

Computational Intelligence for Sustainable Systems

Computational Intelligence for Sustainable Systems:

*Theory, Methods,
and Applications*

By

Wasswa Shafik

**Cambridge
Scholars
Publishing**



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This book first published 2026

Cambridge Scholars Publishing

Lady Stephenson Library, Newcastle upon Tyne, NE6 2PA, UK

British Library Cataloguing in Publication Data

A catalogue record for this book is available from the British Library

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ISBN: 978-1-0364-6743-2

ISBN (Ebook): 978-1-0364-6744-9

This book is dedicated to my family, whose unconditional love, sacrifices, and unwavering belief in my potential have been the foundation of all my achievements. Their tireless support and encouragement throughout this book-writing journey have inspired me to strive for excellence and persevere in the face of every challenge.

I also dedicate this work to my friends, whose patience, understanding, and constant motivation have been my anchor through the highs and lows of this book journey. Your presence gave me strength during the most difficult times, and your faith in me kept me going when I doubted myself.

To my mentors, lecturers, and teachers throughout this journey, thank you for shaping my intellectual path and for your invaluable guidance over the years. Your wisdom and dedication to knowledge have not only informed this book but have also profoundly influenced the way I think, work, and aspire.

To all individuals with any form of disability and marginalised groups, the poor people across the globe who fight to earn a living, and who wish to make it in life, but the conditions fail them, and to those who cultivate life with limited recognition but limitless passion, the seed savers and soil stewards the world forgot, but who never forgot the land.

Finally, I would like to thank everyone who contributed to this journey and made this dissertation possible. I dedicate this book to all aspiring researchers who dare to explore, question, and create. May this book serve as a small contribution to the collective pursuit of knowledge and as an encouragement never to stop learning.

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PREFACE

The integration of Computational Intelligence into sustainable development has become an essential field of study in an era manifested by swift technological advancements and environmental challenges. This book aims to provide a comprehensive exploration of computational intelligence techniques and their applications across various sustainability-driven domains. Leveraging the power of artificial intelligence, fuzzy logic, neural networks, and evolutionary algorithms accelerates the development of a powerful tool for solving complex problems in energy systems, climate change adaptation, smart cities, and agriculture. An intriguing question is how to define, for a system, the general property of being sustainable. What are we asking for when we think that a system is sustainable? What exactly does this mean? Definitions of sustainable systems are strongly related to the principles upon which these systems are built. To give a formal definition is an extremely complex or impossible task, certainly in general. Typically, the theoretical basis for many practical strategies can be found in classical physical models of interacting systems and represents many of the paradigms of optimization. In contrast, thinking in terms of complex system theory and self-organization has brought a more flexible view of how to define optimality, and that optimizing against the same objective, in particular, can lead to radically different strategies for self-organization, whether a particular strategy could be characterized as sustainable, non-sustainable, or unsustainable. In the search for more intelligent strategies to optimize systems, uncertainty, randomness, or non-determinism not only constitute an inevitable part of the complex systems under consideration, but they also play a crucial part in the strategies for optimization themselves. In the field of machine learning and artificial intelligence, we know that we can only speak from learning something from experience if we know exactly what our input will be or if our input is stochastic. The same holds in deterministic optimization. The capacity to deal with noisy inputs is something that is incorporated in quite fundamentally different ways in the solution techniques from those that incorporate knowledge from stochastic optimization. So, 'thinking about risk properly' and 'systematic exposure to as much of the fruitful uncertainty of the environment as possible' are integrally associated with any (optimal) strategy or regularization principle. It cannot be value-free; the evaluation of sustainability itself does and will contain subjective elements.

The term sustainability is defined as “development that sustains the needs of the present without compromising the ability of future generations to meet their own needs.” The three main foundations of sustainability are the environment, society, and economy. Addressing sustainability is critical to the global development of the entire world. Established economic growth is generated in part through the sustained use of technology and knowledge developed in computer science areas. Technological advances contribute to reductions in resource consumption and the generation of waste and pollution while ensuring quality growth. As a result, the goal of sustainable development provides exciting opportunities for the use of technology and challenges the community to tackle issues innovatively. Therefore, it is important to develop innovative and novel methods that can be used throughout various areas to optimize systems for sustainability. However, it should be noted that even with rapid scientific and technological innovations, sustainability is a challenging paradigm shift that challenges the traditional manner of decision-making and design. A number of environmental, ecological, economic, and social challenges presently preclude the transformation of communities and societies toward sustainability and can be classified under several categories. These categories represent barriers to sustainability. In general, it is important to develop techniques that can address the sustainability challenges or be used to understand and predict the barriers to sustainability within these areas. Solutions to these problems are likely to be transferable and applicable more generically in addressing the more fundamental issues that threaten the long-term sustainability of the environment or society.

A sustainable system is a system whose operation serves the needs of the present without destroying the opportunities for the existence and development of future systems. A sustainable system uses resources without depleting them, maintains or improves environmental quality, and is concerned with the balancing of short-term gains with long-term concerns: it attempts to integrate short-term and long-term views and objectives and derives incrementally acceptable paths to the long-term future. Sustainable systems use renewable and recyclable inputs, but within their reproductive rates, they minimize the use of non-renewable inputs and minimize environmental impacts. Sustainable systems have regenerative living systems as the supreme model and use knowledge to follow their finite models. In some systems, sustainable policies have been implemented by intelligent control. We could distinguish two large classes in sustainable systems: humans plus other systems that can maintain other systems in existence, but that are susceptible to over-reproduction and non-reproducing enclosure or preserving systems. The first category includes sustainable

industrial farming and sustainable businesses and industries in general. Also included in this category are the following types of systems: information and communication systems that can support themselves and the two levels of sustaining systems; health care systems that support themselves and humans to produce the next generation of other systems; education systems, research and development systems, and social welfare systems that support humans to produce the next other systems; and communal and regional systems that support inhabitants and businesses in the maintenance of these other systems. The second category includes enclosure systems that protect other systems on another level.

This book is structured into four main parts, each focusing on a critical aspect of computational intelligence and its role in sustainability. The initial part covers the first four chapters that lay the groundwork by exploring the core principles of computational intelligence. Chapter 1 introduces the fundamental concepts of computational intelligence and its intersection with sustainability. Chapter 2 examines the power of neural networks in modeling complex systems, demonstrating their ability to process vast amounts of data and identify patterns. Chapter 3 discusses fuzzy logic and its role in managing uncertainty in decision-making processes. Chapter 4 delves into evolutionary algorithms, highlighting their inspiration from natural selection and their application in solving optimization problems. The second part presents advanced computational techniques and delves cavernous into sophisticated computational methodologies. Chapter 5 provides an overview of deep learning architectures, illustrating their progression from basic structures to complex problem-solving frameworks. Chapter 6 explores fuzzy systems for adaptive decision-making and optimization, emphasizing their flexibility in dynamic environments. Chapter 7 focuses on evolutionary optimization and its ability to find optimal solutions in intricate systems. Chapter 8 presents hybrid computational intelligence, showcasing the synergy between neural networks, fuzzy logic, and evolutionary approaches to enhance problem-solving capabilities. The following part illustrates that Chapters 9 through 12 demonstrate the real-world applications of Chapters 9 to 12 in sustainability. Chapter 9 discusses its role in energy systems, including smart grids and renewable energy solutions. Chapter 10 focuses on smart cities and how computational intelligence contributes to sustainable urban planning. Chapter 11 explores artificial intelligence and evolutionary algorithms in climate change adaptation, emphasizing predictive modeling and mitigation strategies. Chapter 12 examines sustainable agriculture, highlighting the use of fuzzy and evolutionary methods to enhance agricultural efficiency and resilience. Lastly, the fourth part details the identified challenges and suggests the way

forward from Chapter 13 to Chapter 16. Chapter 13 identifies emerging trends in CI and their potential contributions to sustainability. Chapter 14 discusses ethical concerns and environmental responsibilities in the deployment of computational intelligence. Chapter 15 explores the challenges of integrating hybrid computational models into real-world applications. Finally, Chapter 16 envisions the future of computational intelligence and its role in fostering a resilient and sustainable world. We hope this book serves as a useful guide and inspires further exploration into the transformative potential of computational intelligence in addressing global sustainability challenges.

About this Edition

This first edition reflects the theory, latest advancements, and interdisciplinary perspectives on computational intelligence in sustainability. It incorporates updated methodologies, case studies, and emerging trends in artificial intelligence, neural networks, and optimization techniques. Through bridging theoretical foundations with practical applications, this edition serves as a cutting-edge resource for both newcomers and seasoned researchers in the field. Furthermore, the focus on creating inclusive digital futures has been strengthened with new insights and actionable steps to address disparities. With updated exercises and advanced exercises, provided examples, and emerging trends, this edition provides a comprehensive, forward-looking guide for educators, parents, and policymakers navigating the evolving digital landscape. This book is intended for upper-graduate studies, researchers, professionals, and students in the fields of artificial intelligence, sustainable development, environmental sciences, and computational modeling.

Audience

In summary, the book attempts to achieve the following objectives:

- Provide foundational knowledge on computational intelligence, including neural networks, fuzzy logic, and evolutionary algorithms, and their relevance to sustainability (Chapters 1-4).
- Present sophisticated methodologies such as deep learning, adaptive fuzzy systems, and evolutionary optimization to enhance problem-solving in complex systems (Chapters 5-8).

- Showcase how CI contributes to optimizing renewable energy systems and smart grids for efficient energy management (Chapter 9).
- Examine how computational intelligence supports the design and implementation of smart cities for enhanced sustainability (Chapter 10).
- Discuss the application of artificial intelligence and evolutionary algorithms in climate modeling, risk assessment, and mitigation strategies (Chapter 11).
- Investigate the integration of fuzzy logic and evolutionary methods in agriculture to improve productivity, efficiency, and resilience (Chapter 12).
- Analyze the ethical challenges and responsibilities in deploying computational intelligence for sustainable development (Chapter 14).
- Finally, identify emerging research areas, potential advancements, and challenges in integrating hybrid computational intelligence models for sustainability (Chapters 13, 15, 16).

Book Resources and Instructor Support

Within this book, we have used a simplified communication tone so that the materials can be easily read and digested. As you consider using this book, you may need to know that we have developed and written the book with the assumption that the students have basic knowledge of technology, computational intelligence, sustainability, and complex definitions of computing. If this is not true, the instructor may want to spend some time and focus on Chapter 1, Chapter 3, and Chapter 4 to help students gain acceptance knowledge throughout the course. Also, introductory modules on AI, machine learning, and sustainability should be incorporated, along with interactive exercises and case studies to reinforce understanding. This book is designed to offer comprehensive flexibility and engagement for instructors, whether used in a one-semester or two-semester course format.

If the book is adopted for a single semester, the course should focus on foundational concepts and real-world applications. The first three weeks should cover Foundations of Computational Intelligence (Chapters 1-4), ensuring students grasp neural networks, fuzzy logic, and evolutionary algorithms. Weeks 4-6 will introduce Advanced Computational Techniques (Chapters 5-8), emphasizing deep learning, optimization, and hybrid models. Weeks 7-10 will shift to Applications in Sustainability (Chapters 9-

12), discussing computational intelligence's role in the human-centered arena, for instance, energy, smart cities, climate change, and agriculture. The final weeks (11-14) will address Future Trends and Challenges (Chapters 13-16), along with case studies and project work, introducing students to research problems that computational intelligence can be used to solve. In the event that the book is adopted for a two-semester course, in Semester 1, the course will cover foundational principles and methodologies of computational intelligence (Chapters 1-8). Weeks 1-3 will focus on basic concepts, including neural networks, fuzzy logic, and evolutionary algorithms. Weeks 4-6 will introduce advanced computational techniques, such as deep learning, optimization, and hybrid models. Weeks 7-9 will delve into practical applications, exploring how these techniques are used in various domains. The final weeks (10-12) will cover methodologies and tools, providing hands-on experience in implementing CI techniques through exercises and case studies.

INTRODUCTION

At the end of the twentieth century, the relatively recent success in Artificial Intelligence was mainly due to the emergence of new general and specific techniques based on Computational Intelligence. While nascent Psychology inspired Classical Artificial Intelligence, the Computational Intelligence approaches of today have their roots in the powerful idea of borrowing some concepts from Nature and re-implementing them in our machines to solve complex problems facing us. This new and at the same time ancestral way of thinking is not only limited to the traditional techniques of Neural Networks, Fuzzy Logic, Evolutionary and other Natural-Inspired Computation methods, but now it incorporates Statistical Learning Theory and has spread to many fields of Applied Sciences and Engineering. What is even more important: this incorporation of a wide and diverse toolbox of techniques has contributed to an era of success and optimism concerning the near future of research and applied engineering. Strengthened by the incredible success that the use of computers has brought in many different areas of our modern life, from medical to industrial applications, we have to remember that the brain of the human being, Nature's masterpiece, has evolved incredibly in order to solve very specific problems related to survival, namely recognizing patterns in the environment. The Computational Intelligence techniques, all of them based on learning from Nature, have recently achieved similar results as the ones achieved by human beings and are now widely used in many practical applications like automatic data classification, time series prognosis, robotics and control problems, several engineering areas, among many others. Computational Intelligence is an approach to problem solving that integrates the formlessness, the concept, theories, and methods, some of which originated from Natural Science, and the computational techniques, methods, and tools that descended from the Engineering area. However, the use of the term Computational Intelligence as an approach is fairly new, and its popularity rose in the early 1990s when it was first proposed as a term. This book addresses Computational Intelligence methods, tools, and highlights existing applications focused on the Problem-Solving environment, where several different multidisciplinary updated techniques are presented.

Computational intelligence represents a branch of artificial intelligence with roots in the fields of mathematics, philosophy, and physiology. As a result,

a better understanding of the theoretical foundations of computational intelligence, mathematical models, and algorithmic approaches leads to better knowledge, understanding, and practice of computational intelligence-based solutions. The theoretical foundations serve as pillars for all computational intelligence methods and systems that have been proposed. Mathematical modeling represents an essential tool in science and engineering for understanding and replacing real-world systems. Beyond their utility in the exploration, description, and understanding of real-world systems, mathematical models provide a theoretical basis for developing computational intelligence systems. The theoretical foundation of computational intelligence systems consists of three model types: representational or mapping models, behavior or response models, and simulation or replacement models. Representational models describe the mapping from properties of a real-world system into its corresponding system value. The representational model conceptualizes the relation of different variables in the system. Behavior models describe the behavior of a system as time changes, using differential or difference equations. The behavior model can also be used to predict the behavior of a system based on past system performances. Simulation models are used to replicate or imitate the responses of real-world systems. In other words, simulation models allow design problems to be tested with different designs without spending any resources on training a real system. Depending on their degrees of sophistication, simulation models can be very simple compared to the real system or may involve a complete implementation of a product or its subsystem prior to the actual development.

Given the need for greater efficiency in all uses of the planet's resources, computational intelligence methods are needed to address real problems in practical ways, whilst dealing with the uncertainty and vagueness that populate our world. Doing so requires both the ability to model both the areas of concern and the deliberation or decision-making process that interacts with the system. Many academic works on computational intelligence merely describe algorithms. Algorithms are only useful in very specialized circumstances, and even then describe only a very small part of the system's operation. Data, hardware, algorithms, and software architecture interact to make an intelligent system, but it is the model, which is at the heart of the system, that is critical. Model implementation usually takes the form of computer code, but it is the mathematical object created in the process, briefly described here, which creates the ability to achieve intelligent operation. The general aspect of a model is $f(O) = P$, where an operation on an object called the ontology produces a property or observable outcome. One area of computational intelligence where no specific handling

of the data is attempted is when instances of the model output are generated and compared with real data, generally known as the generative approach to machine learning. In particular, the output is called a prior property, in direct relation to Bayes' Theorem. When a more elaborate general form is sought, the relationship is called a generative relationship. When the generation process is compared with the observed data, typically over many observations, it is called generative inference. When the function does not require any estimation, it is known as an exemplar function. More generally, if estimates of the data itself are obtained, it is known as a kernel function, or, more generally, logical or radial models.

A number of algorithmic approaches have been created to solve the optimization problems that represent the basis of computational intelligence. Relying on diverse principles originating in logical and probabilistic reasoning, search theory, and learning, among others, these approaches manage to face various types of decision problems in many areas of management, economy, engineering, etc. Exposing the variety of these strategies certainly would take many books. Below, we choose to present some groups of them, characterizing their main principles and providing examples of models related to the work themes. The list of algorithms below is not exhaustive, presenting our focus on methods that we believe fit better in the area of computational intelligence for sustainable systems. Several other algorithms exist that belong to some other knowledge domains. Moreover, several combination architectures are also spread through the above-mentioned knowledge fields. However, for our aim, the algorithmic approaches that we are detailing would be sufficient for fulfilling tasks in areas of economy, engineering, etc., returning interpreted information. In terms of architectural choices, in various areas we may find different algorithmic choices. These choices are related to the conceptualizations we mentioned above and, mainly, the properties of the specific problems we are dealing with. For example, a different kind of problem generator or specific characteristics of the environment are behind the development of different types of algorithms. In emergency-oriented problems, heuristic algorithms are generally employed in such a way that they generate fast solutions, although these solutions are, in general, not optimal ones.

Sustainability is one of the grand challenges facing civilization in the twenty-first century and involves the balancing of Earth's systems with economic and social systems. Sustainable systems are at the heart of this challenge and are characterized by a coupling of natural, social, and economic systems. It is important to note that the coupling is mutual and interactive, such that the change of condition in one system leads to a change

in condition in the other systems, which leads to the evolution of all systems. Sustainable systems must satisfy several critical needs, including health, safety, and sustainability at a reasonable cost and minimal environmental impact. These needs exist at the global, national, regional, and local levels, and therefore, a crucial requirement for sustainable systems is scalability, which means that design decisions made at any of these levels should not disadvantage the other levels. The primary objective of goals on sustainability and sustainable systems is to create optimum conditions under which human activities and the planet's geological, environmental, and biological systems can coexist, interact, and effect change without upsetting the delicate balance among them. This is a very complex endeavor due to the interactive interdependencies among the natural, social, and economic components and factors in actions associated with the processes of provision of resources, development, operation, and retirement/recycle on different time scales, which may comprise multiple generations. The consequence is that establishing multi-factor computing systems that work in concert to realize specific sustainable goals in an optimized manner is challenging and is usually attempted through empirical methods or simply trial and error. This challenge is being mitigated now through the use of models based on formalized methods from experts in various disciplines such as ecology, earth sciences, economics, and sociology. However, the models do not contain all the factors and parameters needed to predict the dynamic behaviors and effects of possible actions by tenants of the involved systems on one or more of the involved systems over time. In addition, specific goals for the systems at the different levels may conflict. For example, local laws and ordinances for the sustainability of a community may prohibit certain harvesting activities that are allowed by the global and national guidelines for timber and forest products.

Sustainable systems are a new class of systems based on the paradigm of sustainability, the first since the definition of information systems forty years ago. The concept of sustainable systems is a result of the convergence of multiple facets of system characteristics. Sustainable systems are engineered and deployed by humans, whose life cycles are driven by the use of resources, typically modeled and implemented as physical, environmental, or economic entities. The life cycles of sustainable systems contribute positively or negatively to the conditions of the environment, social well-being, and economy. Sustainable systems, by definition, fulfill the requirements and address the constraints of stakeholders during their design, operations, and maintenance. Sustainable systems can only exist in a culture of sustainability that relies on ethical decisions and cooperation between humans and organizations. Important research and practical problems in

sustainable systems are benefit allocation, decision making, and the unit of analysis. The importance of systems that incorporate the principles of sustainability is evident at the personal, organizational, and societal levels. There are many facets to the importance of sustainable systems. First, they increase awareness about being sensitive to other people as well as future generations. Second, the impact of engineering, business, and management decisions on the use of resources is brought to the forefront. No longer can human-centered systems be engineered and deployed in a vacuum, without considering all of the above forces acting collectively; the road map is explicitly defined in the contemporary formulation of the triple bottom line. Third, the principles of equilibrium and diversity become central to developing systems that contribute to long-term planetary well-being, with an emphasis on the harmony of nature and technology. Understanding systems as open systems that affect and are affected by the external environment, whose life cycles contribute positively or negatively to a set of measures we want to maintain, defines the area of research in sustainable systems.

While there is a common understanding of sustainable systems as an interdisciplinary study under the umbrella of sustainability or sustainable development principles, an examination of modeling and managing complex systems for sustainability shows a number of major dilemmas that are referred to as challenges in sustainability. Some of these dilemmas are directly related to different shades of the question “What values do we use to define sustainability?”. This question refers to the essence of sustainability, as sustainability represents a cyclical process of meeting basic human needs today while recognizing that we must do so into the indefinite future and while preserving the diversity and richness of the ecological system that sustains us. Such a definition shows that the primary value of sustainability is the development of a system that possesses dynamic mutuality and stability. However, as mentioned, different stakeholders regard the value of sustainability differently. For some, it could be purely economic. For others, it can be compassion, caring, human dignity, etc. This simple question clearly indicates the complexity and difficulties in the sustainability domain. Additionally, various definitions of sustainable development imply a variety of value orientations. Three major challenges in sustainability derive from such different values: 1. what are the most appropriate indicators of a system's sustainability; 2. how do we evaluate the models of the systems; and 3. how do we integrate the various and sometimes conflicting stakeholders' criteria and concerns during the modeling, analysis, and optimization processes? While the first two challenges are important for the assessment of new models with relevance

and originality, the third challenge is especially important in reality for various reasons. The first is due to the irreversible nature of many environmental changes and human impacts on the environment.

Computational Intelligence has been one of the key technological enablers to flexible yet effective systems in which humans and machines cooperate with confidence. The continuous growth of Computational Intelligence technologies has led to a unique set of capabilities to implement new models and theories, able to decode the real inner workings of organisms and complex systems. CI has promoted a set of innovative paths, leading the design of smart, interactive, sustainable systems. CI will effort to move, step by step, from reactive to active autonomous systems as well as interactive systems able to cooperate with humans when needed. It will aim to solve a larger number of problems and questions and address new issues regarding the role of technology in society. CI represents a continuation of the traditional pursuit of intelligent behavior in machines and a key component in the development of many future intelligent, autonomous, and interactive systems. In return, there are a number of challenges requiring the rethinking of CI and of CI-based systems and methods. We first review CI methods, namely: machine learning, neural networks, fuzzy logic, and evolutionary algorithms. Machine learning methods automatically learn general mappings from training data to actions and further improve with experience. During this long voyage, ML evolved, overcoming initial limitations, both concerning the types of problems that could be solved and the methods that could be implemented. Fragmented, often inconsistent branches were established around peculiar problems or solving principles: Statistical approaches, Connectionist approaches, Kernel methods, Sparse coding models, Graphical models. Recently, these vertical branches have started to unify again, thanks to the claim attributing the CA and Neural Codification approaches as founding principles.

Emerging as a profound subset of Artificial Intelligence, Machine Learning (ML) draws upon the intricate theories and methodologies of Computer Science and Statistics, ultimately epitomizing the quest to replicate human learning capabilities practically and economically. Core to this domain is the ambition to develop analytical tools and programs that harness real-world experiences, thus honing their operational effectiveness over successive trials. Such learning has facilitated the automation of a plethora of tasks, obviating the need for explicit programmatic design. Machine Learning is traditionally partitioned into two cardinal categories: Supervised Learning and Unsupervised Learning. In supervised learning, ML algorithms are trained on a labeled training set, learning an implicit function that relates

the input and output variables. Upon completion, the function can predict the output variable for either new observations or those in a test set. Supervised learning is predominantly utilized for regression and classification tasks. Conversely, unsupervised learning algorithms are supplied with a training set devoid of labels. Here, the internal clustering structure within the data is learned, resulting in the categorized input observations, which have extensive applications in diverse domains such as data mining, information retrieval, consumer behavior analysis, risk modeling, image analysis, and bioinformatics. Inferred categorization delineates yet another category, specifically called semi-supervised learning, that lies between supervised and unsupervised learning. In semi-supervised learning, a small amount of labeled data and a larger corpus of unlabeled data are employed to construct an ML algorithm that optimally performs classification or regression tasks. This hybrid category has gained increasing visibility and popularity among researchers, data miners, and industry practitioners due to the difficulty and expenses associated with gathering labeled data for various applications. Data Derived Intelligent Systems (D2IS), an ML paradigm that has wide-scale applications in nearly every domain, pertains to the automated generation of domain-specific intelligent systems from high-volume, high-variability data.

Neural networks model the human reasoning process to varying degrees of success to simulate intelligent behavior in computers. Neural networks are sometimes referred to as “parallel-distributed processing systems” and are composed of a large number of highly interconnected simple processing elements, called neurons, that are capable of generating patterns of output in response to patterns of input stimulation. Models are constructed that describe the mapping from a chosen input space to a corresponding output space. Neural networks borrowed their basic design principles from studies of the structure and functioning of real neural tissues. During learning, the strengths of the connections between the processing elements are adjusted according to a learning algorithm. Neural network techniques have been around for many more years than most people realize, and backpropagation is just one of more than 50 algorithms for training a multilayer feedforward neural network. Neural networks have been used to solve quite a number of difficult AI problems, including robot control, landslide detection, speech recognition, prediction of stock market trends, recognition of face images, handwriting recognition, diagnosis of diseases, image processing, and numerous others. Today, the vast majority of applications of neural networks are in the fields of automatic identification and pattern classification. Most neural network applications fall within the skills of a typical AI problem

solver. They utilize many of the problem-solving methods described earlier but focus attention on pattern classification and identification tasks.

Fuzzy Logic was conceived in early 1965 as a method of handling the imprecision, uncertainty, or vagueness that is typically present in real-world systems and to devise control systems that can more closely imitate how humans think, learn, and reason. Linguistic variables are utilized to describe, model, and control real-world systems, and fuzzy rules are easy to create and understand, and can also be derived from human expertise and knowledge of how related systems work. Fuzzy Rules are represented in an If-Then expressive form, and fuzzy rules can form a fuzzy rule base with a clear understanding. Fuzzy Logic has contributed greatly to the advancement of many fields and areas. A Fuzzy System can collect and assimilate all the perceived signals from the real world, map them to the output space, and describe what kind of actions it has to take. Fuzzy Systems can also do it backwards. When the desired response is known, the parameters defining the fuzzy rules of the system will be such that the desired output is produced for a known set of inputs. Knowing the parameters, it is also possible to analyze the behavior of the system. Fuzzy logic is a multivalued logic derived from fuzzy set theory to handle the concept of partial truth. It is used in computing that is based on degrees of truth as opposed to the usual true or false Boolean logic on which most computers are based. Fuzzy logic is a key component of fuzzy set theory. The major application area for fuzzy logic is in the use of fuzzy rules to categorize, or classify, figures in the input space. Fuzzy logic has been utilized to benefit many fields, such as expert systems, medical research, computer vision, natural language processing, and pattern recognition.

Evolutionary algorithms (EAs) are powerful global optimization techniques that develop solutions for search and optimization problems inspired by natural evolutionary processes. They maintain a population of candidate solutions and apply random mutation and probabilistic rules similar to those found in natural selection to facilitate the exploration of the search space. EAs are often used in situations where it is difficult to derive a problem-specific optimization method, or cases where there is no solution on which to base a heuristic. Furthermore, EAs are particularly appropriate in solving deceptive problems characterized by many local optima, where most local search methods are ineffective. However, these techniques are neither perfect nor without weaknesses. EAs typically require large computational resources and, unlike problem-specific local search methods, are unlikely to find the global optimum of a search problem. Three conditions characterize EAs. First, EAs consider a population of individuals (candidate solutions).

A population-based strategy allows EAs to explore multiple areas of the solution space simultaneously, increasing their chances of finding the global optimum. Secondly, at the selection stage, EAs choose the fittest individuals preferentially for reproduction and mutation. This naturally skill-selects the fittest individuals, employing higher local search efficiency in promising areas. Thirdly, EAs employ some recursive stochastic random procedure, either globally or locally, to change the genetic structure of the current population through time and generate a new population. The relative simplicity and generic design of EAs result in the strategy's impressive robustness, but they also make it relatively easy for practitioners to set up and apply EAs.

Computational Intelligence (CI) techniques have been successfully employed for developing systems meant for practical applications in most areas of our knowledge and scientific investigations. Environmental dynamics is one such area that poses challenges for sustainable development with the ever-increasing pressures on natural resources and integrated ecosystems. Continuous and rapid changes due to developmental activities and natural disasters have been degrading natural and modified environments towards the loss of biodiversity and key ecosystem functions. Therefore, sustainable management of environmental dynamics requires timely technical decisions to maintain conducive surroundings. CI technologies can contribute significantly to the environmental sector through the development of soft-computing-based systems to realize the smart services for timely spatial and temporal decision support for resource management, pollution control, and biodiversity conservation. CI techniques can help planners and policymakers in various sectors by providing decision support tools to deal with multifaceted problems related to the environment and ecology. CI is gradually finding acceptance in developing traditional but sustainable management structural processes associated with natural resources and ecosystems. The aim is to present a few latest developments and their applications for environmental sustainability. CI technologies can enhance management capabilities in a variety of interlinked ecosystem-based services, including ecosystem-based resource potential estimation, ecosystem-based land evaluation, sensitive areas, resource-based job opportunity generations, global climate and desertification model, land degradation assessment, and future prediction of ecosystem environment.

Public demands for a higher quality of life propel environmental problems. Many research projects show the importance of further development of intelligent systems to manage natural resources for a sustainable future. A large number of intelligent systems have been used for this purpose with

contributions from diffusion models, genetic algorithms, neural networks, advanced optimization methods, and many other computational intelligence methods; often used in conjunction with traditional estimate techniques. Picking, finding, and managing resources such as water, forests, minerals, crude oil, coal, gas, energy, soil, and agricultural resources, power substations, and harvesting planning models, using intelligent systems helps in developing sustainable strategies. An intelligent information system that optimizes the planting season for many different crops in a region based on water requirements, demand for the products, temperature, rainfall, humidity, and health of the soil has been developed. Nutrient resource management has also gained great importance in achieving sustainability, such as optimal fertilizer planning in vineyard production, best available planning approaches for urban wastewater nutrient management, and decision-making models for strategic nutrient resource management. A documentation framework using a multi-agent system that acts as a geoportal, providing visitors with access to information about environmental resources, has been implemented.

The twentieth century witnessed a continuous industrial revolution, which was also a significant contributor to the long-term increased pollution levels. This same century also saw the creation of the Environmental Protection Agency in the United States in 1970. Before that, in 1952, London had already suffered a terrible smog that killed 4,000 people, and that was not the first time that this kind of occurrence had happened. Controlling pollution is indeed an attempt to establish a compromise between economic and environmental policies, but pollution control is recognized not just as a widely explored theoretical work, but also as a practically achievable work that can be made over time. It searches for solutions able to minimize environmental harm while maximizing social welfare. This section embraces an approach that can estimate the extent of individual willingness to pay for pollutant reductions, or at least mentions it as an additional important variable to be considered. Of course, the implementation of pollution standards is associated with increasing marginal costs, in line with the increase in pollution reduction orders. Budget constraints with respect to aggregate willingness to pay limit the degree to which a government can pursue its responsibility. Either from a theoretical or an empirical viewpoint, deriving a cost curve for pollution abatement as a function of pollution reductions in all the non-market associated curves, including the demand curve for the level of pollution treatment, and relating each treatment's cost to the extent of demand, is a virtually impossible task. Here is where computational intelligence fills this gap. There are important estimating problems in considering the demand curve, and these demand

curve problems relegate estimating the Aggregate Willingness To Pay curve to be done in a regional econometric framework, treating it as a regional problem within a developing and estimating pollution regional model framework.

“The current record extinction rate is approximately 1,000 times higher than background, or baseline, extinction rates. The accelerating loss of biodiversity, primarily brought on by anthropogenic activity, is of global concern. Despite best efforts, determining which areas are most critically important for conservation is complicated by spatial-temporal heterogeneity in species composition, lack of knowledge regarding basic biological parameters, high cost of empirical assessments, and unpredictable consequences associated with environmental change. Incorporating functional diversity into systematic conservation prioritization seeks to produce reserve networks that conserve the full spectrum of evolutionary history, that promote ecosystem stability by making ecosystems less susceptible to anthropogenic change, and that enhance ecosystem service provision.”

The quest for more efficient, sustainable energy systems is one of the preeminent challenges of our age, assigned today a monumental priority amongst many. May the possible achievement of such goals, enhanced by computed intelligence, constitute our major stimulus for the development of this collection of works around the theme of such competence and its synergetic integration in existing technologies. In this chapter, we concentrate on the deployment of some of the techniques we espouse in a number of ongoing projects in the energy domain. Today, the development of new, renewable energy stations has become a central part of energy strategies in most parts of the globe. Despite important technological advances related to the design of more efficient solar panels, new turbines for wind generation, and the like, the optimal low-cost operation of these new systems is far from being achieved. Some of the problems related to efficient renewable energy production include the planning of the generation park, including possible combinations of a variety of energy sources, the optimal operation of the units that compose it, the introduction of possible storage systems, to cite a few. These problems are associated with renewable energy generation because new computational intelligence paradigms may be and are being used to solve them. The difficulties relate to the planning of the medium- and long-term energy available fluxes, at the core of which natural source energy development predictions take center stage. New CI techniques are also regularly engaged in the resolution of problems associated with the optimal functioning of the grid and/or intelligent carbon-free distributed control management of energy flows.

They are also called to plan the efficient incorporation of local generation in urban zones. The discussion of the advantages and disadvantages of these and other CI tools for the solution of these problems is central to the discussion in this section.

Renewable energy resources have been aggressively developed in recent years due to their advantages, including sustainability, environmental-friendly, and inexhaustible abundance. However, how to successfully integrate these energy resources into energy systems still presents an important challenge not only for power grids but also for thermal networks, gas grids, energy hubs, and associated systems. For example, the percentage of renewable energy when generating electrical energy is expected to reach 50% in 2030, and then 80% in 2050. The successful integration of renewable energy resources into power grids relies on a variety of means, including but not limited to energy management, device operation, and investment decisions. Such complex problems can be represented by models and solved by methods of computational intelligence. Many tasks in CI for energy systems are directly motivated by engineering aspects, although commonly accompanied by theoretical development. These tasks include forecasting energy outputs from wind farms or photovoltaic panels, supporting large-scale deployment of various energy resources in power grids or microgrids, determining optimal scheduling of battery storage systems or microgrids in energy management systems, aggregating demand response to reduce the peak demand in demand side management, addressing operational optimization and financial planning of integrated energy systems associating electricity, heat, gas, and water sectors, solving optimal investment under uncertainties of renewable energy deployment and electric vehicle adoption, assessing techno-economical impact of various energy policies in energy system digital twins, and providing intelligent control of energy conversion appliances including heat pumps and electric vehicles.

With the progressive electrification of socio-economic development, there is an emerging absolute need for energy sustainability in daily life as well as on an industrial scale. The massive demand for electric energy calls for innovation and efficiency improvement in every step of the supply chain from generation to consumption. The fact that the electric energy can only be generated at a certain place and time and needs to be consumed instantly, together with the growing share of distributed generation, in particular based on renewable energy sources, scattered all over the world, leads to the introduction of the concept of Smart Grid. Smart grids are intelligent networks of electricity supply and demand that connect the producers and

consumers, optimize the generation and consumption in both short and long-term horizons, and ensure the balance at all network nodes in real time. In this direction, computer-aided tools and methodologies from different backgrounds are developed to handle various issues ranging from market price formation and energy flow modeling, to demand response enabling and control, to enhancements of security and robustness. Demand response, implemented through control strategies, is regarded as an effective technology to alleviate scarcity of resources owing to peak demand, improve consumers' comfort, and help utilities balance demand and supply. It incentivizes consumers to modify or curtail their energy consumption during specified timing conditions to help curb in return for compensation. However, demand response cannot be attained without consumer engagement. A thorough understanding of the behavioral willingness of consumers toward demand response is very important in designing an appropriate demand response program. Experimental and numerical market instruments can be engineered to explore consumers' consensus or to help identify the optimal design of institutional Demand Response programs.

Urban development has traditionally played a pivotal role in shaping the course of social and economic growth in nations. However, the sustainability of this development is being questioned by increased urbanization in economies worldwide. Furthermore, the concentration of economic activity in urban locations, coupled with negative externalities resulting from urban systems, leads to local, national, and global ramifications. The latter are primarily responsible for the emerging need for developmental policies that address the sustainability issue. While macroeconomic policy measures are implemented in this regard, computational intelligence can assist in bridging the existing gap between action and intent by offering novel technologies for the early diagnosis and prognosis of potential danger. The trend towards urbanization augurs for the development of smart cities, with building and transportation systems being the main sub-systems of smart cities. The Smart City concept comprises the Digital City for disseminating and exchanging knowledge, the Intelligent Megacity for better education, training, and life by more effective knowledge management, and the Protected City, which encourages STEM to combat crime by reducing opportunities through prevention. The Smart City conveys the sense of expectancy around the use of advanced technologies to help city managers and citizens cope with the challenges of urban growth. In society, information is seen as an enabler, a social lubricant that is vital for effective political decision-making and the efficient use of scarce resources. The processing industry will no longer produce inside its walls, but will engage citizens to create and deliver value via voluntary

consuming continuously. At the same time, the transition towards a service economy will proceed, with brands providing people's "life-support systems" driven by market-oriented software agents vying to gain loyalty. Sensor-equipped smart cities will gather information and exchange it via wireless networks. The interaction and impact of people through intelligent infrastructure will transmit the real-time pulse of the city.

Smart cities have emerged as one of the most advantageous research and development areas for intelligent urban expansion and infrastructure evolution. During the last decades, the sudden rush of cities towards high demographic density has drastically increased the pressure on urban economies and nature. Thus, in order to achieve better modeling of the infrastructure of a megacity, better exploitation of urban resources, higher quality of life for its citizens, and economic and ecological sustainability, it is necessary to conceptualize, design, and implement intelligent solutions, in order to create urban environments that adhere to the principles of computationalism, continuity, inclusion, synergy, afterlife, openness, scalability, and sustainable development. Artificial Intelligence and advanced machine learning, robotics and machine vision, intelligent systems and embedded artificial intelligence hardware, as well as big data processing and fog and cloud infrastructures, among others, contribute impressive solutions for the upgrade of existing infrastructure and the growth of new infrastructure in a way that avoids adverse results of the urbanization explosion.

Despite being a relatively novel concept, smart cities are gaining ground over the more established ideas of urban communities. One of the reasons for this shift is the rapid urbanization movement. The available technologies are facilitating the construction of smart cities by promoting collaborations. More specifically, social media technologies, wireless sensor networks, ubiquitous computing, location-based services, and mobile Internet are significantly influencing our day-to-day lives, how we communicate, and how we perceive and understand our cities. We are indeed in the middle of the greatest shift in how societies operate since the emergence of the industrial era. The mass movement of people to cities has been the most important factor transforming most of the world. Cities have become the world's new growth engines as the majority of GDP growth is now driven by cities. Smart cities integrate the Internet into the physical city, affecting everything from navigation to power management. This installation of technologically equipped physical structures and devices enables users to view or receive information on a real-time basis and to communicate and interact with one another through the connected network. Sustainable

transportation is one of the main drivers of sustainability in Smart Cities, building on its contributing characteristics of efficiency, safety, speed, reliability, affordability, equity, and health.

The need for intelligent optimization of transportation systems arises from the contribution of both private cars and public transportation, along with their interactions. The evolution of various concepts of e-mobility, electric vehicles, autonomous vehicles, Mobility as a Service, High-Occupancy Vehicle and High-Occupancy Toll lanes, Vanpooling and Carpooling, Mobility On Demand, and crowdsourcing found their way into scientific research and are facilitating advances in the implementation of those systems. Those concepts contribute to the shifts towards decarbonization and digitalization of transportation systems, and towards an increase in energy efficiency and reduction of environmental pollution levels. Decarbonization of transportation represents a paradigm shift in the city transport of people and goods. Based on electrification, significant efforts have been applied in e-mobility, as well as in evolving various forms of hydrogen-based transportation modes. Business models and service delivery for particular forms of shared mobility, such as Car-Sharing, Bike-Sharing, and E-Vans, are in constant evolution. Left devoid of privacy reasons, crowdsourcing has generated advantages in traffic condition prediction and impact prediction on dispatching, routing, and pricing by social networks. Parallel to increased investment efforts in digitalization, those technologies have also fostered the development of autonomous driving. The topics mentioned above are becoming frequently approached with a more integrated system perspective, to guarantee the effects of multimodal interchange on improved service delivery.

Accelerating changes in the external environment and the subsequent pressure for continuous product/service innovation and exploration of new business models make it challenging for organizations to carry on their businesses as usual. The development of intelligent assets, in combination with an increased emphasis on business process compliance, flexibility, improvement, and innovation, suggests the need to enhance interoperability, with considered automation and provide mechanisms for better analytics to support more effective and efficient decision making at all levels using the right balance of human cognition and decision support tools. In this respect, decision-making processes are changing, going from a centrally managed hierarchical model to decentralized models, where business teams are organized into virtual units that are ultimately responsible for their performance. Besides the traditional businesses, a large amount of data has emerged from newer models. The influence of digital platforms on

economic and social value creation has resulted in increasing adoption of platform ecosystems and attracting digital intermediaries. Big data is now influencing the development and implementation of business strategies. Companies' digital transformation is paving the way for new research questions regarding the understanding and the support of data-driven decision making. Data-driven decision making implies that decisions are made by taking advantage of the insights contained in data. It relies on predictive models and algorithms mapped into a decision agenda and generates decision recommendations, actionable to a certain extent. The expected advantages include the following: a larger population of decisions that benefit from data; the use of data to assess the potential downside of business decisions ranging from small tactical to major strategic actions; the ability to 'industrial' the decision making, relying on pre-coordinated decision flows to address situations involving a large group of similar decisions.

Social and economic systems are transitioning into a data-driven society. Data-driven strategic decision-making at the operational level is essential to providing positive business outcomes. Organizations are now shifting their focus from data collection to data analytical capabilities to deliver real-time insights for better decision making. Until recently, support for decision-making relied on the concepts of experience, gut feeling, and heuristics. Even with survey-based decision support systems, the decisions are based on historical data, giving only a partial view of the product, market, consumer, or company ecosystems. Big data analytics seeks to overcome such limitations by analyzing real-time operational data and is able to pulse live signals on products, consumers, and markets for a long-term strategic decision with respect to multiple organizational goals and objectives. Though brainstorming, heuristics, and even survey-based methods provide valuable insights for decision-making, the approach is incomplete as they rely more on historical data. Big data analytics, on the other hand, collects data from many different sources within the ecosystem, which in turn helps to know about real-time changes happening in the ecosystem. Big data analytics techniques are used by the smartest of today's organizations as part of their decision-making process to deliver real-time feedback so that corrective actions can be taken to eliminate untenable business situations. Artificial intelligence and machine learning algorithms help this type of analytics by predicting outcomes based on historical data. Even convincing models for artificial intelligence or machine learning begin to unravel. Predictions turn out to be wrong when not based on an accurate appraisal of ecosystem-wide changes. Amidst the fast pace of change today, putative