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This chapter deals with the long-term strategic planning and design of the supply chain. Section 6.1 explains the planning situation and the problem setting. Section 6.2 outlines the formulation of the problem as an optimization model and Sect. 6.3 the use of such models within the strategic planning process. Section 6.4 reviews case reports in the literature and Sect. 6.5 the software modules available in APS.

6.1 The Planning Situation

The design of the supply chain is an essential part of the long-term strategic planning of every manufacturing company. It is based on the decisions about the product program:

- Which products should be offered in which markets and countries in the next years?
- Which products and components should be manufactured at the own production sites?

These decisions are mostly considered superordinated to the design of the supply chain, which then consists in the following decisions:

- Location of the production sites: Are new plants to be installed or existing plants to be shut-down?

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- Allocation of the products and components: Which items should be produced where?
- Facilities within each production site: Is the existing equipment adequate, should it be expanded or shut-down? Should new equipment, for instance a new production line, be installed, for which products or components, with which capacity and technology?

These decisions on the production network imply high investments and have a significant and long-term impact on the company's competitiveness. In the automotive industry, for instance, new products require dedicated body-assembly lines, where the investment and the location are binding for the time to market and the life-cycle of the product, which is about 10 years altogether. Changing the decisions later on is only possible at very high costs. While due to these reasons the design of the production network is of primary importance, the other parts of the whole supply chain must be taken into account as well, i.e. the suppliers and the sales markets, which form the sources and the sinks of the flow through the supply chain. This concerns the selection of materials and suppliers as well as the distribution system between the production sites and the sales markets. However, it is not necessary to consider details of the distribution systems within the various countries or continents, such as the location of warehouses and transshipment points. Instead, a rough estimate of the distribution costs and times between the production sites and the sales markets is sufficient for the supply chain design. The design of production-distribution networks is a subordinate task with a shorter-term impact, as warehouse locations can be changed more easily and are often operated by logistics service providers.

Supply chain design is often considered as the extension of a locational decision problem. However, the locational decisions within the supply chain design are mostly straightforward. There may be a few potential new plant locations, if at all, which could be analyzed one by one and compared. The complexity of the supply chain design consists in the allocation of a large range of products to the production sites and in the decisions on capacities and technology at each site. This includes the critical choice of the appropriate production strategy, between "local for local" and a single world factory, maybe with different results for the different product groups and production phases. Moreover, choices have to be made between highly efficient dedicated production equipment and more flexible multi-purpose equipment as well as decisions on the degree of automation. By contrast, in the design of a distribution network, locational decisions play a major role indeed: There, a variable number of warehouses have to be selected from may be a huge pool of potential locations.

The planning horizon of the supply chain design typically encompasses several years, up to 12 in the automotive industry. It is subdivided into yearly periods so that the decisions on changes in the supply chain structure are assigned to a certain year. Thus, the strategic design starts from the existing supply chain and considers its evolution year by year up to the planning horizon. In contrast, some authors suggest a "green-field" planning over a single period, independent of the existing supply chain, in order to find the ideal configuration for the business in question. However,

the transition there can be expensive and last many years, and if it is reached at all, it is unlikely to still be the ideal. However, the green-field approach may be adequate for the design of a distribution network.

In order to evaluate the structural decisions on the supply chain, it is necessary to consider the impact on the flows of goods, i.e. procurement, production, distribution and sales, which are the drivers of costs and revenue. As there is usually wide scope to determine these flows, operational decisions have to be taken together with the structural decisions. The operational planning level within the strategic supply chain design is similar to the Master Planning (see Chap. 8), but highly aggregated and with yearly periods instead of months or weeks, so that no seasonal fluctuations of activities and stocks within a year are considered.

Which objectives are pursued in the strategic supply chain design? These are primarily financial objectives which are influenced by structural and operational decisions: The structural decisions imply investments for installing new equipment and fixed costs for maintaining it. The operational decisions affect the revenue and the variable costs for all operations along the supply chain. The adequate objective in this context is to maximize the net present value (NPV) of the yearly cash flow which is composed of revenues, investment expenditures, fixed and variable costs. However, a great part of the long-term data required for the supply chain design is highly uncertain. This is true in particular for the demand of future products in various markets, the volume of investments, labor cost, and exchange rates. Therefore, additional objectives play a role, such as to improve the flexibility and the robustness of the supply chain and to reduce risks. These objectives are usually in conflict with the financial objectives.

Two trends in the development of the manufacturing industry have increased both the importance and the complexity of the strategic supply chain design in the last decade, the globalization and the increasing variety of products. The globalization of production sites, suppliers and sales markets has opened new dimensions for decisions about the supply chain, but also increased their impact, for instance because of differences in the national labor costs and taxes, duties and long shipments between continents. These aspects of international trade must be taken into account in the design of the supply chain. The variety of products has increased tremendously in many consumer markets. Up to the 1990s, an automotive manufacturer, for instance, used to launch a new car model every 2 or 3 years, but nowadays, this happens three to five times every year. Therefore, supply network design is no longer an infrequent activity, but some companies have established a regular procedure which has to take structural decisions for new products, such as allocation and technology, at well defined points in time before the start-up (see Schmaußer 2011). The complexity, the frequency and the impact of the supply network design overcharge human planners, if they only use conventional tools such as spread-sheets. The strategic design process for the supply chain requires support by software, which is based on optimization models and algorithms.

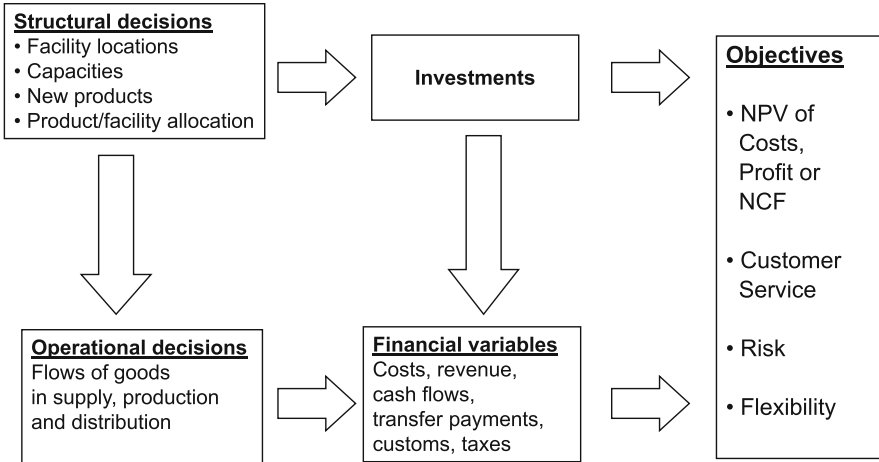


Fig. 6.1 Interdependence between strategic and operational planning levels

6.2 Strategic Network Design Models

6.2.1 Basic Components

As explained in the previous section, network design integrates two planning levels: Strategic structural decisions on the network configuration and mid-term operational decisions on the flows of goods in the network. Figure 6.1 shows the relationships between the planning levels and the objectives.

The financial objectives are affected directly by the strategic decisions on investments as well as by the yearly financial variables resulting from the operations along the supply chain. The latter are also influenced by the investment decisions. For instance, the investment in a new machine can change the variable production cost significantly. Other objectives will be discussed in Sects. 6.2.2 and 6.3.

There is no space here to describe a complete, realistic network design model. In the following, only examples of typical decision variables, constraints and objectives and their relationship will be explained. Note that all names of variables will be written with upper-case initial, data and parameters with lower-case initial. Corresponding to the two planning levels, a network design model contains two major types of decision variables: binary structural variables and continuous flow variables. Both are required to model the main components of a supply chain, i.e. products p , sales markets m , buying markets b , manufacturing and distribution sites s , facilities j , and different countries c . The planning periods $t = 1, \dots, T$ are usually years with a planning horizon T of typically 8–12 years. Structural variables describe either the status of network components or the change of them. Typical status variables are $Location_{s,t}$ indicating whether a site s is “open” in year t or not, and similarly $Machine_{s,j,t}$ indicating, whether a new machine j is available at site s

in year t . $Alloc_{p,s,t}$ may indicate if product p is allocated to a manufacturing site s in year t . The initial status is described by given values of these variables for $t = 0$. Fixed costs may be attached to all status variables. The evolution of the supply chain is driven by change variables such as $Open_{s,t}$ or $Close_{s,t}$ indicating if site s is opened or closed in year t , and $Invest_{s,j,t}$ indicating if an investment takes place in year t for machine j at site s . The capital investments, which constitute a major component of the cash flow, are attached to these variables.

The consistency between different structural variables is ensured by equations such as

$$Location_{s,t} = Location_{s,t-1} + Open_{s,t} - Close_{s,t} \quad \forall s, t \quad (6.1)$$

$$Machine_{s,j,t} = Machine_{s,j,t-1} + Invest_{s,j,t} \quad \forall s, j, t \quad (6.2)$$

which express the impact of the change variables on the status variables, and by logical constraints of the following type: A product can only be allocated to an open site:

$$Alloc_{p,s,t} \leq Location_{s,t} \quad \forall p, s, t \quad (6.3)$$

and, for any product p that requires machine j , this machine must be available:

$$Alloc_{p,s,t} \leq Machine_{s,j,t} \quad \forall s, t \quad (6.4)$$

Often limits are given on the number of products allocated to a site s , say $maxprod_s$:

$$\sum_p Alloc_{p,s,t} \leq maxprod_s \quad \forall s, t \quad (6.5)$$

and on the number of sites, between which a product p may be split, say $maxsplit_p$:

$$\sum_s Alloc_{p,s,t} \leq maxsplit_p \quad \forall p, t \quad (6.6)$$

The flow variables express the quantities per year for the various supply chain processes, e.g. $Production_{p,s,t}$ denotes the quantity of product p manufactured in site s in year t . Further flow variables are shown in Fig. 6.2, which illustrates the flow conservation equations: For every product, site and year the sum of the inflows must equal the sum of the outflows. A particular outflow is the consumption of product p as a material in successor products p' , where $bom_{p,p'}$ is the bill-of-material coefficient, i.e. the consumption of p per unit of p' .

The sales quantities in every market are restricted by upper and lower limits

$$minsales_{p,m,t} \leq \sum_s Sales_{p,s,m,t} \leq maxsales_{p,m,t} \quad \forall p, m, t \quad (6.7)$$

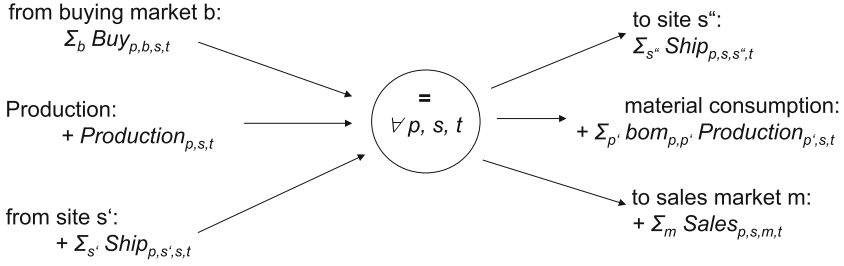


Fig. 6.2 Flow balance equation for product p at site s in year t

or they have to satisfy a given expected demand

$$\sum_s Sales_{p,s,m,t} = demand_{p,m,t} \quad \forall p, m, t \quad (6.8)$$

Flow variables are further restricted by capacity constraints. The capacities may be affected by status variables. An example of a capacity constraint for a single product p at site s is given next.

$$Production_{p,s,t} \leq capacity_s \cdot Alloc_{p,s,t} \quad \forall p, s, t \quad (6.9)$$

where $capacity_s$ is the total capacity of the site s for the product p , which is only available if p is allocated to s . Another example is a machine j that processes a set of products $p \in P$:

$$\sum_{p \in P} prodcoefficient_p \cdot Production_{p,s,t} \leq capacity_{s,j} \cdot Machine_{s,j,t} \quad \forall s, j, t \quad (6.10)$$

$capacity_{s,j}$ is the total of production hours available on machine j at site s per year, provided that this machine has been installed, $prodcoefficient_p$ is the amount of production hours required per unit of product p .

The adequate financial objective for the strategic network design is to maximize the net present value (NPV) of the net cash flow (NCF). In order to avoid a bias of the planning horizon, the residual value of the investments at the planning horizon has to be added. Further objectives will be considered in Sect. 6.2.2. The NCF before tax in year t , NCF_t , is composed of the revenue minus variable costs, fixed costs and investment expenditures in year t . Table 6.1 explains how to model the objective as a linear function of the variables. In the case where the sales have to satisfy a given demand, there is no impact of the decision variables on the revenue. In this case, the objective is reduced to minimize the NPV of costs and capital expenditures. All financial terms have to be converted into one main currency using given estimated

Table 6.1 The net cash flow and the residual value as a linear function of the decision variables in year t

Component	Variables (examples)	Value multiplier
Revenue	Sales	Sales price – Distribution cost per unit
– Variable costs	Flow (Buy, Production, Ship)	Cost per unit
– Fixed costs	Status (Location, Alloc, Machine)	Cost per year
– Capital expenditures	Change (Invest, Open, Close)	Investment expenditure
+ Residual value	Change	Residual value after T-t years

exchange rates. The extension of the model to the NCF after tax will be considered in Sect. 6.2.3.

Thus, the objective is:

maximize NPV NCF

$$= \sum_{t=1}^T NCF_t \cdot (1 + cdf)^{-t} + \left(\sum_{t=1}^T Residualvalue_t \right)^{-T} \quad (6.11)$$

where $Residualvalue_t$ is the value of all investments realized in year t at the planning horizon T .

6.2.2 Dealing with Uncertainty

One inherent characteristic of strategic network planning is that, at the time of planning, a significant portion of the required data for the deterministic model described above cannot be provided with certainty. Product demands, purchase and sales prices, exchange rates etc. are subject to numerous external factors such as the general economic development, market competition and consumer behavior which cannot be known for several years in advance. One way to deal with this inherent uncertainty is to specify not only one set but several sets of data, called scenarios, which reflect different possible future developments, e.g., a best and a worst case scenario in addition to an average case forecast. For each scenario an instance of the deterministic model can be solved and the influence of deviations from the forecast on the structural decisions and objective function value can be observed. However, this approach lacks a coherent definition of how a solution performs on all of the possible future scenarios. Furthermore, it is intuitively clear, that solutions which somehow perform well on all (or many) of the possible scenarios are likely characterized by actively hedging against future uncertainty, e.g., by opening a production site in a foreign currency region to mitigate currency risk or by deploying

more flexible (but also more expensive) or additional machines to mitigate demand risk. As these measures are often associated with additional expenditures and would not provide an advantage if all data were known with certainty, the deterministic model is unlikely or even unable to generate these solutions. In the last years, the development of approaches to account for the inherent uncertainty has been a very active field of research (cf. Klibi et al. 2010, for a recent review). Two main research directions have evolved: the first one seeks to extend the deterministic model in such a way, that its solutions contain certain structures that improve their performance under uncertainty (e.g., a certain way of forming chains of product-plant allocations referred to as the “chaining-concept”, see Kauder and Meyr 2009, and Simchi-Levi and Wei 2012). The second research direction, which will be sketched in the remainder of this section, is based on the methodology of Stochastic Programming (SP) (see Birge and Louveaux 2011, for an introduction to the field).

In this approach we assume, that the uncertainty can be represented by a discrete set of scenarios $\omega \in \Omega$, each with a known probability p_ω . If this is not the case initially, a *scenario generation procedure* (see Sect. 6.3) has to be performed prior to or during the solution of the optimization model. One advantage of the SP approach is that it can be seen as an extension of the deterministic model, which it comprises as a special case if Ω contains just one scenario. In addition to the uncertainty of data, the timing of decisions with respect to this uncertainty has to be modeled. In the strategic network design model the structural decisions have to be determined prior to the first planning period and cannot be altered when a specific scenario realizes. The corresponding decision variables are called *first-stage variables* and are not indexed over the set of scenarios. The operational flow decisions, however, can be adapted to specific data realizations as uncertainty unfolds during the course of the planning periods. Therefore, the flow variables are called *second-stage variables* and are marked as scenario-dependent by a subscript ω . The objective function (6.11) can be represented by a second-stage variable $NPVNCF_\omega$ as the revenue and the variable costs depend on the flow variables and all components may depend on uncertain cost and investment data. Assuming a risk-neutral decision maker, we call a solution consisting of all first-stage and second-stage decision variables *optimal*, if it is feasible for every scenario and if it maximizes the expected net present value of net cash flows:

$$\text{maximize } ENPVNCF = E[NPVNCF] = \sum_{\omega \in \Omega} p_\omega NPVNCF_\omega \quad (6.12)$$

where $E[\cdot]$ denotes the expected value of a random variable. Each constraint which contains second-stage variables or scenario dependent data is replaced by a set of separate constraints for every scenario. For example, in case of demand uncertainty, constraint sets (6.8) and (6.9) are modified in the SP model as follows:

$$\sum_s Sales_{p,s,m,t,\omega} = demand_{p,m,t,\omega} \quad \forall p, m, t, \omega \quad (6.13)$$

$$Production_{p,s,t,\omega} \leq capacity_s \cdot Alloc_{p,s,t} \quad \forall p, s, t, \omega \quad (6.14)$$

Note, that in this version of constraint set (6.14), we assume that the capacity of a site s is known with certainty and hence scenario-independent. Constraint sets of the type (6.1)–(6.6) do not have to be modified as they only contain first-stage variables and no uncertain data. The sketched SP model coincides with a large mixed-integer linear programming model and can be solved with standard MIP solvers. However, as the model also features special structure, specialized solution algorithms can significantly reduce solution times in many cases (see Bihlmaier et al. 2009; Wolf and Koberstein 2013).

As in strategic network design structural decisions last over very long periods of time, the decision maker might want to avoid first-stage decisions that lead to very poor outcomes in some of the scenarios. Likewise, in the case of several alternative optimal solutions, he might want to choose the solution that is associated with the least dispersion of the corresponding distribution of scenario outcomes. One way of incorporating risk-aversion into the model described above is to use a mean-risk objective function of the following type instead of Eq. (6.12):

$$\text{maximize } MEANRISK = ENPVNCF - \lambda \cdot Riskmeasure \quad (6.15)$$

where $\lambda \geq 0$ expresses the decision maker's level of risk-aversion and *Riskmeasure* is a bookkeeping variable representing a suitable risk measure (see Pflug and Römisch 2007 for a discussion of suitable risk measures and Koberstein et al. 2013 for an illustrative application to strategic network design).

6.2.3 Extensions

A few extensions to the basic model of Sect. 6.2.1 are introduced next.

Tax

For the design of a multinational supply chain it is important to consider the NCF after tax, because tax rates and regulations may differ significantly in the concerned countries. The taxable income has to be calculated for every country separately. For this purpose, the transfer payments between the countries and the depreciations resulting from the investments within the country have to be taken into account. The depreciation allowance depends on the tax laws of the country and on the number of years r after the investment has been realized. For example, the depreciation of machine j at site s in year t due to an investment in an earlier year $t - r$ is

$$Depreciation_{s,j,t} = \sum_{r=0}^{t-1} Invest_{s,j,t-r} \cdot allowance_{s,j,r} \quad (6.16)$$

The tax in year t in country c is

$$Tax_{c,t} = taxrate_c \cdot (Revenue_{c,t} - VariableCosts_{c,t} - FixedCosts_{c,t} - Depreciations_{c,t}) \quad (6.17)$$

where each component of the income is obtained by summing up over all activities within country c in year t , including the transfer payments to and from other countries. The transfer payments can be calculated as the cost of the concerned service plus a fixed margin (see Fleischmann et al. 2006; Papageorgiou et al. 2001). If the transfer prices are considered as decision variables, a difficult nonlinear optimization model is obtained even for the operational level with fixed supply chain configuration (see Vidal and Goetschalckx 2001; Wilhelm et al. 2005).

International Aspects

The flows in a global network are subject to various regulations of international trade, in particular duties and local content restrictions. The latter require that a product must contain a mandatory percentage of value added in the country where it is sold. Duties are charged on flows between countries. In the case where component manufacturing and assembly take place in different countries, rules for duty abatement and refunding may apply. The models of Arntzen et al. (1995) and of Wilhelm et al. (2005) incorporate these aspects in particular detail.

Labor Cost

Labor cost is often included in the variable production cost. However, the required working time and work force do not always increase proportionally with the amount of production, but depend on the shift model in use, for instance 1, 2, or 3 shifts on 5, 6 or 7 days a week. To select the appropriate shift model, binary variables $ShiftModel_{w,s,t}$ are introduced indicating which shift model w from a given list $w = 1, \dots, W$ should be used at site s in year t (see Bihlmaier et al. 2009; Bundschuh 2008). The selection must be unique:

$$\sum_w ShiftModel_{w,s,t} = 1 \quad \forall s, t \quad (6.18)$$

and compatible with required working time (the left hand side of (6.9)):

$$\begin{aligned} \sum_{p \in P} prodcoefficient_p \cdot Production_{p,s,t} \\ \leq \sum_w ShiftModel_{w,s,t} \cdot workingtime_{w,s} \quad \forall s, t \end{aligned} \quad (6.19)$$

where $workingtime_{w,s}$ is the available time under shift model w at site s . Then, the labor cost at site s in year t is

$$LaborCost_{s,t} = \sum_w ShiftModel_{w,s,t} \cdot wages_{w,s,t} \quad (6.20)$$

where $wages_{w,s,t}$ is the total of yearly wages at site s in year t under shift model w .

Inventories

The structural decisions may have significant impact on the inventories in the supply network. The way to model this impact depends on the type of inventories:

The *work in process (WIP)* in a production or transportation process is equal to the flow in this process multiplied by the transit or process flow time. Hence, it is a linear function of the flow variable. WIP is considered by Arntzen et al. (1995) and Vidal and Goetschalckx (2001).

Cycle stock is caused by a process running in intermittent batches and is one half of the average batch size both at the entry and at the exit of the process. It is a linear function of the flows only if the number of batches per period is fixed.

Seasonal stock is not contained in a strategic network design model with yearly periods. For smaller periods, it can be registered simply as end of period stock like in a Master Planning model (see Chap. 8).

Safety stock is influenced by the structural decisions via the flow times and the number of stock points in the network. This relationship is nonlinear and depends on many other factors such as the desired service level and the inventory policy. It should rather be considered outside the network design model in a separate evaluation step for any solution under consideration. Martel (2005) explicitly includes safety and cycle stocks in his model.

6.3 Implementation

Network design models as described before yield an optimal solution for the given data and objective. However, in the strategic supply chain planning process, a single solution is of little value and may even give a false sense of efficiency. Defining or determining the “optimal supply chain configuration” is impossible, because a supply chain configuration has to satisfy multiple objectives, and several of those objectives cannot even be quantified.

Besides the well-defined financial objective NPVNCF, other objectives are also important (see Fig. 6.1): Customer service depends on the strategic global location decisions. For instance, the establishment of a new production site or distribution center will tend to improve the customer service in the respective country. But the increase in customer service and its impact are difficult to quantify. The risk of high-impact, low-probability catastrophic events such as natural disasters and the break-down of whole sites or transportation links of the supply network can hardly be represented in the SP approach discussed above. Furthermore, some future scenarios might just be unthinkable or completely unknown to the decision maker such as drastic technological, social or political changes. One way of considering these challenges in the planning process is to deploy qualitative approaches such as the Delphi method, brainstorming and discussion rounds. Another approach is to try to define and measure the supply chain’s ability to react and adapt to unforeseen events. In recent years, several measures and concepts have been proposed for this purpose under terms as flexibility, agility, reliability, robustness, responsiveness and resilience (see the review of Klibi et al. 2010). Finally, criteria such as the political

stability of a country or the existence of an established and fair legal system are very important, but not quantifiable. In order to consider unquantifiable as well as quantitative objectives and constraints simultaneously, we sketch an iterative strategic planning process in Fig. 6.3 joining ideas of Ratliff and Nulty (1997) and Di Domenica et al. (2007):

Generate scenarios: This step uses a model of uncertainty which expresses the behavior of the uncertain data in the view of the decision maker. It may make use of all kinds of econometric, statistical and stochastic techniques, such as multivariate continuous distribution functions, stochastic processes and time series. Historical data, if available, can be used to estimate and calibrate the parameters of this model. Then, a discrete set of scenarios and a vector of related probabilities can be derived which is manageable in the subsequent steps (i.e., in an SP model) and approximates the model of uncertainty as closely as possible. Several methods have been devised for this purpose (see Di Domenica et al. 2007).

Generate alternatives: Solving the (stochastic) optimization problem defined above for different objectives and using a variety of scenario sets as well as single scenarios provides various alternative supply chain configurations. Objectives that are not used in the current optimization can be considered in form of constraints. Additional alternatives can be generated by intuition and managerial insight.

Evaluate alternatives: For any design alternative, the operations can be optimized using a more detailed operational model under various scenarios. The main objective on this level is cost or profit, since the network configuration is given. A more detailed evaluation can be obtained by simulating the operations. This allows the incorporation of additional operational uncertainties, e.g. the short-term variation of the demand or of the availability of a machine, resulting in the more accurate computation of performance measures such as service levels or flow times.

Benchmarking: The key performance indicators obtained in the evaluation step are compared to the best-practice standards of the respective industry.

Select alternatives: Finally, the performance measures computed in the previous steps and the consideration of additional non-quantifiable objectives can be used to eliminate inefficient and undesirable configurations. This can be done based on internal discussions by the project team and by presentations to the final decision makers, such as the board of directors. During this process, suggestions for the investigation of additional scenarios and objectives or modified alternatives may arise. This whole process may go through several iterations.

Many authors report that large numbers of alternatives have to be investigated in a single network design project. Arntzen et al. (1995) report hundreds of alternatives, and the model of Ulstein et al. (2006) was solved several times even in strategic-management meetings.

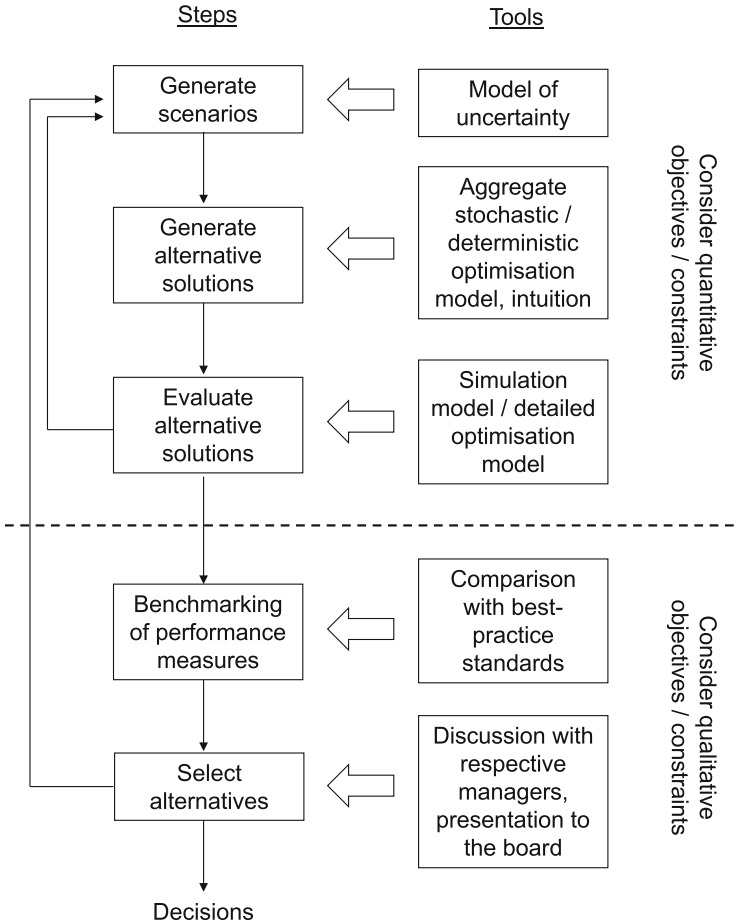


Fig. 6.3 Steps of the strategic network design

6.4 Applications

Strategic network design has been the subject of a rich body of literature in the last decade. Melo et al. (2009) give a comprehensive survey with the focus on locational decisions. It covers both the design of production networks and the more detailed design of production-distribution networks. While the models considered in this review are mainly deterministic (80%), the review of Klibi et al. (2010) is focused on dealing with various types of uncertainties. In the following, recent applications in industry are reviewed which are reported in literature and show the importance of optimization-based supply chain design in various industrial sectors.

6.4.1 Computer Hardware

One of the first studies on the redesign of a huge global supply chain using an optimization model was presented by Arntzen et al. (1995). Addressing decisions on the closing of factories, allocation of products, technologies and capacities, it had a severe impact on the thinning of DEC's supply chain. Wilhelm et al. (2005) consider an international assembly system in the U.S., Mexico and third countries under NAFTA regulations. Laval et al. (2005) determine the European network of postponement locations for the distribution of HP printers.

6.4.2 Automotive Industry

Fleischmann et al. (2006) present a model for the long-term evolution of BMW's global supply chain, which considers, at every location, the capacities and investments in three departments: body assembly, paint shop and final assembly. Bundschuh (2008) develops a similar model for BMW's engine and chassis factories. It permits the flexible use of several design levels, from the global network of sites for component manufacturing and for final assembly up to the detailed configuration of the production equipment and technology choice. The model of Bihlmaier et al. (2009) which was developed for Daimler's global supply chain considers demand uncertainty using stochastic programming. Schmaußer (2011) and Kuhn and Schmaußer (2012) report on a model which is used regularly at AUDI for the allocation of new products and decisions on product standardization and technology.

6.4.3 Chemical Industry

Ulstein et al. (2006) developed a model for Elkem's Silicon Division which addresses decisions on closing existing plants, acquisition of new plants, product allocation and investments in production equipment. A particular feature, due to the energy-intensive processes, are additional flow variables for buying and selling electricity. The results of the model had an impact on reopening a closed furnace and the conversion of existing equipment into the world's largest silicon furnace.

6.4.4 Pharmaceutical Industry

Papageorgiou et al. (2001) present a model for the global production network for active ingredients, the first stage of pharmaceutical production. In addition to the usual supply chain design decisions, this model addresses the selection of future products from a pool of potential products and the time when they should be launched. Sousa et al. (2011) consider the complete pharmaceutical supply chain with primary and secondary production.

6.4.5 Forest Industry

Martel (2005) presents a more detailed model for designing global production-distribution networks with a 1-year horizon, divided into “seasons”. Besides seasonal inventory it also considers cycle and safety stocks as concave functions of the flow through the warehouse. An interesting feature is the choice of marketing strategies which have impact on the demands. It has been used in the paper and forest industry. Vila et al. (2009) extended this type of model to the case of uncertain demands.

6.5 Strategic Network Design Modules in APS Systems

As explained in Sect. 6.1 and in Fig. 6.1, SND contains major elements of the Master Planning level in an aggregated form. Therefore, an SND module in an APS also can be used for Master Planning (see Chap. 7) and is in some APS identical with the Master Planning module. It always provides a modeling feature for a multi-commodity multi-period flow network, as explained in Sect. 6.2. In addition, an SND module permits the modeling of the strategic decisions on locations, capacities and investments by means of binary variables.

SND modules contain an LP solver, which is able to find the optimal flows in a given supply chain for a given objective, even for large networks and a large number of products and materials. However, the strategic decisions require a MIP solver, which is also available in the SND module, but may require an unacceptably long computation time for optimizing these decisions. Therefore, SND modules also provide various heuristics which are usually proprietary and not published.

In contrast to other modules, the SND module is characterized by a relatively low data integration within the APS and with the ERP system. Therefore, it is often used as a stand-alone system. Current data of the stocks and of the availability of the machines are not required for SND. Past demand data from the ERP data warehouse can be useful, but they need to be manipulated for generating demand scenarios for a long-term planning horizon. Technical data of the machines, like processing times and flow times, can be taken from the ERP data as well. But a major part of the data required for SND, such as data on new products, new markets and new machines, is not available in the ERP system. The same is true for data on investments, such as investment expenditures, depreciation and investment limitations.

The modeling tools that are available in the SND module differ in the various APS. Some APS contain a modeling language for general LP and MIP models, which allows the formulation of various types of models as discussed in Sect. 6.2. Other APS provide preformulated components of an SNP model, which describe typical production, warehousing and transportation processes. They allow the rapid assembly of a complex supply chain model, even using click-and-drag to construct a graphical representation on the screen and without LP/MIP knowledge. Of course, this entails a loss of flexibility in the models that can be formulated. But the resulting models are easy to understand and can be explained quickly to the decision makers.

An SND module provides the following main functions within the framework of the strategic planning process explained in Sect. 6.3 and Fig. 6.3:

- Generating scenarios
- Generating alternatives
- Evaluating alternatives
- Administrating alternatives and scenarios
- Reporting, visualizing and comparing results.

The last two functions are particularly important in the iterative strategic planning process which involves large series of design alternatives and scenarios. These functions, the modeling aids and special algorithms for network design make up the essential advantages over a general LP/MIP software system. Section 16.1 gives an overview on the APS that contain an SND module as well as some providers of specific stand-alone tools.

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