Advances in Intelligent Systems and Computing 1009

Edgardo Bucciarelli
Shu-Heng Chen
Juan Manuel Corchado *Editors*

Decision Economics: Complexity of Decisions and Decisions for Complexity

Springer

Advances in Intelligent Systems and Computing

Volume 1009

Series Editor

Janusz Kacprzyk, Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland

Advisory Editors

Nikhil R. Pal, Indian Statistical Institute, Kolkata, India
Rafael Bello Perez, Faculty of Mathematics, Physics and Computing, Universidad Central de Las Villas, Santa Clara, Cuba
Emilio S. Corchado, University of Salamanca, Salamanca, Spain
Hani Hagras, School of Computer Science and Electronic Engineering, University of Essex, Colchester, UK
László T. Kóczy, Department of Automation, Széchenyi István University, Gyor, Hungary
Vladik Kreinovich, Department of Computer Science, University of Texas at El Paso, El Paso, TX, USA
Chin-Teng Lin, Department of Electrical Engineering, National Chiao Tung University, Hsinchu, Taiwan
Jie Lu, Faculty of Engineering and Information Technology, University of Technology Sydney, Sydney, NSW, Australia
Patricia Melin, Graduate Program of Computer Science, Tijuana Institute of Technology, Tijuana, Mexico
Nadia Nedjah, Department of Electronics Engineering, University of Rio de Janeiro, Rio de Janeiro, Brazil
Ngoc Thanh Nguyen, Faculty of Computer Science and Management, Wrocław University of Technology, Wrocław, Poland
Jun Wang, Department of Mechanical and Automation Engineering, The Chinese University of Hong Kong, Shatin, Hong Kong

The series "Advances in Intelligent Systems and Computing" contains publications on theory, applications, and design methods of Intelligent Systems and Intelligent Computing. Virtually all disciplines such as engineering, natural sciences, computer and information science, ICT, economics, business, e-commerce, environment, healthcare, life science are covered. The list of topics spans all the areas of modern intelligent systems and computing such as: computational intelligence, soft computing including neural networks, fuzzy systems, evolutionary computing and the fusion of these paradigms, social intelligence, ambient intelligence, computational neuroscience, artificial life, virtual worlds and society, cognitive science and systems, Perception and Vision, DNA and immune based systems, self-organizing and adaptive systems, e-Learning and teaching, human-centered and human-centric computing, recommender systems, intelligent control, robotics and mechatronics including human-machine teaming, knowledge-based paradigms, learning paradigms, machine ethics, intelligent data analysis, knowledge management, intelligent agents, intelligent decision making and support, intelligent network security, trust management, interactive entertainment, Web intelligence and multimedia.

The publications within "Advances in Intelligent Systems and Computing" are primarily proceedings of important conferences, symposia and congresses. They cover significant recent developments in the field, both of a foundational and applicable character. An important characteristic feature of the series is the short publication time and world-wide distribution. This permits a rapid and broad dissemination of research results.

**** Indexing: The books of this series are submitted to ISI Proceedings, EI-Compendex, DBLP, SCOPUS, Google Scholar and Springerlink ****

More information about this series at http://www.springer.com/series/11156

Edgardo Bucciarelli · Shu-Heng Chen ·
Juan Manuel Corchado
Editors

Decision Economics: Complexity of Decisions and Decisions for Complexity

Springer

Editors
Edgardo Bucciarelli
Department of Philosophical, Pedagogical and Economic-Quantitative Sciences, Section of Economics and Quantitative Methods
University of Chieti-Pescara
Pescara, Italy

Shu-Heng Chen
AI-ECON Research Center - Department of Economics
National Chengchi University
Taipei, Taiwan

Juan Manuel Corchado
Edificio Parque Científico Universidad de Valladolid
AIR Institute
Salamanca, Spain

ISSN 2194-5357 ISSN 2194-5365 (electronic)
Advances in Intelligent Systems and Computing
ISBN 978-3-030-38226-1 ISBN 978-3-030-38227-8 (eBook)
https://doi.org/10.1007/978-3-030-38227-8

© Springer Nature Switzerland AG 2020
This work is subject to copyright. All rights are reserved by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.
The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.
The publisher, the authors and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, expressed or implied, with respect to the material contained herein or for any errors or omissions that may have been made. The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

Dedicated to ***Shu-Heng Chen*** *and* ***Juan Manuel Corchado***:

For all that has been and all that will be together with you both, in the name of education, research, and intellectual social responsibility.

E.B.

Decision Economics: A novel discipline.

Three years ago, very much inspired by the legacy of Herbert A. Simon (1916–2001), we organised a special event in commemoration of the hundredth anniversary of his birth under the umbrella of the 13th International Symposium on Distributed Computing and Artificial Intelligence (DCAI) in the University of Seville, Spain. This was also the first time that we attempted to introduce decision economics as a new branch of economics formally. In the past, from a strictly scientific point of view, the term "decision economics" was occasionally used in conjunction with managerial economics, mainly as an application of neoclassical microeconomics. However, given the increasingly interdisciplinary nature of decision-making research, it is desirable to have a panoramic view that is much broader and much more inclusive than the conventional standard view. Therefore, in our first edition of decision economics, we have provided a tentative definition of "decision economics" so as to register this neologism as a discipline in economics (Bucciarelli, Silvestri and Rodriguez, 2016, p. vii), and we have further added some remarks to elaborate on the proposed definition in subsequent editions (Bucciarelli, Chen and Corchado, 2017, 2019). Our efforts over the last three years have successfully aroused a new wave of interest in decision economics, and the special sessions run over the last three years have now expanded into an autonomous conference, beyond DCAI. This remarkable growth is manifested by a total of 35 chapters that are included in this volume, which is almost double the size of our previous edition.

We are certainly grateful to our collaborating partner DCAI for its determination to support this new series. In addition to that, since this is the first international conference on "decision economics" ever held in the world of economics, we would like to highlight the significance of this milestone. For us, this milestone denotes and corresponds to two important recent developments related to decision economics. The first one is the changing and expanding domain of decision economics, not just in terms of its methodology but also in its ontology. The second one, while also related to the first one, is concerned with AI possibilities and their implications for decision-making in economics and finance. Not only do these two developments shape the structure of the fourth edition of this series, but they also give rise to the subtitle of the volume, namely Complexity of Decisions and Decisions for Complexity. Before leaving room for the individual chapters of this volume, all inspired by a shared framework based on decision economics, let us elaborate on the two underpinning developments.

First, the study of choice-making and decision-making is one of the most well-received inner definitions of economics as well as one of its cutting edge research that is carried out ever since the magnum opus of Lionel Robbins (1898–1984), namely *An Essay on the Nature and Significance of Economic Science* (Robbins, 1932). Robbins states, "For rationality in choice is nothing more and nothing less than choice with *complete awareness of the alternatives rejected*. And it is just here that Economics acquires its practical significance." (Ibid., p. 136; Italics added). With this spirit, the neoclassical economics that followed and strengthened later tended to frame decision problems in an ideal form of logic, endowed with a 'sufficient' degree of knowledge, descriptions and transparency; in this way, complete awareness of the alternatives rejected was ensured. This formulation may have helped economics become a formal – but impersonal and detached from human experience – science (e.g., Stigum, 1990); in any case, an unyielding devotion to it without reservation has also alienated economics itself substantially from many realistic aspects of decision making from both normatively and positively perspectives.

In reality, few non-trivial decision problems have a complete description or are completely describable. Gerd Gigerenzer opens his book *Gut Feelings* (Gigerenzer, 2007) with the following sarcastic story:

> A professor from Columbia University (New York) was struggling over whether to accept an offer from a rival university or to stay. His colleague took him aside and said, "*Just maximize your expected utility*–you always write about doing this.". Exasperated, the professor responded, "*Come on, this is serious*." (Ibid, p. 3; Italics added).

Given the kind of the aforementioned problem, which is fraught with what Michael Polanyi (1891–1976) coined as the *tacit dimension* (Polanyi, 1966), the decision is usually made with the involvement of a set of bounded cognitive abilities, critical skills, knowledge and experience, as well as imagination, gut feeling, affection, emotion, social conformity, cultural routines, and so on and so forth. Unfortunately, this list of added elements has not been sufficiently dealt with in mainstream economics. Decision economics, as a new discipline in economics, acknowledges the interdisciplinary nature of decision-making. Even though the two countervailing forces—*pleasure and pain*—had already been brought into economic theory back in the days of Jeremy Bentham (1748–1832) and Stanley Jevons (1835–1882), it may still be too optimistic to think that these two forces can be properly understood in purely mathematical and quantifiable manner. Had not neoclassical economics been generally oblivious to the complexity of decision problems, a pluralistic approach to decision-making might have already been appreciated. In this regard, decision economics attempts to serve as a bridge between economics and other related disciplines, from biology, and the social sciences, to the humanities, and the computer and cognitive sciences, and also to broaden and to deepen the connection between economics and other disciplines. This scientific pluralism has been pursued in our previous three editions and is also reiterated in this edition. After all, decision economics aims neither to endorse exclusively nor to resemble exactly hard sciences since its subject is considerably different from them and continually changing, starting with its immanent ontology (and ethics) and the underlying plurality of paradigms which should, therefore, be regarded and welcomed. And it is precisely this that makes economics − and decision economics therein − a fascinating science, not at all dismal, but rather worthy of being further explored, studied, and taught not only in the sacred groves of academe. Now that more and more social scientists are approaching and realising the emergence of boundedly rational agents − by the way, is there still any doubt remaining?! − if not even irrational agents, and despite the existence of possible invariants of human behaviour (Simon, 1990), the following quotation from Kurt W. Rothschild (1999) describes the idea concisely: "A plurality of paradigms in economics and in social sciences in general is not only an obvious fact but also a necessary and desirable phenomenon in a very complex and continually changing subject.". (Ibid., p. 5). In the final analysis, accordingly, if anything were to be introduced a different normative standard, it can not elude a rational theory of heuristics this time (Gigerenzer, 2016).

The second point we would like to emphasise is the relationship between AI possibilities and decision economics. Within the cognitive sciences, AI has long been regarded as a tool for building—among others—decision support systems to cope with economic decision-making in increasingly complex business and IT environments. This is why AI is a fulcrum of decision economics, and its functionality has been well demonstrated in Gigerenzer and Selten (2001) and in our previous edition (Bucciarelli, Chen and Corchado, 2019). Nevertheless, with the third wave of the Digital Revolution (e.g. Gershenfeld, Gershenfeld and Cutcher-Gershenfeld, 2017), AI is more than just a toolkit for decision economics; it can go further to redirect the entire research trend and the emerging paradigm of decision economics, supported in the first place by a different structure of thought and cognitive representations than does neoclassical economics. As we have emphasised in the last three editions, decision economics—or Simonian economics—is built upon a broad notion of boundedly rational agents characterised by limited cognitive capabilities, and hence the limited capability to search and generate alternatives, as well as to process data and thus extract information and knowledge. With this inescapable constraint, the search rules and the decision rules that are implementable are naturally required to be bounded in their either computational complexity or algorithmic complexity (e.g. Velupillai, 2010, 2018). That being the case, the criterion based on *complete awareness of the alternatives rejected*, the premise suggested by Lionel Robbins, is difficult to comply with. And not only difficult to comply with, but difficult to convey helpfully, too.

All things considered, in these prolific days of AI with the Internet of everything (e.g. Lawless, Mittu and Sofge, 2019), people are anxious to know what the meaning of decision-making is, should AI in the end be able to take care of all decisions made by humans, definitely, after first handling those routine ones with great success. In fact, today, once in a while, we may have been amazed by the machine intelligence demonstrated by the intelligent assistants or chatbots residing in our smartphones, just to mention one example. People start to wonder again on when and to what extent the Turing test will be passed (e.g. Saygin, Cicekli and Akman, 2000). In 1950, Alan Turing surmised that it may take a century to flag this triumph (Turing, 1950), which is about 30 years from now on. To give a timely review of this progress, we would like to make a preannouncement that Decision Economics 2020 plans to have a celebration on "Turing Tests: 70 Years On" as the main track of the conference, under the aegis of the United Nations.

To conclude this Preface, according to Minsky and Papert (1988), the human's pursuit of machine intelligence has gone through roughly two stages. The first one is more ambitious in that it aims to design machines that can do what humans can do. The McCulloch–Pitts neural network is an example of this (McCulloch and Pitts, 1943). After being in the doldrums for a long while, the second one is more humble; it aims to design machines that can learn what humans can do, entering the era of learning machines or autonomous machines. The Rosenblatt's perceptron (Rosenblatt, 1962) is an example, too, but many other interesting examples have only occurred in recent years. This second-stage machine intelligence substantiates the so-called connectionism initiated by Donald Hebb (1904–1985) (Hebb, 1949) and Friedrich Hayek (1899–1992) (Hayek, 1952), and hence can effectively absorb the tacit knowledge from human experts.

Furthermore, armed with the Internet of everything, it can get access to an essentially infinitely large space to retrieve historical data and to do great analysis based on similarity. Long before, the philosopher and economist David Hume (1711–1776) had already given the greatest guide to modern AI, namely the authority of experience, as we quoted from his *An Enquiry Concerning Human Understanding* in 1748:

> In reality all arguments from experience are founded on the *similarity* which we discover among natural objects, and by which we are induced to expect effects *similar* to those which we have found to follow from such objects. […] and makes us draw advantage from that *similarity* which nature has placed among different objects. From causes which appear *similar* we expect *similar* effects. This is the sum of all our experimental conclusions. (Ibid, 1748, Section IV, Italics added).

Unfortunately, back in the eighteenth, nineteenth or even most of the twentieth centuries, our bounded rationality, constrained by (very) limited memory or archives and further crippled by the limited search capability, non-trivially restricted our ability to take advantage of those *similarities*. Today, when learning machines become an extended part of humans like the idea of cyborgs portraits, then one may wonder not only how decisions will be made, but what the decisions will actually be. Would we be able to have smarter or better decisions? Given this possible future, how should we decide the route leading towards it, that is to say, our decisions for the complexity of our future (Helbing, 2019).

With these two highlights regarding the present and the future of decision economics, let us also make a brief remark on our chosen subtitle. “Complexity of Decisions” shows this volume as a continuation of our second edition of the series (Bucciarelli, Chen and Corchado, 2017), referring to the complex ontology of decisions. If decisions can be arranged in a hierarchy of complexity, then those non-trivial and consequential decisions are expected to locate themselves at the higher levels of the hierarchy, which are often cognitively demanding, radically uncertain, imprecise, vague and incomplete. On the other hand, “Decisions for Complexity” refers to the methods used to make complex decisions and relate this volume to our previous edition (Bucciarelli, Chen and Corchado, 2019). The two subtitles are then further illustrated by the 35 chapters collected in this volume.

Our final remarks are for those scholars who have contributed to the success of DECON 2019. We have had the good fortune of working with an outstanding group of scientists and scholars from several disciplines, starting from the members of the International Program Committee: Beautiful minds and beautiful people, all dedicated to our common cause, and their hard work has made our efforts easier. In particular, without Sara Rodríguez González and Fernando De la Prieta, it is hard to imagine how we would have completed this year’s conference on decision economics and, of course, this special book. Our greatest debt of gratitude is both to the members of the International Program Committee and to each of the contributors in this volume. Among the latter, the winners of the two international awards “Decision Economics 2019” are Robert E. Marks (University of New South Wales, School of Economics, Sydney), for the best paper entitled “Calibrating Methods for Decision Making Under Uncertainty”, and Friederike Wall (University of Klagenfurt, Department of Management Control and Strategic Management), for the best application paper entitled “Coordination and Search for New Solutions: An Agent-based Study on the Tension in Boundary Systems”.

DECON 2019 was organised by the University of Chieti-Pescara (Italy), the National Chengchi Unversity of Taipei (Taiwan), and the University of Salamanca (Spain), and was held at the Escuela Politécnica Superior de Ávila, Spain, from 26th to 28th June, 2019. We acknowledge the sponsors: IEEE Systems Man and Cybernetics Society, Spain Section Chapter, and IEEE Spain Section (Technical Co-Sponsor), IBM, Indra, Viewnext, Global Exchange, AEPIA-and-APPIA, with the funding supporting of the Junta de Castilla y León, Spain (ID: SA267P18-Project co-financed with FEDER funds).

Edgardo Bucciarelli
Shu-Heng Chen
Juan Manuel Corchado

References

Bucciarelli, E., Silvestri, M., & González, S. R. (Eds.): Decision Economics, In Commemoration of the Birth Centennial of Herbert A. Simon 1916–2016 (Nobel Prize in Economics 1978). Springer, Cham (Switzerland) (2016).
Bucciarelli, E., Chen, S. H., & Corchado, J. M. (Eds.): Decision Economics: In the Tradition of Herbert A. Simon's Heritage. Springer, Cham (Switzerland) (2017)
Bucciarelli, E., Chen, S. H., & Corchado, J. M. (Eds.): Decision Economics. Designs, Models, and Techniques for Boundedly Rational Decisions. Springer-Nature, Cham (Switzerland) (2019).
Gershenfeld, N., Gershenfeld, A., & Cutcher-Gershenfeld, J.: Designing Reality: How to Survive and Thrive in the Third Digital Revolution. Basic Books, New York (2017).
Gigerenzer, G.: Gut Feelings: The Intelligence of Unconsciousness. Penguin Books, London (2007).
Gigerenzer, G.: Towards a Rational Theory of Heuristics. In: R. Frantz, L. Marsh (eds.) Minds, Models and Milieux. Commemorating the Centennial of the Birth of Herbert Simon, pp. 34−59. Palgrave Macmillan, London (2016).
Gigerenzer, G., & Selten, R. (Eds.): Bounded Rationality: The Adaptive Toolbox. The MIT Press, Cambridge (MA) (2001).
Hayek, F. A.: The Sensory Order: An Inquiry into the Foundations of Theoretical Psychology. University of Chicago Press, Chicago (1952).
Hebb, D. O.: The Organization of Behavior. John Wiley and Sons, New York (1949).
Helbing, D. O. (Ed.): Towards Digital Enlightenment: Essays on the Dark and Light Sides of the Digital Revolution. Springer-Nature, Cham (Switzerland) (2019).
Hume, D.: An Enquiry Concerning Human Understanding. In: E. Steinberg (Ed.) Hackett Publishing Company, Indianapolis (1977) [1748].
Lawless, W. F., Mittu, R., & Sofge, D.: Artificial Intelligence for the Internet of Everything. Elsevier, Cambridge (MA) (2019).
McCulloch, W. S., & Pitts, W.: A Logical Calculus of the Ideas Immanent in Nervous Activity. The Bulletin of Mathematical Biophysics, 5(4), 115–133 (1943).
Minsky, M., & Papert, S.: Perceptrons: An Introduction to Computational Geometry. The MIT Press, Cambridge (MA) (1988) [1969].
Polanyi, M.: The Tacit Dimension. University of Chicago Press, Chicago (1966).
Robbins, L. C.: An Essay on the Nature and Significance of Economic Science. McMillan & Co, London (1932).
Rosenblatt, F.: Principles of Neurodynamics. Spartan, Washington DC (1962).
Rothschild, K. W.: To Push and to Be Pushed. American Economist, 43(1), 1−8 (1999).
Saygin, A. P., Cicekli, I., & Akman, V.: Turing Test: 50 Years Later. Minds and Machines, 10(4), 463–518 (2000).
Simon, H. A.: Invariants of Human Behaviour. Annual Review of Psychology, 41(1), 1−19 (1990).
Stigum, B. P.: Toward a Formal Science of Economics: The Axiomatic Method in Economics and Econometrics. The MIT Press, Cambridge (MA) (1990).
Turing, A. M. (1950). Computing machinery and intelligence. Mind, 59(236), 433–460.
Velupillai, K. V.: Computable Foundations for Economics. Routledge, Abingdon (UK) (2010).
Velupillai, K. V.: Models of Simon. Routledge, Abingdon (UK) (2018).

Organisation

General Chairs

Edgardo Bucciarelli	University of Chieti-Pescara, Italy
Shu-Heng Chen	National Chengchi University, Taipei, Taiwan
Juan Manuel Corchado	University of Salamanca, Spain

International Program Committee

Federica Alberti	University of Portsmouth, UK
José Carlos R. Alcantud	University of Salamanca, Spain
Barry Cooper†	University of Leeds, UK
Sameeksha Desai	Indiana University, Bloomington, USA
Zhiqiang Dong	South China Normal University, China
Felix Freitag	Universitat Politècnica de Catalunya, Spain
Jakob Kapeller	Johannes Kepler University of Linz, Austria
Amin M. Khan	IST, University of Lisbon, Portugal
Alan Kirman	Aix-Marseille Université, France
Alexander Kocian	University of Pisa, Italy
William Lawless	Paine College, Augusta, USA
Nadine Levratto	Université Paris Ouest Nanterre La Défense, France
Roussanka Loukanova	Stockholm University, Sweden
Nicola Mattoscio	University of Chieti-Pescara, Italy
Elías Moreno	University of Granada, Spain
Giulio Occhini	Italian Association for Informatics and Automatic Calculation, Milan, Italy
Lionel Page	University of Technology Sydney, Australia
Paolo Pellizzari	Ca' Foscari University of Venice, Italy
Enrico Rubaltelli	University of Padua, Italy
Anwar Shaikh	The New School for Social Research, New York, USA

Pietro Terna	University of Turin, Italy
Katsunori Yamada	Osaka University, Japan
Ragupathy Venkatachalam	Goldsmiths, University of London, UK
Peter Vovsha	INRO Research, New York, USA
Stefano Zambelli	University of Trento, Italy

Organising Committee

Juan Manuel Corchado Rodríguez	University of Salamanca, Spain and AIR Institute, Spain
Javier Parra	University of Salamanca, Spain
Sara Rodríguez González	University of Salamanca, Spain
Roberto Casado Vara	University of Salamanca, Spain
Fernando De la Prieta	University of Salamanca, Spain
Sonsoles Pérez Gómez	University of Salamanca, Spain
Benjamín Arias Pérez	University of Salamanca, Spain
Javier Prieto Tejedor	University of Salamanca, Spain and AIR Institute, Spain
Pablo Chamoso Santos	University of Salamanca, Spain
Amin Shokri Gazafroudi	University of Salamanca, Spain
Alfonso González Briones	University of Salamanca, Spain and AIR Institute, Spain
José Antonio Castellanos	University of Salamanca, Spain
Yeray Mezquita Martín	University of Salamanca, Spain
Enrique Goyenechea	University of Salamanca, Spain
Javier J. Martín Limorti	University of Salamanca, Spain
Alberto Rivas Camacho	University of Salamanca, Spain
Ines Sitton Candanedo	University of Salamanca, Spain
Daniel López Sánchez	University of Salamanca, Spain
Elena Hernández Nieves	University of Salamanca, Spain
Beatriz Bellido	University of Salamanca, Spain
María Alonso	University of Salamanca, Spain
Diego Valdeolmillos	University of Salamanca, Spain and AIR Institute, Spain
Sergio Marquez	University of Salamanca, Spain
Guillermo Hernández González	University of Salamanca, Spain
Mehmet Ozturk	University of Salamanca, Spain
Luis Carlos Martínez de Iturrate	University of Salamanca, Spain and AIR Institute, Spain
Ricardo S. Alonso Rincón	University of Salamanca, Spain
Niloufar Shoeibi	University of Salamanca, Spain
Zakieh Alizadeh-Sani	University of Salamanca, Spain
Jesús Ángel Román Gallego	University of Salamanca, Spain
Angélica González Arrieta	University of Salamanca, Spain

José Rafael García-Bermejo Giner	University of Salamanca, Spain
Pastora Vega Cruz	University of Salamanca, Spain
Mario Sutil	University of Salamanca, Spain
Ana Belén Gil González	University of Salamanca, Spain
Ana De Luis Reboredo	University of Salamanca, Spain

Contents

The Editors

Edgardo Bucciarelli is an Italian economist. Currently he is an associate professor of Economics at the University of Chieti-Pescara (Italy), where he earned his PhD in Economics (cv SECS/P01). His main research interests lie in the area of complexity and market dynamics; decision theory, design research, experimental microeconomics, classical behavioural economics, and economic methodology. His main scientific articles appeared, among others, in the Journal of Economic Behavior and Organization, Journal of Post Keynesian Economics, Metroeconomica, Applied Economics, Computational Economics, and other international journals. Several key contributions appeared in chapters of book in Physica-Verlag, and Springer Lecture Notes in Economics and Mathematical Systems. At present, he teaches Experimental Economics, Cognitive Economics and Finance, and Economic Methodology at University of Chieti-Pescara. He is one of the Directors of the Research Centre for Evaluation and Socio-Economic Development, and the co-founder of the academic spin-off company "Economics Education Services". He is the co-founder, organising chair, program committee chair in a number of international conferences.

Shu-Heng Chen is a Taiwanese economist. He earned his PhD in Economics at the University of California (UCLA, Los Angeles, United States) in 1992. Currently, he is a distinguished professor of Economics at the Department of Economics and also the vice President of the National Chengchi University (Taipei, Taiwan). Furthermore, he is the founder and director of the AI-ECON Research Center at the College of Social Sciences of the National Chengchi University and the coordinator of the Laboratory of Experimental Economics in the same University. He is unanimously considered one of the most influential and pioneer scholars in the world in the field of applied research known as Computational Economics. His scientific contributions were directed to the affirmation of the computational approach aimed to the interpretation of the theoretical issues and applied economic problems still today unresolved, from a perspective more connected to reality and therefore different from the dominant neoclassical paradigm. In particular, his most decisive contributions are aimed to the approach based on models with heterogeneous agents and the genetic programming in the socio-economic studies. His work as a scholar is interdisciplinary and focused since the beginning on methodologies related to the bounded rationality and Herbert A. Simon's contributions. Shu-Heng Chen holds the position of Editor of prestigious international economic journals and is author of more than 150 publications including scientific articles, monographs and book chapters.

Juan Manuel Corchado is the vice President for Research and Technology Transfer at University of Salamanca (Spain) where he holds the position of full professor of Computer Science and AI. He is the Director of the Science Park and Director of the Doctoral School of University of Salamanca, in which he has been elected twice as Dean of the Faculty of Science. In addition to a PhD in Computer Sciences earned at University of Salamanca, he holds a PhD in Artificial Intelligence from University of the West of Scotland. Juan Manuel Corchado is Visiting Professor at Osaka Institute of Technology since January 2015, Visiting Professor at University Teknologi Malaysia since January 2017 and a Member of the Advisory group on Online Terrorist Propaganda of the European Counter Terrorism Centre (EUROPOL). Juan Manuel Corchado is the Director of BISITE Research Group (Bioinformatics, Intelligent Systems and Educational Technology) created by him in 2000. He is also editor and Editor-in-chief of specialised journals such as Advances in Distributed Computing and Artificial Intelligence Journal, International Journal of Digital Contents and Applications, and Oriental Journal of Computer Science and Technology.

Calibrating Methods for Decision Making Under Uncertainty

Robert E. Marks(✉)

Economics, University of New South Wales Sydney, Sydney, NSW 2052, Australia
robert.marks@gmail.com
http://www.agsm.edu.au/bobm

Abstract. This paper uses simulation (written in R) to compare six methods of decision making under uncertainty: the agent must choose one of eight lotteries where the six possible (randomly chosen) outcomes and their probabilities are known for each lottery. Will risk-averse or risk-preferring or other methods result in the highest mean payoff after the uncertainty is resolved and the outcomes known? Methods include max-max, max-min, Laplace, Expected Value, CARA, CRRA, and modified Kahneman-Tversky. The benchmark is Clairvoyance, where the lotteries' outcomes are known in advance; this is possible with simulation. The findings indicate that the highest mean payoff occurs with risk neutrality, contrary to common opinion.

Keywords: Decision making · Uncertainty · Utility functions · Simulation · Clairvoyance · Risk neutrality

1 Introduction

This is not a descriptive paper. It does not attempt to answer the positive question of how people make decisions under uncertainty. Instead, it attempts to answer the normative question of how best to make decisions under uncertainty. How best to choose among lotteries.

We must first define "best" and "uncertainty". By "best" we mean decisions that result in the highest payoffs, where the payoffs are the sum of the prizes won across a series of lotteries. The experimental set-up is that each period the agent is presented with eight lotteries, each with six possible known outcomes or prizes (chosen in the range ±$10). No uncertainty about possible payoffs. But there is uncertainty in each lottery about which payoff or prize will occur. The best information the agent has are the probabilities of the six possible prizes or payoffs in each lottery. Each lottery has six possible payoffs, but the values of these payoffs and their probabilities vary across the eight distinct lotteries. Choosing among these is what we mean by "decision making under uncertainty".

© Springer Nature Switzerland AG 2020
E. Bucciarelli et al. (Eds.): DECON 2019, AISC 1009, pp. 1–9, 2020.
https://doi.org/10.1007/978-3-030-38227-8_1

2 Decision Making Under Uncertainty

We model agents as possessing various approaches to this problem.

- A simple approach (the Laplace method) is to ignore any information about the probabilities of payoffs and instead just choose the lottery with the highest average or mean payoff, by calculating the mean of each lottery's six possible payoffs.
- Another method (modelling an optimistic agent) is to choose the lottery with the highest possible best payoff, the max-max method.
- Modelling a pessimistic agent, another method is to choose the lottery with the highest possible worst payoff, the max-min method. Neither of these methods uses the known probabilities, or even five of the six payoffs.
- A fourth method is to use the known probabilities to choose the lottery with the highest expected payoff, weighting each possible payoff by the probability of its occurring, the Expected Value method.
- Three different families of utility functions.

2.1 Clairvoyance

The so-called Clairvoyant decision maker [1] knows the realisation of any uncertainty, so long as this requires no judgment by the Clairvoyant, and the realisation does not depend on any future action of the Clairvoyant. Here, with simulation of probabilistic outcomes, we can model a Clairvoyant who knows the realised outcome (among the six random possibilities) of each of the eight lotteries, while other decision makers remain ignorant of this. We simulate each outcome as occurring with its (known) probability: only one realised outcome per lottery. The Clairvoyant chooses the lottery with the highest realised outcome of the eight.

We can say something of this: if $A_1, ...A_n$ are i.i.d. uniform on (0, 1), then $M_n = \max(A_1, ...A_n)$ has the expectation of $\frac{n}{n+1}$. Here, $n = 6$ and the expected maximum outcome for any lottery must be $\frac{6}{7} \times 20 - 10 = \$7.14$.[1] But the realisation of any lottery is in general less than its maximum outcome, and its simulated realised outcome is generated from the weighted random probability distribution of the six possible outcomes. The Clairvoyant is faced by eight lotteries, and chooses the lottery with the highest simulated *realised* outcome (which the Clairvoyant knows). It turns out (from the simulation) that the expected maximum of these eight realised outcomes is \$7.788.[2] This is the best on average that any decision maker can achieve, given our experimental platform. It is our benchmark.

[1] The lottery outcomes fall randomly in the range $\pm\$10$; see Sect. 4.

[2] With 48 outcomes, the expected maximum outcome across the eight lotteries is \$9.59; the expected maximum of the eight simulated realised outcomes is 81.2% of this maximum.

3 Three Utility Functions

The remaining methods map the known possible payoffs to "utilities", where the utilities are monotone (but not in general linear) in the dollar amounts of the possible payoffs. These methods vary in how the utilities are mapped from the payoffs.

By definition, the utility of a lottery L is its expected utility, or

$$U(L) = \sum p_i U(x_i), \tag{1}$$

where each (discrete) outcome x_i occurs with probability p_i, and $U(x_i)$ is the utility of outcome x_i.

Risk aversion is the *curvature* (U''/U'): if the utility curve is locally –

- linear (say, at a point of inflection, where $U'' = 0$), then the decision maker is locally risk neutral;
- concave (its slope is decreasing – Diminishing Marginal Utility), then the decision maker is locally risk averse;
- convex (its slope is increasing), then the decision maker is locally risk preferring.

We consider three types of utility function:

1. those which exhibit constant risk preference across all outcomes (so-called wealth-independent utility functions, or Constant Absolute Risk Aversion CARA functions; see Eq. (2) below);
2. those where the risk preference is a function of the wealth of the decision maker (the Constant Relative Risk Aversion CRRA functions; see Eq. (5) below); and
3. those in which the risk profile is a function of the prospect of gaining (risk averse) or losing (risk preferring): the DRP Value Functions from Prospect Theory. See Eqs. (6) and (7) below.

Since the utility functions are monotone transformations of the possible payoffs, it would be pointless to consider the max-max, max-min, or Laplace methods using utilities instead of payoff values.

3.1 Constant Absolute Risk Aversion, CARA

Using CARA, utility U of payoff x is given by

$$U(x) = 1 - e^{-\gamma x}, \tag{2}$$

where $U(0) = 0$ and $U(\infty) = 1$, and where γ is the *risk aversion coefficient*:

$$\gamma = -\frac{U''(x)}{U'(x)}. \tag{3}$$

When γ is positive, the function exhibits risk aversion; when γ is negative, risk preferring; and when γ is zero, risk neutrality, which is identical with the Expected Value method.

3.2 Constant Relative Risk Aversion, CRRA

The Arrow-Pratt measure of relative risk aversion (RRA) ρ is defined as

$$\rho(w) = -w\frac{U''(w)}{U'(w)} = w\gamma. \tag{4}$$

This introduces wealth w into the agent's risk preferences, so that lower wealth can be associated with higher risk aversion. The risk aversion coefficient γ is as in (3).

The Constant Elasticity of Substitution (CES) utility function:

$$U(w) = \frac{w^{1-\rho}}{1-\rho}, \tag{5}$$

with positive wealth, $w > 0$, exhibits constant relative risk aversion CRRA, as in (4). In the CRRA simulations, we use the cumulative sum of the realisations of payoffs won (or lost, if negative) in previous lotteries chosen by the agent plus the possible payoff in this lottery as the wealth w in (5). It can be shown that with $w > 0$, $\rho > 0$ is equivalent to risk aversion. With $w > 0$ and $\rho = 1$, the CES function becomes the (risk-averse) logarithmic utility function, $U(w) \approx \log(w)$. With $w > 0$ and $\rho < 0$, it is equivalent to risk preferring.

3.3 The Dual-Risk-Profile DRP Function from Prospect Theory

From Prospect Theory [2], we model the DRP Value Function, which maps from quantity x to value V with the following two-parameter equations (with $\beta > 0$ and $\delta > 0$):

$$V(x) = \frac{1-e^{-\beta x}}{1-e^{-100\beta}}, 0 \le x \le 100, \tag{6}$$

$$V(x) = -\delta\frac{1-e^{\beta x}}{1-e^{-100\beta}}, -100 \le x < 0. \tag{7}$$

The parameter $\beta > 0$ models the curvature of the function, and the parameter $\delta > 0$ the asymmetry associated with losses. The DRP function is not wealth independent.[3] Three DRP functions in Fig. 1 (with three values of β, and $\delta = 1.75$, for prizes between $\pm\$100$) exhibit the S-shaped asymmetry postulated by Kahneman and Tversky [2]. The DRP function exhibits risk seeking (loss aversion) when x is negative with respect to the reference point $x = 0$, and risk aversion when x is positive. We use here a linear probability weighting function (hence no weighting for smaller probabilities). As Fig. 1 suggests, as $\delta \to 1$ and $\beta \to 0$, the value function asymptotes to a linear, risk-neutral function (in this case with a slope of 1).

[3] This does not require that we include wealth w in the ranking of the lotteries, as in CRRA case; instead we choose a reference point at the current level of wealth, and consider the prospective gains and losses of the eight lotteries.

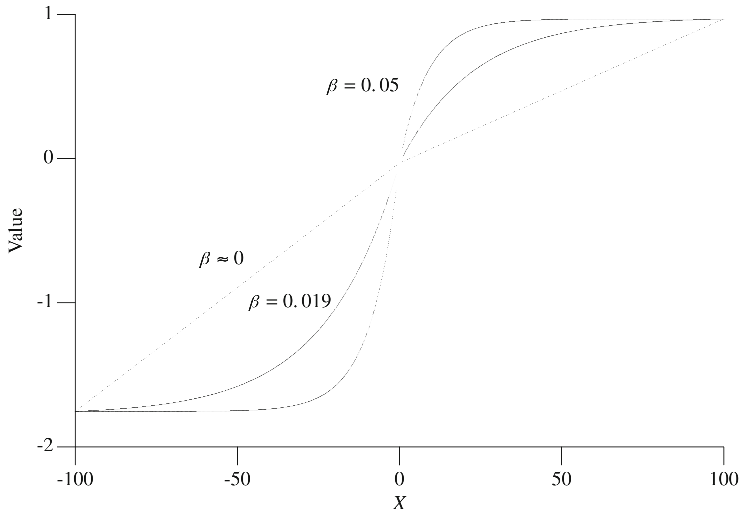

Fig. 1. A prospect theory (DRP) value function ([3])

4 The Experiments, by Simulation

The experimental set-up is to generate eight lotteries, each with six possible outcomes, each outcome with its own probability of occurrence. The outcomes are chosen form a uniform distribution between +\$10 and −\$10; the probabilities are chosen at random so they add to unity for each lottery. The agent has complete information about the outcomes and their probabilities. Then the agent chooses the "best" lottery, based on the method of choice.

The actual realisation of one of the six possibilities from the chosen lottery is simulated, using the generated probabilities: a payoff with a probability of $0.x$ will be realised on average with a frequency of $100x\%$. The realisation of outcome in the chosen lottery is the agent's score (in dollars, say). In each iteration, payoff realisations are derived for each of the eight lotteries.

Agents are presented with n iterations of the proceeding choice, and each iteration generates new lotteries with new possible payoffs and new probabilities of the payoffs. The mean payoff over these n choices is the score of the specific decision method being tested.[4]

General opinion is that firms, at least, are better served by slightly risk-averse behaviour. Too risk averse and attractive prospects are ignored ("nothing ventured, nothing gained"), but too risk preferring is the same as gambling, with the risk of losing heavily. What do our simulations tell us about the best method of decision making under uncertainty?

[4] See the R [4] code at http://www.agsm.edu.au/bobm/papers/riskmethods.r.

5 Results

Table 1 presents the mean results of 10,000 iterations (independent samples) of the eight lottery/six prize experimental platform, with results for:

1. The benchmark Clairvoyant method
2. the Expected Value method
3. the Laplace method
4. the max-max method
5. the max-min method
6. random choice among the eight lotteries.

Table 1. Mean payoffs by method.

Method	Payoff ($)	% Clairvoyant	% EV
Clairvoyant	7.787999	100	
Expected value	3.87175	49.71431	100
Laplace	3.359935	43.14247	86.78
Max-max	1.391732	17.87021	35.95
Max-min	2.427924	31.1752	62.71
Random	0.02162699	0	0

The Clairvoyant would have won $7.79 with perfect foresight. The other methods, of course, cannot see the future, which is the essence of decision making under uncertainty. Expected Value (the risk-neutral decision maker) is second, with 49.7% of the Clairvoyant's score; Laplace is third, with 43.1%. Surprisingly, the (pessimist's) max-min, at 31.2%, is almost twice as good as the (optimist's) max-max, at 17.9%. Unsurprisingly, choosing among the eight lotteries randomly is worst, with effectively a zero mean payoff (of 2.16 cents, or 0.56% of EV).

Table 2 presents the mean results of 10,000 iterations of the CARA method with different values of the risk-aversion coefficient γ: the results show that the best decisions are made when $\gamma \approx 0$, that is when the method is risk neutral and approximates the Expected Value method.

Table 3 present the mean results of 10,000 iterations of the CRRA method with different values of the RRA parameter ρ and reveals that with a CRRA decision maker, again the best profile (the value of ρ that results in the highest expected payoff) is close to zero. That is, as with the CARA method, there is in this set-up no advantage to being risk averse or risk preferring (even a little): the best profile is risk neutrality, as reflected in the Expected Value method. Note that the logarithmic utility method (with $\rho = 1.0$) performs at only 98.88% of the Expected Value method.

Table 4 presents the mean results of 10,000 iterations of twelve DRP functions, combinations of three values of δ and four values of β. The results are

Table 2. CARA mean payoffs, varying γ.

gamma γ	Payoff ($)	% Clairvoyant	% EV
-0.2	3.471413	44.57387	89.66004
-0.16	3.611061	46.367	93.2669
-0.12	3.700547	47.51602	95.57816
-0.08	3.819605	49.04476	98.65321
-0.04	3.858212	49.54048	99.65034
1×10^{-4}	3.871811	49.7151	100.0016
0.04	3.832964	49.2163	98.99824
0.08	3.783976	48.58727	97.73297
0.12	3.72903	47.88175	96.31381
0.16	3.653434	46.91108	94.36131
0.20	3.561462	45.73013	91.98584

Table 3. CRRA, mean payoffs, varying ρ.

rho ρ	Payoff ($)	% Clairvoyant	% EV
-2.5	3.756992	48.24079	97.03601
-2.0	3.811378	48.93912	98.4407
-1.5	3.835013	49.2426	99.05116
-1.0	3.848999	49.42218	99.41239
-0.5	3.866546	49.64749	99.8656
1×10^{-4}	3.87175	49.71431	100
0.5	3.85773	49.5343	99.6379
1.0	3.828434	49.15812	98.88123
1.5	3.805642	48.86547	98.29256
2.0	3.777273	48.5012	97.55984
2.5	3.752105	48.17804	96.90979

Table 4. DRP, % of EV, varying δ and β.

beta β	$\delta = 1.001$	$\delta = 1.2$	$\delta = 1.4$
0.001	100	99.80686	99.44209
0.1	99.59886	98.58363	98.60167
0.2	98.23075	97.98895	97.22377
0.4	96.98482	95.91222	95.2202

the percentages of the EV method. From the mean result for Random in Table 1 (which is +0.56% of EV), we can conclude that the errors in Table 4 are about 1.12% (±0.56%) of EV. Again we see that risk-neutral behaviour, here with $\delta \to 1$ and $\beta \to 0$, is the best method for choosing among risky lotteries.

6 Discussion

Whereas there has been much research into reconciling actual human decision making with theory [5], we are interested in seeing what is the best (i.e. most profitable) risk profile for agents faced with risky choices. Rabin [6] argues that loss aversion [2] rather than risk aversion, is a more realistic explanation of how people actually behave when faced with risky decisions. This is captured in our DRP function, which nonetheless favours risk neutrality as a method.

An analytical study of Prospect Theory DRP Value Functions [7] posits an adaptive process for decision-making under risk such that, despite people being seen to be risk averse over gains and risk seekers over losses with respect to the current reference point [2], the agent eventually learns to make risk-neutral choices. Their result is consistent with our results.

A simulation study [8] examines the survival dynamics of investors with different risk preferences in an agent-based, multi-asset, artificial stock market and finds that investors'survival is closely related to their risk preferences. Examining eight possible risk profiles, the paper finds that only CRRA investors with relative risk aversion coefficients close to unity (log-utility agents) survive in the long run (up to 500 simulations). This is not what we found (see Table 3 with ρ = 1).

Our results here are consistent with earlier work on this topic [3,9] in which we used machine learning (the Genetic Algorithm) to search for agents' best risk profiles in decision making under uncertainty. Our earlier work was in response to [10], which also used machine learning in this search, and which wrongly concluded that risk aversion was the best profile.

7 Conclusion

As economists strive to obtain answers to questions that are not always amenable to calculus-based results, the use of simulation is growing, and answers are being obtained. This paper exemplifies this: the question of which decision-making method gives the highest payoff in cases of uncertainty (where the possible payoffs and their probabilities are known) is not, in general, amenable to closed-form solution. The answer is strongly that risk-neutral methods are best, as exemplified by the Expected Value method. We believe that exploration of other experiments in decision making under uncertainty (with complete information) will confirm the generality of this conclusion. Will relaxing our assumptions of complete information about possible outcomes and their probabilities result in different conclusions? This awaits further research.

Acknowledgments. The author thanks Professor Shu-Heng Chen for his encouragement, and discussants of the previous papers [3,9] in this research program. An anonymous reviewer's comments have improved the paper.

References

1. Howard, R.A.: The foundations of decision analysis. IEEE Trans. Syst. Sci. Cybern. **ssc–4**, 211–219 (1968)
2. Kahneman, D., Tversky, A.: Prospect theory: an analysis of decision under risk. Econometrica **47**, 263–291 (1979)
3. Marks, R.E.: Searching for agents' best risk profiles. In: Handa, H., Ishibuchi, M., Ong, Y.-S., Tan, K.-C. (eds.) Proceedings of the 18th Asia Pacific Symposium on Intelligent and Evolutionary Systems (IES 2014), Chapter 24. Proceedings in Adaptation, Learning and Optimization, vol. 1, pp. 297-309. Springer (2015). http://www.agsm.edu.au/bobm/papers/marksIES2014.pdf
4. R Core Team: R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria (2013). http://www.R-project.org/
5. Arthur, W.B.: Designing economic agents that act like human agents: a behavioral approach to bounded rationality. Am. Econ. Rev. Papers Proc. **81**, 353–360 (1991)
6. Rabin, M.: Risk aversion and expected-utility theory: a calibration theorem. Econometrica **68**, 1281–1292 (2000)
7. DellaVigna, S., LiCalzi, M.: Learning to make risk neutral choices in a symmetric world. Math. Soc. Sci. **41**, 19–37 (2001)
8. Chen, S.-H., Huang, Y.-C.: Risk preference, forecasting accuracy and survival dynamics: simulation based on a multi-asset agent-based artificial stock market. J. Econ. Behav. Organ. **67**(3–4), 702–717 (2008)
9. Marks, R.E.: Learning to be risk averse? In: Serguieva, A., Maringer, D., Palade, V., Almeida, R.J. (eds.) Proceedings of the 2014 IEEE Computational Intelligence for Finance Engineering and Economics (CIFEr), London, 28–29 March, pp. 1075-1079. IEEE Computational Intelligence Society (2015)
10. Szpiro, G.G.: The emergence of risk aversion. Complexity **2**, 31–39 (1997)

Check for updates

Coordination and Search for New Solutions
An Agent-Based Study on the Tension in Boundary Systems

Friederike Wall(✉)

Alpen-Adria-Universitaet Klagenfurt, 9020 Klagenfurt, Austria
friederike.wall@aau.at
http://www.aau.at/csu

Abstract. Boundary systems, setting constraints for managerial decision-makers, incorporate a tension between granting flexibility to decision-makers for finding new options as well as aligning managerial choices with respect to overall objectives. This study employs a computational approach to examine configurations of search strategy and coordination mechanisms in boundary systems for their effects on organizational performance. The results suggest that the complexity of the organizational decision-problem subtly shapes the effectiveness of the configurations – suggesting to employ search strategies providing flexibility to managerial decision-makers when complexity is low and to emphasize tight coordination and exploitative or ambidextrous strategies for higher levels of complexity.

Keywords: Agent-based simulation · Complexity · Coordination · Management control systems · NK fitness landscapes · Search strategy

1 Introduction

According to the prominent "Levers of control" (LOC) framework [1], organizations employ boundary systems to constrain the behavior of managerial decision-makers and, by this, to affect decision-making in the direction of the overall objective. It is well recognized that the boundary system incorporates a certain tension: shaping – or even enforcing – decision-makers' search for novel solutions via exploitation or exploration on the one hand and restricting decision-makers in favor of coordination towards superior solutions to the overall firm's objective on the other [1–3]. This tension, in particular, occurs under behavioral assumptions on decision-makers in the spirit of *Simon* [4,5].

Several, mostly empirical studies were conducted in order to figure out the interrelations of the boundary system with *other* control systems of the LOC-framework or to identify *contingent factors which may affect the effectiveness of the boundary system* (e.g., task complexity) (for overviews see [2,3]). This

© Springer Nature Switzerland AG 2020
E. Bucciarelli et al. (Eds.): DECON 2019, AISC 1009, pp. 10–17, 2020.
https://doi.org/10.1007/978-3-030-38227-8_2

study seeks to contribute to this body of research – though focusing on the balance of components *within* the boundary system – and in particular relates to the growing research emphasizing the *internal fit* of components of management controls [6]. In particular, the study addresses the following research question: *Which effects on overall organizational performance result from certain combinations of search strategy and coordination mechanisms taking complexity of the decision problem to be solved as contingent factor into account?*

For investigating the research question, the paper makes use of an agent-based simulation. A simulation-based research method appears appropriate to capture search processes and an agent-based simulation allows to consider the collaboration of various interacting parties (e.g., units) within an organization (with further references [7]). In the model, the task environment of the organizations is represented according to the framework of NK fitness landscapes [8,9] which was originally introduced in the domain of evolutionary biology and, since then, broadly employed in managerial science [7]. A key feature of the NK framework is that it allows to easily control for the complexity of the decision problem [10,11]. The model captures different search strategies (exploitative, explorative or ambidextrous, [12,13]) and two mechanisms of coordination.

2 Outline of the Simulation Model

Organizational Decision Problem: In the simulations, artificial organizations are observed while searching for superior solutions for a decision-problem which is modeled according to the framework of NK-fitness landscapes: At 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 contribution C_{it} to the overall performance $V(\mathbf{d_t})$ where the C_{it} are randomly drawn from a uniform distribution with $0 \leq C_{it} \leq 1$. The 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} and, thus, captures the complexity of the decision problem in terms of the interactions among decisions. Hence, contribution C_{it} may not only depend on the single choice d_{it} but also on K other choices:

$$C_{it} = f_i(d_{it}; d_{i_1 t}, ...d_{i_K t}), \tag{1}$$

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

$$V_t = V(\mathbf{d_t}) = \frac{1}{N} \sum_{i=1}^{N} C_{it}. \tag{2}$$

Departmental Preferences and Boundaries by Search Strategy: The N-dimensional decision problem is partitioned into M disjoint partial problems of, for the sake of simplicity, equal size N^r. Each of these sub-problems is delegated to one department r – with the particular competencies of department r's head being subject to the boundary system. Department heads seek to maximize compensation which is merit-based and, for the sake of simplicity, results from linear compensation functions based on the contribution $P_t^r(\mathbf{d_t^r})$ of department r's contribution to overall performance V_t (see Eq. 2) as given by

$$P_t^r(\mathbf{d_t^r}) = \frac{1}{N} \sum_{i=1+w}^{N^r} C_{it} \tag{3}$$

with $w = \sum_{p=1}^{r-1} N^p$ for $r > 1$ and $w = 0$ for $r = 1$. In every time step t, each manager r seeks to identify the best – in terms of compensation – configuration for the "own" choices $\mathbf{d_t^r}$ out of the currently available options which are shaped according to the search strategy as part of the boundary system:

Search Strategies: In line with Simon's [4,5] behavioral assumptions, our decision-makers are not able to survey the *entire* search space and, hence, they cannot "locate" the optimal solution of their decision problem "at once". Rather, they search stepwise for superior solutions. In each time step t, each manager r discovers two alternative solutions $\mathbf{d_t^{r,a1}}$ and $\mathbf{d_t^{r,a2}}$ for the partial decision problem compared to the status quo $\mathbf{d_{t-1}^{r*}}$. For these alternatives, boundaries are set by the headquarter in terms of the – required as well as allowed – *distance* to the status quo. In particular, a prescribed search strategy may be exploitative, explorative or ambidextrous. In the former case, the Hamming distances of the alternative options to the status quo equal 1 (i.e., $h(\mathbf{d^{r,a1}}) = \sum_{i=1}^{N^r} \left| \mathbf{d_{t-1}^{r*}} - \mathbf{d_t^{r,a1}} \right| = 1$; $h(\mathbf{d^{r,a2}}) = 1$); in a purely explorative strategy Hamming distances of the two alternatives are higher than 1, i.e., $h(\mathbf{d^{r,a1}}), h(\mathbf{d^{r,a2}}) \geq 2$ allowing for more or less "long jumps". Moreover, the simulations are run for ambidextrous strategies capturing cases of $h(\mathbf{d^{r,a1}}) = 1$ and $h(\mathbf{d^{r,a2}}) \geq 2$.

Formation of Expectations: The decision-makers show some further cognitive limitations: (1) The head of department r cannot anticipate the other departments' $q \neq r$ choices and assumes that they will stay with the status quo, i.e., opt for $\mathbf{d_{t-1}^{q*}}$. (2) The department heads are not able to perfectly ex-ante evaluate their newly discovered options' $\mathbf{d_t^{r,a1}}$ and $\mathbf{d_t^{r,a2}}$ effects on their *actual* value base for compensation $P_t^r(\mathbf{d_t^r})$ (see Eq. 3). Rather, ex ante evaluations are afflicted with noise which is, for the sake of simplicity, a relative error imputed to the true performance [14]. The error terms follow a Gaussian distribution $N(0;\sigma)$ with expected value 0 and standard deviations σ^r for each r; errors are independent from each other. Hence, the *perceived* performance $\tilde{P}_t^r(\mathbf{d_t})$ of manager r – i.e., the perceived value base for compensation – is given by:

$$\tilde{P}_t^r(\mathbf{d_t^r}) = P_t^r(\mathbf{d_t^r}) + e^{r,own}(\mathbf{d_t^r}) \tag{4}$$

With this, each manager r has a distinct partial and imperfect "view" of the true fitness landscape. However, for the status quo option, we assume that department head r remembers the compensation from the last period and, with this, knows the actual performance P_t^r of status quo if implemented again. Based on the evaluation of options, each department head r compiles a list $L_t^r = \left\{\mathbf{d_t^{r,p1}}, \mathbf{d_t^{r,p2}}, \mathbf{d_t^{r,p3}}\right\}$ of preferences where $\mathbf{d_t^{r,p1}}$ indicates the most preferred option out of $\mathbf{d_{t-1}^{r*}}, \mathbf{d_t^{r,a1}}$ and $\mathbf{d_t^{r,a2}}$ (and so forth).

Boundaries Set by the Coordination Mechanism: The next step within each period t is to determine the solution for the organization's overall decision problem $\mathbf{d_t}$. For this, as a part of the boundary system, the model captures two, in a way, extreme modes of coordination in the spirit of Sah and Stiglitz [15]:

Decentralized Mode: The highest level of autonomy is granted to the M departments if each of them is allowed to choose its most preferred option. Then, the overall configuration $\mathbf{d_t}$ results from $\mathbf{d_t} = (\mathbf{d_t^{1,p1}}, ..., \mathbf{d_t^{r,p1}}, ..., \mathbf{d_t^{M_s,p1}})$. The headquarter does not intervene in decision-making directly and its role is limited to registering the achieved performances $P_t^r(\mathbf{d_t^r})$ in the end of each period t and to compensate the department heads accordingly.

Hierarchical Mode: Each department transfers its list L_t^r of preferences to the headquarter which compiles a composite vector $\mathbf{d^C} = (\mathbf{d_t^{1,p1}}, ...\mathbf{d_t^{r,p1}}, ...\mathbf{d_t^{M,p1}})$ from the first preferences and then seeks to evaluate the overall performance $V(\mathbf{d^C})$ (see Eq. 2) this solution promises. However, also the headquarter is not capable to perfectly ex ante evaluate new options, i.e., other solutions than the status quo: the headquarter's evaluations also are afflicted with a relative error following a Gaussian distribution with expected value 0 and standard deviations σ^{cent} resulting in a *perceived* overall performance $\tilde{V}(\mathbf{d^C})$. The headquarter decides in favor of the composite vector, i.e., $\mathbf{d_t} = \mathbf{d^C}$, if $\mathbf{d^C}$ promises the same or a higher performance than the status quo $\mathbf{d_{t-1}}$, i.e., if $\tilde{V}(\mathbf{d^C}) \geq V(\mathbf{d_{t-1}^*})$. If this condition is not satisfied, the headquarter evaluates a vector composed from the departments' second preferences. If this also does not, at least, promise the performance of the status quo, then the status quo is kept, i.e., then $\mathbf{d_t} = \mathbf{d_{t-1}}$.

3 Simulation Experiments

The simulation experiments (Table 1) are intended to provide some findings on the configuration of the boundary system as given by the search strategy and the mode of coordination employed. The simulation experiments are conducted for six search strategies where, for example, a search strategy named "**1–1**" briefly denotes the "exploitation only" case with $h(\mathbf{d^{r,a1}}) = h(\mathbf{d^{r,a2}}) = 1$; for the other strategies see Table 1.

Since the complexity of the underlying search problem shapes the need for coordination, the experiments distinguish four levels of complexity of the decision problem as well as of the interactions among the $M = 3$ departments. For this, two parameters are employed: Parameter K depicts the complexity of the

Table 1. Parameter settings

Parameter	Values/types
Observation period	$T = 250$
Number of choices	$N = 12$
Number of departments	$M = 3$ with $\mathbf{d^1} = (d_1, d_2, d_3, d_4)$, $\mathbf{d^2} = (d_5, d_6, d_7, d_8)$, $\mathbf{d^3} = (d_9, d_{10}, d_{11}, d_{12})$
Interaction structures	Decomposable: $K = 2; K^{ex} = 0$; Near-decomposable: $K = 3; K^{ex} = 1$; Non-decomposable, intermediate: $K = 5; K^{ex} = 3$; Non-decomposable, high: $K = 8; K^{ex} = 5$
Search strategy	"exploitation only": "**1–1**"; "exploration only": "**2–2**"; "**2–3**"; "**3–3**"; "ambidextrous": "**1–2**"; "**1–3**"
Modes of coordination	Decentralized; hierarchical
Precision of ex-ante evaluation	$\sigma^r = 0.05 \forall r \in \{1...M\}$; $\sigma^{cent} = 0.1$ (headquarter)
Simulation runs	Per scenario 2,500 runs with 10 runs on 250 distinct fitness landscapes

entire problem according to the NK framework, and K^{ex} denotes the level of interactions *across sub-problems* and, with that, also *across departments*. The experiments distinguish four different interaction structures (Table 1): (1) In the perfectly decomposable structure the overall search problem is decomposed into $M = 3$ disjoint parts with maximal intense intra-sub-problem interactions, but no cross-sub-problem interactions (i.e., $K^{ex} = 0$). (2) In the nearly decomposable structure with $K^* = 1$ only slight cross-sub-problem interactions occur in that every performance contribution C_i in primary control of unit r is affected by only one choice made by another unit $q \neq r$. In the non-decomposable cases with (3) intermediate or (4) high interactions, a single option d_i affects the performance contributions of $K^{ex} = 3$ or $K^{ex} = 5$ choices, respectively, which are in the primary control of other departments. For each combination of interaction structure, search strategy and coordination mode 2,500 simulations are run.

4 Results and Discussion

Figure 1 displays condensed results for the simulation experiments: For each interaction structure, configuration of search strategy and coordination mode, the final performance $V_{t=250}$ averaged over 2,500 simulation runs is displayed[1]

[1] Confidence intervals at a 99.9 level of $V_{t=250}$ show the following ranges: decomposable: ±0.002 to ±0.004 in decentralized and hierarchical coordination; near-decomposable: dec. ±0.004 to ±0.005; hierar. ±0.003 to ±0.004; non-decomposable intermediate: dec. ±0.005 to ±0.01; hierar. ±0.004 to ±0.005; non-decomposable high: dec. ±0.005 to ±0.01; hierar. ±0.004 to ±0.005.