research trends towards an integration and combination of the features of the domestic and global models, which will allow the simultaneous optimization of facilities and
production-distribution-inventory flows in a global logistics system. It is clear that such a model and solution methodology can yield significant savings for a corporation interested in expanding globally. A drawback of the newer models and solution algorithms is the significant level of technical expertise required to achieve the fast solution times. A very important area of future research is the standardization and technology transfer process of these solution methodologies so that they can be more widely applied. Enterprise resource systems are adopted by global corporations at ever increasing rates and they provide decision makers with the basic data and information necessary for mathematical models. The models and methodologies that will become available in the near future will allow these global corporations to use this information in a timely fashion to increase their profits significantly and to remain competitive.

1.7. References


