

## Chapter 2

# Complex Systems Methodologies for Behavioural Research in Operations Management: *NK* Fitness Landscape

Ilaria Giannoccaro

**Abstract** From a methodology point of view, most Behavioural Operations Management (BOM) studies have employed experiments. However, no reason, either theoretical or practical, exists to limit BOM to experimental research. In this chapter, I discuss my conviction that methodologies coming from complexity science have the proper characteristics to be successfully applied in BOM research, since real operating systems, such as processes, factories, organisations and supply chains, are complex adaptive systems (CASs) where human behaviour is the central driver. Moving from this assumption, I suggest applying complexity science in order to study operating systems in diverse OM contexts and I also propose research questions coherent with a complexity science approach. They concern how operating systems behave, adapt and show new orders in terms of processes, structures and performances. Then, I suggest the adoption of a simulation tool to study CASs to develop BOM models, i.e. *NK* fitness landscape. After reviewing the methodology and its main applications in organisational contexts, I propose how different OM contexts can be modelled and how behavioural factors both at an individual and at a population level might be operationalised through the methodology proposed. Finally, I formulate research questions that might be addressed by applying *NK* fitness landscape.

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I. Giannoccaro (✉)

Department of Mechanics, Mathematics, and Management,  
Polytechnic University of Bari, Viale Japigia 182 70126 Bari, Italy  
e-mail: [ilaria.giannoccaro@poliba.it](mailto:ilaria.giannoccaro@poliba.it)

# 1 Introduction

People significantly affect how operating systems work and perform. Nevertheless, the traditional Operations Management (OM) literature has largely ignored the effect of human behaviour, or at most, has considered it a secondary effect. Traditional OM has incorporated the classical assumptions of neoclassical economics so that humans involved in the management of operating systems are modelled as fully rational decision makers, acting solely to optimise measures of economic value. Oversimplified models of goals, motivation, learning, creativity and of other aspects of human behaviour such as intelligence, risk attitude, overconfidence, conformism, rejection of ambiguity and complexity, have been largely applied (Simon 1955; Chopra et al. 2004; Bendoly et al. 2006; Loch and Wu 2007; Gino and Pisano 2008).

Therefore, it is neither surprising that there is abundant evidence of real operating systems behaving differently in practice from the theoretical predictions, nor that theoretical prescriptions fail to deliver their promised achievements.

Behavioural Operations Management (BOM) is a multi-disciplinary branch of OM, encompassing organisational behaviour, decision science and psychology, that explicitly studies the effects of human behaviour on the performances of operating systems and analyses strategies to improve them (Gino and Pisano 2008; Loch and Wu 2007). In particular, BOM explores deviations from rationality of the decision makers involved in the management of operating systems including factors affecting their behaviour (Siemens 2009), with the aims firstly of providing a better understanding of how operating systems work and perform, and secondly of developing effective implications for the design, management and improvement of operating systems (Gino and Pisano 2008).

From a methodology point of view, most BOM studies have employed experiments. However, no reason, either theoretical or practical exists to limit BOM to experimental research. Loch and Wu (2007) observe to this respect that *“the equation of BOM with experiments seems narrower than the spirit to the attempt to expand OM to incorporate people issues”*. I entirely agree that there is no need to restrict BOM to one methodological approach, i.e. behavioural experiments.

Instead, it is my conviction that methodologies coming from complexity science have the proper characteristics to be successfully applied in BOM research, since real operating systems, such as processes, factories, organisations and supply chains, are complex adaptive systems (CASs) where human behaviour is the central driver. Indeed, in such systems there are a number of independent, multiple and heterogeneous human agents making decisions using heuristics and schemata, self-organising by interacting among each other and co-evolving with the rugged and dynamic environment in which they exist (Choi et al. 2001).

Complexity science offers suitable theories and methodological tools for studying the evolution of CASs. As such, it is well suited to studying the dynamics of operating systems, which is one of the main challenges in OM research (Pathak et al. 2007).

Furthermore, complexity science-based methodologies permit the development of OM models that can easily include behavioural factors. They are particularly suitable to modelling not only the properties of individuals, such as their personal abilities, attitudes and cognitive biases, but also the factors affecting social interactions and characterising groups and populations, which are new behavioural issues that should be included in OM models in accordance with the most recent trend in BOM research (Loch and Wu 2007).

The main advantage coming from the application of complexity science-based methodologies resides in the possibility of understanding how behavioural factors affect the working and evolution of operating systems, allowing them to emerge spontaneously, given the characteristics of the system and the behavioural factors included. Such methodologies allow the difficulty of predicting and understanding which individual agent strategies lead to a desired collective behaviour to be overcome. Moreover, compared to experimental methods, they are less expensive and more effective because experiments could not show all possible events (Loch and Wu 2007).

The aim of this chapter is thus twofold. First, I intend to develop a theoretical framework which classifies BOM research and can help to identify new BOM research directions. This framework is based on the traditional logic for incorporating behavioural factors into OM models, its novelty lies in the proposal to develop BOM models using complexity science methodologies. In this way, I identify opportunities coming from complexity science for doing BOM research and at the same time define the BOM research questions that require methodologies suitable to study CASSs. Next, I intend to show how a complexity-science methodology, i.e. *NK* fitness landscape, should be applied to model operating systems and behavioural factors so as to study their dynamics in different OM contexts.

This chapter is organised as follows. First, I review the main BOM taxonomies so as to identify the most important behavioural factors to be included into OM models. Then, I discuss the theoretical framework I propose, which is based on complexity science. A discussion follows regarding the main characteristics of *NK* fitness landscape and how it can be applied to model different OM contexts and most of the behavioural factors. Finally, I describe future BOM research directions and present some research questions addressable through *NK* fitness landscape, formulated following the proposed approach in a few OM contexts.

## 2 BOM Research: A Review of the Taxonomies

Taxonomies of BOM research classify common assumptions made in the OM literature concerning human behaviour and provide a rationale for identifying possible research questions in many different OM contexts.

Bendoly et al. (2006) classify behavioural assumptions into three broad categories: Intentions, Actions and Reactions. A BOM researcher should question whether assumptions concerning the intentions, actions and reactions of decision

makers are valid and whether they could affect the performance of a given system and in turn the model's recommendations regarding the system.

'*Intentions*' refer to the model's accuracy in reflecting the actual goals of the decision makers.

Common assumptions about decision makers' factor weighting, risk attitude and the existence of not monetary goals such as trust and justice belong to this category.

'*Actions*' refer to the rules or implied behaviour of human players in the model. The most important assumption in this category is to neglect individual differences. Differences exist in human work rate, cognitive limitations, motivations, ability to process feedback, communication methods and personal abilities.

'*Reactions*' refer to the human player's response to model parameter changes. They mainly concern the role of feedback and its impact on human behaviour and the implied rules regarding how decision makers learn, process feedback or are affected by environmental factors.

The taxonomy provided is critical in order to identify behavioural gaps in the different OM contexts such as product development, inventory and DC management, quality management, production and workflow management, procurement and strategic sourcing and supply chain management. The authors give examples of common assumptions and possible behavioural gaps in all the categories in the different OM contexts. Based on this, they provide research questions and potential research directions in BOM.

Similarly to Bendoly et al. (2006) and Gino and Pisano (2008) focus on the cognitive limits of individuals and on the consequent systematic biases that might alter their decisions. They offer a wider classification of the cognitive biases made by individuals in the decision making process. They are classified on the basis of the stage of the decision-making processes in which they occur: (1) the information acquisition stage, (2) the information processing stage, (3) the outcome stage and (4) the information feedback stage (Table 1).

Individual biases could affect human behaviour in many different OM contexts such as product development and R&D, project management, supply chains, forecasting, inventory management, services and management of IT, which are similar in that they involve the acquisition, processing and interpretation of information from different sources. In each setting OM specific biases may occur and affect performances. Here, BOM research is greatly needed.

Gino and Pisano (2008) also suggest that BOM research should follow two complementary directions, i.e. prescriptive and descriptive. The prescriptive direction means that studies are needed which incorporate behavioural factors into OM models. The aim of such research would be normative: to provide valid recommendations and prescriptions on the design, management and improvement of operating systems, thanks to the extension of simplistic behavioural assumptions through improved modelling of human behaviour. The descriptive direction means developing studies that may improve our understanding of the effects of the cognitive biases on system performances so as to provide strategies and interventions to enhance them.

**Table 1** Individual biases at the decision-making stage (Gino and Pisano 2008)

Bias	Description
<i>Acquisition of information</i>	
Information avoidance	People's tendency to avoid information that might cause mental discomfort or dissonance
Confirmation bias	People's tendency to seek information consistent with their views or hypotheses
Availability heuristics	People's tendency to judge an event as likely or frequent depending on the ease of recalling and imagining it
Salient information	People's tendency to weigh more vivid information than abstract information
Illusory correlation	People's tendency to believe two variables co-vary when they do not
Procrastination	People tendency to defer actions or tasks to a later time
<i>Processing of information</i>	
Anchoring and adjustment heuristic	People's tendency to rely too heavily, or anchor, on one trait or piece of information when making decisions
Representativeness heuristics	People's tendency to assume commonality between objects of similar appearance
Law of small numbers	People's tendency to consider small samples as representative of the population from which they are drawn
Sunk costs fallacy	People's tendency to pay attention to information about costs that have already incurred
Planning fallacy	People's tendency to underestimate task-completion time
Inconsistency	People's inability to use consistent judgment strategy across a repetitive set of cases or events
Conservatism	People's failure to update their opinions or beliefs when they receive new information
Overconfidence	People's tendency to be more confident in their own behaviour, opinions, attributes and physical characteristics they ought to be
<i>Outcome</i>	
Wishful thinking	People's tendency to assume that because one wishes something to be true or false then it is actually true or false
Illusion of control	People's tendency to believe that they can control or at least influence outcomes that they have no influence over
<i>Information received through feedback</i>	
Fundamental attribution error	People's tendency to overemphasise dispositional or personality-based explanations for behaviour observed in others while underemphasising situational explanations
Hindsight bias	People's tendency to think of events that have occurred as more predictable than they in fact were before they took place
Misperception of feedback	People's tendency to misperceive dynamic environments that include multiple interacting feedback loop, time delays and nonlinearities

While Bendoly et al. (2006) and Gino and Pisano (2008) exclusively focus on individual cognitive biases, Loch and Wu (2007) extend this view. They start by observing that the aim of BOM is to “*bring people issues back into the discipline*”, and add further insights to BOM research, recognising that BOM should

encompass behavioural factors concerning people's motivation in social interactions and the influence of group dynamics.

Based on this, they identify three behavioural OM categories. The first category is concerned with individual decision-making biases due to cognitive limitations; the second category is referred to individual behaviour driven by social goals in the context of social interactions. This category includes emotional signals motivating human behaviour in social interactions, such as the value given to status, fairness in relationships and a positive social image. The third category concerns collective behaviours that emerge in groups such as culture, knowledge and skills resulting from interacting learning processes activated within a given population.

These novel factors to be incorporated in OM models are considered to be more important than the cognitive biases and path the way to the introduction of new research methodologies particularly suited to dealing with interactions and group dynamics.

Summarising, I suggest two taxonomic criteria for classifying BOM studies: (1) models including the characteristics of individuals, among which, in turn, can be distinguished cognitive biases (for a list see Table 1) and social features such as reputation, social status, fairness; (2) models including the properties of groups and populations such as culture, norms, knowledge and skills.

### **3 A Framework for BOM Research: Opportunities from Complexity Science**

My framework for BOM research is based on the claim that operating systems are CASs (Choi et al. 2001; Surana et al. 2005; Pathak et al. 2007; Bozarth et al. 2009), in which human behaviour is central in determining the evolution trajectories and performances. Indeed, in all OM contexts there are a variety of individuals making decisions on many different aspects and interacting among each other at diverse levels, so that the system is able to spontaneously self-organise and co-evolve with the dynamic environment assuming a new ordered configuration and new properties.

Complexity science is the discipline devoted to the study of CASs (Holland 1995). It provides theories and tools to explain how CASs behave and evolve, making it suitable for adoption in OM study contexts. I therefore propose to resort to complexity science to build OM models.

In the following section, I give theoretical support to the proposed framework for BOM research. First, I discuss the complexity of the OM settings and, then, frame them as complex organisational systems. Then, I suggest BOM research directions by discussing what research questions are feasible through this theoretical approach.

### 3.1 *The Complexity of OM Context*

OM is a multi-disciplinary discipline that investigates the design and management of operating systems, i.e. those systems involved in the development, production and distribution of products and services in the hands of final consumers. Typical OM contexts are:

- Product development and R&D;
- Project management;
- Inventory management;
- Production and workflow management;
- Procurement and strategic sourcing;
- Supply chain management.

A wide body of literature has underlined that operating systems in any context are complex organisations (Choi et al. 2001; Surana et al. 2005; Pathak et al. 2007). Complex organisations are complex systems made up of a large number of parts (agents) that interact among each other in nonlinear ways (Simon 1962). Nonlinearity means that there is not a direct correlation between the size of the cause and the size of the corresponding effect. Nonlinearity implies difficulty in making predictions dependable. Variety is a further fundamental property of the agents in a complex system (Casti 1997).

All the dimensions of complexity are recognisable in OM contexts. For example, supply chains are made up of heterogeneous firms each accomplishing a phase of the production process and interacting together to deliver a product/service to the final customer. Variety characterises supply chains because firms differ in organisational culture, size, location and technology. Supply chains also show nonlinear behaviour such as the bullwhip effect (Choi et al. 2001).

These sources of complexity make the design and management of operating systems a very hard task. The traditional approach to handling complexity in OM contexts is to try to reduce it, for example, employing strategies aimed at reducing the number of parts, their variety and the links among them. Conversely, I suggest employing complexity science from both the theoretical and the methodological point of view.

#### 3.1.1 Framing Operating Systems as CASs

Complexity in OM contexts has been dealt with more recently by framing operating systems as CASs (Choi et al. 2001; Surana et al. 2005; Pathak et al. 2007; Bozarth et al. 2009).

A CAS is a special class of complex systems that emerges over time into a coherent form, and adapts itself and emerges without any singular entity deliberately managing or controlling it (Holland 1995). Adaptation, self-organisation and co-evolution are the main features of CASs.

Adaption means that the system changes, improving its fitness for its environment and creates new forms of emergent order consisting in new structures, patterns and properties. Adaption is possible thanks to self-organisation, i.e. the new order arises from the interaction among agents without being externally imposed on the system (Goldstein 1999); self-organisation results in emergence, that is, a new order of some kind.

Self-organisation and emergence characterise the quasi-equilibrium state at the edge of chaos in which CASs operate, a state of non-complete order just short of chaos. It is a combination of regularities and randomness.

An important point emphasised by many authors is that CASs co-evolve with a changing environment. That is, the dynamic environment, by interacting with the CAS, forces changes in the entities that reside within it, which in turn induce changes in the environment (co-evolution). Kauffman (1993) observes that organisms do not merely evolve; they co-evolve both with other organisms and with a changing environment. He describes co-evolution as a process of coupled, deforming landscapes where the adaptive moves of each entity alters the landscapes of its neighbours.

Framing operating systems as CASs means recognising that the operating systems possess the characteristics of a CAS and that they behave as such. They are made up of a number of independent, multiple and heterogeneous human agents making decisions using personal heuristics and schemata. Interactions among the human agents allow the system to self-organise and co-evolve with the rugged and dynamic environment in which it exists.

CAS theory explains how CASs behave and how a new order emerges (Casti 1997; Johnson 2001). Thus, CAS theory applied to OM is aimed at explaining how heterogeneous agents in OM contexts “self-organize” to create new structures and at understanding how those structures emerge and develop.

### ***3.2 CAS-Based Behavioural Operation Management Research***

My rationale for doing BOM research is to build OM models applying methodologies to study CASs and to incorporate behavioural factors into these CAS-based models.

Following this logic, interesting research directions can be identified. Notice that research questions should be formulated coherently with those addressable by CAS theory.

Exemplar OM research questions addressable by using CAS theory are:

- How do operating systems evolve over time?
- How does variety in the elements affect evolution and the creation of order?
- How do strategies/decisions at single level impact the collective behaviour of the system?



- How does the topology of the pattern of interactions (i.e. due to the task interdependencies of a process, the supply chain structure, the product complexity, the technology, etc.) affect dynamics?
- How does the distribution of decision-making power affect performance?

Such questions can be formulated referring to anyone of the OM contexts mentioned above. Therefore, CAS theory allows one the main challenges of OM research to be faced: how to enrich and extend the body of knowledge on OM in different contexts by studying evolution and dynamism in operating systems, which is an issue currently lacking attention in OM literature (Pathak et al. 2007).

However, in order to do BOM research, behavioural factors including both individual and population properties should be incorporated into the research questions. Both descriptive and prescriptive research can be developed. As said above, the prescriptive approach analyses how operating system should work incorporating the behavioural factors. Instead, descriptive research is aimed at understanding the effect of behavioural factors on the decision-making process and in turn on the performances of operating systems (Gino and Pisano 2008).

For example, one could question:

- How do the operating system (e.g. process, firm and supply chain) evolves in the short and long run in the case of a particular decision maker's bias, such as overconfidence, conformism or anchoring heuristics?
- What new order emerges in the system in the case of individual cognitive biases?
- Is the emergence of a new order affected by a specific behavioural factor?
- Do the considered behavioural factors influence the resulting performances?

To give answers to the research questions above, CAS theory offers suitable tools and methods, as described in the next Section. Whatever the tool and method chosen, the advantage offered by CAS theory is that it permits the effect of behavioural factors and the resulting operating system behaviour to be studied as the spontaneous result of the system's self-organisation and co-evolution with the environment.

## **4 Complexity-Based Methodologies for BOM Research: NK Fitness Landscape**

Recognising the complex nature of operating systems and studying them as CASs provide a rich set of tools to model and analyse their complexity. I limit attention to one methodology largely employed in complexity science literature for the study of CASs, i.e. *NK* fitness landscape.

It has been selected for a variety reasons. Firstly, it has been successfully applied in general management contexts to study organisational behaviour (Davis et al. 2007). It is well suited to behavioural research because it allows individual

and social properties in OM models to be incorporated with ease, as I describe next. Furthermore, the proposed methodology is more suitable than experimental research, the main alternative methodology adopted in behavioural studies in many different fields such as economics, finance, organisation, for dealing with complexity. It is also better adaptive to overcoming the difficulty in predicting and understanding which individual agent strategies are most likely to lead to a desired collective behaviour. In OM contexts characterised by high complexity, experiments indeed could be costly and might not cover all possible events (Surana et al. 2005), while simulation may do this for a fraction of the cost.

Although extensively used in management studies, *NK* fitness landscape is novel in BOM. Moreover, there are even very few examples of applications in OM contexts in the literature (see for example Giannoccaro (2011) for the application of *NK* fitness landscape).

In the next section the methodology is described presenting key concepts and some common research questions which they are used to address. Finally, I discuss how the OM contexts and the behavioural factors might be modelled.

## 4.1 The *NK* Fitness Landscape

### 4.1.1 Description

The *NK* fitness landscape is a simulation technique advanced by Kauffman (1993) in the context of evolutionary biology and consists in a family of fitness landscapes which can be tuned by two parameters,  $N$  and  $K$ . In particular, the stochastic procedure proposed by Kauffman to design fitness landscapes has subsequently become popular in the modelling of organisational decision problems (Levinthal 1997; McKelvey 1999; Gavetti and Levinthal 2000; Rivkin 2001; Siggelkow 2001; Ethiraj et al. 2008; Ghemawat and Levinthal 2008; Ganco and Hoetker 2009; Giannoccaro 2011).

In these studies, the system (e.g. a firm, a product, a technology, a strategy, a plant, a supply chain), is conceptualised as a set of  $N$  elements and  $K$  interactions. Each element may assume different states and, typically, it is assumed that each element occupies a binary state, i.e. 0 or 1.

The following describes applications of *NK* fitness landscape to the modelling of a firm. In such a case, the firm is conceptualised as a set of interdependent decisions. Decisions may concern what new product to be launched, the procurement policy, the production/transportation schedule, the inventory management policy, the adoption of IT, to name a just few possibilities.

A particular  $N$ -digit string  $c = (d_1, d_2, \dots, d_N)$  represents a specific combination of choices regarding the decisions to be made (configuration).

$K$  is the average number of interactions among the decisions  $d_i$ . It models the richness of interactions among the decisions. Two decisions interact with each other when the contribution of a decision to the system payoff depends on the

choice on the interacting decisions. For example, the adoption of a new IT is more or less effective on the basis of the decisions of the managers to invest in workforce formation; the decision to reduce the safety stock could be detrimental for the firm, if the decision on the procurement policy is to adopt a multiple sourcing policy under arm's length strategy conditions, whereas it could be much more effective in the case of a partnership and single sourcing policy.

The pattern of interactions among the decisions is contained in an  $N \times N$  influence matrix where each  $x$  in the  $(i, j)$  position means that the column decision  $j$  influences the row decision  $i$ .

The different ways, in which the firm's choices (0–1) about the decisions are combined, generate  $2^N$  possible configurations, to each of which is associated a fitness value for the overall system, i.e. a firm overall payoff  $P(d)$ . The map from each configuration into the overall payoff is the fitness landscape, where the position in the landscape corresponds to the configuration, and the height, to the payoff of the configuration.

The landscape is thus made up of valleys and peaks. The highest peak (global peak) corresponds to the configuration assuring the highest payoff. Local peaks are configurations with the highest payoffs in the neighboured positions (they correspond to the definition of local optima, while the global peak is the global optimum) and are good configurations.

A specific stochastic procedure is adopted to generate the fitness landscape. For each choice configuration, each single decision  $d_i$  offers a contribution  $C_i$  to the overall payoff, which in turn is calculated by averaging the  $N$  contributions.

Therefore,  $P(d) = [\sum_{i=1}^N C_i(d)]/N$ . The contributions  $C_i$  are drawn randomly from a uniform distribution over  $[0, 1]$ . Note that each  $C_i$  depends not only on the corresponding decision but also on how the decisions interacting with it are resolved.

It is assumed that the firm is engaged in an adaptive walk across the landscape in search of the highest peak. The goal of the search is to identify the choice configuration that yields the highest firm overall payoff, or in other words, to reach the highest peak of the landscape (i.e. the global peak).

Thus,  $NK$  fitness landscape is an optimising decision making problem whose solution is achieved through the simulation of the firm's adaptive walk across the landscape.

The adaptive walk is simulated through a search algorithm. The most commonly adopted is based on an incremental improvement strategy consisting of the following steps: (1) new alternative configurations are proposed by changing a limited number of decisions, (2) all or some of the new alternative configurations are compared with the status quo, (3) a movement of the system to occupy the new configuration if better than the status quo.

A long jump strategy can be also employed (Levinthal 1997; Rivkin 2001), in which case, the system may jump directly (reproduce), with a specified degree of effectiveness (probability), to the best configuration.

The effectiveness of the search is a function of the shape of the landscape. The shape strongly depends on  $K$ . When  $K = 0$ , the landscape is smooth and single-peaked and the search for the global peak is very easy, even using an incremental improvement strategy. When  $K$  increases, the landscape becomes rugged and multi-peaked, i.e. with many local peaks, and the search for the global peak is less effective because the firm may be trapped in one of the local peaks.

The following steps should be followed to employ the  $NK$  fitness landscape methodology:

1. Fix  $N$  and  $K$ ;
2. Fix the interaction matrix;
3. Generate the performance landscape;
4. Define the search algorithm;
5. Release the firm on the landscape;
6. Perform a search for the global peak;
7. Collect performances.

Performances in  $NK$  fitness landscape are measured in terms of efficacy and speed in finding the global peak. The efficacy of a search is commonly measured in terms of overall system payoff computed as a portion of the maximum performance attainable on the landscape. Performance both in long run (at the end of the simulation) and short run (first runs of the simulation) are collected.

Sometimes this performance is accompanied for explanatory purpose, or is estimated, by computing the number of local peaks and sticking points characterising a specific landscape. A local peak is a configuration such that no configuration differing by only one decision exists resulting in a higher payoff. The sticking point is a configuration of choices from which the system does not move, because there is no different configuration in one decision which meets the approval of the decision maker (Siggelkow and Rivkin 2002).

The higher the number of local peaks and the number of sticking points, the lower the efficacy of the system is likely to be since it has a high probability of becoming trapped into a sub-optimal configuration. The number of sticking point is also a measure of search diversity (or exploration), because the higher the number of sticking points, the higher the probability that the system will already be blocked into a sub-optimal configuration in the first stage of search, thus resulting in a low level of search diversity and exploration (Siggelkow and Rivkin 2005).

Search speed is measured as the average improvement in performance experienced during the first stages of a search.

Research questions that can be handled by employing  $NK$  fitness landscape should be framed as “problem solving” or, equivalently, a search for the optimal point on the landscape (Davis et al. 2007). Research questions are commonly formulated in the following terms:

- How long does the system take to find an optimal configuration?
- What is the performance of this configuration?
- What effect does increasing the number of elements ( $N$ ) have on performance?

- What effect does increasing the level of interactions ( $K$ ) have on performance?
- What effect does changing the overall pattern of interactions (interaction matrix) have on performance?
- How do performances change if alternative search algorithms are used?

In organisation studies the most relevant applications concern problems of organisational adaptation, organisational design and organisational behaviour. Specifically, in the latter area of study, they allow the consequences of cognitive limitations of the decision makers involved in the organisations to be analysed (Siggelkow 2011).

#### 4.1.2 Coding OM Contexts into $NK$ Fitness Landscape

Table 2 illustrates how different OM contexts might be modelled using  $NK$  fitness landscape. For each context what  $N$ ,  $K$ , the pattern of interactions and the search algorithm model is described.

In the case of product development and R&D contexts, applications are suggested by explicitly referring to strategic and organisational studies (references are given in the last column of Table 2). I believe that since this context is cross-sectional to OM, strategic management, and organisational theory, applications in these fields could be considered as also pertaining to OM. In such a context,  $N$  and  $K$  are commonly employed to model the product and the technology in terms of the components and the number of interdependencies among them. The configuration of choices represents a specific product design or technology choice. The pattern of interactions describes the product architecture (e.g. modular versus integral). Incremental improvement algorithms are employed to model experiential learning, the wideness of search is used to model exploitation (limited search) and exploration (wide search), and long jump stands for reverse engineering practice or imitation of the leader.

For the other OM contexts I suggest possible ways of coding to identify which variables stand for  $N$ ,  $K$ , the pattern of interactions and the search algorithm. To best of my knowledge, there are no applications of  $NK$  methodology in these OM contexts. The only exceptions refer to a study concerning the inventory and distribution system and a few applications to supply chain management.

#### 4.1.3 Incorporating Behavioural Factors in $NK$ Fitness Landscape

As discussed above,  $NK$  fitness landscape contributes to BOM through the development of CAS-based OM models incorporating behavioural factors. In the next section, I suggest how to code in  $NK$  fitness landscape the behavioural factors classified in (1) bounded rationality and cognitive biases, (2) social factors and (3) population factors.

Table 2 Coding OM contexts into *NK* fitness landscape

OM context	<i>N</i>	<i>K</i>	Pattern of interaction	Search algorithm	References
Product development and R&D	Number of components	Degree of interdependence among components	Product architecture (modular, integral)	Long jump: Imitation by reverse engineering, exploration strategy; Incremental improvement: experiential learning, exploitation strategy	Rivkin and Siggelkow (2003, Siggelkow and Rivkin 2005) and Gavetti and Levinthal (2000)
	Number of product/technology				
Project management	Number of activities/tasks making up project	Degree of interdependence among activities/tasks	Process pattern	Organisational structure of activities	
Inventory and distribution management	Number of stock keeping units, warehouse/DCs	Degree of interconnections	Distribution network	Level of centralisation	
Production management	Number of production sites, products, production tasks	Degree of process/product flexibility, i.e. shifting product production to another site, degree of task interdependence	Topology of the production sites, pattern of task interdependencies (pooled, sequential, reciprocal)	Production strategy	
Procurement and strategic sourcing	Number of suppliers, items to be purchased	Degree of cooperation among suppliers, degree of interrelations among items in bill of materials	Sourcing policy (multiple, single, and double sourcing)		

(continued)

Table 2 (continued)

OM context	$N$	$K$	Pattern of interaction	Search algorithm	References
Supply chain management	Number of supply chain firms, decisions	Degree of inter-firm relationships; density of links in supply chain	Type of integration problem; type of production process	Form of governance	Giannocco (2011) Choi and Krause (2006) Levinthal and Warglien (1999)

## Bounded Rationality and Cognitive Biases

Bounded rationality of the decision maker means that people fail to be fully rational: they have limited cognition and computation capability to identify all the alternatives, determine all eventual consequences of each alternative and select the best according to the decision maker's preferences (Simon 1955).

Bounded rationality can be modelled in *NK* fitness landscape through the search capability of the agent. A local search algorithm, where only one decision is allowed to change, models high cognitive limitation of the decision maker. Instead, higher cognitive intelligence can be modelled by increasing the number of decisions that can be modified at the same time.

For example, to model search capability, Rivkin and Siggelkow (2003, 2005) introduce two variables: the search radius (SR) and the number of alternatives. The SR captures the degree of bounded rationality of the decision maker, namely the ability of the decision maker to make simultaneous changes to a wide range of decisions (Siggelkow and Rivkin 2006; Agarwal et al. 2011). A SR = 1 means that only one decision can be changed. The number of alternatives (ALT) a decision maker that may evaluate reflects the processing power of the decision maker at any organisational level (Siggelkow and Rivkin 2006). A large number of alternatives to be compared with the status quo, models a "smarter" decision maker.

Commonly, the decision maker selects randomly the alternatives to be evaluated. This selection, however, could be differently modelled for incorporating individual biases of decision maker. For example, the decision maker may generate alternatives at random and selected the ALT alternatives with the highest rank. The ranking algorithm is thus a modelling strategy for some individual cognitive biases. For example, confirmation bias could be modelled by a ranking algorithm giving higher rank to configurations having more similarities (i.e. number of decisions with the same choice) with the status quo.

More examples of how some individual biases could be modelled through the *NK* framework are given in Table 3. I suggest different modelling strategies, concerning not only search capability. They include:

- Search algorithm;
- Ranking algorithm for judging alternatives;
- Overall payoff calculation function;
- Decision rule to move, or not to move, into a new configuration;
- Generation of a new landscape along the same simulation.

I limit examples to the cognitive biases classified by Gino and Pisano (2008) and reported in Table 1. However, it should be noted that *NK* methodology allows different cognitive biases to be defined and modelled such as misperceptions of the decision maker about the degree of interactions, and pattern of interactions. In such cases, the modelling strategy adopted is the generation of a landscape different from the actual one, conforming to what the decision maker believes to be the degree and the pattern of interactions.



Table 3 Modelling individual properties through NK fitness landscape

Behavioural factor	Search algorithm	Ranking algorithm	Formula to calculate overall payoff	Decision rule for moving on the landscape	Landscape generation
Cognitive bound	Incremental improvement defined by search radius and number of alternatives				
Information avoidance			Average of $C_i$ not including contributions referring to decisions $i$ that are avoided		
Confirmation bias		Giving higher rank to alternatives more similar to status quo			
Availability heuristics		Giving higher rank to alternatives similar to certain past choices			
Salient information			Weighted average of $C_i$ , with higher weight for certain decisions		
Procrastination				Jumping simulation step	
Anchoring and adjustment heuristics			Average of contributions referring only to most familiar decisions		
Representativeness heuristics					Modifying payoff in landscape so that similar configurations have similar payoffs

(continued)

Table 3 (continued)

Behavioural factor	Search algorithm	Ranking algorithm	Formula to calculate overall payoff	Decision rule for moving on the landscape	Landscape generation
Inconsistency			Using different formulas to calculate overall payoff during simulation		
Conservatism				To maintain status quo configuration even when better configuration is identified	
Overconfidence					Generation of landscape different from actual one
Wishful thinking				Movement to desired configuration, regardless of actual payoff	
Illusion of control	Developing alternatives external to search radius				
Misperception of feedback					No update of landscape when new events occurs

## Social Factors

When a problem involves multiple decision makers, a complex web of interactions emerges among them, affecting how operating systems work and perform. The specific pattern of interactions are the result of the behavioural factors involved.

Thus, to incorporate the social factors in OM models it is necessary to model such a network of interactions, defining the procedure adopted by the multiple decision makers to coordinate among each other in the search for the global peak. This is defined by the organisational structure.

In particular, it is the firm's organisational structure that defines how decision makers coordinate their work to pursue a common goal. It defines the hierarchical position of the decision maker (middle manager or CEO), the responsibility in terms of what decision she/he controls and the level of centralisation of the decisions (Rivkin and Siggelkow 2003, 2005).

Thus, as a modelling strategy for social factors, I suggest inserting them in the organisational structure. They can either influence the formal organisational structure, or be responsible for the existence of an informal organisation structure. Both directions are feasible.

In an *NK* fitness landscape the organisational structure is modelled by defining: (1) how the configuration choices made by the different decision makers are reunified to propose alternative configurations of the overall system, (2) how they are ranked, and, (3) how they are selected. In fact, as there are multiple decision makers, the configuration of the overall system will be computed by merging the alternatives proposed by each decision maker.

For example, in case of a decision maker highly prone to collaborating with the others and strongly committed to the firm's success, rather than to evaluating and ranking the proposed alternatives on the basis of the economic return of the decision maker (local payoff), he/she may evaluate alternatives based on an overall firm payoff.

The fairness, trusting behaviour and reputation of a decision maker can be similarly modelled. For example, a decision maker may trust, or not, that a configuration choice proposed by another decision maker is correct and made in the best interest of the entire organisation, on the basis of the reputation of fairness of the latter. If he/she trusts the other decision maker, he/she could compute his/her own configuration choice using the configuration choice suggested by the other decision maker. Otherwise, if he/she does not trust the other decision maker, he/she may decide to ignore the other's decisions using a random choice configuration.

In the same way other social preference factors could be modelled, such as social status. The decision maker who is responsible for making the merging of local configuration choices suggested by the local decision makers and for proposing the overall system alternative choice (i.e. the CEO) which might prefer to rely more on the choices made by those decision makers with whom he/she has familiarity or those with a good social reputation, neglecting the others.

Alternatively, social factors may also be modelled as an informal organisational structure, which re-allocates decision-making authority to each decision maker on the basis of status, reputation, credibility, capabilities recognised by other individuals. This informal structure should be modelled parallel to the formal one. As a consequence, in the simulation decisions will be made by those decision makers informally empowered with decision-making authority in accordance with the informal organisational structure, regardless of the distribution of decision-making power in the formal one.

### Properties of Groups and Populations

*NK* fitness landscape is a methodology well suited to describing and analysing population properties in operating systems, because it permits collective behaviours to be modelled as the spontaneous result of self-organised, multiple interactions among human decision makers. Population properties emerge over time without any control being exerted by the decision maker or by modeller.

Behavioural factors in an OM context which are particularly interesting to analyse include culture, knowledge and collective learning (Loch and Wu 2007). There are very few examples in the literature of *NK* models incorporating them.

I propose some modelling strategies to do this referring to the model put forward by Press (2008) who modelled the diffusion of best practice within groups of firms belonging to the same production segment of an industrial district. Each firm proposes its own alternative choice configuration and the payoff of each configuration is computed. The best one is selected and transferred to the other firms which then adopt it.

Culture acts as a norm to which each decision maker adheres without questioning it. Therefore, it can be modelled by assuming that the decision makers belonging to the same group or population adopt the same procedure to propose alternatives, the same ranking algorithm, the same formula to compute the overall payoff and/or the same rule regarding decisions to move to a new configuration.

Knowledge may be conceived in simulation as a repository of information accessible to any decision maker. In *NK* models, knowledge can be modelled through the performance landscape. The existence of a common base of knowledge means that decision makers use the same information to make decisions, i.e. the performance landscape. When a population is divided into groups, all the agents within a group have access to the same pieces of the entire body of information, therefore they only know some parts of the entire landscape.

#### 4.1.4 BOM Research Through *NK* Fitness Landscape

What type of BOM research can be done by employing *NK* fitness landscape? Which BOM research directions can be suggested by resorting to *NK* fitness landscape?

**Table 4** *NK*-based research questions for two OM contexts

<i>NK</i> -based research questions	<i>NK</i> -based OM research questions
<i>New product development</i>	
How long does it take to find an optimal configuration?	How much faster is the system at developing a new product/process?
What is the performance of this configuration?	How effective is the new product configuration?
What effect on performance does increasing the number of elements ( $N$ ) have?	What effect on performance does increasing the complexity of the product in terms of number of components have?
What effect on performance does increasing the level of interactions ( $K$ ) have?	What effect on performance does increasing the complexity of the product in terms of number of components have?
What effect on performance does changing the overall pattern of interactions (interaction matrix) have?	What effect on performance does making a product/process more/less modular have?
How do performances change using alternative search algorithms?	Which product architecture offers a correct number of effective alternative configurations?
	What effect on performance do different R&D strategies (e.g. exploitation versus exploration, first entry versus imitation) have?
<i>Supply chain management</i>	
How long does it take to find an optimal configuration?	How much faster is the system at finding an optimal supply chain configuration?
What is the performance of this configuration?	How effective is the supply chain configuration?
What effect on performance does increasing the number of elements ( $N$ ) have?	What effect on performance does increasing the number of firms in the supply chain (i.e. reducing the level of vertical integration) have?
What effect on performance does increasing the level of interactions ( $K$ ) have?	What effect on performance does increasing the number of links among firms have?
What effect on performance does changing the overall pattern of interactions (interaction matrix) have?	What effect on performance does pursuing modular or integral structures have?
How do performances change using alternative search algorithms?	Which supply chain structure offers a correct number of effective alternative configurations?
	What effect on performance do different forms of governance (e.g. centralisation versus decentralisation), have?

In order to answer these questions, we should formulate first OM research questions that are coherent with the use of *NK* fitness landscape. As discussed in Sect. 4.1.1, such research questions refer to how long the system takes to find optimal configurations and the performance of these optimal configurations. Moreover, the *NK* landscape fitness approach is suitable for analysing the effect on performance of the increase in the number of parts making up the system ( $N$ ), the rise in the number of links among them ( $K$ ), the change in the pattern of interactions ( $[M]$ ) and the application of various search algorithms.

**Table 5** Examples of BOM *NK* research questions in the supply chain management context

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*Prescriptive research questions*

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When decision makers are characterised by  
high trust behaviour and reputation,

- how much faster is the supply chain at finding an optimal supply chain configuration?
- how effective is the optimal configuration?
- what effect on performance does increasing the level of vertical integration have?
- what effect on performance does increasing the number of links among firms have?
- what effect on performance do modular versus integral structures have?
- what effect on performance does the degree of centralisation of the decision making power have?

*Descriptive research questions*

Do trust behaviour and high reputation of  
the decision makers influence:

- the speed of the supply chain in finding an optimal supply chain configuration?
  - the effectiveness of the optimal configuration?
  - to what extent increasing the level of vertical integration affects performance?
  - to what extent increasing the number of links among firms affects performance ?
  - to what extent the choice of modular versus integral structures affects performance?
  - to what extent the degree of centralisation of the decision making power affects performance?
- 

Based on this, by adopting the coding of OM contexts shown in Table 3 in an *NK* fitness landscape, specific OM research questions addressable through *NK* fitness landscape can be formulated in any OM context.

Following this procedure, in Table 4 OM *NK*-based research questions are derived for two OM contexts, i.e. product development and R&D and supply chain management. The same questions might hold also for different OM contexts.

Notice that the suggested procedure is general. It may result in different research questions depending on the coding of the OM contexts in the *NK* fitness landscape.

Finally, in order to identify BOM research questions, it is necessary to incorporate behavioural factors into the *NK*-based OM research questions, coherently with both a prescriptive and a descriptive approach.

To do this, it is important to identify which are the most critical behavioural factors to study. I suggest making a list of behavioural factors for any OM context including both individual and population factors and evaluating the importance of each in terms of potential effect on performance in the specific context. If a behavioural factor does not affect how the operating system works and performs, it

is not critical and it is not necessary to study it. In the same way, Gino and Pisano (2008) propose research questions by identifying for each of the considered contexts in which cognitive biases are more likely to occur and to affect performance.

Once the critical behavioural factors have been identified, BOM research questions can be formulated by questioning how behavioural factors affect performance and/or on how the system works and performs, given the included behavioural factors. Research questions should be formulated coherently with those addressable through *NK* fitness landscape.

For example, making explicitly reference to the supply chain management context, the behavioural factors affecting social interactions among decision makers are very relevant. The effective and efficient management of the supply chains indeed depends on how all decision makers interact among each other to reach a common goal. In such a context trust and reputation are key issues influencing the system dynamics (Ireland and Webb 2007; Johnston et al. 2004; McCarter and Northcraft 2007). Examples of BOM *NK* research questions are shown in Table 5.

The same approach can be adopted to generate BOM research questions addressable through *NK* fitness landscape including different behavioural factors by simply substituting “trust behaviour and reputation” in the first sentence of the research question with the factor to be considered.

## 5 Conclusions

There are few studies that have analysed methodological issues in BOM research. Although most BOM studies to date have used experiments, there is no need to constrain the study of how behavioural factors affect the work and the performance of operating systems only to this methodology.

In this chapter I have proposed the adoption of complexity science both from a theoretical and methodological point of view in BOM research. This argument has been discussed viewing operating systems as CASs, i.e. complex systems that are able to self-organise, adapt and co-evolve with a dynamic environment. Many dimensions of complexity are indeed recognisable in operating systems, such as the large number of parts making up the system, the variety of elements, the interconnections among them and the non linear and adaptive behaviours displayed by the system.

Moving from this assumption, I have suggested applying complexity science in order to study operating systems in diverse OM contexts and I have also proposed research questions coherent with a complexity science approach. They concern how operating systems behave, adapt and show new orders in terms of processes, structures and performances. This allows a gap in BOM literature to be filled. The latter has been focused more on adopting static approaches with scarce insights into the effect of behavioural factors on the dynamism and evolution of operating systems.

Is the emergent order affected by behavioural factors? Is the adaptivity of operating systems dependent on behavioural factors? When specific behavioural biases occur, which strategies are most effective in stimulating the system to evolve in a desired direction? Such research questions can be contextualised in any OM context and their answers will provide interesting new knowledge for the field.

I have also suggested the adoption of a simulation tool to study CASs to develop BOM models, i.e. *NK* fitness landscape. After reviewing the methodology and its main applications in organisational contexts, I have suggested how different OM contexts can be modelled and how behavioural factors both at an individual and at a population level might be operationalised through the methodology proposed.

Finally, I have suggested how to formulate research questions that might be addressed by applying *NK* fitness landscape. Using the proposed framework, interesting future research directions in BOM research in one OM context have been suggested.

In conclusion, this chapter wishes to offer two main contributions to BOM research: on the one hand, the suggestion that valuable BOM research is possible thanks to application of complexity science as a theoretical and methodological approach; on the other hand, the provision of a methodological toolkit based on *NK* fitness landscape allowing BOM models to be built.

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Behavioral Issues in Operations Management  
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Methodologies

Giannoccaro, I. (Ed.)

2013, XII, 241 p., Hardcover

ISBN: 978-1-4471-4877-7