Chapter 1
An Introduction to Contemporary Achievements in Intelligent Systems

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1 Introduction

The term intelligent systems is used to describe the necessary level of performance required to achieve the system goals. Intelligence has been observed and scientifically categorized as a biological stimuli response mechanism that is provided to satisfy an intended activity.Intelligence considers cognitive aspects of human behaviour, such as perceiving, reasoning, planning, learning, communicating and innovation. As society evolved, innovative individuals invented tools to assist them in achieving better outcomes. Since the industrial revolution [1], science and mechanization have become central to many academic challenges, driving a paradigm shift from philosophy towards systems engineering techniques. This desire to improve mechanized systems created the need for improvements to automation processes. These achievements extend the pioneering efforts of others stimulating new research and developments [2]. Computational Intelligence (CI) has evolved over the past 60 years [3] with many new fields of study emerging to dissolve obstacles encountered. These attempts relate to efforts at personifying attributes of human behavior and knowledge processes within machines. The resulting *Machine Intelligence* [4, 5] efforts stimulated the study of Artificial Intelligence (AI) [6, 7] and led to the evolution of many contemporary techniques.

Agent technologies, and in particular agent teaming, are increasingly being used to aid in the design of *intelligent systems* [8]. Software engineer have made significant progress in fields, such as knowledge representation, inference, machine learning, vision and robotics [9]. Minsky suggested that AI is the science relating to making machines do things that would be done by a human [10]. AI researchers originally studied science relating to human and animal intelligence. These concepts were initially conceived by Newell and Simon using production systems [11]; however, the study quickly

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divided into two streams with John McCarthy and Nil Nillson considered the Neats (using formal logic as a central tool to achieving AI, while Marvin Minsky and Roger Schanks where considered the scrufs (using a psychological approach to AI). Russel and Norvig entered the argument by describing an environment as something that provides input and receives output, using sensors as inputs to a program, producing outputs as a result of acting on something within that program. The AI community now uses this notion as the basis of definition of an agent [12]. AI technology is becoming the paradigm of choice for the development of complex distributed systems and as the natural progression from pure object oriented programming. Learning has an important role to play in both cooperative and autonomous systems. Agents with predefined behaviors based on a priori knowledge of the system that is modified using feedback from experience will continue to mature. Rather than having purely agent-based applications, we then have cooperative applications involving teams of agents and humans. AI will retain their architectural foundations but the availability of more appropriate reasoning models and better design methodologies will see them being increasingly used in mainstream software development. Furthermore, better support for human-agent teams will see the development of a new class of intelligent decision support applications. For more information, see the evolution of intelligent agents within the world wide web [13] and the ability to embedded automation into modern intelligent systems in a *Human-Agent* environment [14].

This book examines the basic concepts relating to contemporary in *Intelligent Systems* and provides a number of case studies to examine specific examples. Prior to examining those topics, the basic terms are defined to provide clarity and additional references where the reader chooses to seek more information. The following section progressively build the concepts associated with *Intelligent Systems* and some of the techniques used to create them. Hence the discussion review the definition of a system, intelligence, AI and associated intelligent paradigms.

1.1 What Is a System?

A system is defined as "a set of things working together as parts of a mechanism or an interconnecting network" [15]. Other dictionaries qualify the definition based on categories or functionality. For instance, the *American Heritage* dictionary defines a *system* as [16]:

- A group of interacting, interrelated, or interdependent elements forming a complex whole
- A functionally related group of elements, especially:
  - The human body regarded as a functional physiological unit.
  - An organism as a whole, especially with regard to its vital processes or functions.
  - A group of physiologically or anatomically complementary organs or parts. Examples include the nervous system and the skeletal system.
  - A group of interacting mechanical or electrical components.

  - A network of structures and channels, as for communication, travel, or distribution.
  - A network of related computer software, hardware, and data transmission devices.
- An organized set of interrelated ideas or principles.
- A social, economic, or political organizational form.
- A naturally occurring group of objects or phenomena. For example, the solar system.
- A set of objects or phenomena grouped together for classification or analysis.
- A condition of harmonious, orderly interaction.
- An organized and coordinated method; a procedure.
- The prevailing social order; the establishment.

This book discusses the concept of a *system* in relation to intelligent systems using contemporary achievements. The focus is on using software to enhance machine intelligence to control robotic behavior. Examples provided are associated with AI techniques aimed at harnessing knowledge from artifacts collected within the environment or learning algorithms using neural networks.

1.2 What Is Intelligence?

By definition, intelligence is "the ability to acquire and apply knowledge and skills" [15]. The level of *intelligence* grades the ability to think, postulate or even compose a thesis to a solution. This measure examines many skills, compliance to lots of rules and a significant level of expert knowledge in the problem Domain. We measure human intelligence using a variety of Intelligence Quotient (IQ) tests. This measures a wide range of skills to generate a rating using a common standard. Psychologist can administer *professionally engineered* tests, such as the Wechsler Adult Intelligence Scale (WAIS)[1] and the Ravens Progressive Matrices[2]. What is measured and its relevance is the major issue clouding the terminology. Computers appear to achieve intelligent feats, but they are not intelligent, they are merely doing what they are programmed to do!

Intelligence has been defined in several ways [17]:

- the ability to learn or understand from experience,
- ability to acquire and retain knowledge,
- mental ability,
- the ability to respond quickly and successfully to a new situation, and
- use of the faculty of reason in solving problems or directing conduct effectively.

In this book, the concept of intelligence is associated with techniques used to enhance a machines ability to achieve tasks that are currently not supported by existing systems. Research into intelligent systems is evolving, however no scale exists to measure or

[1] See wilderdom.com for more information.
[2] See www.pearsonassessments.com

compare machine intelligence because of the complexity required to normalize the results. Ongoing research into automation may develop an machine intelligence quotient[3], until then, the focus remains on improving the techniques associated with collecting information and generating knowledge.

1.3 What Is an Intelligent System?

An intelligent system is therefore a collective set of techniques that create a mechanism to achieve temporary objectives within a limited space and time using information sensed within its environment. The system uses concept provided or divined in response to its current state and perceived situation based on the constraints of its programming. There is no clear definition, although society is forming a belief that an intelligent system should be a machine that is capable of simulating the human decision making process (exhibit a basic IQ). In reality intelligent machines remain formal or informal systems that gather or manage data, to obtain and process information into knowledge to enable reasoned judgments by human decision makers. The term is not limited to intelligence organizations or services but includes any system, in all its parts, that accomplishes the listed tasks [18].

The concept of embedding intelligence within machines has existed since the first AI conference held at Dartmouth in 1956 [19]. Software has traditionally been used to monitor systems without providing significant direction or control. Machines and production lines are still controlled by operators that require specified skills to achieve predetermined goals. When the required stimuli is missing or delayed, that machine or process become disrupted and may fail. The efficiency of attaining a goal, should not be confused with the intelligence of the machine or operator. Automation is the incarnation of a known sequence of series of processes that contribute to a predefined task. This concept should not be interpreted as intelligence, regardless of the level of technology or efficiency it provides [14]. Applications are increasingly being developed using AI techniques to automate functions traditionally conducted by the human element within the overall system. At present, many of these systems retian one or more humans in the loop, however they are being displaced are more advanced AI techniques evolve.

1.4 What Is AI?

The term AI was born out of a conference held at Dartmouth in 1956 [19] and generally attributed to John McCarthy [3]. He was latter acknowledged as the father of AI and has since reported he should have used the term CI [20]. The concept of AI at that time was documented by Newell and Simon [21, 22] who highlighted their production systems [11] in those examples. The field soon divided into two streams with John McCarthy and Nils Nilsson considered the *Neats*[4], while Marvin Minsky and Roger Schanks where considered the *scrufs*[5]. Minsky has since told reporters in 1982 that,

[3] It would be appropriate to use the term Machine Quotient (MQ) in lieu of machine intelligence quotient because it would reflect the personified association with humans.

[4] Who started using science and formal logic as a central tool to achieving weak AI.

[5] Who retained a cognitive or psychological approach to strong AI.

"AI has one foot in science and one in engineering" [23]. Where as Roszak stated "AIs record of barefaced public deception is unparalleled in annals of academic study" [24]. The definition has become a heated debate, so now we focus on the terms *strong* AI and *weak* AI.

The goal of *strong* AI is to build a machine that is capable of thought, consciousness and emotion (the mind), where *weak* AI merely develops models to test theories about understanding humans and animals, usually in robotic form. These models provides useful tools that help us understand the mind. We know that AI bounds a number of disciplines that include: psychology, philosophy, linguistics and neuroscience.

Psychology: The *Pavlov's dog* demonstrated how to observe behavior, through the study of stimulus and response. Fredholm determined there was a valid set of concepts that explained memory, learning and reasoning [25]. The study of intelligence in AI exhibits this interdisciplinary approach to cognitive psychology.

Philosophy: Simon introduced the theory on computational intelligence. In 1957 he suggested that "within ten years, that most psychological theories would take the form of computer programs" [26]. Descartes introduced the concept of *dualism* where he argued there was a fundamental difference between the mental realm and the physical realm [27]. There is a parallel about the computer program requiring a computer to manifest itself and the mind requiring a brain to exist. This attempts to embody knowledge into machines makes several assumptions regarding ontology and hermeneutics, such as *the sorts of things machines need to know*. There are varying degrees of intelligence in humans, in machines this relies on the computation engine. Walter Grey constructed several robots with a number of sensors for collision detection. *Elsie* wandered autonomously until her battery level fell[6] and provided the illusion of mimicking what appeared to be complex behavior [28]. Similarly, Wilhelm von Osten claimed to train a horse to do maths, albeit gesture driven behavior. Both examples highlight the problems associated with determining an agents capacity solely on behavior.

Linguistics: Chomsky had a predisposition for language and believed the human competency for speech was only shaped by their environment (noting we are born with some knowledge of language).

Neuroscience: This concept forms the foundation of most high-level cognitive processes used in AI.

1.5 Putting AI to Work

In 1966 a robot called *shaky* was built at Stanford [29]. He combined a number of AI techniques to assist him organising blocks within a simple constrained environment.

[6] At which point, she was attracted to a light positioned inside a charging tunnel. When fully charged, she repeatedly continued wandering.

Wheel slippage introduced errors into the *sense, model, plan* and *act* cycle which disrupted perception and positioning within the environment. Unfortunately as the environment became more complex the techniques in this model eventually failed [30]. As AI matured into the modern era, McClelland introduced the connectionist theory which quickly theory gained popularity [31].

McCulloch and Pitts presented the concept of a Neural Networks (NN) by making many parallels to the brain on a highly abstracted level. One obvious difference is the brain only processes information at a rate of approximately 1000 signals per second. It does however conduct millions, possibly billions, of parallel processes simultaneously[7]. The brain has approximately 100 billion neurons with at least 100 trillion synapses interconnected by axons using multiple microtubules. Each neuron behaves like a single processor, which itself runs an application one instruction at a time (serially). It could take billions of instructions to recognise one shape, pattern or image. We are also aware that the brain organises symbols in a hierarchical order based on the frequency of memories or association. This means that *machine learning* must encompass techniques from both the *symbolic* and *connectionist* branches of AI. In symbolic representation the information used for comparison is generally stored within a central or locatable package. We know in the real world, much of that information is distributed, therefore connections are required to enable information to be *evoked*. Literate discussing innovative examples using AI techniques within multi-agent systems is available [32].

1.6 New AI

It was Gregory Bateson who ushered in a new set of principles when he said: "What thinks is a brain in a human being who is part of a system that includes an environment" [33]. Some use the term, *new AI*. If we follow the disembodied theory, we should concentrate on autonomous agent behavior in the everyday world (free of situation) working from the bottom up. The higher-level functions, like knowledge and reasoning should still be approached top-down. Brooks showed this concept using a robot called *genghis* that had fifty-one parallel programs (sub-systems) [34]. Again Luc Steels demonstrated the concept of a shared *lexicon* in agency theory via his *talking heads* experiments [35].

1.7 Intelligent Paradigms

A number of *Intelligent Paradigm* techniques are reported in literature. These include; decision-trees, rule-based, Bayesian, rough sets, dependency networks, reinforcement learning, Support Vector Machines (SVM), NNs, genetic algorithms, evolutionary algorithms and swarm intelligence. Many of these topics are covered in this book. An example of intelligence is to use AI search algorithms to create automated macros or templates [36]. Again Generic Algorithm (GA) can be employed to induce rules using rough sets or numerical data. A simple search on data mining will reveal numerous paradigms, many of which are intelligent. The scale of search escalates with the volume

[7] In comparison the Intel i7-990X Extreme *Gulftown* has six independent cores all running at 3.73 GHz peak (or 12 hyper-threads).

of data, hence the reason to model data. As data becomes ubiquitous, there is increasing pressure to provide an on-line presence to enable access to public information repositories and warehouses. Industry is also increasingly providing access to certain types of information using kiosks or paid web services. Data warehousing commonly uses the following steps to model information:

– data extraction,
– data cleansing,
– modeling data,
– applying data mining algorithm,
– pattern discovery, and
– data visualization.

Any number of paradigms are used to mine data and visualize queries. For instance, the popular *six-sigma* approach (define, measure, analyse, improve and control) is used to eliminate defects, waste and quality issues. An alternative is the SEMMA (sample, explore, modify, model and Assess). Other intelligent techniques are also commonly employed. Although we don't provide a definitive list of such techniques, this book focuses on many of the most recent paradigms being developed, such as Bayesian analysis, SVMs and learning techniques.

1.8 Knowledge

Information, knowledge and wisdom are labels commonly applied to the way humans aggregate practical experience into an organized collection of facts. Knowledge is considered a collection of facts, truths, or principles resulting from a study or investigation. The concept of knowledge is a collection of facts, principles, and related concepts. Knowledge representation is the key to any communication language and a fundamental issue in AI. The way knowledge is represented and expressed has to be meaningful so that the communicating entities can grasp the concept of the knowledge transmitted among them. This requires a good technique to represent knowledge. In computers symbols (numbers and characters) are used to store and manipulate the knowledge. There are different approaches for storing the knowledge because there are different kinds of knowledge such as facts, rules, relationships, and so on. Some popular approaches for storing knowledge in computers include procedural, relational, and hierarchical representations. Other forms of knowledge representation used include *Predicate Logic, Frames, Semantic Nets, If-Then rules and Knowledge Inter-change Format*. The type of knowledge representation to be used depends on the AI application and the domain that Intelligent Agents (IAs) are required to function. [37]. Knowledge should be separated from the procedural algorithms in order to simplify knowledge modification and processing. For an IA to be capable of solving problems at different levels of abstraction, knowledge should be presented in the form of frames or semantic nets that can show the *is-a* relationship of objects and concepts. If an IA is required to find the solution from the existing data, Predicate logic using IF-THEN rules, Bayesian or any number of techniques can be used to cluster information [14].

1.9 Other Effects

Cognitive Science is a field of research attracting significant effort. It was preceded by the process management evolution with many prominent achievements, such as, Taylors introduction to Scientific Management and the Hawthorn Experiments conducted by the National Research Council (NRC). Formalizing organizational systems and behavioral science provides the tools required to decompose human oriented task. Any real-world system takes inputs as sensors will only react appropriately when it is able to modify the outputs. Simulation models rely on the same approach. Agents can be used to monitor sensors and stimulate the decision making required to modify one or more outputs.

Apollo 13 experienced a quintuple fault which required an army of ground crew the challenge of remotely assessing the status/health of the spacecraft prior to rapidly redesigning a new mission plan with revised procedures. The ultimate decision compromised the original mission goal of landing on the moon which was quickly revised to a successful return to earth. The ground crew were required to search for a new unintended reconfiguration of the space crafts subsystems with the required procedures required to effect those changes manually.

Agent technologies, and in particular agent teaming, are increasingly being used to aid in the design of “intelligent systems” [38]. In the majority of the agent-based software currently being produced, the structure of agent teams have been reliant on structures defined by the programmer or software engineer. The development of a model that extends the communications architecture of an agent framework that is adaptable when contacting a series of Multi-Agent System (MAS) or teams. The ideal properties of agents, includes: deliberative agents, reactive agents, interface agents (HCI) and mobile agents [26]. Different systems may be instantiated with a variety of hierarchies, with each level performing predetermined tasks in a subordinate or supervisory role. An Agent Architecture is considered to include at least one agent that is independent or a reactive/proactive entity and conceptually contains functions required for perception, reasoning and decision. The architecture specifies how the various parts of an agent can be assembled to accomplish a specific set of actions to achieve the systems goals. Wooldridge believes that it is essential for an agent to have “the ability to interact with other agents via some communication language” [39].

Research on agents requires the formation of teams of agents in order to dynamically configure the team with the ability to solve the decomposed task of the goal presented. Traditionally all tasks must be completed successfully or the team fails the goal [8]. A dynamic architecture would substitute agents within the team with alternative capabilities in order to succeed. It may even compromise and offer a partial solution and offer it to another system to complete. A good communications framework is required to pass messages between separate agent and other systems. An IA frameworks has recently been extended within the Knowledge-Based Intelligent Information and Engineering Systems (KES) Centre to enable individual students to successfully fast track the development of their research concepts. A Plug n Play concept based on a multi-agent blackboard architecture forms the basis of this research. The authors believe that a core architecture is required for MAS developers to achieve flexibility. Current research focuses on how agents can be teamed to provide the ability to adapt and dynamically organize the required functionality to automate in a team environment. The model is conceptual and is proposed initially as a blackboard model, where each element represents a block of functionality required to automate a process in order to complete a specific task. Discussion is limited to the formative work within the foundation layers of that framework.

1.10 Why Agents?

As stated previously, agents are increasing being used to solve progressively more complex problems. As we approach applications that solve real-world problems, the skills required have risen dramatically. Practical examples of where agents are currently used, include: spell checking, spam filters, travel and event booking systems. The code required to create an agent factory will focus on the needs of the programmer. This code could be linked at compile-time, but more preferably, instantiated and attached during run-time. In order to abstract the inherent complexity of this task, a factory is required. It needs functionality that dynamically wraps and packages a given capability. Intelligent systems can be developed to modify existing code, even when in memory, without loss of state or downtime. Agents are typically used in this process.

2 Chapters Included in the Book

This book includes nine chapters. The following section contains a summary of each topic.

Chapter 2: Market Power Assessment Using Hybrid Fuzzy Neural Network

This research discusses market power assessment as an important aspect of electric market analysis and operation. It proposes a multi output fuzzy neural network (FNN) for market power assessment and for finding on line market power ranking status of the generating company in a competitive power system, using a fuzzy composite market index (FCMI). This index is formulated by combining a Lerner index, a Relative market power and a Nodal Cost indices. In the proposed FNN, a trained multi-output neural network is used as a fuzzy inference engine. The input of the FNN consists of real loads and a bipolar code to represent a trading interval, while the output consists of the fuzzy values of the FCMI. A number of training patterns covering the full operating range of the power system are generated using the system data (such as offer prices and operating constraints) in order to train the FNN. The determined optimal power flow results are used to compute the above three market power indices and the corresponding FCMI. The performance of the proposed method is tested on an IEEE 14 bus system for 20 testing trading periods. The obtained results can be directly uploaded to an open access on-line information system (or to a dedicated web site), so that an independent system operator or customers can make use of this valuable information.

Chapter 3: Coaching Robots: Online Behavior Learning from Human Subjective Feedback

Efforts to coach robots resulted in an a novel methodology to create an agent learning behavior that incorporates both interactive and iterative approaches. The method is called Coaching and allows human trainer to give a subjective evaluation of the robotic agent in real time and the agent can simultaneously update the reward function. The research demonstrates agents capability of learning the desired behavior by receiving simple and subjective instructions (positive and negative) by implementing Coaching framework of typical reinforcement learning. The proposed approach is also effective when it is difficult to determine in advance a suitable reward function for the learning situation. The validation and verification of the investigated method advantages are done through conducting several experiments involving simulated and a real robot arm systems.

Chapter 4: Persian Vowel Recognition Using the Combination of Haar Wavelet and Neural Network

This chapter studies Lip image localization and segmentation as part of lips movement analysis which has significant role in speech recognition. Even after detecting the lips there are still major problems that any vowel (especially Persian) recognition method is faced with, such as: low chromatic in lip region; low contrast luminance; overlap between the lip and facial skin color; and similarity between lips movement in some vowels. A new, automatic and fast approach for the lip extraction based on using the Haar wavelet is proposed here and its output is used as a input feature vector for a hybrid neural network. The proposed algorithm uses the CIE L*U*V* and CIE L*a*b* color spaces in order to improve the contrast between the lip and the other face regions. Subsequently, the lips are modeled and a feature vector with longitudinal and angular parameters is extracted and used as an input for a feedforward backpropagation hybrid neural network. The proposed method is tested on 2200 images and the obtained accuracy shows about 15% improvement when compared with similar methods.

Chapter 5: The Reproduction of the Physiological Behaviour of the Axon of Nervous Cells by Means of Finite Element Models

This research investigates 3D Finite Element modeling solutions for a segment of a nervous cell axon, which take into account the non linear and time varying dynamics of the membrane surrounding it, in order to reproduce its physiological behavior in terms of Action Potentials elicitation and its temperature dependence. A combination of the so called Hodgkin-Huxley equations modeling the dynamics of the membrane voltage-controlled ionic channels, together with the Maxwell equations in Electro Quasi-Static approximation describing the electromagnetic behavior of each medium, is tackled in a numerical procedure implemented in a commercial Finite Elements multi-physical environment. Two different models are investigated: the first one exploits typical thin layer approximation for the axon membrane, proving to be useful when the field solution inside the membrane domain is not of interest; and in the second model the axon membrane is considered a non-linear active medium (exploiting its equivalent electric conductivity), allowing also reproduction of the electric potential inside the membrane, which is more realistic representation of the studied system. Although theoretical, this chapter presents models that open a wide range of applications and extensions in order to understand the true behavior of a complete neuron.

Chapter 6: A Study of a Single Multiplicative Neuron (SMN) Model for Software Reliability Prediction

This is an application oriented investigation that studies the use of a single multiplicative neuron model for prediction of cumulative faults of software. Standard back propagation (BP) and real coded genetic algorithm (GA) with mean squared error as a fitness function are employed for the model parameters optimisation. The performance of the proposed model is tested and evaluated on two real data sets and the obtained results are compared with existing parametric software reliability models, showing the superiority of the investigated SMN model (for both BP and GA training). The advantages of the model are based on its easy applicability on wide range of software failure data and its computational efficiency resulting from simplified NN architecture (no hidden layers).

Chapter 7: Numerical Treatment for Painlev Equation I Using Neural Networks and Stochastic Solvers

This study investigates theoretically and proposes a new stochastic numerical method for solving Painlev I equation. The mathematical model of the equation is formulated with feed-forward artificial neural networks. Linear combination of the networks defines the unsupervised error for the equation. For the networks training genetic algorithm, simulating annealing and pattern search algorithms hybridized with interior point algorithm for rapid local search are implemented and compared. The reliability and the effectiveness of the discussed approach are validated through statistical analysis. Comparison with standard approximate analytic solvers of the equation shows that the proposed stochastic solvers not only produce reliable and effective solutions, but are also superior for larger inputs.

Chapter 8: An Investigation into the Adaptive Capacity of Recurrent Neural Networks

Typical characteristic of any intelligent system is its ability to appropriately adjust its behaviour or modify its structure in response to environmental change. Feed-forward neural networks have commonly been used to model such behaviours. However, the weights of feed-forward neural networks remain static once trained and so can hardly be categorised as adaptive. On the contrary, recurrent networks (RNN) have the capability to exhibit dynamic behaviour having, in general, feedback connections after the applied non-linear activation function. In this work, network architectures with different feedback connections made before and after the non-linear activation function are studied in order to investigate their adaptive capabilities. Backpropagation training algorithms are applied to these networks with a minimum number of recurrent neurons at which adaptive behaviour is attainable. Three benchmark problems are investigated to analyse the performance and the learning ability of the proposed RNN architectures, demonstrating better performances for architectures with feedback connections before the nonlinear activation function when compared with feedback applied after the nonlinear function. These results can be very useful in designing RNN applications for a variety of problems.

Chapter 9: An Extended Approach of a Two-Stage Evolutionary Algorithm in Artificial Neural Networks for Multiclassification Tasks

This chapter studies a modified algorithm which operates with evolutionary artificial neural networks (EANN) to add broader diversity at the beginning of the evolutionary process and extends it to EANN with sigmoidal units. A simultaneous evolution of the investigated architectures and weights is performed with a two-stage evolutionary algorithm. The proposed methodology operates with two initial populations, each one containing individuals with different topologies which are evolved for a small number of generations. At this point half of the best individuals from each population are selected and combined to constitute a single population and the whole evolutionary cycle is applied to this new population. This idea was previously proposed by the authors for product unit neural networks and here it is extended to sigmoidal neural networks. The simulation, testing and validation of the proposed approach is carried out on twelve data sets from the UCI repository and two complex real-world problems that differ in their number of instances, features and classes. The results are analysed using nonparametric statistical tests to show significantly improved accuracy of the proposed models when compared with a standard methodology based on a single population. Moreover, the new methodology proves to be much more efficient than the previously developed by the authors a two-stage algorithm in evolutionary product unit neural networks.

3 Conclusion

An introduction to Contemporary Achievements in Intelligent Systems is provided to orient the reader and define the terminology used in this book. The following collection of case studies highlights the research contributions of many leading subject matter experts in the field of intelligent systems. This book is intended for students, professionals and academics from all disciplines to enable them the opportunity to engage in the state of art developments in:

- **Fuzzy Neural Network:** for commercial Power Assessment;
- **Behavior Learning:** Coaching Robots using On-line Behavior Learning from Human Subjective Feedback;
- **Haar Wavelet and Neural Network:** using Persian Vowel Recognition;
- **Software Reliability Prediction:** A Study of a Single Multiplicative Neuron (SMN) Model;

– **Finite Element Models:** to Reproduce the Physiological Behavior of The Axon of Nervous Cells;
– **Neural Networks and Stochastic Solvers:** Numerical Treatment for Painlev Equation I;
– **evolutionary algorithm in NN:** An extended approach using artificial neural networks for multi-classification tasks; and
– **Recurrent Neural Networks:** An Investigation into their Adaptive Capacity.

Readers are invited to contact individual authors to engage with further discussion or dialog on each topic.

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