

Chapter 2

Engineering Planning and Design

Learning Objectives After you have studied this chapter, you should be able to

- Know the general characteristics of systems design.
- Know the characteristics, advantages, disadvantages, and types of models.
- Know various types of supply chain objectives, constraints, and costs.
- Know the characteristics, advantages, disadvantages, and types of algorithms.
- Know various distance norms and understand their relationship with real-world distances.

The focus of this book is the application of scientific management and engineering design methodologies to the domain of supply chains and logistics. This chapter summarizes first the methodology of engineering design. It continues by providing a classification and characteristics of models and algorithms. The chapter concludes by describing models for the distance between two points at various levels of accuracy, which are some of the most fundamental models used in the management and design of logistic and supply chains systems.

2.1 Engineering Design and Design Process

2.1.1 *Engineering Design*

Industrial engineering, systems engineering, or industrial and systems engineering are engineering disciplines that focus on designing, planning, and managing complex systems using an engineering-based approach. Designing the “factory of the future” or the “supply chain for the twenty-first century” are complex tasks that require knowledge of a broad set of sciences, including engineering, mathematical, physical, computer and information, and behavior sciences as well as economics and business management. Systems engineering addresses both the structure and the behavior of the system to determine the system’s performance. The principles and methodologies of system engineering apply to a large variety of systems, rang-

ing from production systems such as factories and supply chains, to services systems such as health care delivery and transportation.

The goal of engineering design is the creation of an artifact. This artifact can be a physical object, a computer program, or a procedure. The artifact will have a function, i.e. a particular purpose. The following are examples of artifacts created by engineering design. An aircraft is a physical object with as its function transporting goods and people through the air. Quick sort is a computer program with as its function the efficient sortation of a collection of objects based on a single numerical attribute. The plan for the evacuation of a large city in anticipation of a disaster is a procedure with as its function the relocation of people from a particular geographical area. The artifact must function in the physical world and in particular in its physical environment. This environment poses constraints on the functioning of the artifact. During the execution of its function, the artifact will consume a number of resources. This consumption behavior is measured by the performance characteristics of the artifact.

In most engineering disciplines, engineering design has several stages. While the details will differ between various engineering disciplines, the following stages are commonly identified: (1) problem definition, (2) conceptual design, (3) detailed design, and (4) design specification and implementation. During each of these stages, engineering design decisions are made to progress towards the creation of the artifact. During the problem definition stage, decisions are made regarding the boundaries of the design domain, i.e. what can and cannot be controlled by the design effort, and the relevant performance criteria are identified. During the conceptual design, the different components of the artifact with their associated functions are defined. During the detailed design, the physical implementation of the components is determined, as well as their interactions and performance characteristics. During the design specification and implementation, documents are created that communicate the artifact in sufficient detail to other disciplines so that the artifact can be created according to the specifications. In many engineering disciplines, these documents are engineering blueprints. In software engineering these documents may be flow charts or pseudo code. Engineering documents that describe processes are often denoted as *standard operating procedures* or SOP.

Engineering design is one of the fundamental activities of engineers in any engineering discipline. However, engineering design is interpreted differently by the various engineering disciplines and is taught in vastly different ways in engineering colleges. The value of creativity and intuition, especially during the conceptual design stage, is widely accepted. The intuition of an experienced design engineer most often is not learned in an academic course but rather acquired through active participation in design projects. To start this process most engineering programs require a capstone design project as an essential component of an engineering education. This is further support for the contention that engineering design encompasses both elements of art and science. Good engineering design is based on a balanced combination of creativity and systematic methods. There exist a number of references on engineering design, e.g. Pahl and Beitz (1996), Hoare (1996), Ertas and Jones (1996), Park (2007) but they are relatively discipline specific.

A design procedure determines the various decision problems in the design project, in which sequence they are solved, and how they are related. In most of the engineering design projects, this design procedure is not a linear procedure from start to finish through the various phases or design problems. The current design of the artifact may violate some constraints or may have unacceptable or undesirable performance characteristics causing the design procedure to return to an earlier step in the procedure. The engineering design process is essentially an iterative process. However, the process has to progress towards the creation of the artifact; in other words, the engineering design process has to converge. Hierarchical design is an example of a standard decomposition design method, where decisions are divided based on their scope and time permanence into strategic, tactical, operational, and execution decisions. Decisions with longer time permanence function as constraints for decisions with shorter time permanence.

The different design problems solved during the design process have to be consistent. One way to ensure forward consistency is to interpret higher-level decisions as constraints for lower-level design problems. This is a natural mechanism and is often denoted as hierarchical decomposition. However, there exists a second consistency requirement which is called backward consistency. Backward consistency requires that performance criteria values, derived in the lower levels by more detailed models, are used in the higher-level design problems. This creates feedback loops that may cause the design procedure to solve an infinite loop of design problems. A fundamental challenge for any engineering design procedure is to ensure that (1) the various design problems are forward and backward consistent, and (2) that the design procedure converges.

2.1.2 Characteristics of an Engineered Artifact

2.1.2.1 Performance characteristics and feasibility

The terms artifact and engineered systems will be used interchangeably. A performance characteristic is a quantifiable and measurable property or characteristic of the designed system. The combination of all performance characteristics is called the quality of the designed system. A system is said to be feasible if its performance characteristics exceed certain minimally acceptable levels. Failure to do so will yield a defective artifact, which may lead to excessive costs, returns, loss of market share, recalls, and even liability law suits.

2.1.2.2 Total life cycle cost

The life cycle of a system is the time interval starting with its design and ending with its final disposition. A system has several time phases that are components of

its total life cycle. With each phase there are associated types of cost. The major phases and associated cost types are given next.

1. The design time is the time necessary to design, but not to implement, the system. The time spent designing the system should be commensurate with the value of the system. Often there exists a decreasing quality benefit for spending more time during the design phase. A common principle in military planning states “a good plan today is better than a perfect plan tomorrow”. The design cost is composed of all costs to design, but not implement, the system.
2. The production, construction, or implementation time is the time required to build the system. Large systems such as supply chains which involve capital assets, such as manufacturing plants, and logistics infrastructure, such as railroad tracks and ports, may take years or even decades to construct. Even reconfiguring a warehouse in a supply chain may require three to six months. The production, construction, or implementation cost is the cost to create or build the system, but not to operate the system.
3. The operational life time is the time the system is in operation. For most systems in supply chains and logistics this period has the longest duration in its overall life cycle. The operations or operational costs include the fixed and variable costs to operate the system.
4. The disposal time is the required to shut down and dismantle the system. Again large systems may require extensive periods to be shut down in an orderly fashion. The withdrawal of the United States forces from Western Europe in the late twentieth century required more than a decade. The disposal cost includes all the costs to shut down and dismantle the system.

The total life cycle cost is the total cost accrued during the total life cycle of the product. This cost sometimes also all the *total cost of ownership* or TCO.

2.1.3 Traditional Steps in the Engineering Design Process

There exists widespread consensus on the importance of good engineering design, but relatively few formal design methods have been developed. To our knowledge, none exist in the area of supply chains and logistics. The best approach appears to be to follow the traditional major stages in an engineering design process. These traditional steps in the engineering design process provide a framework on which tasks and decisions have to be executed in the various phases of the design project. One of the basic principles in the design methodology is that all the tasks in the current phase of the process have to be completed before the next phase can be started. The process aims to avoid “business-as-usual” designs by delaying the selection of the final design alternative early in the design process. The process also aims to avoid the selection of pre-conceived solutions by formalizing the steps in the process and making each step as much as possible science-based with specific deliverables. The following stages can be distinguished.

2.1.3.1 Formulate the problem

Formulation of the problem requires the definition of the function of the artifact and its physical environment. The more general or wider the problem is formulated, the more solutions are possible and the more diverse the solutions will be. Designing a local delivery system of packages to individual customers is a much more narrowly defined problem than designing a global supply chain for a new type of commercial aircraft. The formulation stage must create at least the following statements: a clear statement of the function of system, the goal of the system, the available budget in time and resources for design and implementation.

2.1.3.2 Collect data and analyze the problem

In the problem analysis stage 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. A formal description of the problem, including constraints and evaluation criteria, is often given in the *request for proposal* or RFP.

2.1.3.3 Generate alternative solutions

The key during this step is to generate as many as possible, high quality, creative solutions. This phase is commonly denoted as “brainstorming” or conceptual design. During brainstorming a group of design engineers and other participants generate as many proposals for solutions as possible within a given period of time. One of the main objectives during the conceptualization phase is to avoid business-as-usual solutions. Change of a system or product is inherently more difficult and risky than maintaining the status quo or use incremental engineering. The design engineers may also have vested interests in the current solution because they were instrumental in its design. Many engineers are risk averse and will try to minimize the resources required for the completion of a design project.

2.1.3.4 Evaluate design alternatives

During this step, the different alternative solutions are evaluated with respect to the different criteria. This involves computing the quality of each alternative with respect to each criterion as well as a structured method to assign relative importance to the different criteria. The performance assessment of any solution includes both a feasibility assessment and an economic evaluation. The feasibility assessment establishes if the proposed design solution satisfies the requirements. The economic evaluation determines the costs and benefits of the alternative solution.

2.1.3.5 Select the preferred design(s)

The best alternative is selected with a systematic method that integrates the scores of the various alternatives with respect to the various criteria. Since the ultimate selection decision often is made by executive people that are not part of the design team, a small number of diverse designs may actually be selected for further design in the next phase.

2.1.3.6 Specify the design

The detailed configuration specification is created. The typical result of this step is a set of detail oriented documents. Examples of such documents are: engineering blue prints, construction diagrams, standard operating procedures, disaster recovery plans, user's manuals, implementation plans and schedules, quality control and testing procedures. The importance of this step in the overall procedure cannot be underestimated. The famous quote by Thomas Edison that "genius is 1% inspiration and 99% perspiration" is often used to support this point.

2.1.3.7 Evaluate the design in use

Recall that the goal of engineering design is the creation of an artifact. In this step the selected design alternative is built. This allows the collection of all kinds of performance data on the implemented design under real-world conditions. The design process may start all over again by adjusting or redefining the objectives, parameters, and constraints. Changing the specification of the design will lead to *engineering change orders* or ECO that describe the modifications to the artifact being built in detail. Managing the engineering changes for a complex system consumes significant amounts of time and resources.

2.2 Modeling

2.2.1 Introduction

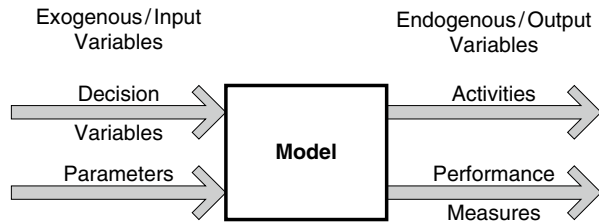
2.2.1.1 Modeling Definition and Model Usage

One of the most fundamental tools used in engineering design is a model. A (supply chain) model is a simplified representation or abstraction of a real-world (supply chain) system. Gass and Harris (1996) define a model as "*A model is an idealised representation—an abstract and simplified description—of a real world situation that is to be studied and/or analysed*". Williams (1999) defines a model as "*a structure which was built purposely to exhibit the features and characteristics of another object.*" Models are created because they are easier to manipulate than the

real-world system or because they provide enhanced insight into the behavior of the real-world system. The enhanced insight may suggest new courses of action or decisions to achieve certain goals. Easier manipulation encourages more extensive experimentation with a variety of input factors. 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 and fall of the Dow Jones industrial stock market index for the coming year depending on whether 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 with respect to supply chain systems, Arntzen 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 supply chain design and a knowledgeable design engineer must carefully evaluate model use and model recommendations.

Models are used primarily to provide assistance when 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 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 and 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.

Fig. 2.1 Model input–output diagram



2.2.2 Modeling Terminology and Framework

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 Fig. 2.1.

Exogenous or input variables are determined outside the model. They can be further divided into *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 divided into *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.

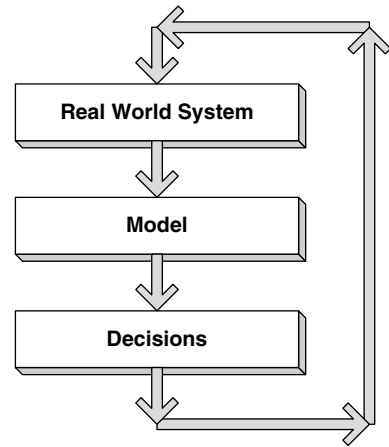
2.2.2.1 Modeling Process and Framework

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 are 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 Fig. 2.2. 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.

2.2.2.2 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 and time consuming 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 are simply not available or the forecasting methods have not been validated.

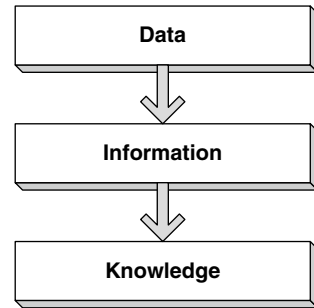
Fig. 2.2 Modeling framework



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 process of computing the statistics of historical orders is called *order profiling* and the process of computing statistics on the customers is called *customer profiling*. The aggregate statistics are then further synthesized and combined with general principles and characteristics to generate 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, compute the sales dollars for each class, and compute the Pareto parameter that indicates the skew of the products. This value of this skew quantitatively represents the knowledge if relatively few products make up most of the sales or if all products are approximately equally contributing to the sales.

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 data 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 less-than-truckload (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 algorithm or database and the total transportation quantity to

Fig. 2.3 Data to knowledge transformation



the regions can be used to compute the center of gravity to estimate the best location for a distribution center. Figure 2.3 illustrates this transformation process from data into information and knowledge.

One example of this transformation process is the computation of the required length of roadway for waiting trucks for an interstate truck weight station. The data collected consisted of the number of trucks passing the proposed location of the weight station during different seasons of the year, days of the week, and hours of the day. A second class of data consisted of the times required to weigh a truck at other weight stations with the same technology. From this data, information was obtained by statistical analysis which determined the average arrival frequency of the trucks and the distribution of the interarrival times, the average time to weigh a truck, and the distribution of the time to weigh a truck. Based on projected growth rates the interarrival times for future periods were then computed. This information was then inserted in the appropriate single-server queuing model to generate the knowledge about the expected number of trucks waiting, the expected waiting time, and the distribution of the waiting time. Finally, based on those waiting statistics, the required length of roadway for waiting trucks was computed.

A second example is based on a real-world distribution system design project. The objective of the project was to design a cost-efficient delivery policy to a group of customers in the continental United States. The customers, the supplier, the products, their characteristics and the customers service policy were all considered to be given and constraints to the distribution system to be designed. 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 (Fig. 2.4).

The ZIP code of each customer was used to determine their geographical location expressed in longitude and latitude. This process is called *geocoding*, which is defined in general as the process that assigns latitude and longitude coordinates to an alphanumeric address. Geocoding can be performed with a variety of programs, such as Microsoft MapPoint, and resources on the Internet, such as Yahoo Maps and Google Earth. The alphanumeric address can be a street address or ZIP codes with 5 (ZIP), 7 (ZIP+2), or 9 (ZIP+4) digits. Once a latitude and longitude coordinates are assigned, the address can be displayed on a map or used in a spatial search. The

Fig. 2.4 Relational database with customer information and demand

Customer Shipments : Table						
CUSTID	County	City	State	ZIP	TotalDemand	
24069	PITTSYLVANIA	Sutherlin	VA	24594	125	
24073	ROCKINGHAM	Hinton	VA	22831	1300	
24074	ROCKINGHAM	Dayton	VA	22821	1075	
24076	ROCKINGHAM	Dayton	VA	22821	100	
24081	AUGUSTA	Weyers Cave	VA	24486	700	
24089	FILLMORE	Lanesboro	MN	55949	1300	
24090	STEARNS	Paynesville	MN	56362	1300	
24094	MCLEOD	Plato	MN	55370	325	
24095	OTTER TAIL	Fergus Falls	MN	56537	375	
24098	STEARNS	Freeport	MN	56331	750	
24105	TILLAMOOK	Nehalem	OR	97131	75	
24116	JACKSON	Grass Lake	MI	49240	3950	
24119	MONTCALM	Edmore	MI	48829	1225	
24126	RUSSELL	Russell Springs	KY	42642	225	
24128	BUCKS	Riegelsville	PA	18077	300	
24133	COLUMBIA	Milville	PA	17846	1200	
24134	LANCASTER	Stevens	PA	17578	650	

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. The supply of the product had to be imported through a container port from Western Europe. Possible selections for the import port were ports located along the eastern seaboard with the Atlantic Ocean and in de Gulf of Mexico (Fig. 2.5).

Further data analysis runs were made to determine the aggregate product demand by state. It can be observed in the next figure that the states with the highest annual demand were California and Wisconsin. The transportation from the port to the distribution center occurred in a single intermodal container. The orders for the products by an individual customer corresponded to a small package. In this case

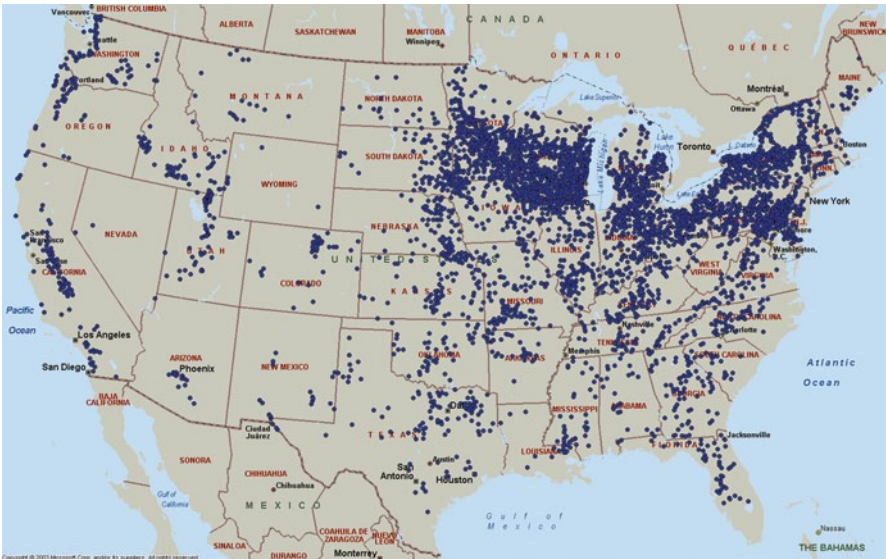


Fig. 2.5 Customer locations



Fig. 2.6 Total customer demand by state

the transportation cost from port to distribution center represented a small fraction of the delivery costs from the distribution center to the customers. Since the delivery transportation costs are roughly proportional to the quantities shipped multiplied by the shipping distance, a good distribution strategy would attempt to locate the distribution center closer to California (Fig. 2.6).

Finally, the logistics domain knowledge that the size of a customer order strongly impacts the delivery transportation cost caused the calculation of statistics on the average size of a customer order 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 (Fig. 2.7).



Fig. 2.7 Average customer order size by state

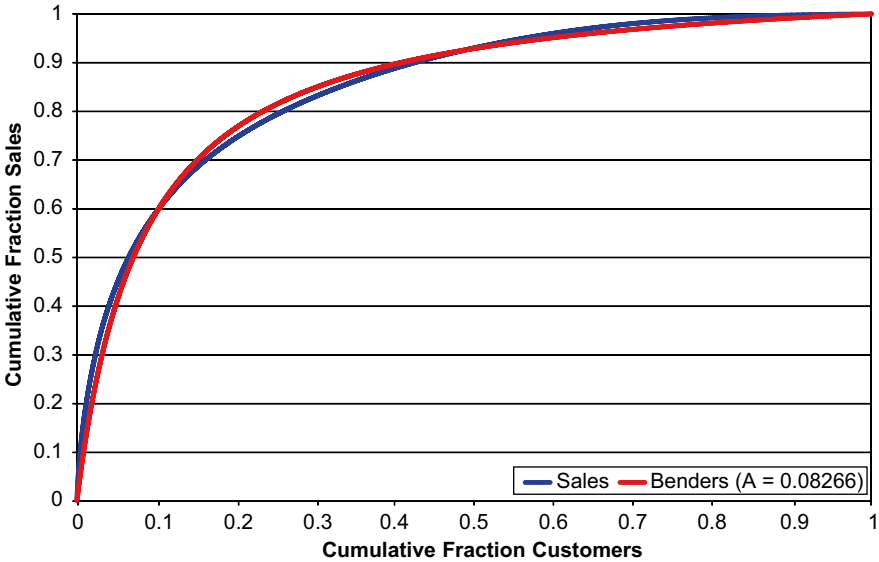


Fig. 2.8 Pareta curve for customer demands

To test the level of concentration of sales among the customers a Pareto analysis was executed. The following Pareto curve shows the cumulative fraction of sales by cumulative fraction of customers, when the customers are sorted by decreasing sales. The Pareto curve of the sales data was approximated by the Bender’s curve with optimal parameter of 0.08266. This small parameter value indicates a strong concentration. Ten percent of the customers make up 60% of the demand and 5% of the customers make up 40% of the demand (Fig. 2.8).

This information was then used to develop the knowledge that for this logistics system a differentiated distribution strategy may be effective. A differentiated distribution strategy serves sub sections of the customers or of the products through distribution channels that have different structures. This is the opposite of a uniform or “one-size-fits-all” distribution strategy. In this particular project, customers in western states such Arizona, southern California, and New Mexico were serviced by a different transportation mode since their average order size was much larger than the orders from customers in the Midwest and the Northeast. A truck with a full truck load (FTL) was dispatched from the distribution center to a break bulk facility located in Arizona. There the full truck load was split into the individual orders of customers in Arizona, southern California, and New Mexico and the orders were then delivered to these customers by a parcel delivery company. Customers located in the other states were served directly by the parcel delivery company from the distribution center.

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 into the logistics system.

2.2.2.3 Model Validation

The scientific validation method consists of the following steps: (1) formulate a hypothesis, (2) design and execute an experiment to test the hypothesis, (3) accept or reject the hypothesis with a certain level of confidence. This scientific validation method implies that you can control the input parameters to correspond to your experiment and test the outcome repeatedly.

It is often infeasible or impractical to validate a model for logistics or supply chain design 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 built. 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. In the following a number of validation approaches are described that are often used in practice to validate the models for logistics and supply chain systems.

One imperfect way to validate a model is to use the model to predict history. This activity is often called (historical) *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 closely the real-world behavior. In a second phase the model is allowed to optimize or set the value of the decision variables. The two outcomes, with and without the aid of the model for setting the decision variables, 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.

In the sensitivity validation method, one or more of the input parameters of the model are changed incrementally around a particular configuration. The changes in the output activities and performance measures are observed and tested to ascertain if the model makes rational changes. For instance, if the purchasing cost of components is increased, the total system cost to satisfy demand should also increase.

Component validation establishes the validity of components of the overall model. It is assumed that if valid components are combined in a valid way, the overall model will also be valid.

Finally, the weakest and most subjective method for model validation is relying on the judgment of experts in the field with respect to the validity of the model. Typically, the output activities and performance measures corresponding to several input scenarios are presented to the experts, who decide if the model outputs make sense. This type of validation is called *face validation* or *sanity check*. Clearly, the

quality of the validation depends strongly on the level of expertise of the experts in the domain area and in modeling methodology.

2.2.3 Supply Chain Model Components and Supply Chain Meta Model

2.2.3.1 Supply Chain Model Components

Recall that supply chain operations is the aggregate term for the activities related to the movement, storage, transformation, and organization of materials. The planning of supply chain activities is divided into four categories depending on the planning time horizon: strategic, tactical, operational, and execution. When planning supply chain activities, there exist the following fundamental components of the supply chain system.

Time Periods

Logistics provides the time and space utility to the organization, while a supply chain provides the time and space and production utility. At the same time, the different planning levels are distinguished by their duration. A fundamental component is the time period(s) in the supply chain planning. If only a single time period exists the planning or model is said to be static. If multiple periods exist the model is said to be dynamic. For a strategic planning model often there are five periods of one year, corresponding to a five year strategic plan. For a tactical planning model the periods are often months, quarters, or semesters. For an operational planning level the typical periods are hours, days, or weeks. For an execution management task, the time periods are typically either seconds or minutes.

Geographical Locations

Supply chain components exist at a particular location in a geographical or spatial area. Typically, the geographical areas become larger in correspondence to longer planning periods. For a strategic model, the areas may be countries or states in the United States. If only a single country is defined then the model is said to be domestic, if more than one country exists the model is said to be global. For operational planning problems such as delivery routing the area may be restricted to a single city.

In strategic supply chain planning, the combination of a country and a period is used very often to capture the financial performance of a logistics system. This combination typically has characteristics such as budget limitations, taxation, depreciation, and net cash flow.

Products

The material being managed, stored, transformed, or transported is called a product. An equivalent term is commodity. It should be noted that the term material is here considered very loosely and applies to discrete, fluid, and gaseous materials, livestock, and even extends to people. If only a single material is defined, the model is said to be single commodity. If multiple materials are defined the model is said to be multi-commodity.

It is very important to determine the type of material being modeled. A first classification is into people, livestock, and products. The products are then further classified as commodity, standard, or specialty. A product is said to be a commodity if there are no distinguishable characteristics between quantities of the same product manufactured by different producers. Typical examples of commodities are low-fat milk, gasoline, office paper, and poly-ethylene. Consumers acquire products solely on the basis of logistics factors such as price, availability, and convenience. A product is said to be a standard product if comparable and competing products from different manufacturers exist. However, the products of different producers may have differences in functionality and quality. Typical examples are cars, personal computers, and fork lift trucks. Consumers make acquisitions based on tradeoffs between functionality, value, price, and logistics factors. A product is said to be a specialty or custom product if it is produced to the exact and unique specifications of the customer. The typical examples are specialized machines, printing presses, and conveyor networks. The product is typically described by a technical specification and the supplier is selected by reputation, price, and logistics factors.

If one or more products are transformed into or extracted from another product, the products are said to have a *Bill of Materials* or BOM. The corresponding material balance equations have more than one product. If the material balance equations can be written in function of a single product, the problem is said to be either single commodity or to have parallel commodities. For example, if based on the requirement for a quantity of the finished product of office paper all the required quantities of intermediate jumbo paper rolls and raw paper pulp can be computed, then all material quantities can be expressed in function of the finished product and a single commodity model would result. The existence of bill of materials equations makes the model significantly harder. Bill of materials can be converging or diverging. Assembly systems have a converging bill of materials where only a relatively few final products are produced from many components. Recycling and reverse logistics systems typically have a diverging bill of materials, when the source is a mixed stream of recyclable materials collected for individual consumers and sorted into separate commodities such as paper, glass, carton, and plastic.

Facilities

The locations in the supply chain network where material can enter, leave, or be transformed are called facilities and are typically represented by the nodes of the

logistics network. Suppliers are the source of materials and customers are the sink for materials. The internal operation of suppliers or customers is not considered to be relevant to the planning problem. The other facilities are called transformation facilities.

Customers

The customer facilities in the network have the fundamental characteristic that they are the final sink for materials. What happens to the material after it reaches the customer is not considered relevant to the planning problem. The customer facilities can be different from the end customers that use the product, such as the single distribution center for the product in a country, the dealer, or the retailer.

For every combination of products, periods, and customers there may exist a customer demand. The demand can be classified as intermittent or regular. A regular demand has a pattern, be it constant, with linear trend, or seasonal. If a demand has no pattern it is said to be intermittent. For example, the demand for flu vaccines has a seasonal pattern, while the demand in developed countries for polio vaccines is said to be intermittent. Intermittent demand or demand for specialty products typically leads to a *make-to-order* or MTO production planning. Regular demand for standard or commodity products may yield a *make-to-stock* or MTS production planning.

Service level constraints are one of the complicating characteristics of customers in supply chain planning. Two prominent service level constraints are single sourcing and fill rate. The single sourcing service constraint requires that all goods of a single product group or manufacturer are delivered in a single shipment to the customer. Single sourcing makes it easier to check the accuracy of the delivery versus the customer order and it reduces the number of carriers at the customer facility where loading and unloading space often is at a premium. A customer may have a required fill rate requirement, which is the minimum acceptable fraction of goods in the customer order that are delivered from on-hand inventory at the immediate supplier to this customer.

Suppliers

The supplier facilities in the network have the fundamental characteristic that they are the original source of the materials. What happens to the material before it reaches the supplier and inside the supplier facility is not considered relevant to the planning problem. The supplier facilities can be different from the raw material suppliers that produce the product, such as the single distribution center for the product in a country.

For every combination of supplier facility, product, and time period there may exist an available supply.

Quantity discounts are one of the complicating characteristics of suppliers in logistics planning. A supplier may sell a product at a lower price if the product is

purchased in larger quantities during the corresponding period. This leads to concave cost curves as a function of the quantity purchased for incremental quantity discounts.

Transformation Facilities

The transformation facilities in the network have the fundamental characteristic that they have incoming and outgoing material flow and that there exists conservation of flow over space (transportation) and time (inventory) in the facility. Major examples of transformation facilities are manufacturing and distribution facilities, where the latter are also denoted as warehouses.

For every combination of transformation facility, time period, and product there may exist incoming flow, outgoing flow, inventory, consumption of component flow, and creation of assembly flow. All of these are collectively known as the production and inventory flows. A facility may have individual limits on each of these flows.

Transformation facilities have two types of subcomponents: machines and resources. Machines represent major transformation equipment such as bottling lines, assembly lines, and process lines. A single facility may contain more than one machine. Each machine may have incoming, outgoing, component flow, and assembly flow for every combination of product and period. A machine may have individual limits on each of these flows. Machines, however, cannot have inventory. A resource represents a multi-product capacity limitation of the facility. Typical examples of resources are machine hours, labor hours, and material handling hours. Products compete with each other in facilities for resources and incoming material flows.

Several complicating factors in the modeling of transformation facilities exist. The first one is the binary nature of the decision to establish or use a facility or not. One can decide to build a manufacturing plant or not, but one cannot build 37.8% of a plant. The decisions for using a plant are thus of the binary type, which makes solving for them significantly harder. The second complicating factor is the related issues of economies of scale and diseconomies of scope. For many manufacturing processes there is a setup cost and a tuning or learning curve. The efficiency of the process grows if this start-up cost can be spread out over a longer steady-state production run. This phenomenon is called economies of scale. The opposite effect occurs when a facility must produce a large variety of products. Each of the products requires its own setup time, which decreases the overall capacity of the facility. Hence, allocation of many different products to a facility, which is known as facility with a large scope, reduces its capacity and increases the various production costs. This diseconomy of scope is also known as the flexibility penalty.

Transportation Channels

Transportation channels, or channels for short, are transportation resources that connect the various facilities in the logistics system. Examples are over-the-road

trucks operating in either full truck load (FTL) or less-than-truck-load (LTL) mode, ocean-going and inland ships, and railroad trains.

For every combination of transportation channel, time period, and product there may exist a transported flow. A channel may have individual limits on each of these flows.

A major characteristic of a channel is its conservation of flow, i.e., the amount of flow by period and by product entering the channel at the origin facility equals the amount of flow exiting the channel at the destination facility at the same or future time period. A second conservation of flow relates channel flows to facility throughput flow and storage. The sum of all incoming flow plus the inventory from the previous period equals the sum of all outgoing flow plus the inventory to the next period. The channels represent material flow in space, while the inventory arcs represent material flow in time. Note that such inventory is extremely rare in strategic logistics models unless the models include seasonal tactical planning.

A channel has two types of subcomponents: carriers and resources. A carrier is an individual, moving container in the channel. The move from origin to destination facility has a fixed cost, regardless on the capacity utilization of the carrier, i.e. the cost is by carrier and not by the quantities of material moved on or in the carrier. Typical examples are a truck, intermodal container, or ship. A carrier may have individual capacities for each individual product or multi-product weight or volume capacities. A resource represents a multi-product capacity limitation of the channel. Typical examples of resources are cubic feet (meters) for volume, tons for weight, or pallets. Truck transportation may be modeled as a carrier if a small number of trucks are moved and cost is per truck movement, or it may be modeled as a resource if the cost is per product quantity and a large or fractional number of trucks are allowed.

There exist several complicating characteristics for modeling transportation channels. The first one is the requirement that an integer number of carriers have to be used. Typically a very large number of potential channels exist in a supply chain model so this requirement will create a large number of integer variables. The second is the presence of economies of scale for the transportation costs. Less common, is the third complicating factor, which requires a minimum number of carriers or a minimum amount of flow if the channel is to be used.

All of the logistics components described so far have distinguishing characteristics. These characteristics can be input data parameters or output performance measures. For example, most of the facilities, channels, machines and their combinations with products and periods have cost and capacity characteristics, which must be captured in data parameters. Sales have a revenue characteristic. The financial quantities achieved in a particular country and during a particular period are an example of output characteristics, which must be captured in performance variables.

Scenarios

So far all the logistics components described were physical entities in the logistics system. A scenario is a component used in the characterization and treatment of uncertainty.

Many of the parameters used in the planning of logistics systems are not known with certainty but rather have a probability distribution. If a parameter has a single value it is said to be deterministic, if it has a probability distribution it is said to be stochastic. For example, demand for a particular product, during a period by a particular customer may be approximated by a normal distribution with certain mean and standard deviation. In a typical logistics planning problem there may be thousands of stochastic parameters. The combination of a single realization or sample of each stochastic parameter with all the deterministic parameters is called a scenario. Each scenario has a major characteristic, which is its probability of occurring. However, this probability may not be known or even not be computable.

A large number of articles and books has been published on the management, design and modeling of supply chains and logistics systems. Some of the more recent books on supply chains that have a strong modeling component are De Kok and Graves (2003), Stadtler and Kilger (2004), Guenes and Pardalos (2005), Shapiro (2006), and Simchi-Levi et al. (2008).

2.2.3.2 Supply Chain Planning Meta-Model

A meta-model is an explicit model of the components and rules required to build specific models within a domain of interest. A logistics planning meta-model can be considered as a model template for the domain of activity planning for logistics systems. The following is a meta-model for the planning of logistics activities and systems. It lists the possible classes of decisions, objectives, and constraints in logistics planning.

Decide on

1. transportation activities, resources, and infrastructure;
2. inventory levels, resources, and infrastructure;
3. transformation activities, resources, and infrastructure;
4. information technology systems;
5. financial conditions for activities, such as transfer prices.

Objective

1. maximize the risk-adjusted total system profit based on the net present value of the net cash flow $NPV(NCF)$ for strategic planning;
2. minimize the risk-adjusted total system cost for tactical and operational planning.

Subject to

1. capacity constraints such as demand, infrastructure, budget, implementation time;
2. service level constraints such as fraction of demand satisfied, fill rate, cycle times, and response times;

3. conservation of flow constraints in space, over time, and observing bill of materials;
4. additional extraneous constraints, which are often mandated by corporate policy;
5. equations for the calculation of intermediate variables such as the net income before taxes in a particular country and a particular period;
6. linkage equations that ensure that the components of the model behave in an internally consistent way, such as flows cannot traverse a facility that has not been established

Difficulties in Solving Supply Chain Models

There are several characteristics that make a logistic model hard to solve

1. A logistics model must be comprehensive and include the different major logistics activities of materials acquisition, transportation, production, and distribution.
2. The scope of a logistics model may include the supply chain from the original raw materials suppliers to the final destination of the products and even reverse logistics. This often implies bill-of-materials equations.
3. The scale of a logistics model, since it may include a very large number of logistics components and a large number of scenarios.
4. The accuracy or fidelity of the model may yield concave or general non-linear costs and constraints.
5. For strategic models, the treatment of uncertainty may yield non-linear and multiple objective functions.
6. Many logistics decisions are of go/no-go type which correspond to either binary or integer variables

Solution Approaches

Many different solution approaches have been applied to logistics models. Some of the more common ones are:

1. Exact mathematical optimization techniques can sometimes be used, but in general logistic models are large-scale, stochastic, non-linear, integer programming problems (LS SNLIP) which cannot be solved in a reasonable amount of time for realistic-size problem instances.
2. To make the problem more solvable it can be decomposed. Most often hierarchical decomposition is used to separate different levels of decision making. Mathematical decomposition techniques can be either primal or dual. Benders decomposition, see Benders (1962), is a typical primal decomposition and Lagrangean relaxation and decomposition is a common dual decomposition technique.
3. Stochastic simulation is often used for operational logistics models. Simulation is most often used when the model is of high fidelity and is less used for aggregate strategic models.

4. Various ad hoc heuristics or local search algorithms such as simulated annealing, genetic algorithms, and neural nets have been applied to logistics models.
5. For operational logistics models, constraint programming has been used successfully. Constraint programming is rarely applied to strategic models.

2.2.4 *Classification of Models by Their Representation Form*

2.2.4.1 **Physical, Analog, and Mathematical Models**

Models can be either physical (iconic), analog, or mathematical (symbolic). The three-dimensional scale models of military aircraft, automobiles, 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* or *iconic* models. Physical models are homomorphic, which means they have the same appearance as the real system being modeled, but they usually have either a much smaller or much larger scale. Physical models of cars or airplanes manufactured out of wood or wax are used in wind tunnels to study their wind resistance and to determine their drag coefficient.

Analog systems do not physically resemble the real system they model but they 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 dispatcher, when planning a truck trip from Chattanooga, TN to Jacksonville, FL, may measure the distances on a map of the interstate road network in the southeastern United States and then route the truck following the shortest path on the map. This would route the truck over the combination of I-75 and I-10 rather than I-16 and I-95 when traveling from Macon to Jacksonville (Fig. 2.9).

A classic 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 the equilibrium on an object subject to static forces. This mechanical analog is illustrated in Fig. 2.10. It

Fig. 2.9 Road network map of the Southeastern United States as a printed analog model

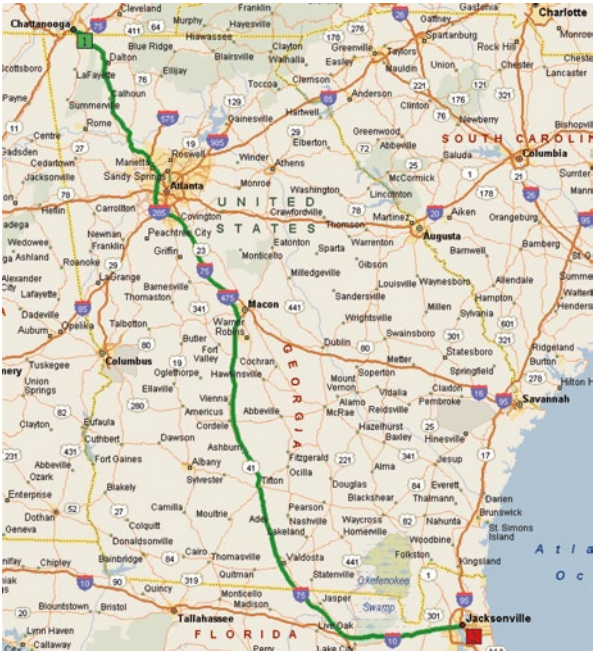
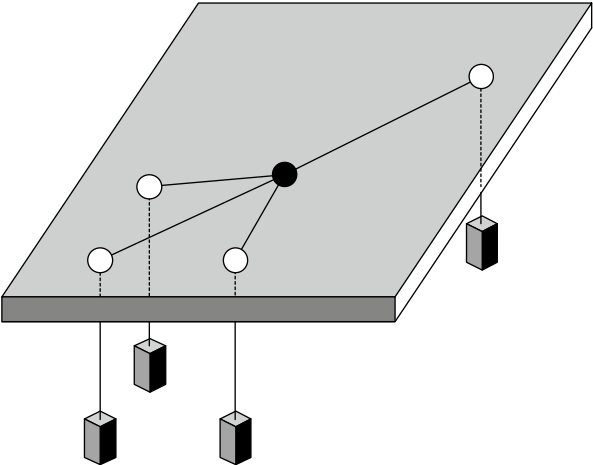


Fig. 2.10 Varignon frame as a mechanical analog model



will be discussed in more detail in the chapter Supply Chain Models in the section on continuous location using Euclidean distances.

Mathematical or symbolic models incorporate the structural properties and behavior of the real system in mathematical relations. Because of the emergence of computers as powerful manipulators of symbolic relations, symbolic models have become the dominant type of models.

Models 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 measures or objective functions. 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. Other common examples of descriptive models are regression, time series, and econometric models.

A widely used normative modeling tool in the design of strategic distribution systems is mixed-integer programming (MIP). The following notation is used in modeling transportation networks. The objective is to find a minimum cost set of flows (x) that satisfy the external flow requirements (b). Examples of external flows are customer demand (outflows) and vendor supplies (inflows). The notation shown is for a single commodity problem, so the subscript p indicating the commodity has been omitted:

- x_{ij} Flow on the directed arc from node i to node j
- c_{ij} Unit cost for one unit flow transported from node i to node j
- b_i External flow for node i (positive for entering, negative for exiting the network, zero for intermediate nodes)
- l_{ij} Lower bound of the flow on the directed arc from node i to node j (often zero)
- u_{ij} Upper bound of the flow on the directed arc from node i to node j

Formulation 2.1 Minimum Cost Network Flow Formulation as a Normative Mathematical Model

$$\begin{aligned}
 \text{Min} \quad & \sum_i^N \sum_j^N c_{ij} x_{ij} \\
 \text{s.t.} \quad & \sum_h^N x_{hi} - \sum_j^N x_{ij} = b_i \quad \forall i \\
 & l_{ij} \leq x_{ij} \leq u_{ij} \quad \forall ij
 \end{aligned} \tag{2.1}$$

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 a mathematical model, but it may not be the best answer to the original real-world problem. The normative mathematical models and their solution algorithms constitute the discipline of mathematical programming.

There exist a separation between the relationships that form the structure of the model and the data. For example, a strategic supply chain design model may contain customer objects that have as one of their characteristics monthly demand for a product. The requirement that customer demand is satisfied every month by shipments from the distribution center is a component of the model. The number of customers and their actual demands are data.

2.2.4.2 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 values. 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 the corresponding stochastic models.

2.2.4.3 Deductive versus Inferential Models

A model is said to be *deductive* if it 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) at which corrugated cardboard boxes can be unloaded from the back of trailer is to assume that boxes are unloaded at a constant speed and to compute this speed by dividing the number of boxes on the trailer (n) by the total time it takes to unload the trailer (ΔT). This represents a top-down approach.

A model is said to be *inferential* if it 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 determine a 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.

2.2.5 Modeling Advantages and Disadvantages

2.2.5.1 Modeling Advantages

Probably the most significant advantage of using models to assist in the decision process of planning or configuring logistics systems results from the execution of the modeling process itself. Developing a supply chain model requires that the organization clearly articulates its business objectives, its standard or allowable business practices, the structure of the organization, and the business operating constraints

and relations. This information can then be shared or presented to everybody involved with the supply chain 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 supply chain. 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 supply chain 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 supply chain questions becomes much faster, easier, and more accurate than would have been possible without modeling assistance.

2.2.5.2 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 been 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 simulation models have been developed with powerful and graphical digital simulation software and then decisions were based on a single model run.

The models for many supply chain 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 h on a personal computer for a facility with no more than ten functional areas. The same computer

program may then require more than 1 or 2 weeks of computing time to prove that this layout is within close range of the best possible layout.

2.2.6 *Modeling Summary*

2.2.6.1 Model Realism versus Model Solvability

There will always exist 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 transient or 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.

2.2.6.2 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. One

should be especially wary of experts that tout the infallibility of their computer models or the optimality of the generated decisions.

2.2.7 Distance Norms used as Simple Models

One of the most fundamental types of models used in the design, analysis, and operation of supply chains and logistics systems is the distance norm used to model the actual transportation 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.

2.2.7.1 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 (Fig. 2.11).

Three norms are frequently used during supply chain analysis and design in the appropriate situations: Euclidean, rectilinear, and Chebyshev.

$$d_{ij}^E = L_2 = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (2.2)$$

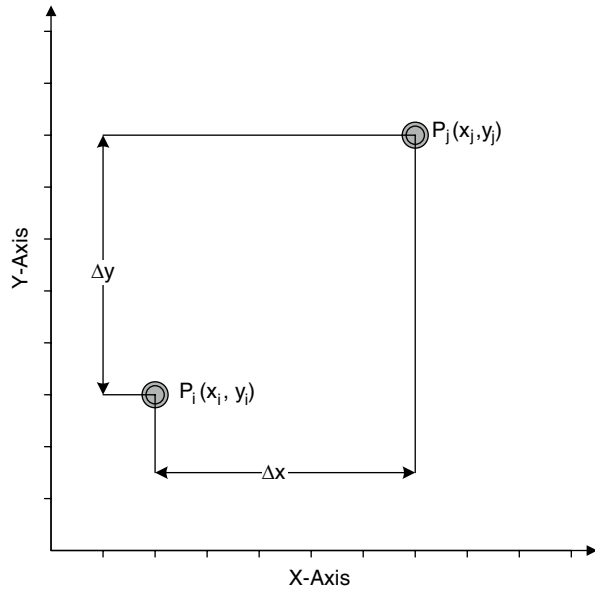
$$d_{ij}^R = L_1 = |x_i - x_j| + |y_i - y_j| \quad (2.3)$$

$$d_{ij}^C = L_\infty = \max\{|x_i - x_j|, |y_i - y_j|\} \quad (2.4)$$

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

$$d_{ij}^n = L_n = \sqrt[n]{|x_i - x_j|^n + |y_i - y_j|^n} \quad (2.5)$$

Fig. 2.11 Distance between two points



where n is equal to 2, 1, and ∞ , respectively, for the Euclidean, rectilinear, and Chebyshev norm.

2.2.7.2 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 two points in a plane. However, the Euclidean distance may not follow a feasible travel path for a particular logistics system due to the internal structure in which case another appropriate distance norm has to be used. In those cases, the Euclidean distance is not the shortest (feasible) travel distance.

2.2.7.3 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 (Fig. 2.12).

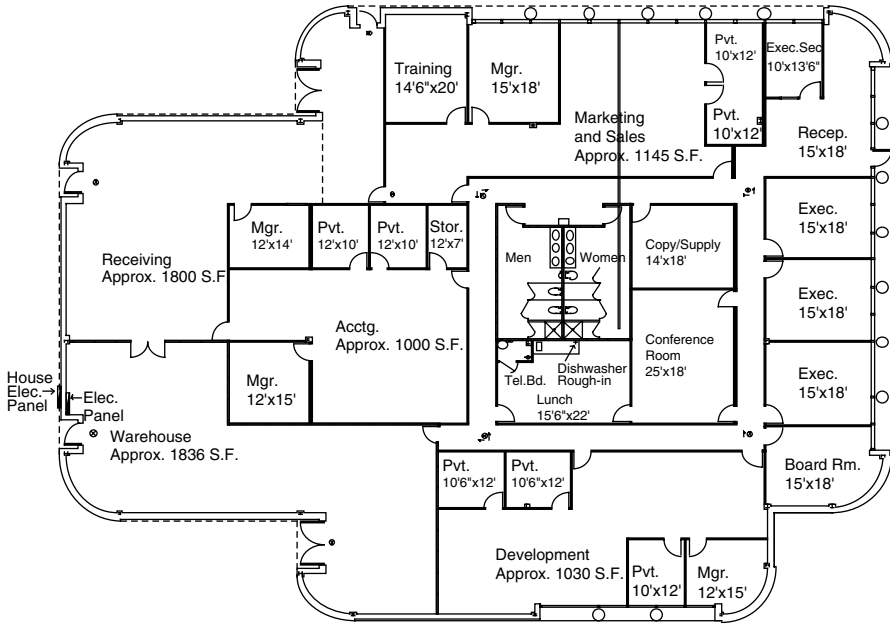


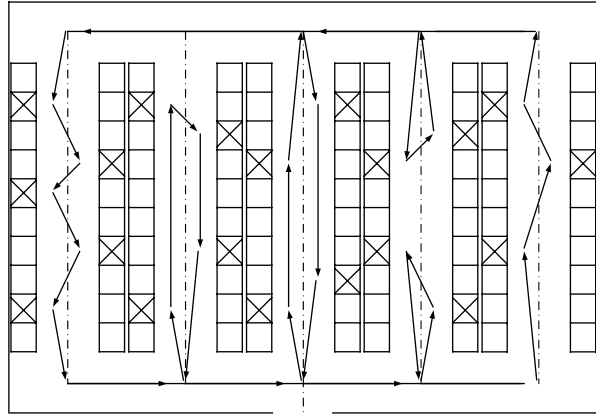
Fig. 2.12 Office layout with rectilinear travel

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 the travel path used by a picker to retrieve cartons from shelves in a warehouse. The picker has to follow the pick aisles or cross aisles, which are arranged perpendicular in a ladder layout (Figs. 2.13, 2.14).



Fig. 2.13 Shelves in a warehouse with ladder layout

Fig. 2.14 Schematic of an order picking tour in a warehouse with ladder layout



2.2.7.4 Chebyshev Norm

Finally, the *Chebyshev* norm is also called the simultaneous travel distance and is used with material handling equipment such as an automated storage/retrieval system or AS/RS and bridge cranes, where travel occurs simultaneously along two axes. In the following bridge example the bridge crane end truck and cross beam move independently from and simultaneously with the trolley and hoist. The end truck moves on a beam mounted on the side wall and supports the cross beam. The trolley moves on the cross beam and contains the hoist (Fig. 2.15).

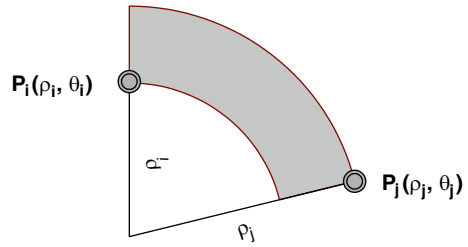
2.2.7.5 Ring-Radial Distance

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 (Fig. 2.16).



Fig. 2.15 Bridge crane example

Fig. 2.16 Ring-radial distance illustration



The ring-radial distance between two points with radius and angular polar coordinates (ρ_i, θ_i) and (ρ_j, θ_j) is given by:

$$d_{ij}^{RR} = \min \{ \rho_i, \rho_j \} \min \{ |\theta_i - \theta_j|, 2\pi - |\theta_i - \theta_j| \} + |\rho_i - \rho_j| \quad (2.6)$$

The angular coordinate θ is expressed in radians. A variant of the ring-radial distance is used in generalized assignment algorithms for the vehicle routing problem to compute the estimated assignment cost of a customer or supplier facility to the sector that represents the vehicle route. The vehicle sector has its tip in the depot. For this variant the radius of the facility is always used, since the vehicle sector has no corresponding radius.

2.2.7.6 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 norm 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 *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 and where the latitude and longitude are expressed in radians:

$$d_{ij}^{GC} = R \cdot \arccos(\cos(lat_i) \cos(lat_j) \cos(lon_i - lon_j) + \sin(lat_i) \sin(lat_j)) \quad (2.7)$$

The earth radius is approximately 6371 km or 3959 miles. By convention the meridian running through Greenwich, England has a longitude that is equal to zero and is

Table 2.1 Coordinate conversion example

		Degrees	Minutes	Seconds	Decimal D.	Radians
<i>Latitude</i>						
Atlanta	GA	33	45	18	33.755	0.589136
Denver	CO	39	44	21	39.739	0.693579
<i>Longitude</i>						
Atlanta	GA	84	23	24	−84.390	−1.472883
Denver	CO	104	59	5	−104.985	−1.832329

Table 2.2 Great-circle distance calculations example

		Arc	Radius	Distance
Atlanta	Denver	0.305515	3957	1209

also called the zero meridian. The latitude of the equator is equal to zero. Finally, the full circumference of a circle corresponds to 360° or 2π radians. Usually, the longitude and latitude coordinates in geographical databases are expressed in degrees, minutes, and seconds. They have to be first converted to decimal degrees and then to radians. The range in radians of the longitude is $[-\pi, \pi]$ and of the latitude is $[-\pi/2, \pi/2]$.

As an example, the distance between the cities of Atlanta, Georgia and Denver, Colorado will be computed. The coordinates of Atlanta are $33^\circ 45' 18''\text{N}$ and $84^\circ 23' 24''\text{W}$ and of Denver are $39^\circ 44' 21''\text{N}$ and $104^\circ 59' 05''\text{W}$. There are 60 min. and 3600 s per degree and the conversion to decimal degrees and radians is shown in the next table. Observe that the decimal degrees and radians are signed to indicate their relative position to the equator and zero meridian (Table 2.1).

The great circle distance calculation between these two cities is shown in Table 2.2, where the radius of the earth and thus also the final distance is expressed in miles.

2.2.7.7 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 2.3).

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 addresses. This route planning can

Table 2.3 Distance adjustment factors in developed countries

	Euclidean	Great circle
Road	1.21	1.17
Rail	1.24	1.20

be obtained from several inexpensive commercial software packages or from 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. Similar software is available for Western Europe. However, obtaining the corresponding reliable and up-to-date information for underdeveloped or developing areas of the world is very difficult. The availability and quality of such information has to be established on a case by case basis (Fig. 2.17).

The over-the-transportation network distance between the cities of Atlanta and Denver is computed based on the above adjustment factor and obtained from a mapping software. For this example Microsoft MapPoint was used. The results are shown in the following table. In this particular case, the difference between the adjusted and actual distance and between the average adjustment factor and the specific and derived adjustment factor for the two cities is 0.6% (Table 2.4).

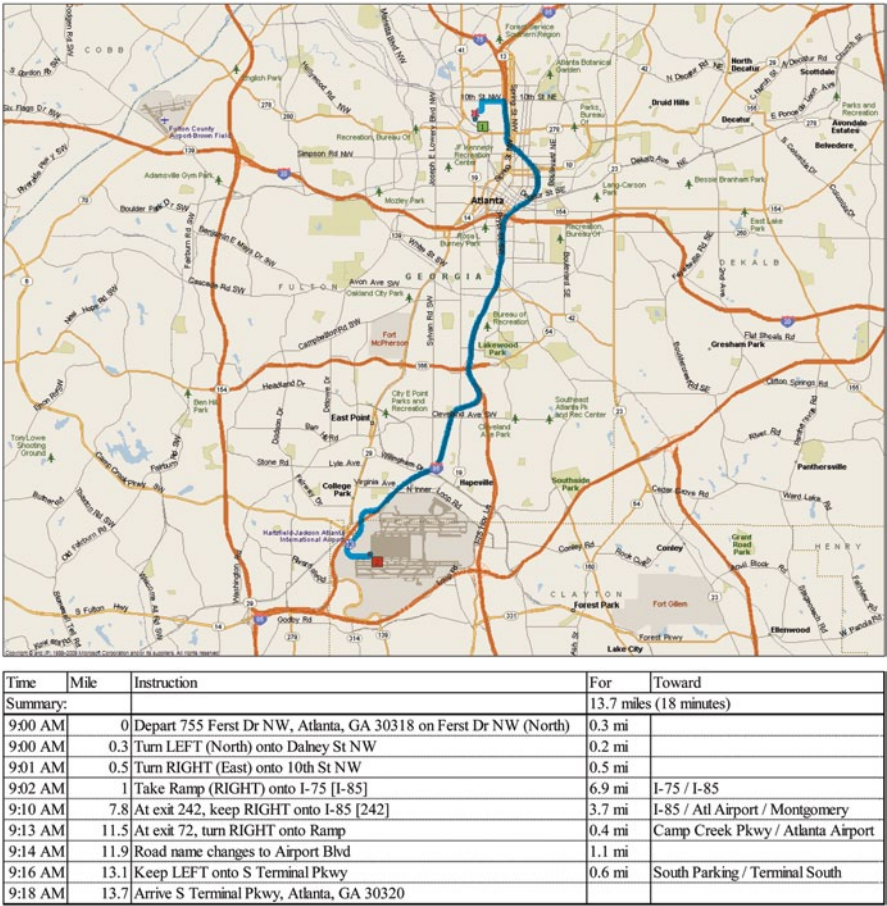


Fig. 2.17 Georgia Tech to Atlanta airport driving instructions

Table 2.4 Network distance calculations example

		Distance				
		Great circle	Factor	Adjusted	MapPoint	Factor
Atlanta	Denver	1209	1.17	1414	1406	1.16

In strategic and high-level logistics planning models, most often distances are approximated based on distance norms multiplied by the appropriate distance adjustment factor. This allows the computation of distances for a large variety of alternatives with minimal computational resources and the approximation accuracy is deemed acceptable. In operational and execution planning models, more accurate information is required and available. Distances are based on over-the-transportation network travel derived from mapping software. In general, the model and data accuracy should be appropriate for the level of logistics planning.

2.3 Algorithms

2.3.1 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.

2.3.2 Algorithm Characteristics

2.3.2.1 Efficient versus Effective

An algorithm is said to be *efficient* when it finds a solution in a 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 the 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

$$a_k n^k + a_{k-1} n^{k-1} + \dots + a_1 n + a_0 \quad (2.8)$$

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 (1976).

It is important to recognize during a supply chain 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 supply chain and 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 supply chain and 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 in a location. 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 candidate distribution centers is 2^N . The computation time required to evaluate all these alternatives grows quickly beyond all reason, as illustrated in Table 2.5. Further information on integer and mixed-integer programming can be found in Nemhauser and Wolsey (1988).

Table 2.5 Algorithm running times

	Problem size			
	10	20	40	80
Run Time				
n	0.001 sec	0.002 sec	0.004 sec	0.008 sec
n^3	0.001 sec	0.008 sec	0.064 sec	0.512 sec
2^n	0.001 sec	1.024 sec	12.43 days	37.43 million millennia

In many instances of supply chain 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.

2.3.2.2 Optimal (Exact) versus Heuristic (Approximate)

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* or *approximate* algorithm. 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 a 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 worst 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.

$$\min z \Rightarrow \left\{ \begin{array}{l} \frac{z_{heuristic}}{z_{optimal}} \leq K \\ \exists p : \frac{z_{p,heuristic}}{z_{p,optimal}} = K \end{array} \right. \quad (2.9)$$

This is 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 supply chain 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 error bound is typically even more difficult to compute than the worst-case error bound.

The *optimality gap* is the worst-case performance bound of a heuristic solution for a particular instance. This gap is often of more 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.

2.3.2.3 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 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.

For example, consider the task of writing a research report before a given deadline. The report contains three sections: introduction, main body, and conclusions. A primal algorithm would create a rough draft of each section and then iteratively refine each section until the quality of the report is satisfactory. A dual approach would first create and refine the introduction until it cannot be improved any further. Then this process is repeated for the main body and finally for the conclusions section. Assuming the quality of the two final reports is the same, the primal approach at any time has a completed reported ready to be handed in.

Many solution algorithms for the design of complex supply chain 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.

2.3.2.4 Construction versus Improvement

A construction algorithm creates a feasible configuration for the supply chain 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 descent* algorithm will choose the first configuration it finds that has a better solution value than the current configuration. A *steepest descent* algorithm will choose the configuration with best solution value among all the configurations it evaluated around the current configuration. 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 descent and steepest descent 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 a 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 or cooling process.

2.3.2.5 Alternative Generating versus Alternative Selecting

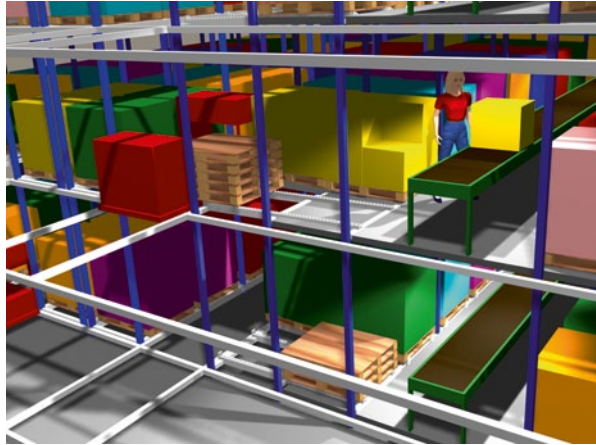
An *alternative-generating* algorithm creates feasible solutions. An *alternative-selecting* algorithm selects the solution of the highest quality from a set of feasible candidate solutions provided to it as input parameters. A prominent example in the design of supply chains of an alternative-generating 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 distribu-

tion 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. Instead of a human expert, sometimes a secondary optimization problem, called the pricing problem, is used to find one or more alternatives that have the potential to improve the overall solution. The specific domain knowledge is imbedded in the pricing problem since it has the function of identifying potentially improving feasible alternatives. 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 supply chain 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

Fig. 2.18 Simulation with animation of a material handling system. (*Illustration courtesy of Retrotech*)



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 supply chain (Fig. 2.18).

Because many supply chains have a natural graphical and geographical 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. A typical screen of a program to design supply chains is shown in the next figure (Fig. 2.19).

2.3.3 Model Hierarchy and Corresponding Solution Technologies

2.3.3.1 Model Hierarchy and Associated Solution Technologies

Organizations typically start with simple models for a particular supply chain 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

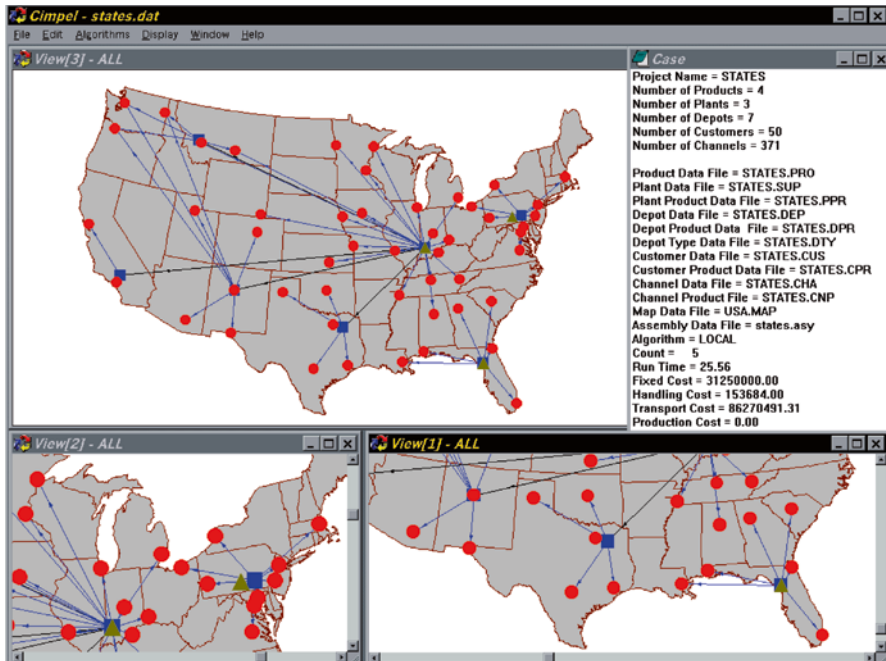


Fig. 2.19 Illustration of the graphical representation of a supply chain

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 deterministic 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.

2.4 Summary and Conclusions

This chapter started off with a review of the definitions and characteristics of the engineering design methodology. Engineering design techniques are necessary to structure the engineering design process so that high-quality supply chains can be created. One of most prominent engineering design techniques is the use of models. The most important characteristics of models were summarized. A supply chain meta-model was presented that provides the structure for various supply chain models. The proper selection of the model, model fidelity and accuracy, and the validation of the model are necessary steps during the design process. Models for transportation distances in supply chain planning and design were used as an illustration of the various levels of models that can and should be used under different circumstances. Solving the model attempts to reach the goal for one or more performance characteristics of the model by determining values for decision variables. Most supply chain design or planning problems are too difficult to be solved by ad-hoc or manual techniques. The classifications and characteristics of solution algorithms were reviewed.

Supply chain planning and design is an especially complex variant of engineering system design. Only the proper application of engineering design methodology and tools can yield high-quality plans and designs in a systematic way in a reasonable amount of time. In order for system engineering methodology to be applicable it is required that all three of data, model, and planning algorithm have been developed for the system in question.

The value of accurate data for modeling-based engineering design was demonstrated repeatedly in this chapter. Most data for supply chain modeling is based on forecasting and this is especially true for tactical and strategic planning models. In the next chapter, forecasting techniques commonly used in supply chain planning and design are reviewed.

2.5 Exercises

True-False Questions

1. A “blue sky” design alternative indicates a design alternative generated without observing any external constraints such budgets or deadlines, (T/F) ____.
2. A model is stochastic if at least one of the input parameters is not known with certainty, (T/F) ____.

3. A significant cost associated with modeling is the cost to collect and validate data, (T/F) _____.
4. An adjustment factor of 1.2 is a reasonable factor (with one significant digit after the decimal point) to approximate the relation between over the road distances in a developed network compared to Euclidean distances, (T/F) _____.
5. An analog model is a replication of the real world system under investigation but generally at a different scale, (T/F) _____.
6. Classic expert system algorithms are often used to assist during the design of strategic logistics systems, (T/F) _____.
7. The process of attaching geographical or location coordinates to alphanumeric address data is known as geocoding, (T/F) _____.
8. The acquisition costs of raw materials belongs to the class of variable costs in a logistics system, (T/F) _____.
9. The fundamental objective of a model is to provide better insight or easier manipulation than can be gained from the real-world system, (T/F) _____.
10. The sole focus of logistics planning is inventory management, (T/F) _____.
11. The United States Census collects a variety of data useful for designing logistics systems in the United States, (T/F) _____.

Emergency Trailers In 2006 in the aftermath of hurricane Katrina, the federal government through its FEMA administration owned and stored many thousands of home trailers. These trailers are to be used as temporary housing in case of disaster. The news story on the trailer storage given at <http://www.newsobserver.com/102/story/411776.html> states that 11000 trailers are being stored nationwide. Develop a decision support model for the number of trailers the federal government should own. Clearly identify all the members of the major components of the model (parameters, decision variables, activities, and performance measures) and how they are computed as well as the objectives and constraints.

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