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MANUSCRIPT

Modeling managerial search behavior based on Simon's concept of satisficing

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Abstract
Computational models of managerial search often build on backward-looking search based on hill-climbing algorithms. Regardless of its prevalence, there is some evidence that this family of algorithms does not universally represent managers' search behavior. Against this background, the paper proposes an alternative algorithm that captures key elements of Simon's concept of satisficing which received considerable support in behavioral experiments. The paper contrasts the satisficing-based algorithm to two variants of hill-climbing search in an agent-based model of a simple decision-making organization. The model builds on the framework of NK fitness landscapes which allows controlling for the complexity of the decision problem to be solved. The results suggest that the model's behavior may remarkably differ depending on whether satisficing or hill-climbing serves as an algorithmic representation for decision-makers' search. Moreover, with the satisficing algorithm, results indicate oscillating aspiration levels, even to the negative, and intense—and potentially destabilizing—search activities when intra-organizational complexity increases. Findings may shed some new light on prior computational models of decision-making in organizations and point to avenues for future research.

Keywords Agent-based simulation · Complexity · Hill-climbing algorithms · NK fitness landscapes · Satisficing · Search

1 Introduction

Computational models of managerial search often comprise adaptive processes based on experiential learning and backward-looking search behavior (e.g., Gavetti and Levinthal 2000; Kollman et al. 2000; Dosi et al. 2003; Ethiraj and Levinthal 2004; Siggelkow and Rivkin 2005; Wall 2017). In computational models of

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managerial search, for capturing experiential learning and backward-looking search behavior, hill-climbing algorithms prevail (for overviews see Ganco and Hoetker 2009; Puranam et al. 2015; Baumann et al. 2019). Hill-climbing algorithms build on the metaphor of a landscape with multiple peaks where the hiker (decision-maker) is moving uphill in order to find a local or even the global peak of that landscape (Wright 1932; Altenberg 1997). In this metaphor, the "landscape" with its peaks and valleys represents, for example, the different levels ("altitudes") of performance (e.g., profit) provided by the combination of choices of a multi-dimensional decision-problem. Employing local search, a particular feature of these algorithms is that a decision-maker would *never* accept or preserve performance-decreasing changes (e.g., Altenberg 1997; Russell and Norvig 2016). This feature of hill-climbing algorithms has been criticized regarding cognitive biases such as escalation of commitment, overconfidence, and confirmation bias (e.g., Staw 1981; Astebro et al. 2014; Mercier 2017). Based on experimental findings, Tracy et al. (2017) recently question that hill-climbing algorithms are appropriate representations of managerial search behavior. In a similar vein, Puranam et al. (2015) and Billinger et al. (2014) argue that, according to experimental results, decision-makers adapt their search behavior to performance feedback (e.g., broadening search when performance declines loom and vice versa). Thus, they conjecture, employing a problemistic search of boundedly rational agents as it was proposed by Simon (1955) and later by Cyert and March (1963) and Greve (2003) would lead to more realistic models (for a recent literature review, see Posen et al. 2018). In this vein, based on empirical and experimental support, it was suggested to study alternative algorithmic representations of managerial search and their effects on model behavior (e.g., Billinger et al. 2014; Puranam et al. 2015; Tracy et al. 2017).

The research presented here follows this line of argumentation. The starting point is the aforementioned body of research suggesting that a search algorithm reflecting problemistic search (i.e., allowing for adaptations to problem structure and performance feedback, [e.g., Cyert and March 1963; Greve 2003; Posen et al. 2018)] may be more appropriate to capture the search behavior of boundedly rational agents than hill-climbing algorithms. On this basis, the paper seeks to contribute to computational management science by proposing and exemplarily applying an alternative algorithm for representing managerial search behavior. In particular, the paper introduces an algorithm for experiential learning and backward-looking search for managers based on Herbert A. Simon's concept of satisficing[1] (Simon 1955) which has turned out being a relevant representation of search human behavior (e.g., Güth 2010; Caplin et al. 2011). According to Simon, satisficing means searching sequentially for options until the decision-maker regards the level of utility achieved as satisfactory. The aspiration level shapes what is regarded as satisfactory. The aspiration level and the maximum number of options searched—depending on the difficulty of the decision problem to be solved—may be subject to adaptation.

Against this background, the paper has a twofold research objective:

[1] The term satisficing results from a merger of the two words: *satis*fying and suf*ficing* in the sense that in the process a solution is found which is both satisfying and sufficing (Hoffrage and Reimer 2004).

1. Introduction of an algorithm for managerial search behavior according to Simon's satisficing concept;
2. Exemplary application of the satisficing algorithm in contrast to hill-climbing algorithms in an agent-based simulation to showcase potential differences and commonalities regarding model behavior.

For this, the paper proceeds as follows: The next section provides an overview of the theoretical background with particular focus on Simon's idea of satisficing, before, in Sect. 3, the algorithm capturing core elements of satisficing is introduced in the context of searching for superior solutions of combinatorial decision problems.

In Sect. 4, the proposed satisficing algorithm is contrasted to hill-climbing algorithms. This is done via the example of an agent-based simulation model of organizations operating on rugged performance landscapes. The performance landscapes are modeled according to the NK framework as initially introduced in evolutionary biology (Kauffman and Levin 1987; Kauffman 1993). The rationale for this choice is that many models dealing with search in organizations build on the NK framework (for overviews, e.g., Baumann et al. 2019; Wall 2016). Hence, the NK model serves as a kind of "quasi-standard" in research on managerial search. This makes the NK model a functional basis for the second research objective mentioned above. A particular feature of the NK model is that it allows to systematically vary the complexity of a search problem in terms of the interdependencies among its sub-problems (Li et al. 2006; Csaszar 2018) which makes it appropriate to study the search behavior for varying levels of difficulty to locate the global maximum. Hence, the illustrative agent-based simulation model presented controls for the level of intra-organizational complexity among subordinate managerial decision-makers. This is particularly relevant in view of the satisficing concept since the difficulty of finding satisfactory solutions drives adjustments, for example, of the aspiration level. The model is outlined in Sect. 4.

Section 5 introduces the experimental settings for the simulations. The simulations are conducted for purposes of explanation and prediction (Za et al. 2018; Burton and Obel 2011) with particular focus on the differences that satisficing vs. hill-climbing search entail for the model behavior. The results are presented and discussed in Sect. 6 followed by concluding remarks.

2 Search and saticficing: foundations and related work

2.1 Preliminary remarks on the theoretical background

In traditional schools of economic thinking, economic actors know, at least in principle, the entire space of solutions for their decision problems. Knowing the whole search space allows them to behave as utility maximizers, i.e., detecting and choosing that option out of the solution space which maximizes the respective utility function (von Neumann et al. 2007). Simon (1955) claimed that there is an "absence of evidence that the classical concepts describe the decision-making process" (p. 104).

Among Simon's arguments is that information gathering on options and their outcomes may not be costless.

However, the cost of search and information has been introduced taking a "classical economic perspective". Stigler (1961) claimed that information on options often is not known in advance but has to be searched, and this may reasonably bring about search costs. Accordingly, in making the concept of utility maximizing more realistic, a decision-maker has to solve a sophisticated problem of economic choice: whether or not, to incur the search cost for better information which requires to forecast the information's benefits (i.e., better choices) in terms of all its future consequences including subsequent choices. Yet, it has been argued that this extended "version" of the utility maximizing model, though economically stringent, does not capture real situations of decision-making for several reasons—among them principal problems of mathematical tractability or cognitive limitations (e.g., Conlisk 1996; Gigerenzer 2002, 2004). Gigerenzer (2002) argues that the rule to stop searching for information when the cost exceeds benefits (Stigler 1961) may paradoxically require more time, knowledge, and computational abilities of decision-makers ("sophisticated econometricians") than in models with unbounded rationality.

2.2 Search in computational management science and its algorithmic representation

Against this background, a large body of research in computational management science, particularly in the vein of agent-based computational economics (Tesfatsion 2003; Chang and Harrington 2006; Chen 2012), is based on the concept of bounded rationality (Simon 1955, 1959). In particular, it is often assumed that economic agents do not dispose of a "theoretical" understanding of their problems, including knowledge of the solution space (an exception is Gavetti and Levinthal 2000); instead, agents have to search stepwise for superior solutions, e.g., solutions that provide better outcome with respect to the objective than the status quo (Safarzyńska and van den Bergh 2010). Hence, in computational models of search, instead of global optimization—with or without constraints imposed by the cost of information—agents often conduct experiential learning and backward-looking search. This is represented by local search, meaning that only one or some attributes of the current state (or policy) are changed; should this change be productive compared to the status quo, the modified policy serves as basis for a new local search. This results in adaptive processes. However, there is evidence that adaptive processes based on experiential learning are biased against new alternatives (e.g., Levinthal and March 1981; Levinthal 1997), especially since adaptation does not correct early sampling errors (hot-stove effect) (Denrell and March 2001).

With the shift from "instantaneous" global optimization to stepwise and local search also the processual perspective—including questions of speed of performance enhancements and of contingent factors—comes into play. In particular, the complexity of decision problems and environmental turbulence are among the predominant contingent factors in the respective stream of research. Computational studies on search behavior have been carried out in various domains like, for example, organizational design, innovation, psychology, and, accordingly, the related approaches in prior research are rather manifold. Overviews are, for example, given in Ganco and Hoetker (2009), Wall (2016), or Baumann et al. (2019).

In computational studies capturing backward-looking search behavior, greedy algorithms and, in particular, hill-climbing algorithms predominate. According to Cormen et al. (2009, p. 414), a "greedy algorithm always makes the choice that looks best at the moment" in terms of "a locally optimal choice in the hope that this choice will lead to a globally optimal solution". A hill-climbing algorithm—employing the metaphor of seeking the highest summit (Wright 1932; Altenberg 1997)—for a move in the landscape requires that the outcome ("altitude") will increase. In other words: the aspiration level is a performance improvement of greater than zero. For example, with a steepest ascent hill-climbing algorithm, that option out of more than one alternatives to the status quo is selected which provides the highest improvement in outcome; if none of the alternatives promises an incline in outcome, the status quo is kept. With this, hill-climbing algorithms are particularly prone to get stuck in local maxima, ridges, or plateaus in a landscape (for overviews, e.g., Cormen et al. 2009; Macken et al. 1991; Selman and Gomes 2006). This is mainly because with these algorithms a short-term decline in favor of a long-term increase would not happen since no choice in favor of an option that provides an inferior outcome than the status quo would ever be made. Hence, hill-climbing algorithms may lead to rather myopic search processes. Moreover, as mentioned in the Introduction, it was argued that this is also in conflict with some cognitive biases which indicate that decision-makers eventually behave in favor of performance declines. These considerations gave rise to questions whether hill-climbing algorithms appropriately capture managerial search behavior (e.g., Tracy et al. 2017).

While hill-climbing algorithms are customary in computational studies capturing managerial search processes, it is worth mentioning that they often serve just as the nucleus: in many models, managerial search is embedded in a broader context. This context is, for example, defined by the incentive schemes shaping managers' objective functions and, thus, the particular "landscapes" managers are searching in (e.g., Siggelkow and Rivkin 2005; Wall 2017). Another contingency factor is the imprecision of managers' information, which may, accidentally, lead to short-term declines but long-term inclines of performance choices (Knudsen and Levinthal 2007; Wall 2016). Furthermore, prior research studied the decomposition of the organizational decision problem (Dosi et al. 2003) or the coordination among managers searching on partitions of the overall decision problem (Siggelkow and Levinthal 2003). Moreover, the learning-based adaptation of the *structure* of search comes into play. For example, based on experience, the organization of search processes (e.g., who searches on which particular decision problem) could be subject to coevolution (e.g., Wall 2018).

However, as mentioned in the Sect. 1, the potential of hill-climbing algorithms to represent managerial search behavior has been questioned, and the very core of the research endeavor presented in this paper is to introduce and illustrate an algorithm for backward-looking search based on Simon's concept of satisficing.

2.3 Simon's concept of satisficing: outline and related work

This section intends to provide an overview of the "satisficing" concept with particular focus on an algorithmic representation for backward-looking search.[2] The following quote captures the core idea (Simon 1955, p. 110):

> In most global models of rational choice, all alternatives are evaluated before a choice is made. In actual human decision-making, alternatives are often examined sequentially. We may, or may not, know the mechanism that determines the order of procedure. When alternatives are examined sequentially, we may regard the first satisfactory alternative that is evaluated as such as the one actually selected.

The satisficing concept is explained and justified extensively in Simon's 1955 paper and subsequent works (e.g., Simon 1959, 1979; for a reconstruction of satisficing from Simon's early works see Brown 2004). One of Simon's arguments is that decision-makers endowed with limited information-processing capabilities may strive for decisions which are good enough with reasonable costs of computation (Simon 1955, p. 106; Simon 1979, p. 498). The quote above indicates on three building blocks which are particularly relevant for an algorithmic representation of satificing. These are[3]:

1. *Sequential procedure*, i.e., options are discovered *and* evaluated sequentially;
2. *Aspiration level*, i.e., options are evaluated with respect to a level of outcome that is regarded satisfactory;
3. *Stopping rule*, i.e., search is stopped when the first satisfactory option is found.

Regarding the stopping rule, Simon introduces further considerations to assure, first, that—at least in the long run—a satisfactory alternative can be found while, second, in the short-term, search can provisionally stop if no satisfactory alternative is identified. For this, in particular, he introduces a dynamic perspective by considering a *sequence of situations* with choices to be made (Simon 1955, p. 111):

> The aspiration level, which defines a satisfactory alternative, may change from point to point in this sequence of trials. A vague principle would be that as the individual, in his exploration of alternatives, finds it *easy* to discover satisfactory alternatives, his aspiration level rises; as he finds it *difficult* to discover satisfactory alternatives, his aspiration level falls. Perhaps it would be possible to express the ease or difficulty of exploration in terms of the cost of obtaining better information about the mapping of A on S, or the combinatorial magnitude of the task of refining this mapping. There

[2] An in-depth analysis of the concept's origin in Simon's work is given by Brown (2004); Radner (1975) introduced a general formulation for purposes of mathematical optimization.

[3] These three elements, in principle, correspond to building blocks proposed by Gigerenzer and Todd (1999) for heuristics, which are search rules, stopping rules and decision rules (see also Gigerenzer and Gaissmaier 2011).

> are a number of ways in which this process could be defined formally. Such changes in aspiration level would tend to bring about a 'near-uniqueness' of the satisfactory solutions and would also tend to guarantee the existence of satisfactory solutions. For the failure to discover a solution would depress the aspiration level and bring satisfactory solutions into existence. [emphasis in original]

As Simon points out, such a mechanism of adjusting aspiration levels assures that, satisfactory solutions exist in the long run. However, as mentioned before, a second aspect is the number of alternatives a decision-maker is willing to explore. In short-term, such an upper bound assures that the search, in principle, may stop even if no satisfactory option is found; however, in a sequence of situations, the maximum number of alternatives searched may be subject to adjustment too (Simon 1955, p. 111):

> Up to this point little use has been made of the distinction between A, the set of behavior alternatives, and $\dot{A}$, the set of behavior alternatives that the organism considers. Suppose now that the latter is a proper subset of the former. Then, the failure to find a satisfactory alternative in $\dot{A}$ may lead to a search for additional alternatives in A that can be adjoined to $\dot{A}$.

Simon mentions these two types of adjustment—i.e., regarding aspiration levels and maximum number of options searched—as examples of how decision-making behavior could be adjusted to the perceived difficulty of finding satisfactory alternatives. Moreover, the two types of adjustments may substitute or complement each other (Simon 1955, p. 112):

> In one organism, dynamic adjustment over a sequence of choices may depend primarily upon adjustments of the aspiration level. In another organism, the adjustments may be primarily in the set $\dot{A}$: if satisfactory alternatives are discovered easily, $\dot{A}$ narrows; if it becomes difficult to find satisfactory alternatives, $\dot{A}$ broadens... The more persistent the organism, the greater the role played by the adjustment of $\dot{A}$, relative to the role played by the adjustment of the aspiration level.

Hence, for an algorithmic representation, the above "list" of building blocks of satisficing could be extended by

4. *Adjustment of aspiration level*, with downward (upward) adjustment when the decision-maker finds it difficult (easy) to identify a satisfactory alternative;
5. *Adjustment of maximum number of options explored*, with broadening (narrowing) adjustment when the decision-maker finds it difficult (easy) to identify a satisfactory alternative.

The concept of satisficing stimulated a large body of further research in various domains reaching from psychology and economics to multi-agent systems (e.g., Bianchi 1990; Gigerenzer 2002; Todd and Gigerenzer 2003; Parker et al. 2007; Schwartz 2008; Rosenfeld and Kraus 2012).

For example, key elements of satisficing are among the foundations of “the adpative toolbox” comprising “fast and frugal heuristics” introduced by Gigerenzer (2002). Moreover, Simon’s satisficing provides a basis for Selten’s prominent “aspiration adaption theory” (Selten 1998, 2002). However, particularly the idea of aspiration levels has given rise to questions on how they are initially set and how they are updated (e.g., Bianchi 1990; Lant 1992; Güth 2007; Schwartz 2008). Another stream of research studies the effects of aspiration levels in an organizational context, especially of aspirations in terms of organizational targets (e.g., Mezias 1988; Washburn and Bromiley 2012; Joseph and Gaba 2015).

A further body of research seeks to test how far satisficing captures real human decision-making behavior empirically. For example, in an experimental study Caplin et al. (2011) find considerable support for key elements of satisficing behavior, namely sequential search and stopping a search process when a decision-maker regards the level of outcome satisfactory. Another stream of research refers to the conditions when decision-makers seek to behave as maximizers or satisficers, i.e., to styles of decision-making (e.g., Schwartz et al. 2002; Parker et al. 2007).

Close in spirit to these research efforts, is the paper of Billinger et al. (2014) which presents an experimental study on how decision-makers adapt their search behavior to the complexity of the decision problem. The authors find that search behavior is adjusted to subjective reference points of performance feedback which reflect success and failure. In particular, success narrows the search activities to local search; in contrast, failure promotes more distant search. Since the complexity of a decision problem makes it more difficult to find successful solutions, complexity affects the feedback that decision-makers receive in their search for new alternatives, leading to an adaptation of individuals’ search behavior (with further references, see also Puranam et al. 2015; Posen et al. 2018).

3 Algorithmic representation of satisficing managerial search behavior

3.1 Preliminary remarks

This section introduces a computational model of organizations with decision-making agents that employ satisficing in backward-looking search behavior following Simon’s concept as introduced in Sect. 2.3. The model is presented for decision-making agents facing a multidimensional binary decision problem. This modeling choice builds on two arguments:

First and most important, as it was outlined above, a considerable body of research in computational management science employs the prominent NK framework. In its standard form, the NK framework comprises *N*-dimensional binary bit strings as the vector of choices or features adapted throughout adaptive processes based on some kinds of learning or evolution. Hence, modeling the satisficing concept for binary decision problems eases the integration into prior research.[4]

Second, a fixed dimensionality binary decision problem facilitates to model satisficing search behavior. For example, the maximum number of alternatives (see Sect. 2.3) and the term neighborhood can be figured out easily. However, the author believes that the simplifying assumption of binary decision problems does not limit, in principle, transferring the proposed algorithm of satisficing search behavior to other types of decision problems.

3.2 Process structure of satisficing search

Subsequently, satisficing search behavior of a manager r is described where manager r may be one out of M managers in an organization (i.e., $r = (1, \dots, M)$). Manager r faces an N^r-dimensional binary decision problem.

According to the behavioral assumptions of Simon (1955), manager r is not able to survey the *entire* search space and, hence, cannot "locate" the optimal solution of its decision problem "at once". Instead, manager r employs a time-consuming search process to identify solutions with superior performance, or even the optimal solution, regarding manager r's objective.

As outlined in Sect. 2.3, a particular feature of satisficing search behavior is that, when searching for superior performance, an agent may adapt the aspiration level and the maximum number of alternatives discovered before the agent decides to stop searching. Hence, the proposed model comprises three adaptive processes which are related to each other: In each period t of time,

1. manager r sequentially searches for novel options to its particular decision problem within the institutional framework given which includes, for example, division of labor or rewards provided (Sect. 3.3);
2. manager r adjusts the aspiration level a^r that a newly found option will have to meet to be selected in the next period based on the performance improvements resulting from the solutions implemented in the past (Sect. 3.4);
3. manager r adjusts the maximum number $s^{max,r}$ of options to be discovered before search is stopped depending on the number of options that manager r had to search for before a satisficing alternative was found in the past (Sect. 3.5).

Figure 1 shows the principle process of satisficing search behavior of a manager r. Subsequently, the model is described in more detail.

[4] In Sect. 4, this paper presents simulation experiments for managerial decision-makers within organizations. The organizations face a binary decision problem according to the NK-framework. The subsequent description of satisficing search behavior follows some notational conventions of the NK framework.

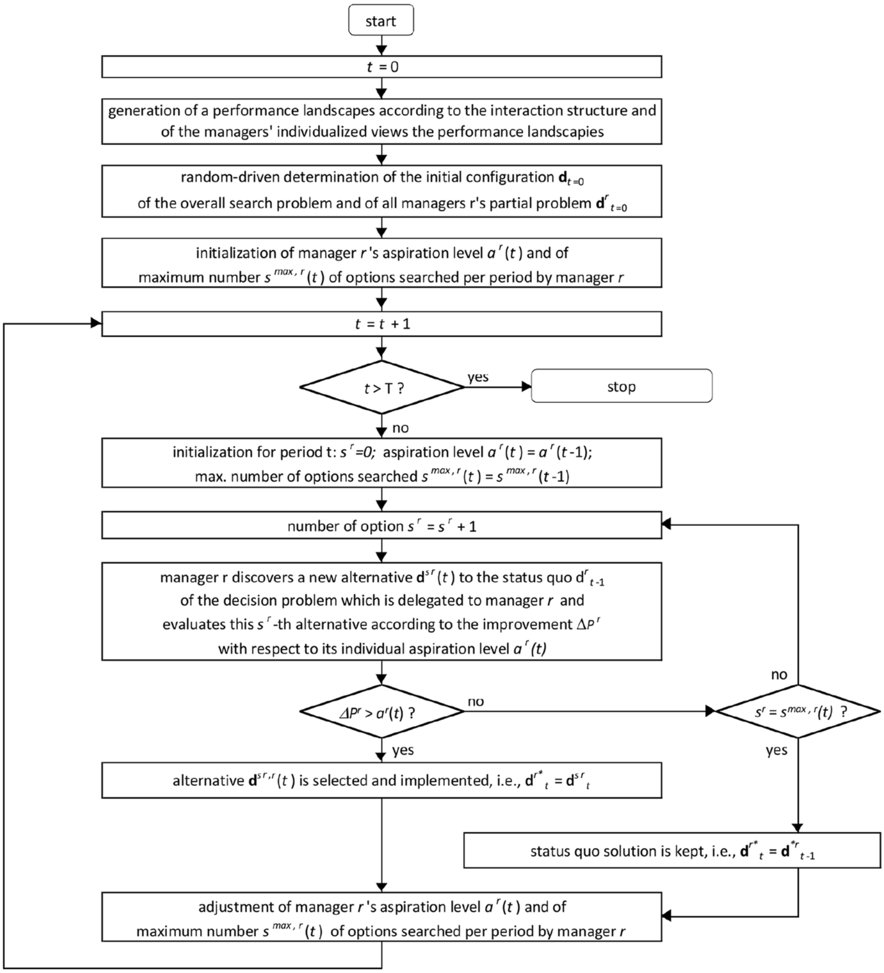


Fig. 1 Process structure of satisficing search behavior

3.3 Sequential search for new options

A key feature of satisficing search is that new options are discovered *and* evaluated sequentially: the agent discovers one novel option $\mathbf{d}_t^{s^r}$ and evaluates (i.e., searches for "cues" in the terminology of Simon (1955) whether it promises a performance improvement compared to the status quo $\mathbf{d}_{t-1}^r$ that, at least, meets the aspiration level $a^r(t)$, i.e., when

$$\Delta P_t^r \geq a^r(t) \tag{1}$$

with

$$\Delta P_t^r = P(\mathbf{d}_t^{s^r}) - P(\mathbf{d}_{t-1}^r) \tag{2}$$

If so, this option is implemented, and search is stopped for this time step t; otherwise, the next option is searched and evaluated as far as the maximum number of options $s^{max,r}(t)$ is not reached yet (see Fig. 1).

With manager r facing an N^r-dimensional binary decision problem, at maximum, $2^{N^r} - 1$ alternative configurations $\mathbf{d}^r$ compared to the status quo could be implemented. Hence, the upper bound for the maximum number of options is

$$s^{max,r} \leq 2^{N^r} - 1 \tag{3}$$

For an algorithmic representation of satisficing, defining a sequence of the agent's discoveries of new options is necessary. For the sequence of options' discovery, various possibilities are feasible. For example, one obvious way is to let the agent *randomly* discover one out of the $2^{N^r} - 1$ alternatives (if an option has been discovered before in that time step t, the random draw is repeated).

However, the simulation experiments presented subsequently employ a "closest-first" search policy which reflects the idea of neighborhood search: a manager r starts searching in the immediate "neighborhood" of the status quo. Should this not lead to a satisficing option, manager r extends the "circle" of search around the status quo. As outlined in Sect. 2.3, this modeling choice of the sequence is broadly supported by experimental evidence (Billinger et al. 2014; Puranam et al. 2015; Posen et al. 2018).

Hence, the sequence follows increasing Hamming distances of discovered alternatives to the status quo where the Hamming distance of an alternative option $\mathbf{d}_t^{s^r}$ to the status quo is given by

$$h(\mathbf{d}_t^{s^r}) = \sum_{i=1}^{N^r} \left| \mathbf{d}_{t-1}^r - \mathbf{d}_t^{s^r} \right| \tag{4}$$

Hence, the search starts with alternatives with a Hamming distance $h(\mathbf{d}_t^{s^r}) = 1$, then followed by options with a Hamming distance of two and so forth, as long as neither the aspiration level is met nor the maximum number of options $s^{max,r}$ to be considered is reached. Among the options with equal Hamming distance the sequence is given at random.[5]

The rationale for a sequence given by increasing Hamming distances is as follows: This sequence appears particularly appropriate to capture the idea of stepwise improvement of a given configuration. With respect to the cost of search and change, small steps (i.e., Hamming distance equal to 1) could be assumed to show lower cost than more distant options which require more changes. Hence, the "closest-first" *search policy* may be based on considerations of cost of search and change.

[5] For example, with a decision problem of $N^r = 3$, three alternatives to the status quo with a Hamming distance $h(\mathbf{d}_t^{s^r}) = 1$, three alternatives with $h(\mathbf{d}_t^{s^r}) = 2$ and one with $h(\mathbf{d}_t^{s^r}) = 3$ exist. A manager first discovers nearest neighbors; next, options with $h(\mathbf{d}_t^{s^r}) = 2$ are found etc. where the sequence among equal-distanced options is randomly given.

However, it is worth mentioning that other forms of the sequence of searching are arguable too: For example, a manager may be rewarded based on the particular novelty of the options chosen, which could give reason to start searching with the most distant alternatives possible.

3.4 Adaptation of the aspiration level

As mentioned in Sects. 2.3 and 3.2, a core element in satisficing is the aspiration level. Newly found options are evaluated according to whether or not they promise to meet the aspiration level, and the aspiration level is subject to adaptation based on experience (Simon 1955): The aspiration level may increase (decrease) depending on how easy (difficult) it was to find a satisfactory alternative in the past.

In the proposed model of satisficing search behavior, the aspiration level is adjusted according to the performance experience, i.e., an improvement or deterioration of performance (see Eq. 2) achieved over time. In particular, the aspiration level $a^r(t)$ is captured as an exponentially weighted moving average of past performance changes where α^r denotes the speed of adjustment for manager r (Levinthal and March 1981; Böergers and Sarin 2000; Levinthal 2016), i.e.,

$$a^r(t+1) = \alpha^r \cdot \Delta {P^r}_t + (1 - \alpha^r) \cdot a^r(t). \tag{5}$$

It is worth emphasizing that the aspiration level could also become negative—i.e., a performance *decline* becoming acceptable—if declines happened in the past. This establishes a contrast to hill-climbing algorithms where decision-makers would not accept performance declines (see Introduction). Section 6.1 comes back to this aspect.

3.5 Adaptation of the maximum number of options searched

In a similar vein, the space of options in which a manager searches for satisfactory alternatives may be dynamically adjusted. When it turns out to be difficult to find satisfactory options, the search space for alternatives is broadened; when finding satisfactory options is easy, search space is narrowed (Simon 1955). As mentioned in Sect. 2.3, this type of adjustment is supported by experimental results (Billinger et al. 2014).

In the modeling effort presented here, this is captured as adjustment of the maximum number $s^{max,r}$ of options that the decision-making agent r may consider in the next time step. In particular, if in period t a maximum number of options, i.e., $s^r(t) = s^{max,r}$, was searched and evaluated without that a satisfactory alternative to the status quo was identified, then for $t+1$ the (potential) search space increases. For this, again, an exponentially weighted moving average of past search spaces is employed where β^r denotes the speed of adjustment for manager r. Hence, the search space results from

$$s^{max,r}(t+1)=\begin{cases}\beta^r\cdot(s^r(t)+1)+(1-\beta^r)\cdot s^{max,r}(t)\\ \quad \text{if}\, s^r(t)=s^{max,r}(t)\,\text{and}\,\Delta P^r{}_t<a^r(t)\\ \\ \beta^r\cdot(s^r(t))+(1-\beta^r)\cdot s^{max,r}(t)\text{else}\end{cases} \tag{6}$$

However, since the maximum search space $s^{max,r}$ has to be an integer, the moving average according to the upper case of Eq. 6 is to be rounded up or down which is done according to

$$s^{max,r}(t+1)=\lfloor s^{max,r}(t+1)+0.5\rfloor \tag{7}$$

Hence, with Eq. 7, the "adjusting" procedure in Eq. 6 does not necessarily result in an adjusted space $s^{max,r}(t+1)$ of options for the next period.

4 Example: an agent-based model of search in collaborative organizations based on satisficing vs. hill-climbing

4.1 Overview

This section intends to contrast, employing an example, the adaptive walks of organizations with satisficing managers to organizations with managers employing a hill-climbing algorithm as familiar in the domain of agent-based computational organization science.

To this end, the model captures artificial organizations that use only a few organizational design elements. In particular, organizations do not comprise more elements than the decomposition of an overall decision problem into sub-problems, the delegation of sub-problems to decision-making managers, and a headquarters rewards managers according to their respective performance. One may think of the decision-making managers as being the heads of respective departments. However, in terms of the concept of Agent Action Diagrams (AAD) proposed by Li et al. (2019), the model explicitly only captures the "thinking" parts of the managers's actions (e.g., searching and evaluating of options, decision-making); the "command" and "execution" actions related to the choices made are not explicitly modeled; rather, it is assumed that these actions are put forward according to the choices.[6] The Appendix outlines the agent entity organization diagram and the agent entity action attribute diagram according to the AAD concept (Li et al. 2019).

Hence, the model captures simple—for not to say: simplistic—organizations which refrain from many design elements as, for example, more sophisticated coordination mechanisms like organizational routines (e.g., Gao et al. 2018; Gao and Akbaritabar

[6] The likewise applies to the headquarters' actions: The model does not explicitly capture the headquarters' "thinking" actions (i.e., decomposition of the overall task, observation of the status quo), the "command" actions (i.e., delegation of sub-problems) and execution action (i.e., rewarding) which is why the they are not further documented in the Appendix.

2021) or team-based compensation (e.g., Siggelkow and Rivkin 2005; Wall 2017) which were incorporated in many agent-based models.

The rationale for this is to study the effects of the satisficing compared to the hill-climbing algorithm on managerial search in organizations in as pure a form as possible and without being entangled with organizational mechanisms that are intended to align individual behavior with organizational objectives.

In the following, first, the overall organizational decision problem, its decomposition, and delegation to managers are introduced (Sect. 4.2). Next, a description of managers' objective functions and information basis (Sect. 4.3) follows. Third, search and decision-making via hill-climbing are briefly outlined in contrast to satisficing (Sect. 4.4).

4.2 Decision problem and structure of the organizations

In the simulation model, artificial organizations are observed while searching for superior solutions for a decision problem according to the framework of NK-fitness landscapes (Kauffman and Levin 1987; Kauffman 1993). In particular, at each time step t the organizations face an N-dimensional binary decision problem, i.e., $\mathbf{d_t} = (d_{1t}, ..., d_{Nt})$ with $d_{it} \in \{0, 1\}$, $i = 1, ..., N$, out of 2^N different binary vectors possible. Each of the two states $d_{it} \in \{0, 1\}$ provides a distinct contribution C_{it} to the overall performance $V(\mathbf{d_t})$. The contributions C_{it} are randomly drawn from a uniform distribution with $0 \leq C_{it} \leq 1$. Parameter K (with $0 \leq K \leq N-1$) reflects the number of those choices d_{jt}, $j \neq i$ which also affect the performance contribution C_{it} of choice d_{it}. Hence, K captures the complexity of the decision problem in terms of the interactions among decisions: this means that contribution C_{it} may not only depend on the single choice d_{it} (being 0 or 1) but also on K other choices:

$$C_{it} = f_i(d_{it}; d_{i_1 t}, ... d_{i_K t}), \tag{8}$$

with $\{i_1, ..., i_K\} \subset \{1, ..., i-1, i+1, ..., N\}$. In case of no interactions among choices, K equals 0, and K is $N-1$ for the maximum level of complexity where each single choice i affects the performance contribution of each other binary choice $j \neq i$. The overall performance V_t achieved in period t results as normalized sum of contributions C_{it} from

$$V_t = V(\mathbf{d_t}) = \frac{1}{N} \sum_{i=1}^{N} C_{it}. \tag{9}$$

The organizations have a hierarchical structure and comprise two types of agents: (1) one headquarter and (2) M managers. The organizations make use of division of labor. In particular, the N-dimensional overall decision problem is decomposed into M disjoint partial problems, and each of these sub-problems is exclusively delegated to one manager $r = (1, \ldots, M)$. For the sake of simplicity, the sub-problems are of

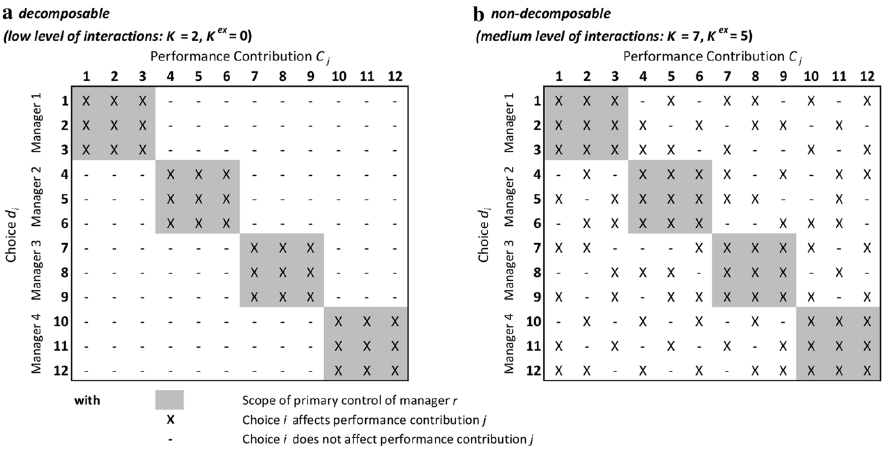


Fig. 2 Examples of **a** decomposable and **b** nearly decomposable interaction structures

equal size N^r.[7] Each manager r is endowed with decision-making authority on its "own" partition of the organization's decision problem.

The headquarter seeks to maximize the overall performance V_t according to Eq. 9. However, its role is restricted to—at the end of each time step t—observing the overall performance V_t, observing each manager's performance contribution and rewarding managers accordingly.

Depending on the complexity K of the N-dimensional decision problem and the particular structure of interactions among the M sub-problems, indirect interactions among the managers' choices may result. Let K^{ex} denote the level of interdependencies across managers' sub-problems. In case that interdependencies across sub-problems exist, i.e., if $K^{ex} > 0$, then the performance contribution of manager r's choices to overall performance V is affected by choices made by other managers $q \neq r$ and vice versa (see, for example, Fig. 2b).

4.3 Managers' objective functions and information

The managers seek to maximize compensation which is merit-based and depends on the performance contribution $P_t^r(\mathbf{d_t})$ of manager r to overall performance $V(\mathbf{d_t})$ according to Eq. 9. Hence, we have

$$V_t = V(\mathbf{d_t}) = \sum_{r=1}^{M} P_t^r(\mathbf{d_t}) \tag{10}$$

with

[7] With $N \in \mathbb{N}$ this requires that N is divisible by M without remainder.

$$P_t^r(\mathbf{d_t^r}) = \frac{1}{N} \sum_{i=1+w}^{N^r} C_{it} \tag{11}$$

and with $w = \sum_{m=1}^{r-1} N^m$ for $r > 1$ and $w = 0$ for $r = 1$.

For the sake of simplicity, compensation of manager r depends linearly on the value base $P_t^r(\mathbf{d_t})$ for all levels of P_t^r. Hence, by increasing the performance contribution P_t^r of the partial solution for the N^r-dimensional sub-problem to the overall organization's decision-problem, manager r also increases its compensation.

However, when making choices on their respective partial configurations $\mathbf{d_t^r}$, the managers show some further cognitive limitations (apart from not knowing the entire space of solutions and, thus, having to search for options):

First, manager r cannot anticipate the other managers' $q \neq r$ choices; rather manager r assumes that the fellow managers will stay with the status quo, i.e., opt for $\mathbf{d}_{t-1}^{q*}$. This is since, at the the beginning of every period, manager r gets knowledge of the solution $\mathbf{d}_{t-1}^{*}$ to the overall decision problem of the organization and, hence, of the fellow managers' choices. However, the model does not capture any further mutual perceptions among managers (e.g., sympathy, social identification) between managers (e.g., Smarzhevskiy and Solovev 2020; Ellemers et al. 2004).

Second, manager r is not able to perfectly ex-ante evaluate the effects of any newly discovered option $\mathbf{d}_t^{s^r}$ on the value base for compensation $P_t^r(\mathbf{s}^{\mathbf{d}^r}_t)$ (see Eq. 11). Rather, ex ante evaluations are afflicted with noise which is, for the sake of simplicity, an relative error imputed to the actual performance (Wall 2010; for further types of errors see Levitan and Kauffman 1995; for further models of managerial search capturing imperfect evaluations see Carley and Zhiang 1997; Chang and Harrington 1998; Knudsen and Levinthal 2007). The error terms $e^r(\mathbf{d}_t^{s^r})$ follow a Gaussian distribution $N(0;\sigma)$ with expected value 0 and standard deviations σ^r; errors are assumed to be independent from each other. Hence, the value base of compensation $\tilde{P}_t^r(\mathbf{d}_t^{s^r})$ of a newly discovered $\mathbf{d}^{s^r}$ option as ex ante *perceived* by manager r is

$$\tilde{P}_t^r(\mathbf{d}_t^{s^r}) = P_t^r(\mathbf{d}_t^{s^r}) + e^r(\mathbf{d}_t^{s^r}) \tag{12}$$

Thereby, when making decisions, each manager r has a different "view" of the actual fitness landscape which results from (1) the decomposition of the overall decision problem and the delegation of sub-problems and (2) from the managers' individual "perceptions" due to the individualized error terms σ^r. However, for the status quo option $\mathbf{d}_{t-1}^{r*}$, it is assumed that manager r remembers the compensation from the last period. From this, manager r also knows the *actual* performance P_t^r of the status quo, should the manager choose to stay with it in time step t and if, in case of interactions across sub-problems, also the fellow managers stay with the status quo.

4.4 Search strategies

In every time step t, each manager r seeks to identify a superior configuration for its partial decision problem $\mathbf{d_t^r}$ with respect to the value base of compensation. The search strategy shapes the options a manager can choose. The simulation model contrasts adaptive walks of organizations with *satisficing* managers to those organizations with managers employing a *steepest ascent hill-climbing algorithm* as frequently employed in computational management science. In Sect. 3, the model of satisficing search was introduced. Hence, at this point, a short outline of hill-climbing in the context of the model follows.

In particular, as already mentioned, in the model the managers cannot survey the *entire* search space and, hence, they have to search stepwise for superior solutions. Following a hill-climbing algorithm, a manager searches in the neighborhood for a fixed number $s^{max,r}$ of alternatives and opts for an alternative only if it promises a higher performance ("fitness") than the status quo. The distance to the status quo defines the term neighborhood and, in the context of the NK-model, is measured by the Hamming distance $h(\mathbf{d}_t^{s^r})$ of an alternative option to the status quo $\mathbf{d}_{t-1}^r$ according to Eq. 4.

In the most simple case, the neighborhood is set to $h(\mathbf{d}_t^{s^r}) = 1$ and the number of alternatives is $s^r = s^{max,r} = 1$, too. This means that only one alternative to $\mathbf{d}_{t-1}^r$ is discovered where—usually at random—one bit is flipped. However, the "allowed" neighborhood of search could be broader than one, and also the number of alternatives the manager identifies could be higher than one. Both is often employed in models of organizational search (e.g., Siggelkow and Rivkin 2005; Wall 2017; for overviews Chang and Harrington 2006; Baumann et al. 2019). If the number of alternatives $s^{max,r}$ identified providing a performance incline is higher than one, that option with the highest incline is selected (steepest ascent hill-climbing). Hence, three aspects of this hill-climbing algorithm (HCA) appear noteworthy in comparison to the satisficing algorithm (see Sect. 3):

1. In the HCA, the number s^r of newly discovered alternatives per period equals the maximum number of alternatives allowed, i.e., $s^r = s^{max,r}$. Moreover, the maximum number of alternatives is not subject to adaptation based on experience over time like in satisficing.[8]
2. The HCA employs an aspiration level of zero: alternatives with a performance incline compared to the status quo are worth being selected by a manager (i.e., $a^r > 0$). Additionally, unlike in satisficing, the aspiration level is not adapted according to experience.[9]
3. In the HCA, options are not searched *and* evaluated in sequence with a stop of searching when an alternative meets the aspiration level like in satisficing. Instead, in case that the HCA is parametrized to two or more alternatives to be searched (i.e., if $s^{max,r} > 1$), the search stops when $s^{max,r}$ alternatives are identified. Then, these $s^{max,r}$ options are evaluated against the status quo and against each other to figure out the steepest ascent.

[8] In this sense, the HCA could be regarded as a special case according to Eq. 6 with $\beta = 0$.

[9] With this, the HCA may be regarded as a special case according to Eq. 5 with $\alpha = 0$.

Table 1 Parameter settings

Parameter	Values/Types
Applying to all scenarios/types of managers	
Observation period	$T = 250$
Simulation runs	Per scenario 2500 runs with 25 runs on 100 distinct fitness landscapes
Number of choices	$N = 12$
Interaction structures	Decomposable: $(K = 2; K^{ex} = 0)$ (see Fig. 2a) non-decomposable: –Low: $(K = 3; K^{ex} = 1)$; $(K = 4; K^{ex} = 2)$; –Medium: $(K = 5; K^{ex} = 3)$; $(K = 6; K^{ex} = 4)$; –High: $(K = 7; K^{ex} = 5)$ (see Fig. 2b)
Number of managers	$M = 4$ with $\mathbf{d}^1 = (d_1, d_2, d_3)$, $\mathbf{d}^2 = (d_4, d_5, d_6)$, $\mathbf{d}^3 = (d_7, d_8, d_9)$, $\mathbf{d}^4 = (d_{10}, d_{11}, d_{12})$
Managers' precision of ex-ante evaluation	$\sigma^r = 0.05$ for all managers $r = (1, \dots, M)$
Satisficing type of managers	
Aspiration level	
–In the beginning	$a^r(t = 0) = 0$ for all managers $r = (1, \dots, M)$
–Speed of adjustment	$\alpha^r = 0.5$ for all managers $r = (1, \dots, M)$
Max. number of alternatives	
–In the beginning	$s^{max,r}(t = 0) = 2$ for all managers $r = (1, \dots, M)$
–Speed of adjustment	$\beta^r = 0.5$ for all managers $r = (1, \dots, M)$
Hill-climbing type of managers	
HC2-strategy	$s^r = 2$ alternatives per period with $h(\mathbf{d}^{r,a1}) = 1$ and $h(\mathbf{d}^{r,a2}) = 1$ for all managers $r = (1, \dots, M)$
HC6-strategy	$s^r = 6$ alternatives per period with $h(\mathbf{d}^{r,a1}) = 1$, $h(\mathbf{d}^{r,a2}) = 1$, $h(\mathbf{d}^{r,a3}) = 1$, and $h(\mathbf{d}^{r,a4}) = 2$, $h(\mathbf{d}^{r,a5}) = 2$, $h(\mathbf{d}^{r,a6}) = 2$ for all managers $r = (1, \dots, M)$

The paper presents the results of simulations for organizations with managers employing satisficing versus hill-climbing search. For this, the next section introduces the particular parameter settings of the simulation experiments.

5 Simulation experiments and parameter settings

The simulation study seeks to provide insights into how satisficing managerial search behavior compared to hill-climbing behavior affects the organizations' resulting adaptive walks. Table 1 displays the parameter settings which are explained in the remainder of this section.

The parameter settings in the upper part of Table 1) apply to experiments with both satisficing and hill-climbing types of managers. As such, organizations are observed for 250 periods[10] when searching for superior solutions to an $N = 12$ -dimensional decision problem. The overall decision problem is decomposed into $M = 4$ equal-sized sub-problems of which each is delegated exclusively to a subordinate manager. The Appendix provides a graphical description following the "agent action diagram (AAD)" approach (Li et al. 2019).

The experiments are conducted for different levels of complexity of the organizations' decision problems: In particular, the organizations may have a perfectly decomposable interaction structure of decisions which captures situations where, for example, the task of an organization is perfectly decomposable along geographical regions or products without any interdependencies across regions or products, respectively (Galbraith 1974; Rivkin and Siggelkow 2007; Simon 1962). Figure 2a gives an example of a situation with no interactions across managers' sub-problems (i.e., $K^{ex} = 0$). Alternatively, the interaction structures captured in the experiments may exhibit a low, medium, or high level of interactions across sub-problems. For example, Fig. 2b shows a case of a high level of cross-problem interactions (i.e., $K^{ex} = 5$). This interaction structure may represent situations caused by certain constraints of resources (budgets or capacities), by market interactions (prices of one product may affect the price of another) or functional interrelations (e.g., the product design sets requirements for logistics or procurement processes) (Thompson 1967; Galbraith 1973; Rivkin and Siggelkow 2007; Li et al. 2021).

When ex-ante evaluating newly discovered options, the managers suffer from some noise (see Eq. 12) following a Gaussian distribution with mean 0 and a standard deviation of 0.05. This parametrization intends to reflect some empirical evidence according to which error levels around 10% could be a realistic estimation (Tee et al. 2007; Redman 1998).

Regarding experiments for organizations resided by satisficing managers (see middle part of Table 1), the aspiration levels of performance enhancements start at a level of zero for two reasons: first, this corresponds to hill-climbing (see Sect. 4.4) and, hence, eliminates one source of potential differences between the two modes in the experiments. Second, this "conservative" setting captures the desire to avoid, at least, situations of not-sustaining an already achieved performance level. For satisficing search, the maximum search space starts at a moderate level of just two alternatives, which also relates to a search space often specified for hill-climbing search in computational management science. Regarding the speed of adjustment for both the aspiration level of performance enhancements and the maximum number of alternatives, the present observation and the past are weighted equally with α^r (Eq. 5) and β^r (Eq. 6), respectively, set to 0.5.

The simulations experiments comprise two different steepest ascent hill-climbing strategies (see the lower part of Table 1). In particular, in the "HC2"-strategy, in every time step, each manager discovers two alternatives to the respective status quo, each alternative with one bit flipped compared to the status quo and thus captures local search. With the "HC6"-strategy, in every time step, 6 alternatives to the

[10] The observation period T was fixed based on pretests which indicate that the results do not principally change for longer observation periods.

Table 2 Condensed results of baseline scenarios

Search type	Performance change in first periods ($V_{t=10} - V_{t=0}$)	Final performance $V_{t=250}$ (± CI*)	Frequ. of glob. max. found in $t = 250$ (%)	Ratio of periods with altered config. **d** (%)
Decomposable interaction structure, $K^{ex} = 0$				
Satisficing	+ 0.3110	0.9928 ± 0.0010	60.0	22.4
HC2 hill-climbing	+ 0.2609	0.9507 ± 0.0031	15.3	12.3
HC6 hill-climbing	+ 0.3207	0.9960 ± 0.0007	66.6	20.6
Non-decomposable interaction structure: medium, $K^{ex} = 3$				
Satisficing	+ 0.1119	0.8551 ± 0.0082	9.8	59.8
HC2 hill-climbing	+ 0.1749	0.8900 ± 0.0046	6.8	10.9
HC6 hill-climbing	+ 0.0781	0.7516 ± 0.0091	4.9	83.5

*Confidence intervals at a level of 0.999. For parameter settings see Table 1

current configuration are discovered, i.e., 3 with Hamming distance 1 and 3 with Hamming distance of 2.[11]

The HC2-strategy corresponds to agent-based models in prior research which study local search—often in comparison to other forms of search (e.g., Levinthal 1997; Jain and Kogut 2014)—and, thus, serves as a basis for comparisons of simulation results obtained with satisficing agents. In contrast, the HC6-strategy serves another purpose in the experiments: it captures a kind of "upper bound" of feasible partial alterations given the overall decision-problem of the size $N = 12$ and its decomposition into four equal-sized sub-problems. Hence, the HC6-strategy provides a broad search space and an obvious question is whether search spaces in satisficing (see Eq. 6) may evolve to the same high level.

6 Results and discussion

In order to be clear and concise in exploring the parameter space, the results of the simulation experiments are presented in two steps. Following the idea of factorial design of simulation experiments (Lorscheid et al. 2012), Sect. 6.1 introduces results of two baseline scenarios to analyze the principal effects of satisficing vs. hill-climbing managerial search behavior. In particular, organizations facing a decomposable decision-problem (i.e., $K^{ex} = 0$) and organizations which have to deal with a medium level of complexity (i.e., $K^{ex} = 3$) are studied. Section 6.2 provides an analysis of the sensitivity to intra-organizational interactions for a broader range of complexity levels of the organization's decision-problem.

[11] Hence, in the HC6-strategy each manager r identifies 6 out of the 7 possible alternatives to the $N^r = 3$ -dimensional partial decision problem, see fn. 5. The only option that is not feasible is switching each bit of the 3-dimensional sub-problem of each manager. The space of alternatives considered could also be regarded as indication on managers' capabilities as in Rivkin and Siggelkow (2003).

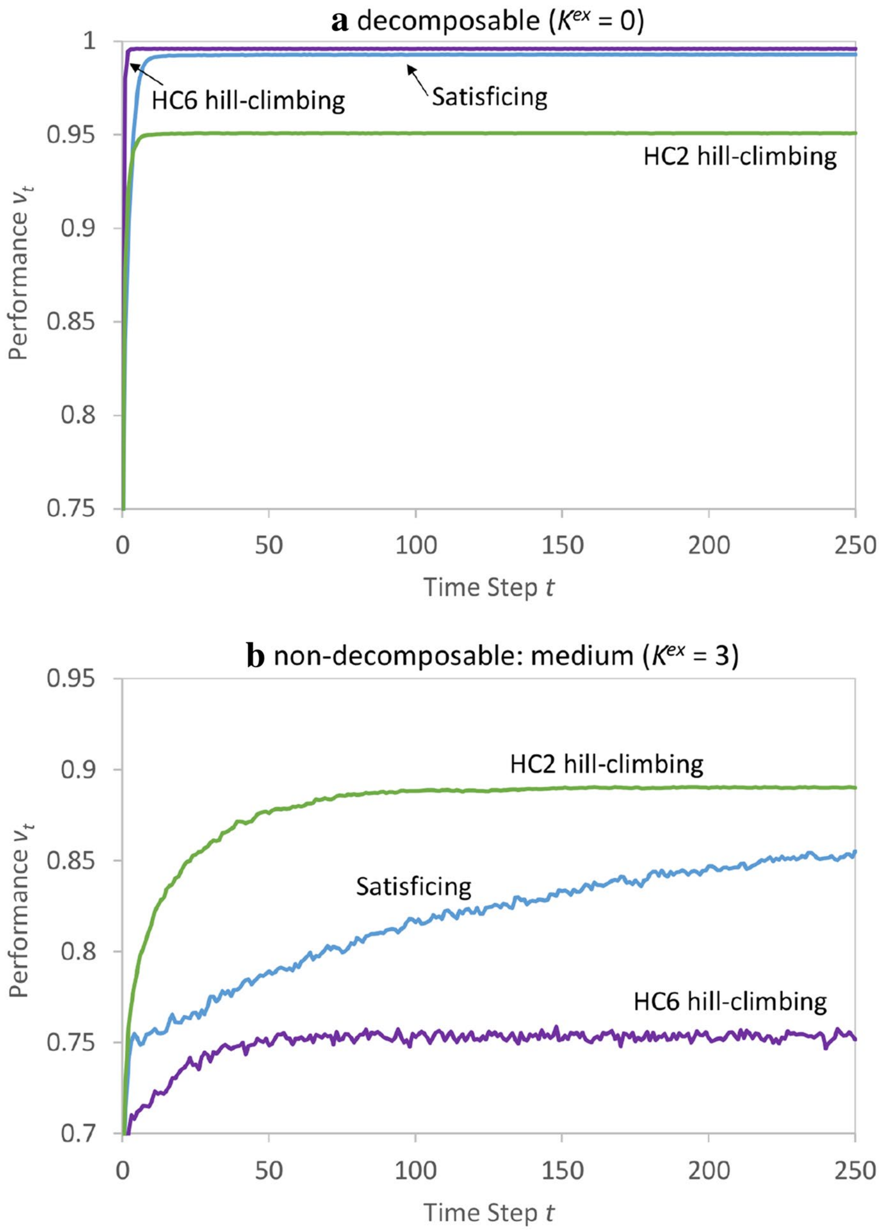


Fig. 3 Adaptive walks of the baseline scenarios. Each line represents the average of 2500 simulations. For parameter settings see Table 1

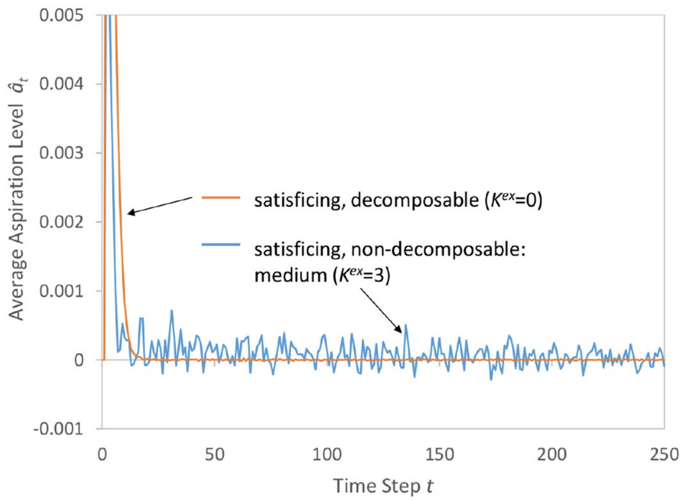


Fig. 4 Adaptation of aspiration levels in the baseline scenarios. Each line represents the average of 2500 simulations. For parameter settings see Table 1

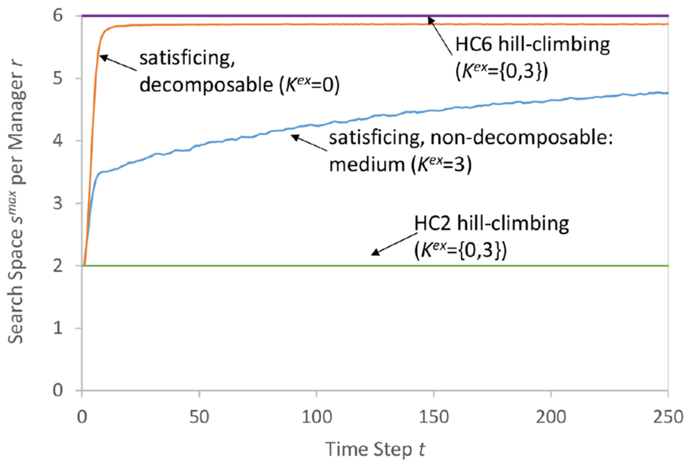


Fig. 5 Adaptation of maximum search space per manager in the baseline scenarios. Each line represents the average of 2500 simulations. For parameter settings see Table 1

6.1 Baseline scenarios

Table 2 reports condensed results obtained from the simulation experiments for the baseline scenarios. For each scenario (i.e., combination of interaction structure and search strategy), the respective 2500 simulation runs were analyzed with respect to several metrics.[12]

The performance change achieved on average in the first ten periods informs about the speed of performance enhancement at the beginning of the adaptive walks, which may be particularly relevant in turbulent environments (Siggelkow and Rivkin 2005). However, with respect to satisficing, the usually high performance inclines at the beginning of search are particularly interesting for the adjustments of aspiration levels and search spaces. The final performance, i.e., performance $V_{t=250}$ achieved in the last period of the observation time on average in the 2500 simulation runs per scenario, informs about the effectiveness of the search processes. This also applies to the relative frequency of how often the global maxima in the respective performance landscapes have been found in the 2500 simulation runs per scenario. The ratio of periods in which a new configuration $\mathbf{d_t}$ is implemented characterizes the adaptive walks more into detail.

Figure 3 plots the performance levels obtained in the course of adaptive walks over time for each scenario. Figure 4 displays the adaptation of aspiration levels over time for the two satisficing scenarios. Please, recall, in the hill-climbing scenarios, aspiration levels are zero (see Sect. 4.4), which is why they are not plotted. Figure 5 reports on the adjustment of the search spaces in satisficing search for the decomposable and the non-decomposable structure; the search spaces of the scenarios employing hill-climbing are fixed, as is also indicated in the figure.

The following discussion of results mainly focuses on satisficing search behavior in contrast to the hill-climbing strategies (and less on comparing the hill-climbing modes against each other).

The plots in Fig. 3 indicate that the performance enhancements obtained via satisficing search behavior are at medium levels compared to the two hill-climbing modes (which, however, perform differently well in the two interaction structures) for both interactions structures under investigation. The results reported in Table 2 also suggest that satisficing search is at medium levels regarding initial performance enhancements and final performances. For the frequency of global maximum found, satisficing search outperforms both hill-climbing models in the non-decomposable structure. With satisficing, the ratio of periods with altered configurations is at a notably high level compared to the HC2 strategy. In the case of a decomposable structure, it even exceeds the level of the HC6 strategy. For a closer analysis of results, it appears helpful also to consider the adjustment processes of the aspiration levels and maximum search spaces as plotted in Figs. 4 and 5, respectively.

[12] In the analysis of simulation experiments, the metrics related to performance V_t are given relative to the global maxima of the respective performance landscapes: otherwise, the results were not comparable across different performance landscapes.

6.1.1 Decomposable interaction structure

Each manager faces a partial binary problem in the decomposable interaction structure without any interactions among the managers' problems existing. Hence, the organization's overall performance maximum could be found by identifying the sub-problems' optimal solutions. Therefore, with a broad search space enabled at the managers' site as with the HC6-strategy, it is not surprising that the adaptive walks quickly reach performance levels close to the maximum of 1. With managers employing satisficing behavior, the performance levels achieved are close to that of the HC6-strategy. Moreover, the maximum number of alternatives per manager increases rather quickly to nearly the high level of 6 as fixed for the HC6 strategy and remains at this high level (see Fig. 5).

The explanation for this is as follows: in the decomposable structure, managers likely find configurations with high or even the maximum performance level for their partial problem. However, from a very high (or maximal) performance level, it becomes more difficult (or impossible) to further increase performance. However, according to the behavioral assumptions underlying the idea of bounded rationality (Simon 1955), the managers are not aware of whether they already have identified the optimal solution. In consequence, since managers experience it difficult to further increase performance, according to the satisficing concept, the search space is increased. It remains at a high level in the—potentially futile—attempt to increase performance further.

The adaption of aspiration levels follows an inverse adjustment: After a high incline in the first periods—due to high inclines of performance at the beginning—the aspiration levels decline quickly to a level of zero: with being close to the best configuration (or having it found already), further performance enhancements are unlikely (or even impossible) and, hence, the aspiration levels of decision-making managers, persistently, remain at a level of zero. However, a closer analysis reveals that the aspiration levels *oscillate* closely around zero. This is because the managers in the model are not capable of evaluating options perfectly. Hence, false-positive choices may occur, which then affect the aspiration levels and may turn them to the negative (see Eq. 5).[13]

6.1.2 Non-decomposable interaction structure

In the non-decomposable structure, the link between managers' sub-problems and the overall decision-problem is more complicated than in the decomposable case for two reasons. First, when searching for superior solutions to their partial decision problems, managers do not necessarily increase overall performance. Hence, maximizing parochial performance and the overall performance of the organization may conflict with each other. The second reason refers to managers' cognitive limitations

[13] In other words: When decision-makers can evaluate options perfectly, in the decomposable structure, the aspiration levels do not oscillate around zero. Instead, after an initial incline, they decline to equal zero.

regarding their fellow managers' choices. Due to interactions among sub-problems, manager r's choice for the partial problem $\mathbf{d}^r$ may affect the performance $P_t^q(\mathbf{d_t^q})$ (Eq. 11) of another manager $q \neq r$ and vice versa. Since, in the model, the managers notice their fellow managers' choices with one period of delay, this may lead to frequent, time-delayed mutual adjustments in order to keep up with the fellow managers' choices, which again induces mutual adjustments and so forth. These considerations reflect the lower performance levels achieved, the lower frequencies of the global maximum found, and the higher ratios of altered configurations compared to the decomposable structure reported in Table 2. These results, in principle, correspond to prior research employing computational models of organizations (e.g., Carley 1992; Rivkin and Siggelkow 2007; Siggelkow and Rivkin 2005). However, the differences across search strategies are remarkable, which is analyzed in more detail in Sect. 6.2.

In the satisficing strategy, the adjustments of maximum search spaces and aspiration levels deserve closer inspection. Regarding the adjustment of maximum search spaces in the satisficing strategy (Fig. 5), for the non-decomposable structure, we again notice an increase over time—though up to a lower level of about 5 per manager and with a lower gradient compared to the decomposable structure. This may result from the following effects: as argued above, in non-decomposable structures, it is rather difficult to identify solutions that induce performance enhancements. However, when finding promising options becomes more difficult, with satisficing the maximum search space is increased. At the same time, this may counteract the peril of sticking to local maxima, and the peril of inertia is the more pronounced, the higher the complexity K (or K^{ex}) of a decision-problem.[14]

The adjustment of aspiration levels plotted in Fig. 4 shows the inverse development, and aspiration levels decline over time. Contrary to the decomposable case, now the aspiration levels oscillate remarkably around a level of zero. Hence, an interesting question is what may cause these oscillations. Like in the decomposable structure, the imperfect evaluations contribute to oscillations of aspiration levels: imperfect ex-ante evaluations may lead to performance declines due to false-positive choices. Accordingly, these "negative" experiences are reflected in the adjustment of the aspiration levels. Additionally, in the non-decomposable structure, interactions among sub-problems combined with cognitive limitations regarding the choices of fellow managers further induce oscillating aspiration levels:

1. When making their choices in time step t, decision-makers assume that their fellow managers stay with the status quo. This is particularly problematic in case of interactions among decision-problems and may cause "surprises" and, in consequence, frequent mutual adjustments (which happens in about 60% of periods, see Table 2);

[14] However, the search space is at a lower level than with satisficing in the decomposable structure. This is because, in the decomposable structure, high levels of performance are found very quickly. With this, further performance enhancements are difficult to achieve, which leads to an extension of the search space close to the upper bound.

Fig. 6 Sensitivity of **a** final performance, **b** frequency of global maximum found and **c** ratio of alterations ▶ to intra-organizational complexity. Each mark represents the average of 2500 simulations. For parameter settings see Table 1

2. The actual choices of fellow managers are revealed only at the end of period t which causes a time-delay in the aforementioned mutual adjustments to the other managers' choices;

Hence, due to interactions combined with alterations by fellow managers, performance declines may happen which reduce aspiration levels even below zero.

In sum, intra-organizational complexity in combination with imperfect information in decision-making reasonably causes frequent alterations of configurations **d** and oscillations of aspiration levels in the satisficing strategy. We return to this aspect in Sect. 6.2. Taking a more general perspective on the baseline scenarios, one may summarize the findings in the following hypotheses:

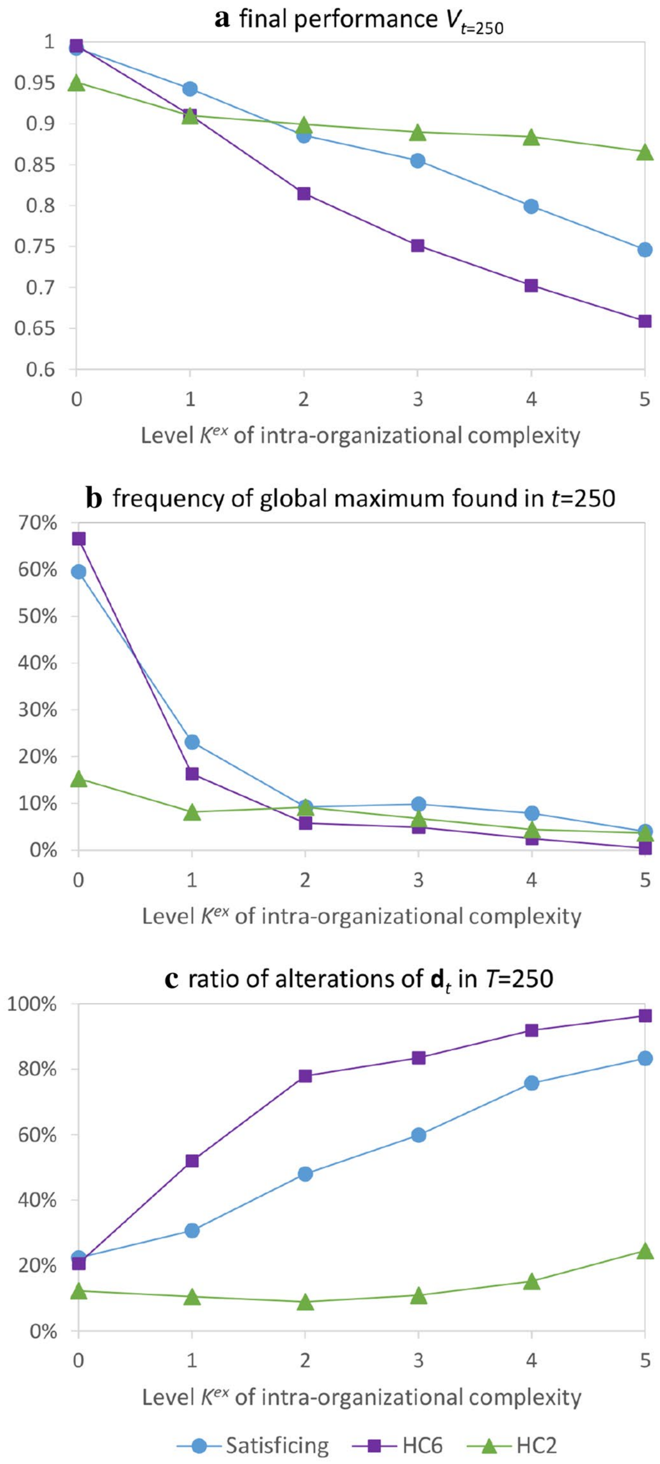
(1) Organizations in which decision-makers with satisficing search behavior reside and which already have identified configurations providing high levels of performance are likely to employ extensive search and aspiration levels which enforce to (just) maintain the performance.
(2) Intra-organizational complexity combined with cognitive limitations of decision-makers showing satisficing search behavior induces high levels of search activity and oscillating aspiration levels.

These hypotheses could be related to organizations' maturity, and organizational learning in terms of both performance level achieved and organizations' focus on searching for novel solutions.

6.2 Sensitivity to intra-organizational complexity

The next step of analysis considers simulation results for all levels of intra-organizational complexity from $K^{ex} = (0, \ldots, 5)$. Thereby, we intend to provide more detailed insights into potential differences of satisficing behavior compared to hill-climbing search. For this, Fig. 6 displays—for the three search strategies under investigation—(a) the performance level achieved on average of 2500 runs in the last period of observation, (b) the relative frequency of runs in which the global maximum was found in the last period, and (c) the average ratio of periods in which the organizations implement a new solution to their decision problem.

The results reveal that, for all search strategies, the final level of performance decreases with increasing intra-organizational complexity, which is broadly in line with prior research (e.g., Rivkin and Siggelkow 2007; Levinthal 1997). However, as shown in Fig. 6a, the search strategies are differently sensitive to an increase in intra-organizational complexity. The HC2-strategy—allowing only two alternatives and with just 1-bit changes each—is comparably robust with about 8.5 percentage points (p.p.) between highest and lowest final performance. In contrast, this difference is


a final performance $V_{t=250}$
1
0.95
0.9
0.85
0.8
0.75
0.7
0.65
0.6
0 1 2 3 4 5
Level K^{ex} of intra-organizational complexity
b frequency of global maximum found in t=250
70%
60%
50%
40%
30%
20%
10%
0%
0 1 2 3 4 5
Level K^{ex} of intra-organizational complexity
c ratio of alterations of $\mathbf{d}_t$ in T=250
100%
80%
60%
40%
20%
0%
0 1 2 3 4 5
Level K^{ex} of intra-organizational complexity
Satisficing
HC6
HC2

about 25 p.p. with satisficing and 34 p.p. with the HC6-strategy. Hence, these strategies—allowing for more alternatives considered and longer jumps—are notably sensitive to intra-organizational complexity in terms of performance declines.

These results might be counter-intuitive since one may expect that search strategies allowing to consider more alternatives and making even longer jumps outperform the HC2-strategy since this strategy is much more "restrictive" regarding search space and extent of change. Moreover, concerning satisficing the result is particularly interesting: with this strategy, the decision-makers sequentially discover and ex-ante evaluate alternatives—and this with increasing Hamming distances starting with two options with 1-bit changed. Hence, intuition may suggest that satisficing should not perform worse but even more successfully than the HC2-strategy. Moreover, it is worth mentioning that the satisficing strategy tends to show higher ratios of locating the optimal solution as Fig. 6b suggests.

The more extensive search spaces and longer jumps employed in satisficing—and likewise with the HC6-strategy—result in a remarkable increase in alterations as shown in Fig. 6c. For example, for high intra-organizational complexity ($K^{ex} = 5$), with satisficing in about 83% of the periods and with HC6 hill-climbing in almost every period, another solution for the overall decision problem is implemented.

An interesting question is what causes these effects. The explanation may lie in the destabilization of the search when the strategy allows for more alternatives and long jumps as is the case with satisficing and HC6 hill-climbing. In particular, interactions among managers' sub-problems and imperfect information at the managers' site subtly interfere. Each manager $r = (1, \ldots, M)$—when making its decision in t without knowing what the fellow managers intend to do—may not only have been surprised by the actual performance P^r achieved in $t-1$. Moreover, the fellow managers' choices in $t-1$ which—due to intra-organizational interactions—have affected r's performance in $t-1$ may be another source of surprise for manager r. This eventually lets manager r adapt configuration $\mathbf{d}_t^r$ and so forth—resulting in *frequent time-delayed mutual adjustments*. Hence, search behavior that is more flexible in terms of more options and longer jumps makes it more likely that a manager discovers alternatives that (eventually falsely) promise to increase r's performance. In this sense, the flexibility of search may induce some harmful "hyperactivity" of searching when intra-organizational complexity increases. The ratios of alterations increasing in the intra-organizational complexity with satisficing, or HC6 provide support for this conjecture (Fig. 6c).

These considerations may be summarized as follows: Search behavior that is more flexible in terms of considering a higher number of options and longer jumps as captured in satisficing is more prone to destabilizing ("hyperactive") mutual adjustments than more restrictive forms of search behavior.

As mentioned before, prior research often employs algorithms like our HC2-strategy to represent local search for superior solutions to organizations' overall decision problem. In doing so, prior research puts considerable emphasis on complexity, i.e., interactions within the overall decision problem. The sensitivity analysis presented here suggests that satisficing search is remarkably more sensitive to intra-organizational complexity than local search via hill-climbing. This appears particularly relevant since satisficing has received considerable support in behavioral experiments (see Sects. 1 and 2.3), thus, maybe a more realistic computational representation of managerial search behavior than hill-climbing algorithms.

7 Conclusion

At the center of this paper are the questions of representing managerial search behavior in computational models and how the representation may affect models' results. Prior research questions that hill-climbing algorithms—predominating in computational organization science—represent managerial search behavior appropriately. At the same time, there is considerable empirical and experimental evidence on the relevance of satisficing behavior in actual human behavior. This serves as a starting for this paper which makes two contributions.

First, the paper introduces an algorithmic representation for backward-looking search according to Simon's concept of satisficing (Simon 1955). The satisficing algorithm may complement other models of managerial search in (agent-based) computational organization science and, in this sense, may contribute to the ongoing discussion on how to model human decision-makers (e.g., Gode and Sunder 1993; Chen 2012; Hommes 2006; Billinger et al. 2014; Puranam et al. 2015; Posen et al. 2018).

Second, in an agent-based simulation model of decision-making organizations, the proposed algorithm of satisficing is applied and contrasted to the steepest ascent variant of hill-climbing. Apart from decision-makers' incomplete knowledge of the solution space, the model captures further aspects of bounded rationality. The simulation experiments suggest that, first, with satisficing for organizations already operating at a high performance level intense search activities may emerge. Second, oscillating aspiration levels (including accepting performance declines) and potentially destabilizing search activities may occur when intra-organizational complexity is high. Third, a sensitivity analysis reveals that satisficing is considerably more sensitive to intra-organizational complexity in terms of performance declines than hill-climbing algorithms.

In sum, from a more general perspective, the results suggest that the type of search algorithm the decision-making agents employ (i.e., whether they follow the satisficing concept or a hill-climbing approach) may subtly shape the model's behavior. These findings may shed some new light on prior modeling efforts building on hill-climbing algorithms, and may even suggest to revisit the respective computational studies in future research efforts (in a similar vein, Tracy et al. 2017).

The simulations presented in this paper require relativizing remarks, which also point to future research activities. First of all, it has to be emphasized that the satisficing concept captures some more modeling choices and parameter settings than typically showing up for hill-climbing. This applies particularly to the search sequence and the adjustments of aspiration levels and of the maximum number of options. For example, the simulations presented in this paper assume a "closest first" sequence of search and exponential weighting with equal focus on past and presence for the adjustments "built-in" in the satisficing concept. While there is considerable experimental evidence on this proximity-driven "closest first" sequence, other types of sequence may apply depending on the particular context (Puranam et al. 2015; Greve 2003). Moreover, there is a considerable body of empirical and experimental research on aspiration levels, and especially on the interrelation of organizational and individual aspirations in conjunction with the adjustments of aspirations (e.g., Lant 1992; Lant and Shapira 2008; Washburn and Bromiley 2012; Joseph and Gaba 2015). Hence, an obvious further step would be to explore the effects of satisficing on model behavior for a broader parameter space with a particular focus on the reference to the reality of managerial decision-making.

Moreover, the simulation model introduced in this paper captures relatively simple—for not to say: simplistic—organizations. In particular, the organizational arrangements do not comprise much more than the division of labor (i.e., decomposition into sub-problems and delegation to subordinate managers) and a simple incentive scheme that rewards parochial performance. Hence, an interesting question is how satisficing search behavior shapes results for organizations with more sophisticated institutional arrangements. Of interest may be, for example, how different coordination mechanisms could counteract the destabilizing effects of satisficing in the case of higher levels of intra-organizational complexity compared to hill-climbing. Studying the satisficing algorithm in models of more sophisticated organizational arrangements will, on the one hand, contribute to linking this representation of managerial search behavior to prior research in computational organization theory; on the other hand, it would allow studying the effects of satisficing in more realistic models of organizations.

Appendix

This appendix provides an overview of how the artificial organizations are mapped in the multi-agent simulation, according to the approach of the agent action diagram (AAD) as introduced by Li et al. (2019). Among the particular features of the AAD approach is the differentiation between agents' "thinking", "command", and "behavior" actions. However, it is worth mentioning that, in the "rudimentary" organizational structure in our model as reflecting the paper's particular focus, the command and behavior actions are only captured implicitly in the model (for this, see also Sect. 4.1). Figure 7 shows (a) the agent entity organization diagram and (b) the entity action attribute diagram for the managerial decision-makers (for the headquarters, see footnote 6) according to the AAD concept (Li et al. 2019).

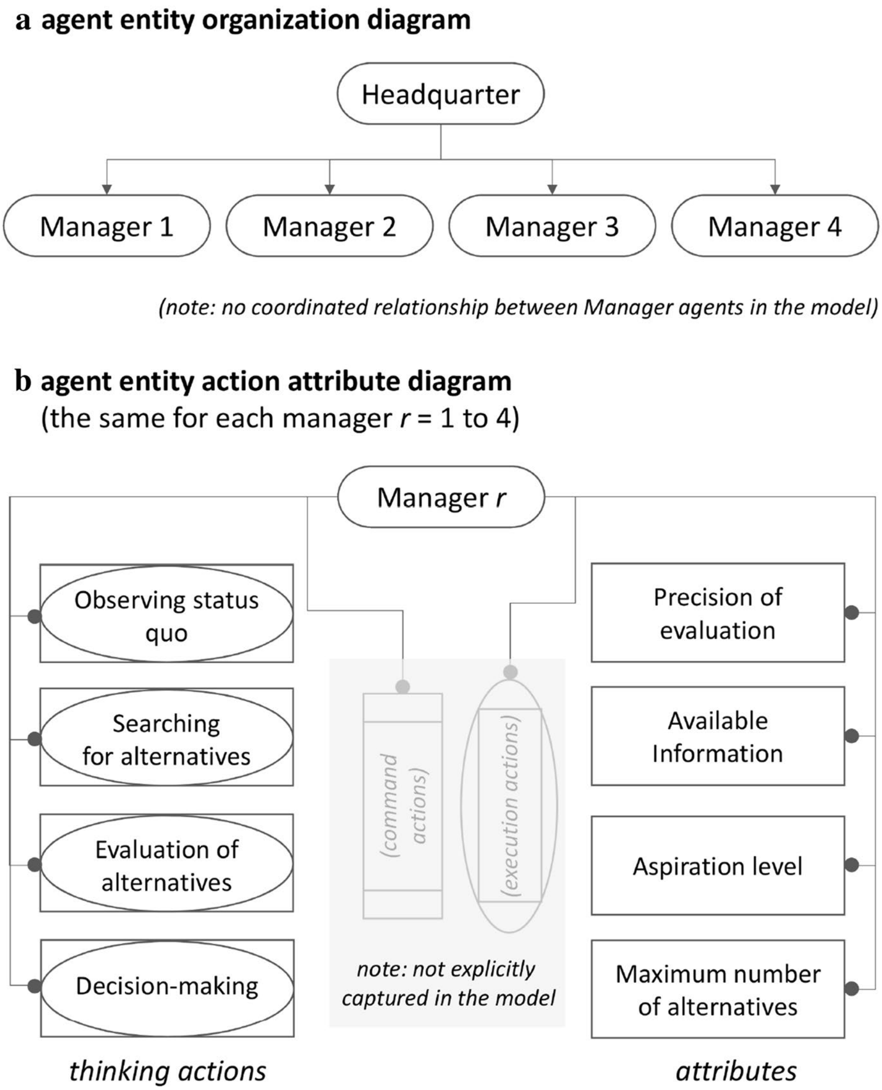


Fig. 7 Agent entity organization diagram (**a**) and agent entity action attribute diagram for managers (**b**) of the agent-based model. For parameter settings see Table 1

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