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Small- or Medium-Sized Enterprise Uses Operations Research to Select and Develop its Headquarters Location

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Abstract. Location decisions are strategic and usually multicriteria. In decision making, companies need to anticipate future developments at potential locations. Company-driven and municipal development measures change location conditions over time. For location-seeking companies, the realization of municipal measures is fraught with uncertainty. They are planned by several municipal actors, and their long-term implications are hard to predict. Thus, the early-systematic consideration of company-internal and -external development measures is vital for decision makers (DMs) in a future-oriented location assessment. In our paper, we develop a robust decision support framework for companies to solve the regional facility location and development planning problem (RFLDP). Our framework includes a quantitative planning approach based on established operations research (OR) optimization models and a practical guideline for a structured acquisition of relevant data. The chief executive officer (CEO) (or DM) of a small- or medium-sized enterprise (SME) asked us to solve his acute RFLDP. For this, we proposed a systematic workflow and accompanied the SME's regional facility location and development planning. In doing so, we structured the CEO's decision-making process effectively and created an objective-transparent basis for his strategic decisions. The core feature of our work is the inclusion of the human factor of DMs, as we interacted with the CEO along his decision-making process to gradually develop decision recommendations. As a result, the SME benefited from a better-informed and transparent planning process. We recommended a decision option that was structurally superior to other options, which emerged from the CEO's intuition and conventional facility location problem solution approaches. Other stakeholders also benefited from the results of our work.

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Keywords: facility location problem • location development • real-life case study • optimization • interactive decision making

Introduction

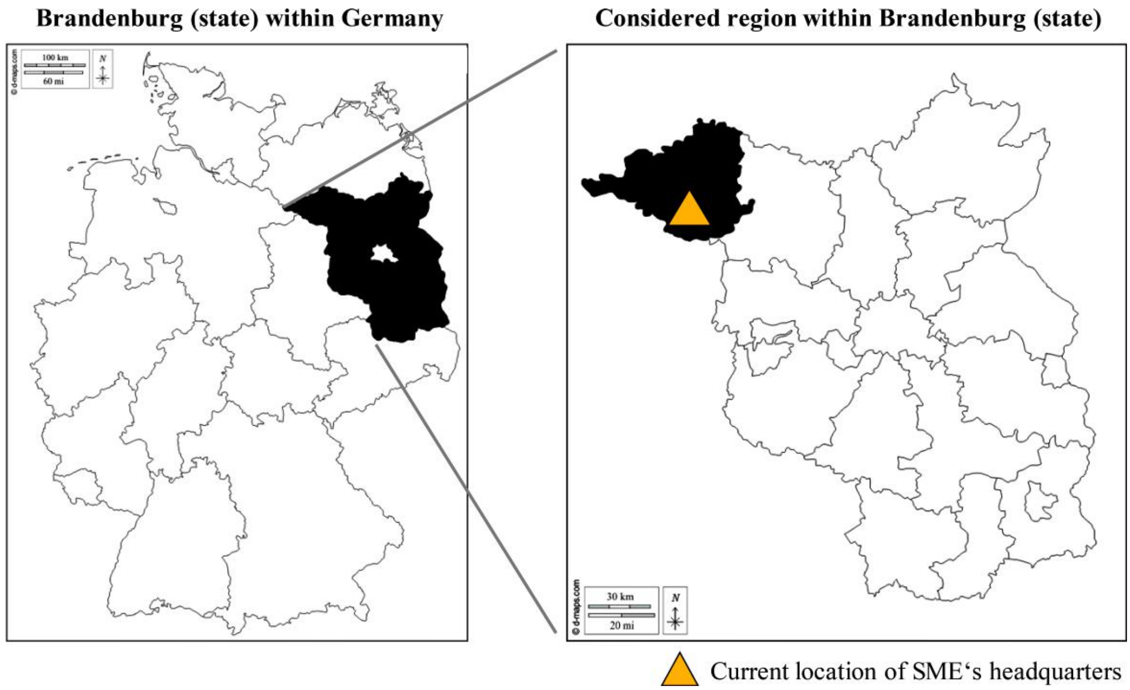
The current location of the headquarters of the small- or medium-sized enterprise (SME) is historically grown in an economically emerging region within the northwest of Brandenburg (state), Germany (Figure 1).

The SME is active in the construction industry, with a focus on scaffolding. Its main business is the setup and rental of scaffolds for all kinds of construction projects for private, commercial, and public customers. The small company employs about 20 people at the current location.

The SME's chief executive officer (CEO) decided to relocate the headquarters because he was dissatisfied with the framework conditions of the current location. His dissatisfaction was due to a poor transportation infrastructure (e.g., long highway distance), technical infrastructure (e.g., low broadband speed), and social infrastructure (e.g., almost no education opportunities nearby) at the current location. Consequently, the CEO searched for a new location (i.e., property) with better conditions than the current location. Initially, the CEO asked for vacant locations at the regional business promotion agency (BPA), which is well networked with relevant municipal actors (MAs) within the considered region.

A number of potential locations in different municipalities were presented to the SME by the BPA. The CEO was faced with a typical facility location problem (FLP) and had to decide on the most suitable location thereof. For this, the CEO needed to assess the framework conditions of all potential locations along multiple decision-making criteria (i.e., *location factors*) that he found relevant. For each location factor, the CEO had specific requirements. At the decision time, the characteristics of the potential locations were quite diverse with respect to the location factors (Figure 2).

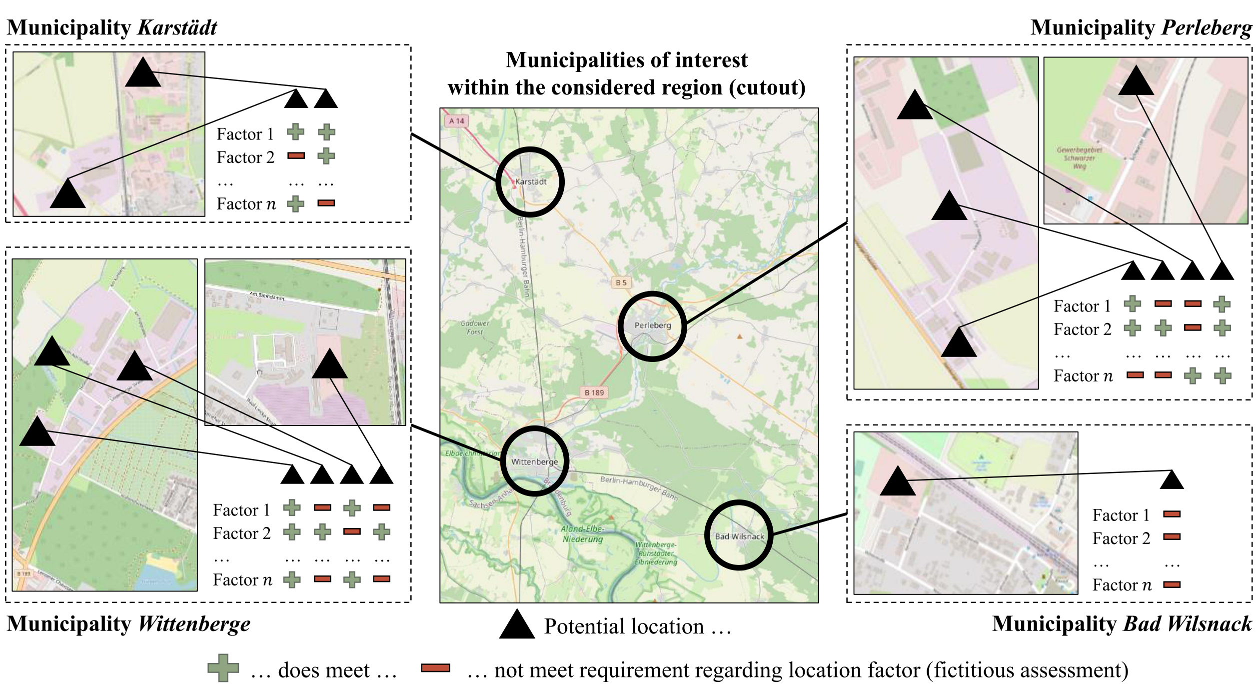
Figure 1. (Color online) Macro View of the SME's Location



Source. Own illustration based on d-maps.com (2022).

Furthermore, the CEO was aware that the current characteristics of potential locations will change over time for two reasons. First, the CEO knew about location development plans of various MAs. Once realized, the *municipal measures* will actively change the framework conditions of at least one potential location. At the decision time, neither the CEO nor the BPA was able to state with certainty whether the municipal measures will be realized in future as planned (in terms of time and effectiveness). Second, the CEO considered own measures

Figure 2. (Color online) Micro View of the Potential Locations



Source. Own illustration based on openstreetmap.org (2022).

to proactively change framework conditions of potential locations.

Faced with the regional facility location and development planning problem (RFLDP), the CEO had to decide both on the selection of a location and its development over time by means of the company's own measures, considering uncertain municipal location developments. Given the complex decision situation and the CEO's lack of experience in conducting location analyses, he was unable to systematically make an objective decision. Instead, he had to make an intuitive decision based on his gut feeling. The CEO asked us for systematic decision support in the context of his acute RFLDP.

In this paper, we give insights into our scientific planning accompaniment of the SME. By using proper operations research (OR) methods of multiobjective and robust optimization, we provide the CEO recommendations for future-robust decisions on location selection and development. To this end, we extend our deterministic RFLDP decision support framework (Kik et al. 2022) by a robustness analysis to cope appropriately with planning uncertainties. Our results formally underline the need for the SME's intended relocation and show that there are many decision options superior to those the CEO would have intuitively opted for without our support.

We organize our paper's remainder as follows. First, we state the *Problem Setting* and summarize its main characteristics. Second, we address *Related Work*. Third, we introduce our *Robust Decision Support Framework* for solving real-life RFLDPs. Fourth, we describe our *Planning Accompaniment Workflow* to support the SME. We give documented insights into the implementation of our proposed method, regarding the *Guideline Application (First Phase)*, *Planning Approach Application (Second Phase)*, and *Management Discussion (Third Phase)*. Fifth, we highlight the *Benefits* resulting from our work. Sixth, we elaborate *Success Factors* for future fruitful practical applications of our method by companies. Finally, we give *Conclusions* on our key findings.

Problem Setting

For a verbal statement of the problem setting, we describe the relevant *planning task*, decision situation, objectives, and framing conditions in the RFLDP context. The planning task is first to design "location configurations" (i.e., decision options) and second to choose the most suitable one. A location configuration is a specific combination of one potential location and one bundle of *company-driven measures* for its development. Through integrated planning, we determine the most suitable location configuration by deriving decision recommendations for selecting a location and its targeted development based on multiple criteria. The targeted development is based on a measures plan that contains optimal allocations of company-driven measures to a potential location within a planning horizon. This plan also contains a proper scaling of each measure, as companies must decide on intensities of their measures in practice. Decisions on location developments are continuous, in contrast to binary decisions on location selections. This is illustrated by the following three exemplary questions that a company might ask itself when planning to develop a location:
(1) by how many square meters should the area be expanded?; (2) by how many megabytes per second should the broadband be improved?; and (3) for how many kids should a nursery school be set up? The selection of a location configuration is subject to uncertainties, especially in terms of temporal location developments through municipal measures. From a company's perspective, future company-external measures are hard to forecast. Thus, at the decision time, it is uncertain whether municipal measures will be realized in the future at planned times (or at all) and with planned effectiveness. To specify these uncertainties analytically meaningful with probabilities is hardly possible, as reliable historical data usually do not exist. This is mainly due to the heterogeneity of municipal measures and their irregular (and often one-time) realizations.

Therefore, the RFLDP is a multicriteria *decision situation* under uncertainty. Given the specifics of the planning uncertainties, the RFLDP is classified as a robust FLP according to Snyder (2006). In general, robust decision making requires appropriate rules that reflect the typical risk aversion of decision makers (DMs) in strategic (location) planning (Rosenhead et al. 1972, Lempert et al. 2006). These rules must reflect risk aversion in a differentiated way because competitive companies usually do not pursue hyperconservative (location) decisions resulting from extreme risk aversion (Scholl 2001).

The location configurations are evaluated regarding two *objectives*. First, for designing configurations, the objective is to minimize the sum of (undesired) deviations from location factor–specific targets (Kik et al. 2022). Second, for choosing the most robust configuration as the recommended decision option for a DM, the objective is to maximize the robustness (i.e., insensitivity) toward uncertain municipal location developments.

In the design of a location configuration, *frame conditions* must be fulfilled. These are determined by constraints related to a company's requirements and budget. Constraints related to company requirements ensure that location factor–specific requirements are met as best as possible (or absolutely for knock-out criteria). Constraints related to budget ensure that payments that go along with decisions made (i.e., for setting up and developing a certain location) do not exceed a company's restrictive budget cap.

To conclude, the RFLDP is a complex decision situation. Consciously making long-term favorable location decisions is difficult in the absence of a supportive method. To solve real-life RFLDPs, OR methods of multicriteria and robust optimization must be combined.

Related Work

We address the related work in three directions. First, we briefly describe the relevant work on the RFLDP. Second, we give a concise overview of optimization methods that can be used to deal with uncertainties in the FLP context. Third, we discuss the general fitting of these methods to solve real-life *RFLDPs under uncertainty*.

As relevant work related to the RFLDP, thus far only the approach of Kik et al. (2022) exists, which considers temporal adaptations of potential locations within a systematic anticipation of company-internal and -external developments. Although there are plenty of dynamic models in the FLP literature (see Arabani and Farahani (2012) for a comprehensive overview), no model supports decision making in targeted location development. Thus, the authors develop a deterministic RFLDP decision support framework and point out its superiority over conventional FLP models. Using a real-life case study, they show that their novel method yields alternate and structural superior recommendations for location decision making.

To deal with uncertainties in the FLP context, a large body of optimization models exists in the literature (see Snyder (2006) for a comprehensive overview). The models are classified as either *stochastic* or *robust*. For both model types, scenarios are the main data input and used to describe any kind of uncertainties. Stochastic and robust models have the same overall aim: find locations that perform best possible given potential occurrences of conceivable environmental states. However, they achieve the aim differently. Whereas stochastic FLP models optimize an expected outcome (e.g., cost or profit), robust FLP models optimize a certain performance outcome (e.g., worst case or regret performance).

Stochastic FLP models are either mean-based or probabilistic. *Mean-based models* recommend locations based on specific rules for *decision making under risk*, which differ substantially in terms of the risk attitude they imply. These are the *mean rule* and the *mean-variance rule*, which imply risk neutrality and (extreme) risk aversion, respectively (Chan et al. 2001, Ricciardi et al. 2002, Shen et al. 2003, Ravi and Sinha 2004, Velarde and Laguna 2004, Listes and Dekker 2005, Snyder et al. 2007, Berman et al. 2017). Location recommendations of *probabilistic models* are based exclusively on probabilities. Uncertainties are considered either within the constraints system or the objective function of a model. *Chance-constraint models* recommend locations that meet certain constraints with a reasonably high probability (Min and Melachrinoudis 1996, Colomé et al. 2003, Shiode and Drezner 2003, Silvia-Saravia et al. 2018, Kınay et al. 2019, Wang and Qin 2020). *Max-probabilistic models* recommend locations that are most likely to achieve an optimal objective function value (OFV) (Berman et al. 2003a, b; Drezner and Suzuki 2004).

Robust FLP models are primarily differentiated in terms of their underlying recommendation for dealing with probabilities. On the one hand, the common recommendation by Kouvelis and Yu (1997) allows robust location decisions in the complete absence of probabilities (Baron et al. 2011, Bello et al. 2011, Li et al. 2020). On the other hand, the less applied recommendation by Mulvey et al. (1995) necessarily requires probabilities to make robust location decisions (e.g., Parizi et al. 2018). Robust FLP models are secondarily differentiated based on two risk-averse rules for *decision making under uncertainty*. The rarely applied *minimax* rule recommends robust location decisions exclusively based on a worst-case consideration, which implies an extreme risk aversion (such FLP models are barely known). The commonly applied *minimax regret* rule for making robust location decisions differentially reflects risk aversion depending on the DM's needs (Daskin et al. 1997, Chen and Lin 1998, Averbakh and Berman 2003, Averbakh 2005, Conde 2007, Puerto et al. 2008, Baron et al. 2011, Bello et al. 2011, Berman and Wang 2011, Wang 2014, Higashikawa et al. 2015, Marques and Dias 2015, Parizi et al. 2018, Arumugan et al. 2019, Li et al. 2020, Baldomero-Naranjo et al. 2021). Using the minimax regret in its *absolute* or *relative* form, the degree of risk aversion can be increased or decreased, respectively. Beyond FLPs, the minimax regret is a common decision-making rule under uncertainty (see Aissi et al. (2009) for a literature review).

As the general fitting, robust optimization seems most promising for the further development of the deterministic model of Kik et al. (2022) to deal appropriately with uncertainties concerning municipal location developments. This is for two reasons. First, contrary to stochastic optimization, robust optimization allows planning detached from probabilities, which are hard to specify in the RFLDP context. Here the recommendation by Kouvelis and Yu (1997) is particularly suitable. Second, robust optimization allows a differentiated handling with risk aversion of strategic decision makers and thus avoids hyperconservative location decisions due to extreme risk aversion. This can only be achieved by applying the minimax regret rule for decision making in the RFLDP under uncertainty.

Robust Decision Support Framework

Our robust RFLDP decision support framework consists of two interplaying components. The components are a quantitative planning approach to determine a robust location configuration and a guideline for the structured acquisition of the data required for planning.

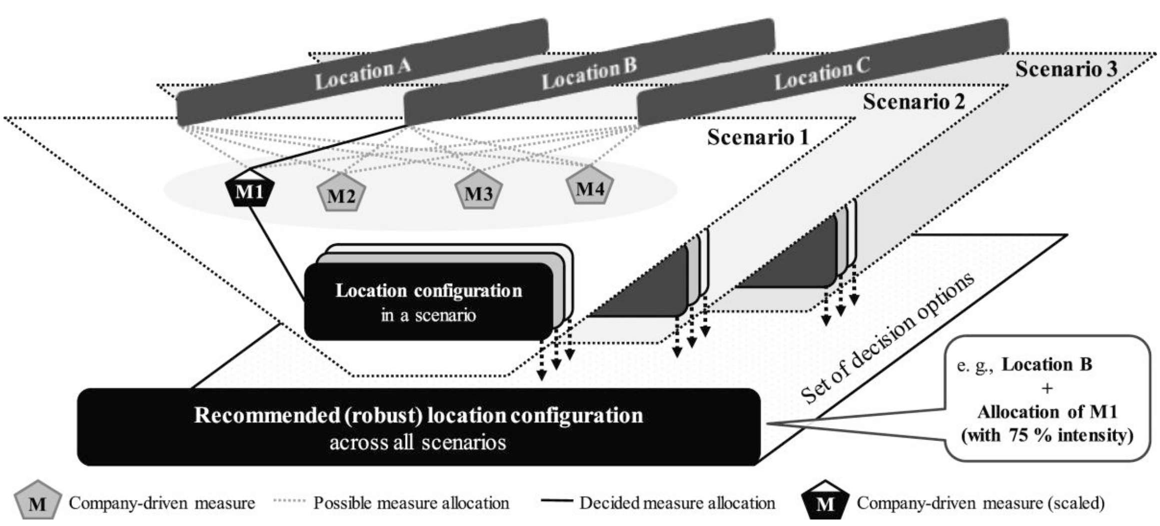
Quantitative Planning Approach

To determine a robust location configuration for a certain RFLDP, we use two different optimization models in a consecutive way. These are first a *scenario-based deterministic model* and second a robust model. In the following, we give a conceptual description of the two-step optimization on which our developed quantitative planning approach is based. In Appendix A, we describe the technical details and mathematical formulations of both models. For the conceptual description, we consider a simplified RFLDP decision situation (Figure 3).

In the first step, we solve the scenario-based deterministic model to design location configurations in different deterministic baseline scenarios. As a result, we create the database required for robust planning. The model is based on the weighted goal programming (WGP), which is an established multiobjective decision-making (MODM) algorithm (see Jones and Tamiz (2010) for technical details). Scenarios are the main input to our model, which we use to describe possible future realization paths for uncertain municipal location developments. For each scenario, a location configuration is designed for each potential location by allocating an optimal bundle of individually scaled company-driven measures. In doing so, we (implicitly) define a finite set of decision options and generate relevant data (i.e., location configuration–specific regret values) required for our robust planning. We choose a MODM-based modeling path because of the continuous nature of location development decisions. Our MODM-based modeling has two major advantages over an alternative modeling using multiattribute decision-making (MADM) approaches (e.g., multiattribute utility theory (MAUT), analytic hierarchy process (AHP), analytic network process (ANP), preference ranking organization method for enrichment evaluations (PROMETHEE), or élimination et choix traduisant la realité (ELECTRE)). First, MODM supports not only discrete decisions on location selections but also continuous decisions on location developments in terms of scaling company-driven measures. Second, with a MODM-based modeling, we reduce the complexity of planning in the RFLDP by avoiding unnecessary deep combinatorics in the decision making. Because MADM only allows a discrete consideration of location developments, the planning would be overcomplicated for the following reason. DMs would have to (explicitly) define location configurations or decision options themselves. For this, they would have to anticipate possible combinations of potential locations and bundles of company-driven measures having different intensities (0%–100%). In real-life RFLDPs, multiple locations and measures are usually considered, which makes the number of combinations unmanageable for DMs. Overall, compared with MADM, MODM enables a more realistic representation of the *RFLDP setting*.

In the second step, we solve the robust model to identify a robust location configuration. This is characterized by being the most insensitive (and thus recommended) decision option to all conceivable realizations of uncertain municipal location developments across the scenarios. We adapt the model following the recommendation by Kouvelis and Yu (1997) for robust optimization and use minimax regret rules for two reasons. First, the recommendation makes our robust planning possible without hard-to-specify probabilities. Second, the minimax regret rules allow us to consider risk aversion of strategic DMs in a differentiated way in our planning.

Figure 3. Two-Step Optimization to Determine a Robust Location Configuration for a RFLDP (Simplified)



Notes. In the simplified decision situation, there are three potential locations (A–C). For each location, we determine an optimal bundle of potential company-driven measures (M1–M4) for location development. Each bundle is determined by allocating the measures to the respective locations. The intensity of each allocated measure is scaled individually to ensure a targeted development of a location. Per location, an optimal measures bundle is identified in each scenario (1–3). In this example, nine location configurations or decision options (3 locations × 3 scenarios) are defined, whereof the robust is recommended.

As a result of our two-step optimization, we derive recommendations for robust decisions on location selection and development. Our developed approach extends the deterministic planning of Kik et al. (2022) by supporting robust decision making in location planning and development in a conceptional nexus that does not yet exist in the FLP literature. A meaningful implementation of our approach in real life places high requirements on the quantity and quality of the required data.

Guideline

To meet the data-related requirements, we use a guideline to enable companies a structured acquisition of the data required for robust planning. It is based on a guideline for deterministic RFLDPs that is provided by Kik et al. (2022) and includes practical instructions on how to effectively collect and operationalize data. In this paper, the original guideline is further developed to deal with uncertainties in the RFLDP of the considered SME. In Figure 4, we sketch a conceptual frame and structure our guideline in three areas ((a)–(c)). In each area, we answer one of three common questions companies ask when faced with the challenging data situation in RFLDPs:

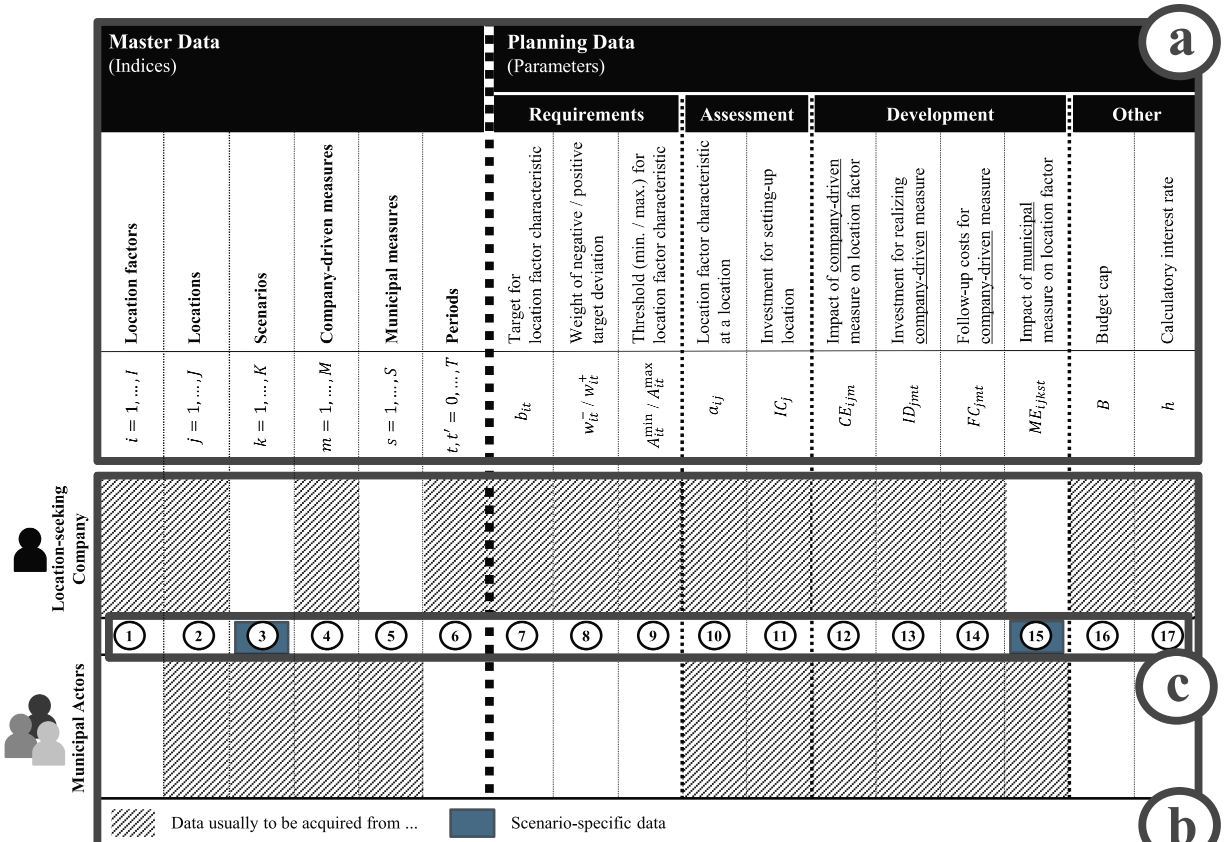
(1) Which data are required for robust planning? (Answered in area (a))

(2) Where can the data be acquired? (Answered in area (b))

(3) How can the data be collected and operationalized in a structured way? (Answered in area (c))

The original guideline is extended by instructions (3) and (15) to acquire scenario-specific data. Instruction (3) allows companies to generate meaningful K scenarios to describe uncertain municipal location developments. To determine a finite set of scenarios K, companies usually need to inquire at MAs. For a systematic scenario generation, we recommend using well-known scenario techniques (Owen 1999, Lindgren and Bandhold 2002, Wright and Cairns 2011, Schwenker and Wulf 2013). Instruction (15) allows companies to meaningfully parametrize potential *effectiveness of municipal location development measures for a scenario* (ME_{ijkst}). We advise companies to roughly estimate the specifications of the parameters ME_{ijkst} because a hyperaccurate data collection is very

Figure 4. (Color online) Conceptual Frame of Our Guideline for the Structural Acquisition of Data (According to Kik et al. 2022)



Notes. In area (a), we give a compact overview of the relevant data and differentiate between master (indices) and planning (parameters) data. We divide the latter into location requirements, assessment, development-related data, and other data. In area (b), we show three ways to acquire data. Some data are only available company-internal, on request at MAs, or both (see gray hatchings). In area (c), we refer to our instructions (1–17) for the collection and operationalization of data.

time-consuming and further subject to uncertainties. Several rough estimates can cover the widest range of conceivable parameter values, which is sufficient and more reasonable for our scenario-based strategic planning.

For the other 15 instructions, we refer to Kik et al. (2022). By applying our guideline to the SME's RFLDP, we can bridge the CEO's information gap through a well-structured data acquisition (see *Guideline Application (First Phase)* section). Thus, we ensure that the data requirements of the models are met and that our planning approach is effectively implementable in real life.

Planning Accompaniment Workflow

The workflow of our planning accompaniment of the SME was divided into three main phases (Figure 5). We organized four meetings with the CEO and the representatives of the BPA. For the CEO, the participation took a total of about six hours, which is quite reasonable for strategic planning.

In the *first phase*, we applied our guideline to acquire data. We first collected the master data (first meeting) and then the planning data (second meeting). Afterward, the data were operationalized. We checked the created database for plausibility together with the CEO and the BPA and made adaptations if necessary (third meeting). In the *second phase*, we applied our quantitative planning approach to compute results. In the *third phase*, we analyzed the results in interaction with the CEO (fourth meeting). In a discussion-based framing process, we narrowed down his location requirements in a stepwise manner. After each step, the impact on the decision recommendation was analyzed. Once the CEO's requirements and constraints were fully integrated, he understood our final recommendation for robust decisions and trusted it. As part of the discussions, we also jointly analyzed relevant levers for developing given conditions of potential locations.

In the next sections, we explain for each phase how we proceeded, what challenges we overcame, and what we achieved.

Guideline Application (First Phase)

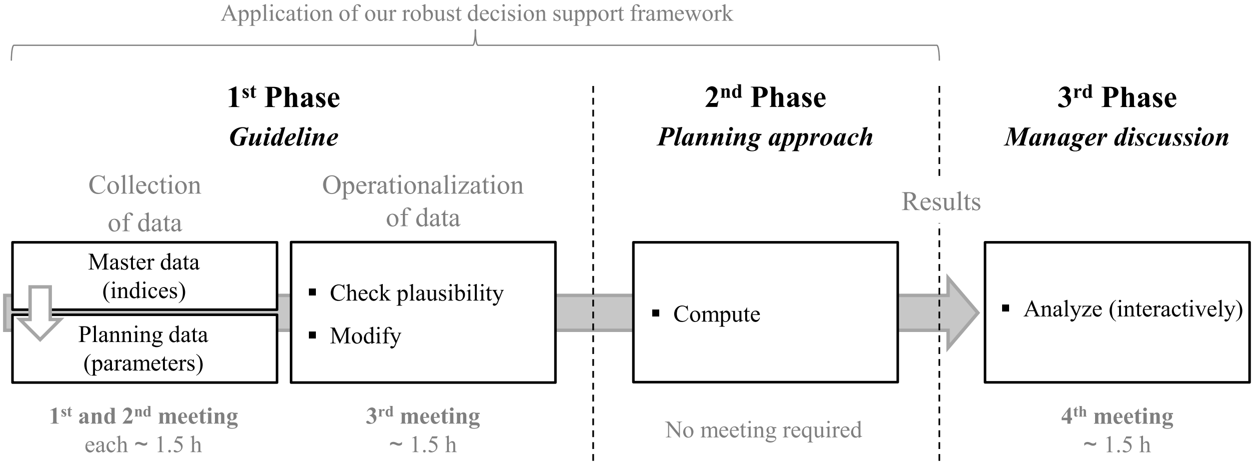
To structurally collect the required data, we applied our further developed guideline. Based on its conceptual frame (see *Guideline* section), we interviewed the managers along the three guiding questions in two meetings. Herein, both the CEO and BPA were asked predefined and spontaneous questions. By operationalizing and jointly checking the data, we created the database required to implement our planning approach and closed the CEO's information gap in his RFLDP. In the next section, we present the master data and planning data used for our planning.

Master Data

We considered $I = 17$ location factors to assess $J = 11$ locations. For a proactive location development, the CEO intended $M = 1$ company-driven measure for *developing charging stations* ($m = 1$) for the SME's battery electric vehicle fleet. We considered $S = 13$ municipal measures for location development, seven of which are likely to be realized in the future. For six municipal measures, no definite plans by MAs are known, but the BPA considers them conceivable in the future. Uncertainties regarding the realizations of municipal measures were described in $K = 5$ scenarios (see *Scenario Generation*). Finally, a five-year planning horizon with $T = 3$ *periods* was considered for the SME's strategic location selection and development.

In the operationalization of master data, qualitative (i.e., not directly measurable) location factors had to be quantified. For this purpose, we adapted a four-level maturity scale (level "4" is the best possible characteristic). The levels were specified together with the CEO and

Figure 5. Our Three-Phase Workflow for the Planning Accompaniment of the SME in its RFLDP Under Uncertainty



the BPA. Taking the location factor *visibility* ($i = 5$) as an example, we differentiated locations based on whether they are localized at a (4) highly frequented inner- or outer-city main street, (3) main access street, (2) access street (e.g., dead-end road), or (1) low-frequented public street.

Planning Data

With the acquired planning data, we formalized the CEO's location requirements, the location assessment, the location development, and the main peripherals of the SME's RFLDP.

The CEO specified his location requirements by setting for each location factor a *targeted characteristic* (b_{it}) and a *weight* (w_{it}^- / w_{it}^+) representing its importance. Furthermore, the CEO defined *thresholds* ($A_{it}^{\min} / A_{it}^{\max}$) for certain factors whose characteristics must not fall below or exceed a certain level. The CEO stated that the requirements will remain constant in the next five years. An exception is the target (b_{it}) for the *charging infrastructure* ($i = 16$). In the future (period t_1), the CEO will need five instead of initially four charging stations. Most requirements were easily specified by the CEO. Some data were obtained from open sources, such as realistic targets for *business tax* ($i = 3$). In specifying weights, the CEO struggled to assess each location factor's importance, given their multitude. To support him, we provided strategies for both an intuitive and an AHP-like weighting using pairwise comparisons. All operationalized targets, weights, and thresholds are given in Table B.1 (Appendix B).

For location assessment, we considered the *characteristics of locations* (a_{ij}) regarding the location factors and the *setup investment per location* (IC_j). The parameters had to be specified systematically. On the one hand, we lacked relevant data. To specify a_{ij}, we acquired most data by structured searches on public platforms (e.g., online map services). Data not publicly available were provided by the BPA. To specify IC_j, we elicited the SME's setup plans for the new location and estimated the expected investments per location. The plan was to set up an office building and a warehouse. On the other hand, we could not directly compare the characteristics of the location factors (a_{ij}), owing to their quite different units. To ensure comparability and thus a consistent location assessment, we normalized the parameters a_{ij} with location factor–specific constants N_i. The summation normalization technique was used to compute the constants because it is suitable in case of high-level incomparability and is computationally robust (Tamiz et al. 1998, Jones and Tamiz 2010). The operationalized characteristics of all potential 11 locations are given in Table B.2 (Appendix B).

For location development, we considered the effectiveness of company-driven and municipal development measures on location factor characteristics (CE_{ijm} / ME_{ijkst}). We also considered the investments (ID_{jmt}) and follow-up costs (FC_{jmt}) associated with the realizations of company-driven measures. We set the effectiveness of the SME's measure developing charging stations ($m = 1$) equal to the CEO's future target for charging infrastructure ($i = 16$). Accordingly, we considered that $m = 1$ can improve the characteristic of factor $i = 16$ by up to "+5 charging stations" at a location, if allocated to it. The development of five stations would have required an investment of €15,000 (ID_{jmt}) and would have incurred follow-up costs of €2,083 (FC_{jmt}) per period (specifications based on NPM (2020)). The realizations of the considered $S = 13$ municipal measures were planned at different times over the next five years. We were aware that some of them will affect several location factors and not necessarily to the CEO's satisfaction. This is to be illustrated by the example of location $j = 7$. There, the *bus stop elimination* ($s = 4$) will negatively affect both the *train station accessibility* ($i = 12$) and the *public transit accessibility* ($i = 13$) in the future (t_2). By contrast, the *highway construction* ($s = 3$) will improve the *highway proximity* ($i = 10$) and the *customer accessibility* ($i = 15$) there in the future (t_2). The operationalized effectiveness of location measures on decision-relevant location factors are given in Table B.3 (Appendix B).

As the RFLDP's main peripherals, we considered the SME's budget cap (B) of €250,000 and a calculatory interest rate (h) of 8% per year. The latter is used to discount future payments associated with realizations of location development measures taken by the SME.

Scenario Generation

We generated $K = 5$ scenarios to describe the uncertainty associated with the $S = 13$ municipal location development measures as company-external input to our planning. The scenarios were future visions of the potential locations' conditions, each of which may possibly result from a specific municipal development path. The paths included scenario-specific effectiveness of municipal measures (ME_{ijkst}) and differed in their contribution to the CEO's long-term location satisfaction. We generated the scenarios jointly with the SME and the BPA. This was done in a mind experiment–like scenario design that aimed to cover the widest possible spectrum of conceivable municipal measures and their effectiveness. We abstained from estimating probabilities for the occurrence of the respective scenarios. Reliable estimates were not possible to make.

Our $K = 5$ scenarios were one basic, two extreme, and two moderate scenarios. In the *basic scenario* ($k = 1$), we considered seven municipal measures that are likely to be realized in future and their effectiveness (see *Location Development* in Appendix B). We call it the baseline development path. Each of the following alternate development paths is a variation of the baseline path because of conceivable (positive or negative) occurrences in the planning horizon.

As extreme scenarios, we considered a worst case and best case. In the *worst-case scenario* ($k = 2$), we reduced the set of municipal measures to four measures, each of which negatively affects certain location factor characteristics and thus the CEO's location satisfaction. In $k = 2$, the major (negative) occurrence is the nonrealization of highway construction ($s = 3$), which would normally have a positive effect on the conditions of several locations in t_2. Further conceivable (negative) occurrences were the *increase of business tax* ($s = 8$), *increase of property tax* ($s = 9$), and *migration branch representation* ($s = 10$). In the *best-case scenario* ($k = 3$), by contrast, we reduced the set of municipal measures to nine measures, each of which positively affects certain location factor characteristics and the location satisfaction of the CEO. As a major (positive) occurrence, we considered a significantly earlier realization of the highway construction ($s = 3$) in t_0. Further conceivable (positive) occurrences were the *setup public bus stop* ($s = 11$), *decrease business tax* ($s = 12$), and *decrease property tax* ($s = 13$).

As moderate scenarios, we regarded a semiworst case and semibest case. As in the basic scenario ($k = 1$), we also considered the seven municipal measures that are likely to be realized in future. Of these, the focus was exclusively on the highway construction ($s = 3$), for whose realization we described alternative paths in the moderate scenarios. In the *semi–worst-case scenario* ($k = 4$), the major (negative) occurrence was a delayed realization of $s = 3$ at an unspecified time beyond the planning horizon. In the *semi–best-case scenario* ($k = 5$), we considered a slight earlier realization of $s = 3$ in t_1 as the major (positive) occurrence.

We used the generated scenarios as an essential input for our quantitative planning approach.

Planning Approach Application (Second Phase)

To derive recommendations for decisions on the location selection and development for the SME, we implemented our quantitative planning approach in the optimization software AIMMS. We used the GUROBI 9.1 solver to solve our two optimization models sequentially and to generate results. This was done on a computer with a 2.7-GHz CPU and 16 GB RAM. In the following, we go into first our deterministic and then our scenario-based robust results.

Deterministic Results

We initially generated results with the deterministic RFLDP model of Kik et al. (2022). This was done in two distinct (deterministic) planning settings—first in the RFLDP setting that (mostly) coincides with the SME's real-life planning extent. Thus, company-driven and municipal location developments over time are considered, but uncertainties regarding the latter are neglected. Second was in the *conventional setting*, in which any location developments are neglected. For this, the RFLDP model's extent is reduced to fit the usually covered planning extent of existing FLP models in literature. The RFLDP setting includes 4,005 constraints, 1,760 variables (11 of them integers), and 6,488 nonzeros. Our computer took 0.02 seconds to determine the optimal location configuration. The problem instance of the setting differs slightly and is thus not explicitly indicated here. The results per setting are given in Table 1.

In view of the results, the decision recommendations differ between the settings. This holds for the location selection. In the RFLDP setting, the selection of location 3 is recommended, whereas in the conventional setting, it is location 1. Thus, the systematic anticipation of location developments yields alternate decisions compared with common FLP decision making. We anticipated the future municipal measure highway construction ($s = 3$) considerably improving the conditions of location 3. It proves to be superior to location 1 from a long-term perspective. The results show that location developments were decisive in the SME's RFLDP, and a systematic consideration of these strongly affected the recommended location selection.

Robust Results

To generate robust results given the uncertainty in the RFLDP, we applied our quantitative planning approach introduced in this paper. Considering all $K = 5$ scenarios,

Table 1. Our Results in Two Distinct Deterministic Planning Settings: RFLDP vs. Conventional

		Location development			
			Allocation period and intensity		
Setting	Location selection	Company-driven measure	t_0	t_1	t_2
RFLDP	$j = 3$	Developing charging stations ($m = 1$)	80%	20%	—
Conventional	$j = 1$	—	—	—	—

Notes. In the RFLDP setting, we derived decision recommendations for both the selection and development of a location. For the optimal location development, we generated a measure plan for the SME. It includes the recommendation to allocate the company-driven measure $m = 1$ to location $j = 3$ in the periods t_0 and t_1 and to scale its intensity by 80% and 20%, respectively. Following our recommendation would result in setting up five charging stations at $j = 3$ over time and thus fulfill the SME's targets regarding charging infrastructure ($i = 16$). In the conventional setting, by contrast, we only derived a location selection recommendation. "Not applicable" is indicated by a dash (—).

the planning setting of the RFLDP under uncertainty contains 8,647 constraints, 5,952 variables (11 of them integers), and 14,008 nonzeros. The problem instances differ slightly between the scenarios. Our computer took 0.16 seconds to determine a robust location configuration. The scenario-based deterministic model is solved exactly once per location-scenario-combination (see *Mathematical Formulation* in Appendix A). Therefore, the fully enumerative solving of the model results in a larger problem instance, compared with the *deterministic RFLDP setting* (see *Deterministic Results*). We compare the results in both RFLDP settings in Table 2.

Given the results, structural differences regarding the decision recommendations for location selection are observed between both settings. In the setting of RFLDP under uncertainty, location 4 is recommended, in contrast to location 3 in the deterministic RFLDP setting. Hence, our additional robustness analysis in location planning and development yields alternate location decisions compared with those resulting from a mere deterministic planning. The deterministic planning ignores the fact that location 3 is only recommendable (or optimal) if a certain one of the five scenarios occurs. In the four other scenarios, location 3 proves to be unfavorable. We consider this in our robust planning and alternatively recommend location 4, which is robust and performs best across all scenarios. For three of five scenarios (including the worst case), location 4 is actually optimal (see Appendix C).

Consequently, we hold that uncertainties associated with the realizations of municipal measures for location development must be considered in the RFLDP planning in a proper way. This allows us to give the SME's CEO robust (and more adequate) decision recommendations.

Management Discussion (Third Phase)

We enriched our final management discussion by two means. First, we involved the DM's human factor into the planning process. Thus, we interacted with the CEO in his decision making when reporting and jointly analyzing our results for sensitivity. Second, we incorporated a manager-friendly visualization of our results. Here, we jointly identified and discussed promising levers for the further development of potential locations. In the next section, we describe both used means in more detail.

Interactive Decision Making

The process of our interactive results report and analysis was as follows. Our starting point (SP) was the simplest planning setting, which comprised the minimum data required to run our planning approach. Here, we considered as master data location factors i and locations j, and we considered actual characteristics of locations (a_{ij}) as planning data. Proceeding from the SP, we gradually added further data in five steps. We demonstrated the implications of each data on the decision recommendations to the CEO. In doing so, we increased his awareness and allowed him to respecify initial data (if necessary) based on the gained knowledge (Figure 6).

First, we added targets (b_{it}) per location factor. We considered those initially set by the CEO as one "target strategy." In addition, we included two alternate strategies (with a stricter or more convenient setting of targets). The strategies led to the same decision recommendation ("select location $j = 1$"), and thus, the CEO decided against a respecification of initial targets.

Second, we added weights (w_{it}^{+}/w_{it}^{-}) per location factor. We considered two "weighting strategies" based on intuition or pairwise comparisons, which we proposed earlier to the CEO. The decision recommendation ("select location $j = 1$") remained unchanged. Thus, the CEO retained the intuitive weighting strategy, which he said better reflected his preferences.

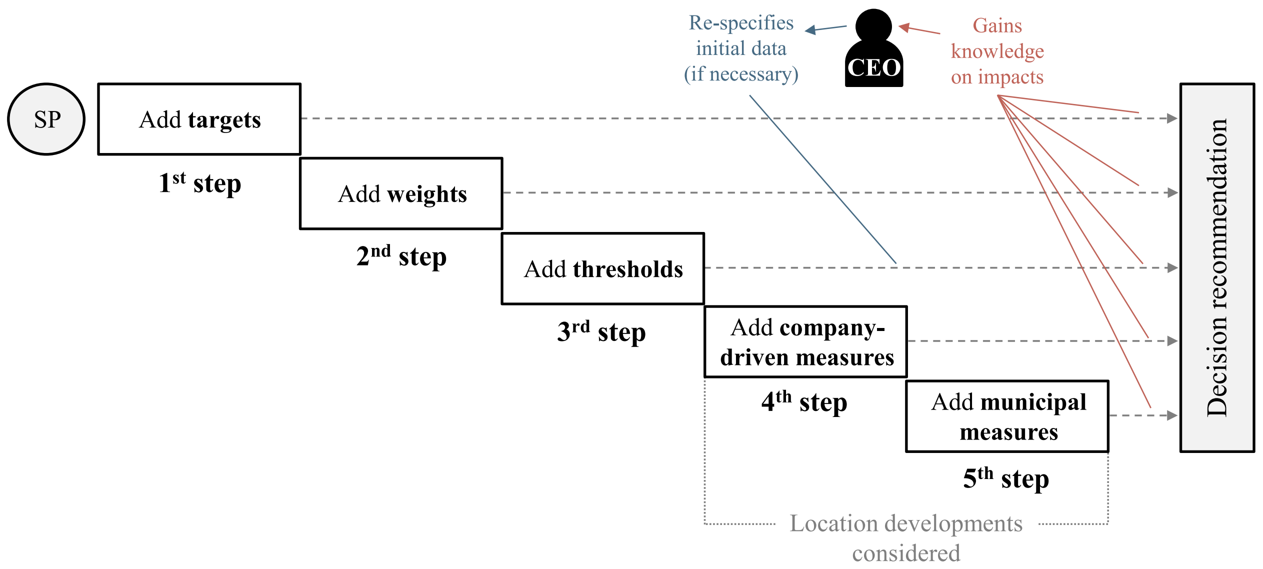
Third, we added thresholds ($A_{it}^{\min}/A_{it}^{\max}$) per location factor. We found that some of the CEO's initial thresholds were set too strict, given the potential locations' conditions. Consequently, most of the locations were excluded, as they fell below and/or exceeded certain thresholds. Nevertheless, the decision recommendation ("select location $j = 1$") remained unchanged. Having gained this knowledge, the CEO decided to soften some of his initial thresholds to avoid such hasty exclusion of potentially relevant decision options for the SME.

Table 2. Our Results in Two Distinct RFLDP Settings: Planning Under Uncertainty vs. Deterministic Planning

		Location development			
			Allocation period and intensity		
RFLDP setting	Location selection	Company-driven measure	t_0	t_1	t_2
Uncertainty	$j = 4$	Developing charging stations ($m = 1$)	80%	20%	—
Deterministic	$j = 3$	Developing charging stations ($m = 1$)	80%	20%	—

Notes. Although the recommended location selection differs between the settings, the respective recommended measure plans for the optimal company-driven location development are structurally identical for two reasons. First, the locations recommended for selection in each setting have identical initial characteristics regarding the charging infrastructure ($i = 16$). Second, the characteristics are not affected by municipal developments at either location in scenario. The result in the RFLDP under uncertainty is based on the scenario-specific regrets of the respective location configurations (see Table C.2 in Appendix C), which we designed by means of our planning approach. The results in the deterministic RFLDP setting are adopted unchanged from the prior subsection. "Not applicable" is indicated by a dash (—).

Figure 6. (Color online) Our Results Report and Analysis by Interacting with the CEO in Decision Making in Five Steps



Fourth, we added the CEO's company-driven location development measure developing charging stations ($m = 1$) and its effectiveness on location factor characteristics (CE_{ijm}). With the allocation and targeted scaling of $m = 1$, the decision recommendation ("select location $j = 1$") did not change. From here on, we refer to location configuration $j' = 1$ as the recommended decision option. The CEO decided to stick to our proposed measure plan.

Fifth, we finally added the municipal location development measures and their (scenario-specific) effectiveness on location factor characteristics (ME_{ijkst}). We conducted our analysis to cope with the uncertainties associated with municipal location developments. This resulted in an alternate decision recommendation that differed structurally from the previous one. The recommended decision option was the robust location configuration $j' = 4$. However, if the CEO had not respecified his initial thresholds on our advice, the decision option $j' = 4$ would have been hastily excluded and thus not recommended in the absence of our interaction.

Overall, the interactive process made our results traceable and acceptable to the CEO.

Location Development Levers

Beyond our decision recommendation ($j' = 4$), we identified and discussed further levers for location development jointly with the SME and the BPA. In this context, we investigated whether and to what extent the conditions of nonoptimal locations are further developable toward the location conditions identified as best as possible (i.e., optimal) in our analysis. For this, we focused on the basic scenario ($k = 3$) and assumed that it described the most conceivable path of realizing municipal location developments.

To identify concrete development levers, we started by making the SME and the BPA aware of the needs for action at the potential locations. To this end, we used two visual means. First, we adapted a *traffic light system* for an OFV-based ranking of the designed location configurations to visually differentiate between their qualities. Second, we used *radar charts* to visualize the real-life deviations related to certain location configurations from the CEO's targets and thus restored the meaning of the OFVs for practice (Figure 7).

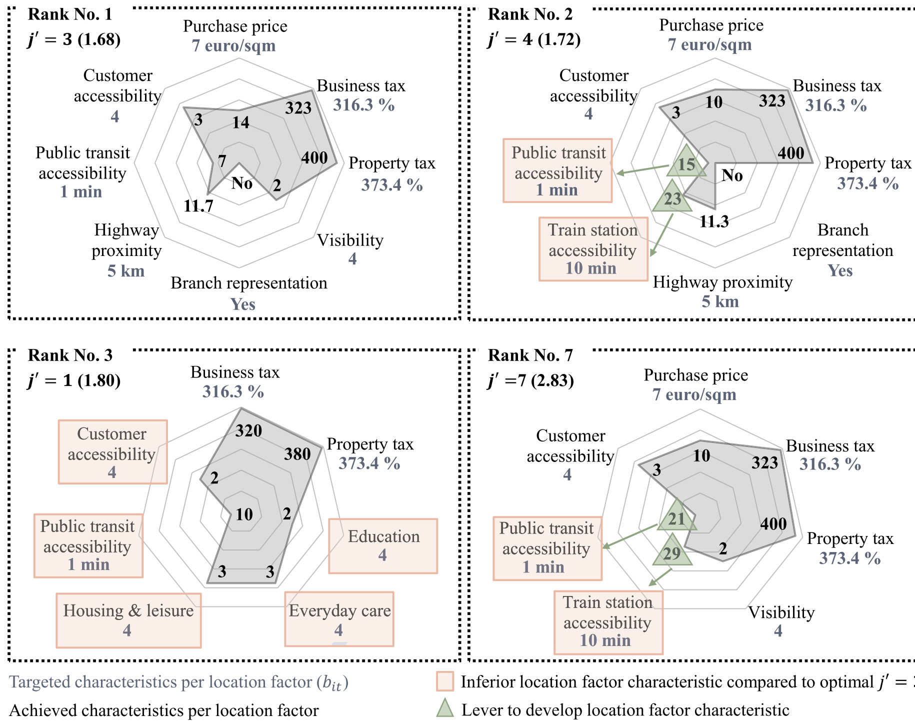
For the next procedure, we focused on four location configurations in our ranking. We considered three promising configurations, $j' = 3$, $j' = 4$, and $j' = 1$, which we considered "equally good," as their OFVs differed slightly. We also considered the less promising configuration $j' = 7$, which was the intuitively favored option by the CEO.

With the help of our radar charts—for example, in two of the four location configurations—we achieved a key finding. In case of the intuitively favored configuration ($j' = 7$), we detected high (undesired) target deviations regarding train station accessibility ($i = 12$) and public transit accessibility ($i = 13$). Compared with the first-ranked configuration ($j' = 3$), $j' = 7$ was clearly inferior regarding the long-term characteristics of the factors $i = 12$ and $i = 13$. This was also true for location configuration $j' = 4$, which we identified as robust (see Robust Results).

Once we revealed the weaknesses and needs for action at certain locations, we identified concrete development levers to enhance some of their inferior characteristics in a targeted way. For both location configurations $j' = 4$ and $j' = 7$, we identified the municipal measure setup public bus stop ($s = 10$) as the central lever for enhancing

Figure 7. (Color online) Traffic Light–Based Location Configuration Ranking and Visualization of Target Deviations in Radar Charts

Rank No.	Location configuration (OFV)	Traffic light (OFV–OFV)
1	**$j' = 3$ (1.68)**	0–2.22
2	**$j' = 4$ (1.72)**	
3	**$j' = 1$ (1.80)**	
4	$j' = 5$ (2.24)	2.23–4.44
5	$j' = 6$ (2.26)	
6	$j' = 2$ (2.41)	
7	**$j' = 7$ (2.83)**	
8	$j' = 8$ (2.84)	
9	$j' = 9$ (3.41)	
10	$j' = 10$ (3.90)	
11	$j' = 11$ (6.66)	4.45–6.66



Notes. (1) Traffic light–based ranking: The location configurations j' were ranked by an ascending sorting of their OFVs. Based on the traffic light system, we visually classified j' as either promising, less promising, or not recommendable at all. (2) Radar charts: Each chart's outer edge represented the CEO's targets (b_{it}) per location factor. Thus, the closer the achieved characteristic of a location factor was to it, the better. All location factor characteristics shown were after location development (optimization). Only those location factors were shown whose characteristics (undesirably) deviated from the respective b_{it}. With rectangles, we marked for the nonoptimal j' (1, 4, 7) with respect to which location factors had inferior characteristics compared with the optimal j' (1). The triangles marked the levers for a targeted development of location factor characteristics toward the outer edge of a chart or to achieve the respective b_{it}.

the train station accessibility ($i = 12$) as well as the public transit accessibility ($i = 13$). If $s = 10$ is realized by MAs in future, this would have the following implications on both location configurations. The configuration $j' = 4$ would achieve the minimum OFV (0.89) and would move up in the ranking from no. 2 to no. 1, with a clear lead over configuration $j' = 3$ (whose OFV 1.68 would remain unchanged), which would fall from no. 1 to no. 2 in the ranking. The intuitively favored configuration $j' = 7$ would achieve a lower OFV (2.14) than before (2.83) and would rank up from no. 7 to no. 4.

When asking the responsible MAs, we found out that a setup public bus stop ($s = 10$) is currently not planned for location development. However, they stated that $s = 10$ could be realized in the future if there are concrete company needs. The identified location development levers showed two promising opportunities. On the one hand, the CEO could make use of the gained knowledge to influence the municipal measures planning for location development purposefully and in his favor in negotiations with relevant MAs. On the other hand, the BPA could communicate the identified needs for action and levers purposefully to the responsible MAs, who could thus proactively approach the SME and acquire it for their location(s).

Finally, we note that location configuration ($j' = 11$), ranked last, included the current location of the headquarters of the SME. Thus, our results underline the need for relocation.

Benefits

For both the SME and the BPA, we achieved quantitative (measurable) and qualitative (not measurable) benefits through our planning accompaniment described in the sections before.

On behalf of the SME, the quantitative benefit is an alternate decision recommendation, which we derived by means of our planning approach. We proved that the decision we recommend not only is structurally different compared with the decision option intuitively favored by the CEO but also measured superior, as we compared their respective OFVs. Furthermore, we showed that our recommended location configuration is robust against uncertain municipal location developments compared with other potential location configurations. Our numerical results allowed the CEO to get rid of his (misleading) intuition in his location decision making.

There are three qualitative benefits for the SME. First, the CEO benefits from an improved decision-making process, which we structured effectively and transparently. Especially, we strongly enriched the phases of data acquisition and results reporting or analysis by suggesting our guideline-based procedure in interaction with the CEO as DM. Second, the CEO profits from a well-founded and transparent basis for company-internal and company-external communications. For example, the CEO could use the results prepared by us to comprehensibly explain his location decision to the SME's staff or to purposefully negotiate with MAs about potential locations. Third, the CEO benefits from avoiding a blinders effect in decision making because we fostered an exploratory location analysis. When there are many data to be considered for a decision, DMs often intuitively narrow to a very few of many decision options. The CEO also tended to do so before asking us for support. Without our support, the CEO would have hastily ruled out the robust location configuration we recommended.

For the BPA, the quantitative benefit is the disclosure of objective location-specific weaknesses within the region for which it is responsible. In addition, the BPA profits from the gained knowledge about promising location development levers to eliminate these weaknesses.

There are two qualitative benefits for the BPA. First, the BPA gained a deep understanding on the specific location requirements of the SME. We succeeded in forging a close relationship between the BPA and the SME, which is a solid base for the CEO's long-term commitment to the region. Second, the BPA sees huge potential in the use of our decision support framework on its own. Consulting with companies to identify suitable locations is the BPA's (or usually a BPA's common) core task. However, the consultations are often based on individual experiences and intuitions of the BPA's staff. The BPA stated that our procedure coincides with the common consulting process, and thus, our method would enrich the consulting services by transparency, systematics, and replicability of location recommendations for companies.

Success Factors

We elaborate four success factors for effective and meaningful real-life implementations of our planning workflow. These are prerequisites that applying companies must fulfill.

First, an *open-mindedness* of DMs from the initiation of planning to closing is needed. Location decisions are made by managers who must be receptive to our proposed method. They need to be the driving forces throughout the implementation of our planning workflow and shall transfer their attitude top-down to the staff involved in planning. Especially, managers must be convinced of our method's practical value added. To create conviction and to foster openness, we refer to our successful real-life case studies in this work and the work by Kik et al. (2022).

Second, *organizational prerequisites* must be created to successfully implement our planning workflow. The management must nominate someone for the responsibility of coordinating the planning workflow, from data acquisition to presentation of results. This can be either an individual, a project team, or a department with at least two individuals. The location project's extent must be considered when sizing the responsibility. For example, cross-regional location searches can be very effortful and likely demand the effort of multiple individuals. Managers shall keep in mind that either way, location planning is usually very time-consuming and takes months, so that appropriate people and time capacities are arranged in time.

Third, *technical prerequisites* must be created to use our quantitative planning approaches (or optimization). Thus far, we run and solve our models by means of license-bound software, which companies need to purchase. Once installed, the model files are directly usable and can be shared. We note that license costs can be avoided because the models can also be migrated to open-source software (e.g., the Python-based optimization software "Pyomo") and run. The associated effort is moderate, presuming that basic programming skills are available.

Fourth, the decision making at the end of the workflow must be *iterative* and *in dialogue* with managers. We showed that the inclusion of the human factor in planning can considerably improve its outcome when DMs are actively involved in the stepwise finding of the best solution. In each iteration of this dialogue, managers need to be made aware of critical implications of restrictions and parameters on the recommended solution. This step-by-step decision-making process is of great advantage, as the high effort associated with data for location planning can be shrunk. It is not necessary to have many data ready in advance and to specify data hyperaccurately, which may not have a critical impact on the solution.

External experts or consultants can alternatively support and coordinate the implementation of our planning workflow on a company's management request (such as we did in the SME's case). Nevertheless, the success factors remain and must be fulfilled mostly by externals. Although the support by externals relieves a company, it strongly limits its influence on success factors.

Conclusions

When looking for a new location for his SME's headquarters within a region, the CEO knew about future municipal developments at the locations available for selection. However, the developments' implications on the conditions of the potential locations were quite hard to predict and thus uncertain. We were asked to support the SME's location decision making. To this end, we developed a robust decision support framework. We applied it within a well-structured scientific accompaniment of this regional location planning and development.

The result of our systematic-methodical planning accompaniment was a sound basis for the CEO's decision making. We derived decision recommendations for both the selection of the best suitable location and its targeted development over time. Our recommended decision option proved to be superior to alternate decision options that emerged from the CEO's intuition and conventional FLP models. The recommended decision option's superiority was justified by the fact that it will best contribute to the CEO's long-term satisfaction. Furthermore, it proved to be robust against any conceivable uncertain municipal location developments over time. Overall, we showed that our robust planning has clear advantages over a deterministic planning. With our robust planning, the effort to acquire data increases just slightly, but this is worthwhile for companies because more adequate location decisions can be achieved.

In the closing management discussion of our results, we boosted the CEO's location decision-making process by integrating his human factor and increasing transparency. We interacted with the CEO during the reporting and analysis of our results to make him aware of the planning output's sensitivity and to ensure traceability and acceptance of our decision recommendations. We visualized the results of our planning in a manager-friendly way and thus provided the CEO a useful and transparent basis for both negotiations with MAs about potential locations and his decision making. Through our support of the SME's regional location selection and development, we prevented the SME from making poor decisions by pointing out promising decision options and their implications for the CEO's long-term location satisfaction.

Given the potentials of our developed decision support framework, we see its promising further developments in two directions. On the one hand, we are working on suitable algorithms or adaptations of our optimization models to formalize and enhance our proposed interactive decision making. Here, we focus on the development of a practicable human-machine interface to allow DMs to give intuitive feedback to the system so that the human factor can be best integrated into our OR-based planning. For this purpose, model adaptations toward *interactive goal programming* (see Jones and Tamiz (2010) for technical details) are particularly promising. On the other hand, we are working on adaptations of our decision support framework that will allow fruitful applications by BPAs and MAs to consult location-seeking companies in the future.

Appendix A. Optimization Models

A.1. Notation

In this appendix, we provide the notation of indices, parameters, and variables considered in our optimization models.

We define the indices as follows:

- i Index of location factors, $i = 1, \ldots, I$
- j Index of locations, $j = 1, \ldots, J$ (with location configurations j')
- k Index of scenarios, $k = 1, \ldots, K$
- m Index of company-driven location development measures, $m = 1, \ldots, M$
- s Index of municipal location development measures, $s = 1, \ldots, S$
- t, t' Index of periods, $t, t' = 0, \ldots, T$ (with decision point t_0)

We consider the following parameters:

- a_{ij} Characteristic of factor i at location j (at decision point t_0)
- $A_{it}^{\min}$ Minimum threshold for characteristic of factor i in period t
- $A_{it}^{\max}$ Maximum threshold for characteristic of factor i in period t
- b_{it} Target for characteristic of factor i in period t
- B Company budget cap for the location setup and development
- CE_{ijm} Effectiveness of company-driven measure m on factor i at location j
- d_t Discount rate in period t, with $d_t = (1+h)^{-t}$
- δ_j Maximum regret of location configuration j' across all scenarios k, with
  - $\delta_j^{abs} = \max_{k \in K} u_{jk} - u_k^*$ (absolute regret) or
  - $\delta_j^{rel} = \max_{k \in K} \frac{u_{jk} - u_k^*}{u_{jk}}$ (relative regret)
- FC_{jmt} Follow-up costs for company-driven measure m at location j in period t
- h Calculatory interest rate
- IC_j Investment for the setup of location j
- ID_{jmt} Investment for company-driven measure m at location j in period t
- ME_{ijkst} Effectiveness of municipal measure s on factor i at location j in period t in kth scenario
- u_{jk} OFV of location configuration j' in scenario k
- u_k^* Minimum OFV in scenario k, with $u_k^* = \min_{j \in J} u_{jk}$
- w_{it}^+ Weight of positive deviation from target for factor i in period t
- w_{it}^- Weight of negative deviation from target for factor i in period t

We aim to determine a binary and a continuous decision variable:

- $x_j = \begin{cases} 1, & \text{Binary variable to indicate that location configuration } j' \text{ is selected} \\ 0, & \text{otherwise} \end{cases}$
- y_{mt} Continuous variable for the allocation and dimensioning of company-driven measure m to/at location j in period t

For this purpose, we determine the following auxiliary variables:

- d_{it}^+ Positive deviation from target for factor i in period t
- d_{it}^- Negative deviation from target for factor i in period t
- y'_{mt} Cumulative follow-up costs for company-driven measure m in period t
- ζ Least maximum (i.e., minimax) regret

A.2. Mathematical Formulation

To solve the RFLDP under uncertainty, we first run the scenario-based deterministic model (A) and then the robust model (B). In the following, the mathematical formulations for the optimization models (A) and (B) are given and technically explained in more detail.

A.2.1. (A) Scenario-Based Deterministic Model for Location j^* in Scenario k^*

$$\text{Min} \quad \sum_{i=1}^{I}\sum_{t=0}^{T}(w_{it}^{+}\cdot d_{it}^{+}+w_{it}^{-}\cdot d_{it}^{-}) \tag{A.1}$$

subject to

$$a_{ij^*}+\sum_{t'=0}^{t}\sum_{m=1}^{M}y_{mt'}\cdot CE_{ij^*m} + \sum_{t'=0}^{t}\sum_{s=1}^{S}ME_{ij^*k^*st'}-d_{it}^{+}+d_{it}^{-}=b_{it} \qquad \forall i\in I,\ t\in T. \tag{A.2}$$

$$a_{ij^*}+\sum_{t'=0}^{t}\sum_{m=1}^{M}y_{mt'}\cdot CE_{ij^*m} + \sum_{t'=0}^{t}\sum_{s=1}^{S}ME_{ij^*k^*st'} \geq A_{it}^{\min} \qquad \forall i\in I,\ t\in T. \tag{A.3}$$

$$a_{ij^*}+\sum_{t'=0}^{t}\sum_{m=1}^{M}y_{mt'}\cdot CE_{ij^*m} + \sum_{t'=0}^{t}\sum_{s=1}^{S}ME_{ij^*k^*st'} \leq A_{it}^{\max} \qquad \forall i\in I,\ t\in T. \tag{A.4}$$

$$IC_{j^*}+\sum_{m=1}^{M}\sum_{t=0}^{T}(y_{mt}\cdot ID_{j^*mt})+\sum_{m=1}^{M}\sum_{t=0}^{T}(y'_{mt}\cdot FC_{j^*mt})\cdot d_t\leq B \tag{A.5}$$

$$y'_{mt}\geq\sum_{t'=0}^{t'<t}y_{mt'} \qquad \forall m\in M,\ t\in T. \tag{A.6}$$

$$y_{mt}\in[0,1] \qquad \forall m\in M,\ t\in T. \tag{A.7}$$

$$d_{it}^{+},\ d_{it}^{-},y'_{mt}\geq 0 \qquad \forall i\in I,\ m\in M,\ t\in T. \tag{A.8}$$

A.2.2. (B) Robust Model

$$\text{Min } \zeta \tag{A.9}$$

subject to

$$\zeta\geq\delta_j\cdot x_j \qquad \forall j\in J. \tag{A.10}$$

$$\sum_{j=1}^{J}=x_j \tag{A.11}$$

$$x_j\in\{0,1\} \qquad \forall j\in J. \tag{A.12}$$

$$\zeta\geq 0 \tag{A.13}$$

The scenario-based deterministic model (A) is a reduced version of the deterministic model introduced by Kik et al. (2022). Model (A) is mandatory for generating the required database for the robust planning. For this, model (A) is solved in full $J \times K$ enumeration to determine an optimal company-driven measures plan for several conceivable future patterns. Each pattern is characterized by the predefinition of a location j^* to be selected under the expectation of a scenario k^*. Thus, the $J \times K$ enumeration is characterized by a successive consideration of all conceivable location-scenario combinations. The result is a designed (finite) set of location configurations j' (i.e., decision options) for each scenario k, where each j' achieves a specific OFV u_{jk}. For each k, the optimal j' that achieves the minimum OFV u_k^* is identified. Based on the determined OFVs, a $J \times K$–sized regret matrix is generated for robust planning. The objective function (A.1) aims to minimize the sum of unwanted target deviations over time, which are penalized with preferential weights. Model (A) includes seven types of Constraints (A.2)–(A.8). Constraints (A.2) serve to compute the auxiliary variables d_{it}^{+} and d_{it}^{-} for target deviations regarding location factor i. The targeted characteristics b_{it} are compared with given characteristics of factor i at location j, which change over time owing to realizations of company-driven and uncertain municipal location development measures. Constraints (A.3) and (A.4) ensure that location j will not undercut or exceed a minimum or maximum threshold respecting a critical characteristic of factor i. Constraint (A.5) ensures that the budget cap of a company is not exceeded by the sum of financial expenses for setting up and developing a location j. Constraints (A.6) serve to determine the cumulated follow-up costs that go along with the allocation and dimensioning of company-driven measures m over time. Constraints (A.7) and (A.8) define the value domain of decision and auxiliary variables of model (A).

Based on the $J \times K$ regret matrix, the robust model (B) is solved subsequently. Its Objective Function (A.9) aims to minimize the overall maximum regret ζ in consideration of four types of Constraints (A.10)–(A.13). In conjunction with Constraints (A.10), it is ensured that the value of ζ is equal the least maximum regret, which is specified by the parameter δ_j per location configuration j' across all scenarios k. The parameter δ_j can be determined based on either the absolute (δ_j^{abs}) or relative (δ_j^{rel}) regret rule, which weights unfavorable scenarios differently and thus implies a diverging degree of risk aversion. This allows us to represent a DM's risk aversion in a flexible way. Constraint (A.11) specifies that exactly one location configuration j' is selected. Constraints (A.12) and (A.13) define the value domain of the relevant decision and auxiliary variables of model (B).

We characterize both optimization models (A) and (B) as *mixed-integer linear programs* (MILPs). The models are implemented in the optimization software AIMMS. We use the GUROBI 9.1 solver to solve RFLDP instances relevant to the practice within a few seconds.

Appendix B. Planning Data

B.1. Location Requirements

Table B.1. Location Requirements of the SME's Manager (Targets, Weights, and Thresholds) per Location Factor i

				Weight (w_{it}^-/w_{it}^+)		
i	Location factor	Unit	Target (b_{it})	Intuitive	Pairwise	Threshold ($A_{it}^{\min}/A_{it}^{\max}$)
1	Size	sqm (K)	10	3 (w_{it}^-)	10 (w_{it}^-)	6 ($A_{it}^{\min}$)
2	Purchase price	€/sqm	7	2 (w_{it}^+)	5 (w_{it}^+)	18 ($A_{it}^{\max}$)
3	Business tax	%	316.3	2 (w_{it}^+)	2.5 (w_{it}^+)	—
4	Property tax	%	373.4	2 (w_{it}^+)	3 (w_{it}^+)	—
5	Visibility	Scale 1–4	4	2 (w_{it}^-)	9 (w_{it}^-)	1 ($A_{it}^{\min}$)
6	Branch representation	Binary	Yes	1 (w_{it}^-)	1 (w_{it}^-)	—
7	Education	Scale 1–4	4	1 (w_{it}^-)	4.5 (w_{it}^-)	—
8	Everyday care	Scale 1–4	4	3 (w_{it}^-)	2.5 (w_{it}^-)	—
9	Housing and leisure	Scale 1–4	4	3 (w_{it}^-)	3.5 (w_{it}^-)	—
10	Highway proximity	km	5	3 (w_{it}^+)	10 (w_{it}^+)	25 ($A_{it}^{\max}$)
11	Federal road proximity	km	1	3 (w_{it}^+)	10 (w_{it}^+)	5 ($A_{it}^{\max}$)
12	Train station accessibility	min	10	2 (w_{it}^+)	5 (w_{it}^+)	25 ($A_{it}^{\max}$)
13	Public transit accessibility	min	1	2 (w_{it}^+)	9 (w_{it}^+)	10 ($A_{it}^{\max}$)
14	Employee catchment area	min	20	3 (w_{it}^+)	7 (w_{it}^+)	35 ($A_{it}^{\max}$)
15	Customer accessibility	Scale 1–4	4	3 (w_{it}^-)	6 (w_{it}^-)	—
16	Charging infrastructure	Number of stations	4	1 (w_{it}^-)	6 (w_{it}^-)	—
17	Broadband infrastructure	Mbps	50	1 (w_{it}^-)	6 (w_{it}^-)	—

Notes. The parameter specifications reflect the location requirements (at the decision point t_0), which remain mostly constant over time. The target for charging infrastructure ($i = 16$) tends to increase to five stations in future (in t_1). The weights are given according to both the intuitive strategy (parameters 1–3) and the pairwise comparison strategy (parameters given as percentages, for which the cumulation equals 100%). "Not applicable" is indicated by a dash (—).

B.2. Location Assessment

Table B.2. Characteristics of Locations j per Location Factor i at the Decision Point and Location Setup Investments

			Location										
i/j	Location factor	Unit	1	2	3	4	5	6	7	8	9	10	11
1	Size	sqm (K)	10	10	10	10	10	10	10	10	10	6.6	8
2	Purchase price	€/sqm	7	7	14	10	8.5	10	10	10	10	20	28
3	Business tax	%	320	320	323	323	323	323	323	323	323	323	350
4	Property tax	%	380	380	400	400	400	400	400	400	400	400	350
5	Visibility	Scale 1–4	4	2	1	4	2	3	2	2	2	1	2
6	Branch representation	Binary	Yes	Yes	No	No	No	No	Yes	Yes	Yes	No	No
7	Education	Scale 1–4	2	2	4	4	4	4	4	4	4	4	2
8	Everyday care	Scale 1–4	3	3	4	4	4	4	4	4	4	4	3
9	Housing and leisure	Scale 1–4	2	2	4	4	4	4	4	4	4	4	3
10	Highway proximity	km	0.95	3.5	14.9	11.3	11.4	11.7	27	27.5	27.7	25.2	32
11	Federal road proximity	km	0.1	1.9	0.9	0.35	0.45	0.7	0.85	0.8	1.4	3.3	9.1
12	Train station accessibility	min	10	9	7	23	24	27	24	25	32	29	4
13	Public transit accessibility	min	10	4	4	15	16	19	11	14	18	6	4
14	Employee catchment area	min	20	23	12	13	13	14	23	24	21	23	17
15	Customer accessibility	Scale 1–4	2	2	2	3	3	3	2	2	2	2	2
16	Charging infrastructure	Number of stations	0	0	0	0	0	0	0	0	0	0	0
17	Broadband infrastructure	Mbps	50	50	1,000	50	50	50	1,000	1,000	1,000	0	50
Location setup investments		€ (K)	183	183	244	216	199	216	216	216	216	246	242

Notes. The parameter specifications reflect the potential location's characteristics (at the decision point t_0) before realizations of company-driven and municipal location development measures. To normalize the parameters, location factor–specific constants N_i were computed with $N_i = \sum_j |a_{ij}|$ by means of the summation normalization technique.

B.3. Location Development

Table B.3. Effectiveness of Municipal Location Development Measures s on Characteristics of Locations j per Location Factor i

			Location								
i/j	Location factor	Unit	1	2	3	4	7	8	9	10	11
5	Visibility	Scale 1–4	—	—	+2	—	—	—	—	—	—
			—	—	$s = 1$	—	—	—	—	—	—
6	Branch representation	Binary	—	—	+1	+1	—	—	—	—	—
			—	—	$s = 7$	$s = 7$	—	—	—	—	—
9	Housing and leisure	Scale 1–4	+1	+1	—	—	—	—	—	—	—
			$s = 2$	$s = 2$	—	—	—	—	—	—	—
10	Highway proximity	km	—	—	−3.2	—	−26.6	−26.2	−26.1	−19.6	−12.5
			—	—	$s = 3$	—	$s = 3$	$s = 3$	$s = 3$	$s = 3$	$s = 3$
11	Federal road proximity	km	—	—	—	—	−0.4	—	−0.45	—	—
			—	—	—	—	$s = 5$	—	$s = 5$	—	—
12	Train station accessibility	min	—	—	—	—	+5	—	—	—	—
			—	—	—	—	$s = 4$	—	—	—	—
13	Public transit accessibility	min	—	—	—	—	+10	—	+7	—	—
			—	—	—	—	$s = 4$	—	$s = 4$	—	—
14	Employee catchment area	min	—	—	—	—	−3	—	−4	—	—
			—	—	—	—	$s = 5$	—	$s = 5$	—	—
15	Customer accessibility	Scale 1–4	—	—	+1	—	+1	+1	+1	+1	—
			—	—	$s = 3$	—	$s = 3$	$s = 3$	$s = 3$	$s = 3$	—
17	Broadband infrastructure	Mbps	+950	+950	—	—	—	—	—	—	—
			$s = 6$	$s = 6$	—	—	—	—	—	—	—

Notes. Only selected location factors and locations are indicated, whose characteristics tend to change over time because of realizations of the following municipal location development measures in different periods: *street exploitation* ($s = 1$) in t_0, *retirement housing setup* ($s = 2$) in t_2, highway construction ($s = 3$) in t_2, bus stop elimination ($s = 4$) in t_2, *industrial park access road relocation* ($s = 5$) in t_2, *fiber connection establishment* ($s = 6$) in t_0, and *immigration branch representation* ($s = 7$) in t_0. The effectiveness of the company-driven measure of charging station development for electric vehicles ($m = 1$) is not explicitly indicated. Its realization would result in up to five, irrespective of the location. "Not applicable" is indicated by a dash (—).

Appendix C. Robust Optimization Results

Table C.1. Computational Results Achieved with Our Quantitative Planning Approach in the RFLDP Under Uncertainty Part 1: Ranking of Location Configurations j' Based on Their Scenario-Related OFVs

Rank no.	Basic ($k = 1$)	Worst case ($k = 2$)	Best case ($k = 3$)	Semiworst case ($k = 4$)	Semibest case ($k = 5$)
1	$j' = 3$ (2.81)	$j' = 4$ (3.05)	$j' = 4$ (2.27)	$j' = 4$ (3.10)	$j' = 1$ (3.00)
2	$j' = 4$ (3.02)	$j' = 3$ (3.58)	$j' = 9$ (2.70)	$j' = 1$ (3.23)	$j' = 3$ (3.09)
3	$j' = 1$ (3.15)	$j' = 1$ (3.68)	$j' = 7$ (2.74)	$j' = 3$ (3.67)	$j' = 4$ (3.10)
4	$j' = 2$ (3.90)	$j' = 5$ (4.18)	$j' = 3$ (2.89)	$j' = 2$ (3.98)	$j' = 7$ (3.64)
5	$j' = 5$ (4.15)	$j' = 6$ (4.20)	$j' = 5$ (2.96)	$j' = 5$ (4.20)	$j' = 2$ (3.75)
6	$j' = 6$ (4.17)	$j' = 2$ (4.43)	$j' = 1$ (3.00)	$j' = 6$ (4.26)	$j' = 8$ (3.95)
7	$j' = 7$ (4.26)	$j' = 8$ (5.26)	$j' = 6$ (3.02)	$j' = 8$ (4.89)	$j' = 5$ (4.20)
8	$j' = 8$ (4.33)	$j' = 7$ (5.94)	$j' = 8$ (3.09)	$j' = 7$ (5.26)	$j' = 8$ (4.23)
9	$j' = 9$ (4.79)	$j' = 9$ (6.10)	$j' = 2$ (3.75)	$j' = 9$ (5.59)	$j' = 6$ (4.26)
10	$j' = 10$ (6.33)	$j' = 10$ (6.79)	$j' = 10$ (5.42)	$j' = 10$ (7.14)	$j' = 10$ (6.30)
11	$j' = 11$ (9.07)	$j' = 11$ (9.29)	$j' = 11$ (8.88)	$j' = 11$ (9.89)	$j' = 11$ (9.50)

Notes. The OFVs are sum-normalized and given in brackets. For each scenario k, the location configurations j' are ranked based on ascending OFVs (u_{jk}). In each scenario, the first-ranked j' achieve the respective minimum or scenario-optimal OFV (u_k^*). The first-ranked j' values vary across the scenarios. The values u_{jk} and u_k^* were used to compute the scenario-related regret value per location configuration j', which are given in Table C.2.

Table C.2. Computational Results Achieved with Our Quantitative Planning Approach in the RFLDP Under Uncertainty Part 2: Scenario-Related (Absolute | Relative) Regrets per Location Configuration j'

j'/k	Basic ($k = 1$)	Worst case ($k = 2$)	Best case ($k = 3$)	Semiworst case ($k = 4$)	Semibest case ($k = 5$)
$j' = 1$	0.34 | 0.11	0.63 | 0.17	0.72 | 0.24*	0.12 | 0.04	0 | 0
$j' = 2$	1.09 | 0.28	1.38 | 0.31	1.47* | 0.39*	0.87 | 0.22	0.75 | 0.20
$j' = 3$	0 | 0	0.54 | 0.15	0.62* | 0.21*	0.57 | 0.15	0.09 | 0.03
$j' = 4$	0.20** | 0.07**	0 | 0	0 | 0	0 | 0	0.10 | 0.03
$j' = 5$	1.34* | 0.32*	1.14 | 0.27	0.69 | 0.23	1.09 | 0.26	1.19 | 0.28
$j' = 6$	1.35* | 0.33*	1.15 | 0.27	0.75 | 0.25	1.15 | 0.27	1.25 | 0.29
$j' = 7$	1.45 | 0.34	2.89* | 0.49*	0.47 | 0.17	2.16 | 0.41	0.64 | 0.18
$j' = 8$	1.52 | 0.35	2.21* | 0.42*	0.81 | 0.26	1.78 | 0.36	0.95 | 0.24
$j' = 9$	1.98 | 0.41	3.05* | 0.50*	0.43 | 0.16	2.49 | 0.44	1.22 | 0.29
$j' = 10$	3.52 | 0.56	3.74 | 0.55	3.15 | 0.58*	4.04* | 0.57	3.30 | 0.52
$j' = 11$	6.26 | 0.69	6.25 | 0.67	6.60 | 0.74*	6.79* | 0.69	6.50 | 0.68

Notes. A ranking of location configurations j' is neither appropriate nor required here. In each scenario k, the regret values "0" achieved by the respective j', represent the optimal solution in k. The robust j' was determined successively in two steps, first by identifying the maximum regret per j' across all k (*) and second by determining the least maximum regret across all j' and k (**), which indicates the recommended (i.e., robust) j' for a RFLDP under uncertainty according to the minimax regret rule. The absolute and relative regrets were computed with u_{jk}–u_k^* and u_{jk}–u_k^*/u_{jk}, respectively.

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Verification Letters

Frank Borchard, Managing Director, SGP SCHWAN Gerüstbau Prignitz GmbH, 19366 Bad Wilsnack, Germany, writes:

"I am writing to you as the managing director of the SGP SCHWAN Gerüstbau Prignitz GmbH in Bad Wilsnack (Brandenburg), Germany, to confirm the application of a OR/MS method in location planning practice and its results as reported by David Kik, Matthias G. Wichmann, and Thomas S. Spengler. Our current location problem in brief: we want to relocate our present headquarter within our region in near future and are currently within the process of location search.

"The authors proposed a decision support for the regional location selection and development which provided a high-valuable benefit regarding our outstanding location decision. Especially, thanks to the methodical consideration of location developments.

"On the one hand, the results achieved with the planning model serve as a founded decision basis for me. This comes along with a highly beneficial transparency for conducting purposeful negotiations with the municipalities and to make the location decision clearly understandable for my employees. Thanks to the model results, I can critically examine my (subjective) gut feeling regarding the location decision from an (objective) methodological point. A key finding here is that my gut feeling guides me to a location that is currently not good compared with the conditions of the other location candidates. But the future conditions of the "gut-feeling location" will be quite satisfying due to municipal location developments, which are planned today and realized in future.

"On the other hand, the guideline for the collection of relevant data structured my decision-making effectively. Due to this I was able to anticipate planning eventualities in my early location search, especially, with respect to the impact of future municipal location developments on the location candidates. Mr. Kik moderated through the guideline which enriched the structured communication with representatives of the business promotion organization.

"I am highly satisfied with the achievements. This positive experience motivates me for future collaborations with OR/MS researchers on issues related to the construction industry, If you require further information, please feel welcome to contact me."

Christian Fenske, Head, Technologie- und Gewerbezentrum (TGZ) Prignitz GmbH, 19322 Wittenberge, Germany, writes:

"I am the head of *Technologie- und Gewerbezentrum (TGZ) Prignitz GmbH.* As a business promotion service agency, we aim to establish ideal location conditions for companies across the municipalities within our area of responsibility – the county of Prignitz in Germany. We are the main contact for companies that intend to newly locate or relocate their location point of business within Prignitz.

"**In this context, we are delighted to inform you that the decision support method for companies to choose and develop potential locations (proposed by David Kik, Matthias G. Wichmann, and Thomas S. Spengler) has been applied in real-world.** The methodology has supported an outstanding location decision of a SME from construction industry that has intended a relocation within Prignitz, and thus has inquired us previously on possible vacant locations. **Although the proposed decision support is for companies, we also benefited from its application in practice.** The findings resulting from the conducted regional location analysis by Mr. David Kik has helped us to identify objective weak points within our county of Prignitz (e.g., a poor public transport infrastructure within certain business parks). Based on this knowledge, we are able to seek structured discussions with the respective municipalities in order to initiate target-oriented location developments for the elimination of the identified weak points.

"By participating in the discussions between Mr. David Kik and the SME's manager, we have gained a keen understanding respecting the actual and future location requirements of the latter in a more formalized and systematic way by means of the developed guideline for the location analysis.

"Further, we believe that there is a great potential for the application of the developed method by business promotion service agencies to enrich daily work in a methodological manner. We could conceive to make use of such a decision support as proposed by the authors to provide a systematic consultancy for companies that seek for locations within our county of Prignitz.

"Overall, the authors' work makes a significant positive contribution at the interface between us as a business promotion service agency and companies within the context of regional location planning."

David Kik has a doctorate in business administration, with a focus on production and logistics. Until 2022, he was a research associate at the Institute of Automotive Management and Industrial Production (AIP) at TU Braunschweig. He investigated facility location problems, especially on a regional level. He provided model-based analyses on the potentials of anticipating company-driven, municipal, and collaborative location developments regarding the quality of corporate location decisions.

Matthias G. Wichmann has held the chair for business administration–production management at Chemnitz University of Technology since 2020. After studying business informatics, he earned his doctorate and habilitation in business administration at the TU Braunschweig. He represented a chair at the TU Bergakademie Freiberg (2019–2020). His research focuses on energy- and resource-oriented production management, challenges of digitalization, and methods of operations research.

Thomas S. Spengler is head of the Institute of Automotive Management and Industrial Production (AIP) at TU Braunschweig. His research focuses on model-based decision support in production, logistics, and sustainability management. He is an adjunct professor of industrial engineering at the University of Rhode Island. Since 2020, he has been a member of the scientific advisory board of the German government.