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Robust capacitated facility location model for acquisitions under uncertainty

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ABSTRACT

We study a new robust formulation for strategic location and capacity planning considering potential company acquisitions under uncertainty. Long-term logistics network planning is among the most difficult decisions for supply-chain managers. While costs, demands, etc. may be known or estimated well for the short-term, their future development is uncertain and difficult to predict.

A new model formulation for the robust capacitated facility location problem is presented to cope with uncertainty in planning. Minimizing the expectation of the relative regrets across scenarios over multiple periods is the objective. It is achieved by dynamically assigning multi-level production allocations, locations and capacity adjustments for uncertain parameter development over time. Considering acquisitions for profit maximization and its supply-chain impact is new as well as the simultaneous decision of capacity adjustment and facility location over time. The solution of the novel robust formulation provides a single setup where good results can be achieved for any realized scenario. Hence, the solution may not be optimal for one particular scenario but may be good, i.e. the highest expected profit to gain, for any highly probable future realization. We show that robust mixed-integer linear programming model achieves superior results to the deterministic configurations in exhaustive computational tests. This dynamic robust formulation allows the supply-chain to favorably adapt to acquisitions and uncertain developments of revenue, demand and costs and hence reduces the potential negative impacts of uncertainty on supply-chain operations.

1. Introduction

At a time of economic uncertainty and volatility, companies are more and more looking for new and preferably more stable sources of growth. Leading companies, like Daimler AG identified emerging markets as sources for growth: the world's largest truck maker is producing trucks especially for India and other emerging markets (BusinessWeek, 2010).

In order to serve rapidly emerging markets and exploit the growth potential, companies have to define market entry strategies, which consider among others, specific market factors and uncertainty about future economical developments, e.g. demand or cost volatility. The chosen market entry strategy potentially impacts the companies' existing supply chain and thus the long-term logistics network planning which is among the most difficult decisions that supply chain managers have to face. The new supply chain might need integration into the existing supply chain. The overall network needs to be tested if the number and location of the sites, their capacities and the distributed quantities are still cost efficient.

The question of the location and size of new facilities, as well as which customers to serve from where, are inherently strategic and long-term in nature. This stems from the fact that the construction of a new plant requires an immense capital investment and once such a decision has been implemented it is extremely difficult to reverse (Aghezzaf, 2005).

Furthermore, the impact of such a decision spans over a long time horizon, as facilities usually function for years. While costs, demands, operating conditions, etc. may be known or at least estimated quite well for the short-term, their future development is highly uncertain and difficult to predict. Therefore, a solution that may be optimal for a given forecast of future demand can turn out to be far from optimal if this forecast does not materialize.

Under such conditions a decision maker would usually try to defer such a decision until the realization of the future development becomes known. As this is not possible in many situations, the decision about a new location has to be taken now and the

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company must then react to the future development. Therefore a supply chain manager usually searches for a solution that is robust to uncertain future realizations. This means, that the solution may not be optimal for one particular scenario of the future development but may turn out to be good, i.e. the least expensive to adapt, for any highly probable realization of the future.

In this paper we study a dynamic and robust capacitated facility location problem for the complex decision of entering a new market. Our robust approach is able to deal with different demand, revenue and cost development scenarios and provides solutions which allow a corporate decision maker to evaluate the costs of uncertain developments. Furthermore, by proposing a multi-period model in which location, capacity and customer-facility assignment decisions can be adjusted over time, we enable a decision maker to adjust his decisions from period to period and react according to the realized situations.

Facility location problems have been studied extensively in the literature. Comprehensive surveys are given by Aikens (1985), Brandreau and Chiu (1989), Owen and Daskin (1998) and Melo, Nickel, and da (1997). A generic framework for dynamic location problems is provided by Melo, Nickel, and da (2004).

Our model enables the assessment and planning of different market entry strategies. This is to our knowledge mainly untapped from the Operations Research perspective. Different studies, (Hamacher, Ruzika, & Tanatmis, 2006), apply the notion of acquisition in the context of project acquisition prioritization or focus on the acquisition of technology (Verter, 2002). Foreign direct investments, e.g. acquisitions are mostly analyzed detached from capacity and facility location problems (Müller, 2007). Neither the analyzed studies on acquisition nor the literature on facility location presented above, cope with the decision and impact of acquiring sites (facilities and depots) as a supply chain design feature in the way outlined in this paper.

To account for the uncertainty of a long-term planning horizon, we implemented a new robust mathematical programming model formulation. By this, an optimal solution for a set of scenarios is concluded. In recent years, there has been a growing interest in robust solutions for many decision problems, as important parameters of these problems depend heavily on the changing realization of the future. Aghezzaf (2005) points out that due to the uncertainty in predicting unstable market factors it is not viable and unrealistic to take capacity and location decisions based on only deterministic solutions. Poojari, Lucas, and Mitra (2008) identify movements in market factors such as technology, foreign exchange rate, taxation schemes, and resource availability as specific sources of uncertainty. Further, interest-rates, inflation, demand and price volatility are mentioned as important drivers for planning decisions and are also subject to uncertainty. Even uncertain political, social, environmental and ethical developments can potentially impact network planning decisions. The variety of these uncertainty sources shows how different the supply chain might be affected by uncertainty. The impact of uncertain developments might vary in terms of duration, criticality/intensity and costs. Some of the mentioned uncertainties with critical impact on operation are more likely to have a very low probability to occur and are mostly neglected by practitioners. An estimation of such events or even an anticipation might be very difficult and hardly possible to be included in the planning decision. Therefore, planning models are investigated which take into account the uncertain variations of future realizations. By taking such an approach, a robust model can be developed to provide solutions that are nearly optimal for many realizations of the future (Lucas, MirHassani, Mitra, & Poojari, 2001). An overview of the different approaches for dealing with uncertainty in planning is given by Sahinidis (2004). Ben-Tal and Nemirovski (1998) developed an approach for robust convex optimization that solves the robust counterpart of the uncertain problem. Their approach is quite pessimistic, as the constraints of the problem must hold for all possible values of the data. A less conservative approach is presented by Bertsimas and Sim (2004), in which they consider the trade-off between the probability of a constraint violation and the effect this has on the objective function. A robustness approach to planning in which uncertainty is modeled via a Monte Carlo simulation and the decisions are taken based on the simulation results is investigated by Landeghem and Vanmaele (2002). Marianov and Fresard (2005) introduce a robust model to provide good results for any scenario obtained from a sample of very different but equally likely scenarios. According to Poojari et al. (2008) scenario-based planning plays an important role to gain insights in robustness, risks and flexibility of planning decisions. Escudero, Kamesam, King, and Wets (1993) suggest using scenarios to represent uncertain parameters in stochastic optimization models. This approach is also the foundation of the concept of robust optimization as presented by Mulvey, Vanderbei, and Zenios (1995). In their paper they show the difference to the concept of stochastic optimization and the benefits that robust optimization offers in comparison to it. The main benefits are that the stability of the solution is taken into account by the control variables and by applying error terms and the penalty function constraints can be relaxed to produce good solutions even if no feasible solution across all scenarios exist.

We obtain robust solutions by applying the concept of robust optimization as presented by Mulvey et al. (1995) on our capacitated facility location problem. Over the last years robust optimization has evolved significantly, especially the works of Ben-Tal and Nemirovski (1998) and Bertsimas (lately Bertsimas & Sim, 2004) contributed to this evolution. These latest approaches model the uncertainty parameters as uncertainty sets; if only limited information is available this is also referred as "data-driven". Bertsimas and Sim (2004) provide a prescriptive methodology for constructing uncertainty sets. Despite the current discussions, the concept according to Mulvey et al. (1995) is applied in this contribution. We believe that by providing scenario probabilities assigned by practitioners as well as selected scenarios that do not necessarily adhere to distributions or structure of the uncertainty set, a higher adoption in practice might be achieved.

When deciding on a market entry strategy we consider future demands, achievable unit prices and cost stability as the most relevant uncertainty parameters and hence, the bases for our robust model.

As further distinction to existing literature, we augmented the common cost minimization objectives by also considering the revenue potentials and thus implementing a profit maximization objective. The model analyses whether it is more attractive to either ship products from the domestic sites to a distant market, to build own sites or to acquire one or more companies in that market.

The objective of cost minimization can be found in most supply chain network design models (Shen, 2006). Usually it is required that every customer's demand is fully satisfied and thus, only the associated costs are studied. However, if a company seeks to maximize its profit, it might not always be optimal to satisfy all potential demand, especially if the associated costs exceed the additional revenues. A literature review by Current (1990) shows that most objective maximization models study the maximization of demand and only a limited amount of studies was dedicated to profit maximization objectives (see also Hansen, Labbe, Peeters, & Thisse (1987) as well as Hansen, Peeters, & Thisse (1995)). The demand maximization is often derived from maximization of market share or customer utilization (see Aboolian, Berman, & Krass (2007), Drezner, Drezner, & Salhi (2002) and Fernandez, Pelegrin, Plastria, & Toth (2007)). Profit maximization contributions for supply chains (Goetschalckx, Vidal, & Dogan, 2002; Alonso-ayuso, Escudero, Garin, Ortuno, & Perez, 2003; Zhang, 2001; Guillen, Mele, Bagajewicz, Espuna, & Puigjaner, 2005 or Shen, 2006) are not focusing on capacitated facility location problems in the way herein presented.

The remainder of the paper is organized in four sections: first we present a Deterministic Capacitated Facility Location Problem for Market Entry when the demand is known with certainty. We then extend the deterministic model to a robust model formulation and present a numerical example to assess the different model performances. Finally, we discuss the results and close with our conclusions.

2. Dynamic logistics network model for market entry

Vidal and Goetschalckx (1997) conclude after an extensive review of supply chain models that these lack in detail and more research is needed to fill this gap. In order to be useful in practice, models need to be extended or developed with the goal of complying with the complexity of industrial cases (Thanh, Bostel, & Péton, 2008) and thus provide a higher level of detail. A sound model that incorporates important factors, and thus provides enough details, can be both meaningful and useful to practitioners (Bhutta, Huq, Frazier, & Mohamed, 2003). They can use it to assess and study probable scenarios and conclude decisions based on these results. We contribute to filling the identified gap by presenting the comprehensive Deterministic Capacitated Facility Location Problem for Market Entry (CFLP-ME). Relevant cost factors of supply chain planning like, amongst others, costs for maintenance of sites but also for distribution of goods are considered. Our general model structure is related to the work of Aghezzaf (2005). The flow of a single product type between a set of geographically dispersed facilities, depots and customers is assumed. Facilities distribute products to dispersed customers via storage depots. Each facility can deliver products directly to all depots. Depots dispatch the products to the customers. If no recipient is assigned, the delivering site is supposed to shut down.

We enhance Aghezzaf's model (Aghezzaf, 2005) such that we maximize potential profits, we consider dynamic supply chain changes through acquisitions and have different depot types. Further, we allow both facilities and depots to be opened and closed during the planning horizon. Both sites are also capable of adjusting capacities dynamically over time. Economical uncertainty is accounted for by three different parameters (demand, revenues per unit, cost volatility) rather than one. Different developments of these parameters are the foundation for the scenarios under consideration. These will be discussed in more detail in the application section. In the following we will refer to the acquiring company seeking to expand its operations by acquisitions as the "domestic" company and its domestic customers in the domestic market. The customers, demands and sites in the market of the potentially acquired company will be referred to as "foreign". This does not limit any company from being international or having other global operations. It is merely meant to allow a better distinction. The satisfaction of the foreign demand depends on the expected profit in accordance to the market entry strategy. In such we consider the following options to participate in the foreign market (see also Fig. 1):

- Delivery from domestic depots;
- Opening of own facilities and depots in the new market;
- Acquisition of one or more specific acquisition targets.

We observe that there are other possibilities for market entry such as joint ventures or contracting a third party in the target market to distribute the products. However, these strategies would not require significant adjustments to the own supply chain and are thus not further considered. Acquisition targets are companies, each comprising a fixed amount of facilities, depots, potential market share and potential revenues per unit sold. By acquiring a company, all associated facilities and depots can be used for production and distribution in the foreign market. Domestic facilities are equipped with the same starting and maximum operating capacity. In contrast, depots have different starting and maximum capacities depending on the designated depot size, e.g. big, medium or small. The capacity indicates how many products can be handled by a site (facility or respectively by depot) in a specific period. The capacity can be adjusted for both types of sites depending on current demand up to the maximum capacity. After acquiring a target, the capacities of all associated sites will be optimized to match demand and increase profit. The size (big/medium/small) and thus the maximum capacity of acquired depots are assumed to be fixed.

2.1. Deterministic Capacitated Facility Location Problem for Market Entry (CFLP-ME) and notation

The following mixed-integer optimization model provides a deterministic formulation for the CFLPME that maximizes profits by deciding if and how to enter a new market. Demands, revenues per unit and cost stability are known with certainty. Profits are realized by weighting costs of production (incl. opening/closing of facilities, capacity adjustments and handling costs), transportation and acquisition against expected revenues and budget constraints.

With this set of tools, decision-makers are supported in assessing the attractiveness of specific market entries in order to maximize potential profits and the impact on the existing domestic supply chain. In this section, we only highlight specific components of our formulation explicitly to allow a focused discussion on the relevant and new aspects. Indices, parameters or variables concerning only components of the acquisition objects are highlighted with *. Commonly used and required notations and constraints are provided in the appendix. We introduce standard indices for sets like T for the planning horizon, I for facilities, J for

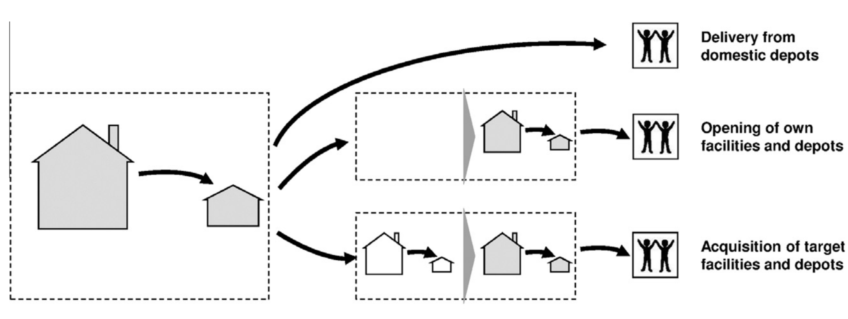

Fig. 1. Market entry strategies for a foreign market.

depots and L for customers. B is introduced as the set of the potential acquisition targets. The set $A \setminus B$ contains the domestic company (a') and its demand as well as the "available" market to be served by all companies in B and the domestic company.

2.1.1. Parameters of the model

The resource utilization of a product at either facility or depot is formulated by the parameter a with the specific indices. Costs for shipping the products from facilities to depots as well as from depots to customers are indicated by c accompanied by specifying indices. e is used for costs associated to capacity changes per unit. The costs to open or close a specific site are labeled by the parameter f, costs to change the size of a domestic depot are named cmc. Operation (g) and maintenance (h) costs are also implemented in this model. These costs are considered in the objective function and simultaneously apply to the costs related to operations in an entered market. Sites are further defined by initial capacities, available at the beginning of the first period. Minimum and maximum capacities define the boundary in which sites must operate if open. Further parameters are:

d_{lta}	potential product demand from customer l of company a in period t (units)
k_{at}	revenue per unit sold of company a in period t (Euro/unit)
κ_t	budget utilization to acquire company a (%)
φ_t	cost volatility factor in period t applied on costs for acquired companies (%)
$y^{f^*}_{i^*a} \in \{0,1\}$	facility i^* of acquisition target a open {= 1} (no dimension)
$y^{d^*}_{j^*a} \in \{0,1\}$	depot j^* of acquisition target a open {= 1} (no dimension)

The cost volatility factor φ_t is modeled as a random parameter and reflects possible uncertainties regarding the cost stability in the target market. These can stem from exchange rate fluctuations, inflation, rising wages or fluctuating raw material prices. All costs related to market entry are also subject to the cost volatility factor φ_t. The costs to acquire a company with related sites are represented by the parameter κ_a. Acquiring a company is mostly associated with large investments. Since only a certain yearly budget is available for investments, we implemented a company's acquisition as a fraction of the available budget (b), which is blocked every period and relative to the size of the acquired company. Further, it is assumed that every company sells products at individual prices since product quality and features may differ between products of different companies. The price (revenue per unit) at which a company sells a product is reflected by the parameter k_{at}. The decision variables consist of mainly four categories. Indicated by the variable x are the decisions on the quantity of products being shipped to a specific site or customer. The variables v and w define the proposed capacity adjustments and resulting capacities of a site per period. The decisions on changing the status of sites are mapped by the variable y for building or closing a domestic site (including the depot size) and by the o for acquiring companies. These changes are tracked with the variables *new* (if domestic depot is built), z (for facility shut downs or openings), *mch* (for depot size changes) and p (for acquisitions).

The objective of the model is to maximize a company's profit considering various acquisition options. Thus, the objective function over the total planning horizon consists of the difference between potential revenues and associated costs:

+ revenues from domestic market (rev_dom): $\sum_{j\in J}\sum_{l\in L}\sum_{t\in T}\sum_{a\in A} k_{at} x^{dc}_{jlta}$
+ revenues from new market, if entered (rev_new): $\sum_{j^*\in J^*}\sum_{l\in L}\sum_{t\in T}\sum_{a\in A} k_{at} x^{d^*c}_{j^*lta}$

Reduced by:

– transportation costs to customers at domestic and new market (cos_trans):

$$\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\sum_{a\in A} c^{fd}_{ij} x^{fd}_{ijta} + \sum_{j\in J}\sum_{l\in L}\sum_{t\in T}\sum_{a\in A} c^{dc}_{jl} x^{dc}_{jlta} + \sum_{i^*\in I^*}\sum_{j^*\in J^*}\sum_{t\in T}\sum_{a\in A} c^{f^*d^*}_{i^*j^*} \varphi_t x^{f^*d^*}_{i^*j^*ta} + \sum_{j^*\in J^*}\sum_{l\in L}\sum_{t\in T}\sum_{a\in A} c^{d^*c}_{j^*l} \varphi_t x^{d^*c}_{j^*lta}$$

– maintenance costs depending on installed capacity of each site (cos_main):

$$\sum_{i\in I}\sum_{t\in T} h^f_i w^f_{it} + \sum_{j\in J}\sum_{t\in T} h^d_j w^d_{jt} + \sum_{i^*\in I^*}\sum_{t\in T}\sum_{a\in A} h^{f^*}_{i^*} \varphi_t w^{f^*}_{i^*ta} + \sum_{j^*\in J^*}\sum_{t\in T}\sum_{a\in A} h^{d^*}_{j^*} \varphi_t w^{d^*}_{j^*ta}$$

– operation costs depending on produced goods (cos_op):

$$\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\sum_{a\in A} g^f_i x^{fd}_{ijta} + \sum_{j\in J}\sum_{l\in L}\sum_{t\in T}\sum_{a\in A} g^d_j x^{dc}_{jlta} + \sum_{i^*\in I^*}\sum_{j^*\in J^*}\sum_{t\in T}\sum_{a\in A} g^{f^*}_{i^*} \varphi_t x^{f^*d^*}_{i^*j^*ta} + \sum_{j^*\in J^*}\sum_{l\in L}\sum_{t\in T}\sum_{a\in A} g^{d^*}_{j^*} \varphi_t x^{d^*c}_{j^*lta}$$

– capacity adjustment costs of each site (cos_cap):

$$\sum_{i\in I}\sum_{t\in T} e^f_i v^f_{it} + \sum_{j\in J}\sum_{t\in T} e^d_j v^d_{jt} + \sum_{i^*\in I^*}\sum_{t\in T}\sum_{a\in A} e^{f^*}_{i^*} \varphi_t v^{f^*}_{i^*ta} + \sum_{j^*\in J^*}\sum_{t\in T}\sum_{a\in A} e^{d^*}_{j^*} \varphi_t v^{d^*}_{j^*ta}$$

– status change costs, e.g. opening/closing/size changes (cos_stat):

$$\sum_{i\in I}\sum_{t\in T} f^f_i z^f_{it} + \sum_{j\in J}\sum_{t\in T}\sum_{m\in M} f^d_{jm} new_{jtm} + \sum_{j\in J}\sum_{t\in T}\sum_{m\in M} cmc_m mch_{jtm}$$

– costs for acquiring a company (cos_acq):

$$\sum_{a\in A}\sum_{t\in T} b_t \kappa_a \varphi_t p_{ta}$$

The objective function is formulated in the following equation:

$$Max \begin{pmatrix} rev\_dom + rev\_new \\ -\cos\_trans - \cos\_main - \cos\_op \\ -\cos\_cap - \cos\_stat - \cos\_acq \end{pmatrix} \tag{1}$$

Subject to (selection)

$$\sum_{j\in J} x^{dc}_{jlta'} + \sum_{j^*\in J^*, b\in B} x^{d^*c}_{j^*ltb} \leqslant \sum_{a\in A} d_{lta} o_{ta} \quad \forall l \in L, t \in T \tag{2}$$

$$\sum_{j\in J} x^{dc}_{jlta'} \geqslant d_{lta'} \quad \forall l \in L, t \in T \tag{3}$$

$$\sum_{j\in J} x^{dc}_{jlta'} \leqslant \sum_{a\in A\setminus B} d_{lta} \quad \forall l \in L, t \in T \tag{4}$$

$$\sum_{j^*\in J^*} x^{d^*c}_{j^*lta} \geqslant d_{lta} o_{ta} \quad \forall l \in L, t \in T, a \in B \tag{5}$$

$$\sum_{j^*\in J^*, a\in B} x^{d^*c}_{j^*lta} \leqslant \sum_{a\in A\setminus\{a'\}} d_{lta} o_{ta} \quad \forall l \in L, t \in T \tag{6}$$

$$\sum_{i\in I} x^{fd}_{ijta} = \sum_{l\in L} x^{dc}_{jlta} \quad \forall j \in J, t \in T, a \in A \tag{7}$$

$$w^f_{it} \leqslant cap0^f_i + \sum_{r\in T, r\leqslant t} v^f_{ir} \quad \forall i \in I, t \in T \tag{8}$$

$$w^d_{jt} \leqslant cap0^d_j + \sum_{k\in T, k\leqslant t} v^d_{jk} \quad \forall j \in J, t \in T \tag{9}$$

$$\sum_{j\in J, a\in A} a^f x^{fd}_{ijta} \leqslant w^f_{it} \quad \forall i \in I, t \in T \tag{10}$$

The model seeks to maximize the total profit from selling products in the domestic market and from a potential sales extension in the new market (1). It assumes that demand is satisfied as long as it contributes to profit maximization (2). Domestic demand is required to be fully satisfied to avoid a loss at the home market (3). The potential satisfaction of foreign demand from the domestic sites is covered by constraint (4). The foreign production and mapping to demand is covered by constraints (5) and (6) and apply only if the acquisition target is purchased. Constraint (7) matches the delivered products from depots to customers with the quantities of delivered products from facilities to depots. By this, no stock is built and the exact amount of produced goods will be used to satisfy immediate demand. Because of the possibility to adjust capacities dynamically, we refrained from implementing stock policies. Constraints (8) and (9) define the herein used dynamic capacity adjustments. Based on the initial capacity of a site at the beginning of the first period, cumulated capacity changes (v) per period are added. The production activities are bound to the available capacity of each site through constraint (10). Further constraints are formulated and provided in the appendix. These consider mainly capacity restrictions, status changes (open, close, size changes, acquisition status) and product utilization.

Clearly the CFLP-ME belongs to the class of NP-hard problems, since it is a generalization of the well-known NP-hard CFLP (see also Aghezzaf, 2005).

2.2. Robust Capacitated Facility Location Problem for Market Entry (RCFLP-ME) and notation

As described in the introduction, the entry into a market is always accompanied with uncertainty regarding how that market develops in the future. Expected revenues, price stability as well as demand are considered in this work as the main drivers for uncertainty. Corporations should thus, not only consider the economic efficiency of their supply chain for the expected realizations but also the robustness and flexibility of their supply chain to adapt to changing and unanticipated developments. A supply chain, re-shaped by an acquisition that was decided based on forecasts, can be less efficient, if the demand projection does not realize. Even worse, the whole acquisition could be disadvantageous if the forecasts vary too much from future realization. For that, it appears reasonable to design supply chains robust to uncertain developments. These designs might not be optimal for a particular realization of the future, but are probably the least expensive to adapt for any highly probable realization (Aghezzaf, 2005).

In literature, especially scenario-based planning plays an important role to gain insights in robustness, risks and flexibility of planning decisions (Poojari et al., 2008). Therefore we adopt the scenario-based concept of robust optimization as introduced by Mulvey et al. (1995) to obtain such a robust supply chain design. Aghezzaf (2005) further elaborates this approach and provides a sound description of the applied mechanics. Goal programming formulations are integrated with a scenario-based description of the problem data, in order to generate solutions that are less sensitive to the possible future developments. The objective is to find a solution that remains close to optimal for any realization of the scenario, also called solution robust, as well as almost feasible for any scenario, called model robust. These so-called robust optimization models have two distinct components: a structural component and a control component. As structural (also: design) component we define the more strategic decision of when and where to open or close sites (site location plan). This, along with the site status (opened/closed/acquired) and size (small/medium/big), has to be decided in advance. Thus, newly opened sites are not supposed to be shut down again and the other way around. The values of the structural components are fixed for any future realization. The control variables may change per scenario depending on the realization of the uncertain parameters and on the optimal values of the design variables. Capacity adjustments and the resulting capacity as well as the product flows from the facilities to the depots and customers form the control variables. Sites are able to change capacities dynamically within one period depending on demand, e.g. it is possible to reduce assembly line speed or contractors to reduce overall capacity.

Model-robustness is being accounted for by introducing error variables for potential capacity shortages in the facilities. Capacity shortages (u^f) are weighted with penalty costs (λ) in the objective function to keep the shortages minimal. Solution robustness is modeled via the regret of the robust solution in comparison to the optimal solutions of different scenarios.

To present the robust optimization model, we need to introduce some additional notation:

2.2.1. Additional index

S Set of possible scenarios. Scenarios comprise different developments of the uncertainty parameters to account for uncertain market developments.

2.2.2. Additional parameters of the robust model

We extend the uncertainty parameters for product demand (d), revenue (k) and cost volatility (φ) from the deterministic model by the index s to distinguish them by scenario. The explicit formulation is provided in the appendix.

- p_s probability of specific scenario to occur with $\sum_{s\in S} p_s = 1$
- $\widehat{W}_s$ best objective value obtained under scenario s by deterministic model (Euro)
- λ_i costs per unit shortage of capacity in facility i (Euro), respectively λ_{i^*}

The additional decision variables of the robust model are as follows:

- u^f_{its} capacity shortage in facility i in period t in scenario s (units), respectively $u^{f^*}_{i^*ts}$
- Re_s regret associated with scenario s compared to the best solution of s

For the decision variables we enhance the shipped products x, capacity changes v and resulting capacity w as control variables specific for each scenario. The remaining decision variables defined for the deterministic model also apply and form the design variables for the robust model. In such they apply across all scenarios. These adjusted decision variables can be found in the appendix. With the enhanced index, parameters and variables, the objective function for the RCFLP-ME can be formulated by following equation:

$$\mathrm{Min}\left\{\sum_{s\in S} p_s \frac{Re_s}{\widehat{W}_s}\right\} \tag{11}$$

Subject to
(21)–(31) of the appendix and

$$Re_s = \left(\widehat{W}_s - W_s + \sum_{i\in I, t\in T} \lambda_i u^f_{its} + \sum_{i^*\in I^*, t\in T} \lambda_{i^*} u^{f^*}_{i^*ts}\right) \quad \forall s \in S \tag{12}$$

$$\sum_{j\in J, a\in A} a^f x^{fd}_{ijtas} - u^f_{its} \leqslant w^f_{its} \quad \forall i \in I, t \in T, s \in S \tag{13}$$

$$u^f_{its} \leqslant y^f_{it} cmax^f_i \quad \forall i \in I, t \in T, s \in S \tag{14}$$

The remaining constraints, with similarities to the deterministic model constraints are provided in the appendix.

There exist different approaches to define objective functions for robust model formulations. Aghezzaf (2005) adds capacity shortage penalties to the objective function and minimizes them over all scenarios without consideration of regrets. Marianov and Fresard (2005) perform a regret analysis and minimize the highest cost over all scenarios without a specific robust objective function. (Bredström, Flisberg, & Rönnqvist, 2013) state that a common argument against using robust optimization is that it is too conservative or that the objective value of some scenarios might be too large or pessimistic.

In our objective function formulation (11) we mitigate this argument by minimizing the relative (weighted) regret per scenario in proportion to the optimal value of each scenario. The regret is determined by the gap between the optimal deterministic solution for each scenario and the robust solution (12). Capacity shortages u^f need to be compensated by e.g. additional shifts (13) which are usually more expensive. These costs are represented by the penalty costs λ.

Most of the defined constraints for the robust model apply comparable mechanics as those for the deterministic model only augmented by the index s to take all scenarios into account. Therefore, we provide them only in the appendix. A description of these constraints is provided in the section of the deterministic model and respectively in the appendix. With this configuration, the robust model sets the structural components (here the location plan for all sites) which minimizes the relative regret across all scenarios.

3. Model application and results

In this section we show the robustness and effectiveness of the RCFLP-ME by comparison to the results of each deterministic planning approach (CFLP-ME) in a fictive setting where the future is assumed uncertain. As in Jayaraman, Guide, and Srivastava (1999), we first provide an introduction to one fictive company configuration with different scenarios and then we conclude the results after applying the models. Since we could not apply the model on a real company and its parameter configuration yet, we conducted significant efforts in deriving a good order of magnitude for our applied data. The proposed samples are based on data derived from expert interviews and acute research. The main characteristics of the domestic market before running the model are presented in Table 1. The model is applied over a period of 12 years.

The market considered for entry is located in the Middle East and dominated by three major players, whose characteristics are given in Table 2. There is also some free demand in the new market with a total share of 5% to be satisfied by any AT or from the domestic market. A proprietary unit price sets the defined product prices of each company into relation. By such AT 1 has the highest price and AT 2 the lowest. These differences stem from perceived and available product differentiation attributes, like brand image, design or installed features. The buying company would be able to maintain these prices. The remaining market shares are scattered amongst many very small players. The acquisitions, capacities and customer delivery plan can be re-optimized by the model in order to improve profit performance of the whole company. It is assumed that a specific amount of an acquired company's customers can be retained by the buying company.

Table 1
Characteristics of the domestic market.

Description	Value
No. of customers	100
No. of facilities (o/c)	3/6
No. of open depots	3 (big)
No. of depots for activation	13
No. of pot. facilities to build in new market	1
No. of pot. depots to build in new market	2

Table 2
Characteristics of the foreign market.

Acquisition target	Market share (%)	No. cus.	No. fac.	No. dep
AT 1	23	23	3	5
AT 2	17	17	2	3
AT 3	10	10	1	2

The CFLP-ME and RCFLP-ME will formulate a recommendation regarding the companies to acquire, the domestic site location plan, which includes the status of each site (open/close) as well as the size of the depots over a given period. An integral part of this recommendation will be the assignment of delivery quantities and capacities to all owned sites, including acquired sites. This will be concluded per scenario by the CFLP-ME and simultaneously for all scenarios by the RCFLP-ME.

Four different and varying scenarios of future business developments are implemented. They mainly differ in altering customer demand, different achievable unit prices per company and volatile price stability over the planning horizon. The cost volatility factor for each scenario is randomly picked from the interval [0.1, 0.3]. We consider this interval as sufficiently well selected in order to impact the optimization decision but yet preventing the model to just mitigate the randomness of the volatility factor. To match potential fluctuation over the planning horizon, the cost volatility factor is implemented with a randomly selected decrease or increase trend. This intensity of the selected trend depends on the current planning period and the total amount of considered periods. For the revenues, we randomly picked the supposed mean value from the interval [75, 120]. A standard deviation of 15% based on a log-normal distribution is assumed which is proofed suited for modeling economic stochastic variables such as demands (Kamath & Pakkala, 2002). The unit price per scenario is also subject to a randomly selected increasing or decreasing trend over the planning horizon.

The demand scenarios are based on a log-normal distribution. Again, we account for potential fluctuation over time, by implementing different demand trends. Depending on whether the demand will increase, decrease or develop randomly, different mean values (randomly picked between 9,000 and 1,500 units) and standard deviations (between 100 and 300) are assumed. All three uncertainty parameters are combined to provide a variety of different scenarios. The uncertainty and its inherent volatility are selected to have an impact on the model.

We decided to keep the number of scenarios limited. In real world business, decision makers would consider and rely on only a few very probable or very extreme scenarios. Since building a huge amount of scenarios via Monte-Carlo-Simulations would significantly increase the complexity of supply chain planning, it seems not feasible in practice. Further, scenarios, developed by companies are mostly enriched with business sense, market intelligence and gut feeling to apply to market dynamics more specific. They are perceived to be more efficient than computationally calculated scenarios. Also, a large number of scenarios would either lead to similar probabilities per scenario or to very low probabilities for many scenarios. The first case would not match real circumstances. In the second case the scenarios with very low probability would not significantly contribute to objective optimization.

We reckon difficulties in resting our conclusions only on four scenarios and thereby extracting general insights. Thus, we applied the CFLP-ME and RCFLP-ME on 18 sets, each consisting of four different scenarios. The sets differ by locations of customers and sites, assumed cost configuration and implemented demand trends.

All Mixed-Integer Problem formulations described were implemented and solved using IBM ILOG CPLEX Optimization Studio Version 12.2, on a Pentium Intel Core i7 PC with a 1.6 GHz processor and 4 GB of RAM on the Windows 7 (64 Bit) operating system. Due to the efficient model formulations and a limited set of scenarios, the deterministic model was able to solve an entire set on average in about 1.5 min. The robust model required between 4 and 45 min to complete the calculations.

A robust model is in its solution process much more time consuming compared to a deterministic model which optimizes simply one scenario. Solution times of real-world scenarios in the robust case are typically hours to days while a deterministic model can be solved in minutes or few hours. The increased solution time would be an issue in more operational planning phase, for instance in routing or scheduling applications. A location decision is much more a strategic task and computation times are normally not critical. From our experience solution times of one or two days are accepted by practitioners.

We analyzed the performance of our robust solution by benchmarking its results with those by implementing the deterministic solution of each scenario. For the benchmark, we compare the profit of each scenario and the expected profit of the entire set by calculating the sum of all scenario profits multiplied by their probability. We will first present the results of an arbitrary set with 4 scenarios. After that, a summary of the results for multiple sets will be provided.

Table 3. summarizes the results for Set 13. The columns identify which scenario is realized. The rows contain the considered configuration, where "*R*" denotes the robust configuration, and e.g. "*D*" the configuration obtained from the deterministic solution of scenario 1. The entries in the table show the gap ratio between the optimum profits of the realized scenario compared to the profit of the applied configuration. For that, the target value of the applied configuration is divided by the optimal target value of the specific scenario. We ranked the configurations by comparing how close they get to the optimum values. The closest configuration gets rank 1. In brackets the rank of the configuration in comparison to the other configurations per scenario realization is provided. The "opt. sol." connotes the optimal solution of the deterministic model for the specific scenario. However, the configuration does not necessarily provide good results in case another scenario realizes.

For our demonstrated set, we can observe that the robust solution's gap is at least as small as the other configurations, in most cases even smaller. The robust configuration provides a higher profit or a profit at least as high as the best other deterministic configuration. The robust configuration should thus be implemented by the company rather than relying on single deterministic solutions.

Compared across the entire set, no single configuration outperforms the robust model configuration. The robust model has the highest rank and thus concludes the highest expected profit compared to the other configurations.

If scenario 1 or 2 realize, Configuration D4 is not able to find a solution because the demand is exceeding the maximum capacities of the installed sites. To allow equal test conditions, the penalty for capacity shortages was removed from the robust model formulation. The penalty was used as an auxiliary to consider model robustness during optimization. For the tests, the resulting optimal site location plans of all configurations were locked, and the scenario specific data applied on the location plans. Therefore the penalty is not required for testing the robust configuration. Translated into practice this has severe impact on business. The company would have only limited possibilities to build additional capacities on short notice. It either would have to acquire the products from other suppliers at a higher price or could not meet the demand. This would induce the risk of losing the customer or could even lead to contractual charges. With the robust configuration all scenarios can be solved. We acknowledge that the gaps to the optimum solutions are rather small. This is of course highly depending on the model parameters, like the values of handling or transportation costs. It is obvious though that the robust configuration always falls between the optimal configuration and the other deterministic configurations. Since it is not possible to derive a configuration that provides the optimum results for every scenario realization, the robust configuration, as it is superior to the deterministic solution, is quite desirable.

Clearly, for each studied set (Table 4), the solution of the robust model is among the best solutions per scenario (highlighted by its high rank) but also achieves the highest expected profit for each implemented scenario set. Some configurations show higher ranks for specific scenarios but these configurations are less efficient for other scenarios.

Furthermore, we analyzed if the robust model performs better for different types of problem variations (e.g. increasing demand). Therefore, we implemented different sets where we varied the development of the demand, so that in one of the scenarios the demand increased strongly whereas in the second scenario it decreased. Scenarios 3 and 4 consisted of only minor demand variations (Table 5).

Our results show, that the robust model finds a solution that is feasible for every scenario, including scenario 1 (where we consider a strong increase in demand), whereas the deterministic solutions for the other scenarios are not feasible in this case. Also, the comparison of the deterministic solutions for each scenario with the robust solution shows, that while both are feasible for every other scenario, the robust solution performs better with regard to the objective.

Our second analysis focused on the variation of the transportation costs (Table 6). In the first scenario the transportation costs were low and increased through scenarios 2 to 4. Our results show that the optimal deterministic solution for scenario 1 is either not feasible or performs worse for the other scenarios than the robust

Table 3
Expected profit rankings for Set 13.

Scenario Configuration	Scenario 1 gap ratio (rank)	Scenario 2 gap ratio (rank)	Scenario 3 gap ratio (rank)	Scenario 4 gap ratio (rank)	Expected profit gap ratio (rank)
D1:	Opt. sol.	0.999 (3)	0.9985 (3)	0.9969 (4)	0.9988 (4)
D2:	0.9982 (2)	Opt. sol.	0.9995 (2)	0.9988 (2)	0.9994 (2)
D3:	0.9968 (3)	0.9998 (2)	Opt. sol.	0.9988 (3)	0.9991 (3)
D4:	– (no sol.)	– (no sol.)	0.9928 (4)	Opt. sol.	0.2938 (5)
R:	0.9992 (1)	0.9999 (1)	0.9998 (1)	0.9991 (1)	0.9996 (1)

Table 4
Expected rankings per scenario and set.

Set	Scen. Conf.	Scen. 1 rank	Scen. 2 rank	Scen. 3 rank	Scen. 4 rank	Exp. profit rank
1	D1:	Opt. sol.	4	3	4	4
	D2:	2	Opt. sol.	1	1	2
	D3:	3	3	Opt. sol.	2	5
	D4:	2	1	1	Opt. sol.	2
	R:	1	2	2	3	1
2	D1:	Opt. sol.	3	3	3	3
	D2:	2	Opt. sol.	1	2	4
	D3:	3	1	Opt. sol.	2	4
	D4:	1	2	2	Opt. sol.	1
	R:	1	2	2	1	1
3	D1:	Opt. sol.	2	2	1	4
	D2:	2	Opt. sol.	1	2	3
	D3:	2	1	Opt. sol.	2	1
	D4:	1	2	2	Opt. sol.	5
	R:	2	1	1	2	1
4	D1:	Opt. sol.	4	4	1	5
	D2:	3	Opt. sol.	1	2	2
	D3:	4	1	Opt. sol.	3	3
	D4:	1	3	3	Opt. sol.	4
	R:	2	2	2	2	1
5	D1:	Opt. sol.	2	2	1	2
	D2:	no sol.	Opt. sol.	1	no sol.	4
	D3:	no sol.	1	Opt. sol.	no sol.	4
	D4:	2	4	4	Opt. sol.	3
	R:	1	3	3	2	1
6	D1:	Opt. sol.	2	2	2	4
	D2:	2	Opt. sol.	1	1	2
	D3:	2	1	Opt. sol.	1	2
	D4:	no sol.	no sol.	no sol.	Opt. sol.	5
	R:	1	1	1	1	1
7	D1:	Opt. sol.	2	2	1	2
	D2:	2	Opt. sol.	1	2	5
	D3:	3	1	Opt. sol.	3	4
	D4:	1	2	2	Opt. sol.	2
	R:	1	2	2	1	1
8	D1:	Opt. sol.	3	3	4	3
	D2:	2	Opt. sol.	2	2	2
	D3:	3	2	Opt. sol.	1	4
	D4:	no sol.	no sol.	4	Opt. sol.	5
	R:	1	1	1	3	1
9	D1:	Opt. sol.	3	2	4	2
	D2:	2	Opt. sol.	3	3	3
	D3:	3	2	Opt. sol.	2	4
	D4:	no sol.	no sol.	4	Opt. sol.	5
	R:	1	1	1	1	1
10	D1:	Opt. sol.	3	3	4	3
	D2:	2	Opt. sol.	1	2	2
	D3:	3	2	Opt. sol.	3	4
	D4:	no sol.	no sol.	4	Opt. sol.	5
	R:	1	1	2	1	1
11	D1:	Opt. sol.	3	3	4	3
	D2:	no	Opt. sol.	2	2	4
	D3:	1	2	Opt. sol.	3	2
	D4:	no sol.	no sol.	4	Opt. sol.	5
	R:	2	1	1	1	1
12	D1:	Opt. sol.	2	2	4	2
	D2:	3	Opt. sol.	3	2	4
	D3:	2	1	Opt. sol.	3	3
	D4:	no sol.	no sol.	no sol.	Opt. sol.	5
	R:	1	3	1	1	1
13	D1:	Opt. sol.	3	3	4	4
	D2:	2	Opt. sol.	2	2	2
	D3:	3	2	Opt. sol.	3	3
	D4:	no sol.	no sol.	4	Opt. sol.	5
	R:	1	1	1	1	1
14	D1:	Opt. sol.	3	3	4	2
	D2:	no	Opt. sol.	1	1	4
	D3:	2	2	Opt. sol.	3	3
	D4:	no sol.	no sol.	4	Opt. sol.	5
	R:	1	1	2	2	1

Table 5
Expected rankings per scenario and set (depending on the demand variation).

Set	Scen. Conf.	Scen. 1 rank	Scen. 2 rank	Scen. 3 rank	Scen. 4 rank	Exp. profit rank
15	D1:	Opt. sol.	2	2	3	2
	D2:	no sol.	Opt. sol.	4	2	4
	D3:	no sol.	3	Opt. sol.	1	3
	D4:	no sol.	no sol.	no sol.	Opt. sol.	5
	R:	2	1	1	4	1
16	D1:	Opt. sol.	2	2	5	2
	D2:	no sol.	Opt. sol.	3	2	3
	D3:	no sol.	3	Opt. sol.	2	3
	D4:	no sol.	3	3	Opt. sol.	3
	R:	2	1	1	1	1

Table 6
Expected rankings per scenario and set (depending on variation of the transportation costs).

Set	Scen. Conf.	Scen. 1 rank	Scen. 2 rank	Scen. 3 rank	Scen. 4 rank	Exp. profit rank
17	D1:	Opt. sol.	no sol.	no sol.	no sol.	2
	D2:	3	Opt. sol.	2	4	4
	D3:	5	4	Opt. sol.	no sol.	3
	D4:	3	no sol.	2	Opt. sol.	4
	R:	2	1	1	1	1
18	D1:	Opt. sol.	5	5	5	5
	D2:	2	Opt. sol.	3	3	3
	D3:	2	3	Opt. sol.	3	3
	D4:	1	2	2	Opt. sol.	2
	R:	5	1	1	1	1

solution. Furthermore, the robust model finds a solution that is feasible for all scenarios and the comparison with the other solutions shows that the results obtained are on average better.

The results in Tables 5 and 6 show that the solutions obtained through the implementation of a robust model, that takes into account all possible future developments, outperform the solutions of the deterministic model of the "worst case"-scenario. Although this robust model may not always provide the best solution over all scenarios considered, the results taken as a whole are usually better. All in all, the computational examples support our research in providing a network planning approach robust to uncertain developments of the future.

4. Conclusions and further research

We presented a capacitated facility location model for acquisitions, robust to uncertain realizations of demand, revenues and cost developments. The robust model achieved excellent results in our computational test. We showed that the robust configuration outperformed the configurations suggested by the deterministic model as soon as other scenarios realized. In many cases, the robust solution was even very close to the optimum results of each individual scenario. However, we acknowledge that this is not necessarily an overall proof of the model's general efficiency. In terms of validity and reliability, the model is based on three pillars. First, the concept of robust optimization accounts per se for volatile parameter developments. Second, the applied data was derived from expert interviews and acute research. Third, rather than just one uncertainty parameter, we applied three of them. Nevertheless, validity and reliability might be further strengthened by real company data and additional uncertainty parameters. The applied cost volatility factor might be disaggregated into several, more detailed parameters like inflation and economic growth. Varying transportation costs bound to oil prize developments could also be added. Our research is consequently focusing on studying and analyzing the specific "levers" of the robust model. First, we are currently investigating performance improvements in proportion to the number of considered scenarios. Our hunch is that a significant increase in the number of scenarios is not likely to increase the performance of the solutions. This would also mean that the robust model might perform well even if a scenario emerges, that was not considered when solving the model. The model would then provide truly robust solutions. Second, we analyze the results with varying data configurations, like transportation costs, fixed costs, site locations, etc. preferably with a test configuration to be derived from a real company. Various ways to define robust objective functions were described. Our future aim is to systematically analyze the differences of robust formulations and approaches in terms of performance and results, e.g. those based on robust counterparts. For this, enhanced solution approaches and algorithms, possibly also tailor-made to the problem, will be developed which will significantly improve the run-time of a larger sample. This might lead to an even more applicable tool for decision makers considering the impacts of acquisitions on the supply chains under uncertainty.

Appendix A

Occurring indices:

I	set of facilities (open and close, $I := I^o \cup I^c$), respectively I^* for acquirable facilities
J	set of depots (open and close, $J := J^o \cup J^c$), respectively J^* for acquirable depots
L	set of customers
M	set of depots sizes ($M := \{s,m,l\}$)
T	planning horizon ($T := \{1,2,\ldots,\tau\}$)
A	companies (incl. set of acquisition targets B)

Parameters of the deterministic model ($*$ applies to acquisition targets):

a^f, a^{f^*}	facility utilization of product (Euro/Unit)
a^d, a^{d^*}	depot utilization of product (Euro/Unit)
$c^{fd}_{ij}, c^{f^*d^*}_{i^*j^*}$	unit shipping costs of product between facilities and depots (Euro/Unit)
$c^{dc}_{jl}, c^{d^*c}_{j^*l}$	unit shipping costs of product between depots and customer l (Euro/Unit)
$e^f_i, e^{f^*}_{i^*}$	costs to change capacity of facilities per unit (Euro/Unit)
$e^d_j, e^{d^*}_{j^*}$	costs to change capacity of depots per unit (Euro/Unit)
$h^f_i, h^{f^*}_{i^*}$	variable maintenance costs of facilities depending on installed capacity (Euro/Unit)
$h^d_j, h^{d^*}_{j^*}$	variable maintenance costs of depots depending on installed capacity (Euro/Unit)
$g^f_i, g^{f^*}_{i^*}$	variable operation costs of facilities depending on processed products (Euro/Unit)
$g^d_j, g^{d^*}_{j^*}$	variable operation costs of depots depending on processed products (Euro/Unit)
$cap0^f_i, cap0at^{f^*}_{i^*}$	initial capacity of facilities (Units)
$cmax^f_i, cmaxat^{f^*}_{i^*}$	maximum capacity of facilities (Units)
$cmin^f_i, cminat^{f^*}_{i^*}$	minimum capacity of facilities (Units)
$cap0^d_j, cap0at^{d^*}_{j^*}$	initial capacity of depots (Units)
$cmax_m, cmaxat^{d^*}_{j^*}$	maximum depot capacity, for domestic depots depends on size m (Units)
b_t	total budget for site changes in period t (Euro)
f^f_i	fixed costs to open a facility i (Euro)
f^d_{jm}	fixed costs to open a depot j depending on depot size m (Euro)
$cini_m$	initial depot capacity depot depends on size m (Units)
cmc_m	fixed costs to change magnitude m of depots (Euro)

Decision variables:

x^{fd}_{ijta}	quantity of products shipped in period t from facility i to depot j of company a (units). x^{fd}_{ijtas} for each scenario of robust model
x^{dc}_{jlta}	quantity of products shipped in period t from depot j to customer l of company a (units). x^{dc}_{jltas} for each scenario of robust model
$x^{f^*d^*}_{i^*j^*ta}$	quantity of products shipped in period t from acquired facility i^* to acquired depot j^* of company a (units). $x^{f^*d^*}_{i^*j^*tas}$ for each scenario of robust model
$x^{d^*c}_{j^*lta}$	quantity of products shipped in period t from acquired depot j^* to customer l of company a (units). $x^{d^*c}_{j^*ltas}$ for each scenario of robust model
v^f_{it}	capacity change in facility i in period t (units). v^f_{its} for each scenario of robust model
v^d_{jt}	capacity change in depot j in period t (units). v^d_{jts} for each scenario of robust model
$v^{f^*}_{i^*ta}$	capacity change in facility i^* in period t (units). $v^{f^*}_{i^*tas}$ for scenarios of robust model
$v^{d^*}_{j^*ta}$	capacity change in depot j^* in period t (units). $v^{d^*}_{j^*tas}$ for each scenario of robust model
w^f_{it}	capacity of facility i at start of period t (units). w^f_{its} for each scenario of robust model
w^d_{jt}	capacity of depot j at start of period t (units). w^d_{jts} for each scenario of robust model
$w^{f^*}_{i^*ta}$	capacity of facility i^* at start of period t (units). $w^{f^*}_{i^*tas}$ for scenarios of robust model
$w^{d^*}_{j^*ta}$	capacity of depot j^* at start of period t (units). $w^{d^*}_{j^*tas}$ for scenarios of robust model
$y^f_{it} \in \{0,1\}$	indicates if facility i is open {= 1} in period t (no dimension)
$y^d_{jtm} \in \{0,1\}$	indicates size and if depot j is open in period t (no dimension)
$new_{jtm} \in \{0,1\}$	tracks status changes for depot j
$z^f_{it} \in \{0,1\}$	indicates if facility i has changed its status from period $t-1$ to t (no dimension)
$mch_{jtm} \in \{0,1\}$	indicates if depot j has changed its size m from period $t-1$ to t (no dimension)
$o_{ta} \in \{0,1\}$	indicates if company a has been purchased {= 1} in period t (no dimension)
$p_{ta} \in \{0,1\}$	indicates status changes of company a form period $t-1$ to t (no dimension)

Constraints of deterministic model:

$$\sum_{i^*\in I^*} x^{f^*d^*}_{i^*j^*ta} = \sum_{l\in L} x^{d^*c}_{j^*lta} \forall j^* \in J^*, t\in T, a\in A \tag{15}$$

$$\sum_{j^*\in J^*} a^{f^*} x^{f^*d^*}_{i^*j^*ta} \leqslant w^{f^*}_{i^*ta} \forall i^* \in I^*, t\in T, a\in A \tag{16}$$

$$\sum_{l\in L, a\in A} a^d x^{dc}_{jlta} \leqslant w^d_{jt} \forall j\in J, t\in T \tag{17}$$

$$\sum_{l\in L} a^{d^*} x^{d^*c}_{j^*lta} \leqslant w^{d^*}_{j^*ta} \forall j^* \in J^*, t\in T, a\in A \tag{18}$$

$$\sum_{j\in J, a\in A} a^f x^{fd}_{ijta} \leqslant cmax^f_i y^f_{it} \forall i\in I, t\in T \tag{19}$$

$$\sum_{j^*\in J^*} a^{f^*} x^{f^*d^*}_{i^*j^*ta} \leqslant cmaxat^{f^*}_{i^*} y^{f^*}_{i^*a} o_{ta} \forall i^* \in I^*, t\in T, a\in A \tag{20}$$

$$z^f_{it} = y^f_{i,t-1} - y^f_{it} \forall i\in I^o, t\in T\setminus\{1\} \tag{21}$$

$$z^f_{it} = y^f_{it} - y^f_{i,t-1} \forall i\in I^c, t\in T\setminus\{1\} \tag{22}$$

$$\sum_{t\in T} z^f_{it} \leqslant 1 \forall i\in I \tag{23}$$

$$p_{ta} = o_{ta} - o_{t-1,a} \forall a\in B, t\in T\setminus\{1\} \tag{24}$$

$$new_{jtm} \geqslant y^d_{jtm} - \sum_{m\in M} y^d_{j,t-1,m} \forall m\in M, j\in J^c, t\in T\setminus\{1\} \tag{25}$$

$$new_{jtm} \leqslant y^d_{jtm} - y^d_{j,t-1,m} \forall j\in J^c, m\in M, t\in T\setminus\{1\} \tag{26}$$

$$new_{jtm} \leqslant y^d_{j,t-1,m} - y^d_{jtm} \forall j\in J^o, m\in M, t\in T\setminus\{1\} \tag{27}$$

$$new_{jtm} \geqslant y^d_{j,t-1,m} - \sum_{m\in M} y^d_{jtm} \forall m\in M, j\in J^o, t\in T\setminus\{1\} \tag{28}$$

$$mch_{jtm} \geqslant y^d_{jtm} - y^d_{j,t-1,m} - new_{jtm} \forall j\in J^c, m\in Mt\in T\setminus\{1\} \tag{29}$$

$$mch_{jtm} \geqslant y^d_{jtm} - y^d_{j,t-1,m} \forall j\in J^o, m\in Mt\in T\setminus\{1\} \tag{30}$$

$$\sum_{m\in M} y^d_{jtm} \leqslant 1 \forall j\in J, t\in T \tag{31}$$

$$w^{f^*}_{i^*ta} \leqslant cap0at^{f^*}_{i^*} + \sum_{r\in T, r\leqslant t} v^{f^*}_{i^*ra} \forall i^* \in I^*, t\in T, a\in A \tag{32}$$

$$w^{d^*}_{j^*ta} \leqslant cap0at^{d^*}_{j^*} + \sum_{r\in T, r\leqslant t} v^{d^*}_{j^*ra} \forall j^* \in J^*, t\in T, a\in A \tag{33}$$

$$w^f_{it} \leqslant cmax^f_i y^f_{it} \forall i\in I, t\in T \tag{34}$$

$$w^{f^*}_{i^*ta} \leqslant cmaxat^{f^*}_{i^*} y^{f^*}_{i^*a} o_{ta} \forall i^* \in I^*, t\in T, a\in A \tag{35}$$

$$w^d_{jt} \leqslant \sum_{m\in M} cmax_m y^d_{jtm} \forall j\in J, t\in T \tag{36}$$

$$w^{d^*}_{j^*ta} \leqslant cmaxat^{d^*}_{j^*} y^{d^*}_{j^*a} o_{ta} \forall j^* \in J^*, t\in T, a\in A \tag{37}$$

$$w^f_{it} \geqslant cmin^f_i y^f_{it} \forall i\in I, t\in T \tag{38}$$

$$w^{f^*}_{i^*ta} \geqslant cminat^{f^*}_{i^*} y^{f^*}_{i^*a} o_{ta} \forall i^* \in I^*, t\in T, a\in A \tag{39}$$

$$w^d_{jt} \geqslant cini_m y^d_{jtm} \forall j\in J, t\in T, m\in M \tag{40}$$

$$w^{d^*}_{j^*ta} \geqslant cap0at^{d^*}_{j^*} y^{d^*}_{j^*a} o_{ta} \forall j^* \in J^*, t\in T, a\in A \tag{41}$$

$$\begin{pmatrix} \sum_{i\in I} f^f_i z^f_{it} + \sum_{\substack{j\in J,\\ m\in M}} f^d_{jm} new_{jtm} + \sum_{i\in I} e^f_i v^f_{it} + \sum_{j\in J} e^d_j v^d_{jt} + \sum_{\substack{j\in J,\\ m\in M}} cmc_m mch_{jtm} \\ + \sum_{\substack{i^*\in I^*,\\ a\in A}} e^{f^*}_{i^*} \varphi_t v^{f^*}_{i^*ta} + \sum_{\substack{j^*\in J^*,\\ a\in A}} e^{d^*}_{j^*} \varphi_t v^{d^*}_{j^*ta} + \sum_{a\in A} b_t \kappa_a \varphi_t o_{ta} \end{pmatrix} \leqslant b_t \quad \forall t\in T \tag{42}$$

$$\begin{matrix} x^{fd}_{ijta}, x^{dc}_{jlta}, x^{f^*d^*}_{i^*j^*ta}, x^{d^*c}_{j^*lta}, v^f_{it}, v^d_{jt}, v^{f^*}_{i^*ta}, v^{d^*}_{j^*ta}, w^f_{it}, \\ w^d_{jt}, w^{f^*}_{i^*ta}, w^{d^*}_{j^*ta}, y^f_{it}, y^d_{jtm}, new_{jtm}, z^f_{it}, mch_{jtm}, p_{ta}, o_{ta} \end{matrix} \geqslant 0 \tag{43}$$

Facilities are bound to deliver products only when open (resp. acquired) and up to the maximum capacity of the facility by (19) and (20). Site status changes for open and closed sites between periods are tracked by constraints (21)–(28). Changes in depot size are tracked by constraints (29) and (30). Depot can only have one size at a time (31). Constraints (32) and (33) apply the similar capacity adjustment mechanics on acquisition targets as described in Section 2.1 Furthermore, all open sites must operate below a maximum capacity (34)–(37) and at least at a minimum capacity (38)–(41). Constraint Eqs. (42) limits all investment costs to the available budget for each period.

For the robust model an extension of the deterministic model is required to consider the all scenarios. In such, all control variables in the constraints defined above for the deterministic model require an enhancement by the index s and thus, apply for all s in S. These are, the W_s, the objective function of the deterministic model (1) with all control variables augmented by s, constraints (2)–(10), constraints (15)–(20) and constraints (32)–(43). Constraints (13) and (14) are applied on all acquirable sites.

$$\sum_{j^*\in J} a^{f^*} x^{f^*d^*}_{i^*j^*tas} - u^{f^*}_{i^*ts} \leqslant w^{f^*}_{i^*tas} \tag{44}$$

$$u^{f^*}_{i^*ts} \leqslant y^{f^*}_{i^*t} o_{ta} cmaxat^{f^*}_{i^*} \tag{45}$$

$$u^f_{its}, u^{f^*}_{i^*ts} \geqslant 0 \quad \forall i\in I, i^* \in I^*, t\in T, a\in A, s\in S \tag{46}$$

It is assumed that the potential capacity shortage compensation by u^f_{its} is only possible if the specific facility is open (constraints (14) and (45)).

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