Chapter 1
Introduction to Economic Modeling

Abstract This chapter introduces economic modeling based on artificial intelligence techniques. It introduces issues such as economic data modeling and knowledge discovery, including data mining and causality versus correlation. It also outlines some of the common errors in economic modeling with regard to data handling, modeling, and data interpretation. It surveys the relevant econometric methods and motivates for the use of artificial intelligence methods.

1.1 Introduction

This chapter introduces the topic of economic modeling (Baumol and Blinder 1982; Caldwell 1994; Holcombe 1989; Lange 1945; de Marchi and Blaug 1991). In this book, modeling is defined as the process of creating mathematical and conceptual frameworks for describing economic phenomena. In other words, the outcome of a modeling process, as defined in this book, is a conceptual or mathematical framework that describes how various concepts in economics actually work. The mechanisms, whether mathematical or conceptual, adopted in this book are based on an artificial intelligence framework. Artificial intelligence has been successfully applied to problems such as missing data estimation (Marwala 2009), engineering (Marwala 2010), political science (Marwala and Lagazio 2011a) and condition monitoring (Marwala 2012).

In this book, we define artificial intelligence techniques as mathematical or conceptual processes that are inspired by how nature works. For example, in describing how the gross domestic product is influenced by variables such as average educational levels and international trade volume, we could use a neural network which is based on how a human brain works, to construct a mathematical model that will relate these variables to the gross domestic product. This book will follow this line of thinking, of applying artificial intelligence methods, to describe how various aspects of the economy actually work.

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1.2 Economic Concepts

In this section we describe various economic matters that are addressed in this book, and these include the stock market, options, derivatives, industrialization, economic development and political stability.

1.2.1 Stock Market

One important component of the economy that is considered in this chapter is the stock market (Hamilton 1922; Preda 2009). When companies are listed in the stock market, their net worth is calculated and part of the company is offered to the public to buy shares of that company. This instrument of listing a company in the stock market and thus allowing the public to buy shares in the company is vital for a company to be able to raise financial capital. One additional element that comes about as a result of publicly trading shares is that the price of the stock can end up not reflecting the intrinsic value of the shares. This may result in the over-pricing or underpricing of stock as a result of the lack of knowledge of the real value of stock. For a trader in the stock market, whose primary objective is to maximize financial returns, it is important for there to be instruments that would enable the trader to be able to predict the future price of stocks. In this book, we apply artificial intelligence to predict the future prices of stocks. Applying artificial intelligence techniques for stock market prediction has been conducted quite extensively in the past by practitioners such as Lunga and Marwala (2006), Leke and Marwala (2005) as well as Khoza and Marwala (2011).

1.2.2 Options and Derivatives

As described by Pires and Marwala (2004, 2005), many corporations and companies are exposed to risk in many ways. If a firm's business model is based on exports, then it is exposed to the volatility of the exchange rate. For instance, a diamond mining company is exposed to risk from the diamond price because if the diamond price drops then the mining concern can lose money. Corporations seek to protect themselves from this risk and so what they normally do is that they enter into an agreement to sell diamond at a particular fixed exchange rate and diamond price for the future months. This contract is fixed and the company will neither make nor lose any extra money. The two contracts, the company takes, are known as futures contracts. Because the contract doesn't permit the owner to require any additional money if diamond price increases or the exchange rate weakens, then the company doesn't pay a premium for the contracts. This reduction of risk is called hedging (Ross et al. 2001).

Another mechanism in which companies hedge against this risk is by acquiring options. An option is the right, not the obligation, to buy or sell an underlying asset at a later date, which is called maturity date, by fixing the price of the asset at the present time (Hull 2003). An option that affords the owner the right to buy the asset is called a call option and an option that affords the owner the right to sell the asset is called a put option.

There are two types of options and these are European and American styled options. European options are exercised on the maturity date and American options are exercised on any date leading up to the maturity date. In the example above, with the diamond mining company, the company could buy a commodity put option, permitting the company to sell diamond at a particular price at a fixed time and purchase an exchange rate call option permitting the company to trade at a particular exchange rate at a later date. Options differ from futures in that the owner of the option is offered the right and not the obligation to exercise and thus make them valuable and so companies can benefit from favourable situations in the market and still protect themselves from unattractive effects in the market. The difference between futures and options is that if an unwanted state of affairs happens, then the owner loses the premium that was paid to buy the option. Because of this reason, options are acquired at a premium and there is difficulty identifying the value of this premium. Black and Scholes (1973) formulated a model for pricing options but the difficulty with their model was that it was only applicable for pricing European options (Hull 2003). American options are more difficult to price (Hull 2003) because there is a second random process in the contract because it is not known when the option will be exercised and thus offers the owner of the option an extra level of flexibility (Jarrow and Turnbull 2000).

1.2.3 Economic Development

In this chapter we apply the concept of a developmental state to understand economic development. In order to understand the concept of a developmental state, it is important to highlight some of the characteristics of a developmental state (Thompson 1996; Woo-Cumings 1999). Developmental states generally put strong emphasis on technical education and the development of numeracy and computer skills within the population. This technically oriented education is strategically used to capacitate government structures particularly the bureaucracy. What emerges out of this strategy is that the political and bureaucratic layers are populated by extremely educated people who have sufficient tools of analysis to be able to take leadership initiatives, based on sound scientific basis, at every level of decision making nodes within the government structure. Developmental states have been observed to be able to efficiently distribute and allocate resources and, therefore, invest optimally in critical areas that are the basis of industrialization such as education. The other characteristic that has been observed in successful developmental states is economic nationalism and emphasis on market share over profit. They protect their embryonic domestic industries and focus on aggressive acquisition of foreign technology. This they achieve by deploying their most talented students to overseas universities located in strategic and major centres of the innovation world and also by effectively utilizing their foreign missions (Marwala 2006). Furthermore, they encourage and reward foreign companies that invest in building productive capacity such as manufacturing plants with the aim that the local industrial sector will in time be able to learn vital success factors from these companies. On constructing a harmonious social-industrial complex, developmental states strike a strategic alliance between the state, labour and industry in order to increase critical measures such as productivity, job security and industrial expansion. Even though developmental states do not create enemies unnecessarily and do not participate in the unnecessary criticism of countries with strategic technologies that they would like to acquire, they are, however, sceptical of copying foreign values without translating and infusing them with local characteristics.

1.2.4 Industrialization

The objective of a developmentally oriented state is to create a society in which the citizens are intellectually, socially, economically, and politically empowered. In order to accomplish this objective, certain conditions need to be in place to mobilize social, economic, and political forces to capacitate the state to stimulate the productive forces that would ensure that this goal is achieved. One viewpoint concerning the instrument through which these productive forces can be galvanized is to reorient the country such that adequate productive forces are unleashed to advance industrialization (Marwala 2005a, b; Xing and Marwala 2011).

One critical aspect of industrialization is manufacturing. Building a manufacturing base in a country requires many factors to be in place such as a large number of engineers as well as access to minerals such as copper. The goal of industrialization is to create a country that produces goods and services with high added values. For example, instead of exporting minerals unprocessed, people can be employed to beneficiate these minerals and manufacture goods such as watches and thus add economic value to the final products. The process by which countries add aggregate economic values to the products and services they offer is directly dependant on the level of industrialization in the country's economy.

1.2.5 Political Stability

One important aspect of building a vital economy in a country is political stability, which is characterized by the absence of conflict. One important characteristic of a progressive society is a society which is situated within a state that is at peace with itself, its neighbors, and the international community. Consequently, a democratic society as a matter of principle should aspire for global peace and inspire a culture of the highest form of human development (Marwala and Lagazio 2011a).

Granted that peace is a necessary condition to construct an economically stable society it is, consequently, important to comprehend the anatomy of militarized interstate conflicts and use this understanding to build peaceful, stable, and economically prosperous states in a peaceful and stable international context. The ability to scientifically understand the causes of militarized interstate conflict and then to apply this knowledge to build and spread peace in the international context is indisputably an essential initiative. This book proposes an artificial intelligence perspective to unpack some of the complex behaviours that interstate conflicts display in order to understand the fundamental drivers of war and, therefore, detect early instances of tensions in the international relations arena and, thereby, maximize economic activities (Marwala and Lagazio 2011b).

When a business concern intends to invest in a country, the first criterion to investigate is the stability of a country. Militarized interstate conflict is defined as a threat of military conflict by a country on another (Marwala and Lagazio 2011b). This phenomenon has been modeled extensively and quite successfully using artificial intelligence in the past. Tettey and Marwala (2006a) successfully applied a neuro-fuzzy system for conflict management whereas Habtemariam et al. (2005) successfully applied support vector machines for modeling and managing militarized interstate conflict. Marwala and Lagazio (2004) successfully applied the multi-layered neural networks and genetic algorithms to model and then control militarized interstate disputes, while Tettey and Marwala (2006b) applied a neuro-fuzzy system and genetic algorithms for modeling and controlling militarized interstate disputes. On modeling militarized interstate disputes, it is often important to extract information from the observed data in a linguistic fashion so that these can be used for policy formulation. Tettey and Marwala (2007) applied a neuro-fuzzy system to extract such information from a conflict dataset, while Crossingham et al. (2008) applied optimized rough sets and standard rough sets to extract information from an interstate conflict database.

1.3 Econometrics

Econometrics is a field that applies mathematics and statistics to study economics (Lamy 2012; Spanos 2012; Baldauf and Santos Silva 2012). This is essentially achieved by building mathematical models to explain economic phenomena. Suppose we would like to build a model that relates *car sales* to *inflation*: this necessarily implies that there exists a causal relationship between *inflation* and *car sales*. Mathematically speaking, this relationship may be written as follows:

$$\textit{car sales} = f\,(\textit{inflation}) \tag{1.1}$$

The function f can be models such as neural networks or even be linear or linguistic in the case of fuzzy logic. There are three main criticisms that are leveled at traditional econometric modeling and these are described in the next sub-sections.

1.3.1 Linear Assumptions

Traditional econometric models usually assume that relationships are linear, and this assumption is not valid for the majority of the real world cases (Pesaran 1987; Swann 2008). Therefore, it has become essential to build models that are non-linear (Moffitt 1980; Adcock 1995). A neural network has been found to be useful in modeling highly non-linear data because the order of non-linearity is derived or learned directly from the data and not assumed as is the case in many traditional non-linear models.

1.3.2 Static Models

Once the model in Eq. 1.1 is identified, it is generally assumed that the model is valid for all times, which is obviously not the case. It is, therefore, important to build a model that autonomously adapts while it is in use, and traditional econometric techniques have not been very successful in addressing this shortcoming. With the advent of evolutionary programming, it has become quite possible to build models that evolve (Marwala 2005a, b; Nguyen et al. 2012). This book will also address the issue of constructing dynamic models as opposed to building static models within the context of economic modeling.

1.3.3 Causality Versus Correlation

The issue of causality is a problem that has concerned philosophers for many years (Simon and Rescher 1966; Kar et al. 2011; Fallahi 2011). For example, the relationship in Eq. 1.1 inherently assumes causality, that is, the fact that inflation levels influence car sales. However, it might be that this is not the case and what is really the truth is that variables *inflation* and *car sales* are just correlated. This book will address this matter.

This book will deal with the problems of static models, linear assumptions, and causality versus correlation problem by applying artificial intelligence which is described in the next section.

1.4 Artificial Intelligence

This section presents an overview of artificial intelligence techniques which are applied for economic modeling in this book.

1.4.1 Neural Networks

One important type of artificial intelligence techniques is a neural network. Neural networks are computational tools that may be viewed as being inspired by how the brain functions and applying this framework to construct mathematical models. Neural networks estimate functions of arbitrary complexity using given data. Supervised neural networks are used to represent a mapping from an input vector onto an output vector, while unsupervised networks are used to classify the data without prior knowledge of the classes involved. In essence, neural networks can be viewed as generalized regression models that have the ability to model data of arbitrary complexities. There are many types of neural networks and the most common neural network architectures are the multilayer perceptron (MLP) and the radial basis function (RBF) (Bishop 1995). Neural networks have been applied successfully in many different areas of varying complexities. Soares et al. (2006) applied neural networks in flight control, while Shukla et al. (2012) applied neural networks for software maintenance. Xing et al. (2010) applied neural networks for machine clustering while Nelwamondo et al. (2009) applied neural networks and dynamic programming for missing data estimation in biomedical applications. Because of these extensive successes of neural networks, this book will apply neural networks for modelling economic data.

1.4.2 Support Vector Machines

Support vector machines are supervised learning approaches used largely for classification, and originated from statistical learning theory and were first introduced by Vapnik (1998). The use of support vector machines to model complex systems has been a subject of research for many years. Successful implementations of support vector machines to model complicated systems include Marwala et al. (2007) who applied this method for damage detection in structures, Msiza et al. (2007) who applied this method for forecasting the water demand time series, as well as Patel and Marwala (2009) who applied support vector machines for caller behavior classification. Due to these successful applications of support vector machines, this book also applies support vector machines for modelling economic data.

1.4.3 Autoassociative Networks

An auto-associative network is a model that is trained to recall its inputs. These networks are sometimes called auto-encoders or memory networks (Kramer 1992; Fu and Yan 1995; Marseguerra and Zoia 2006; Marwala 2012; Turova 2012). This means that, whenever an input is presented to the network, the output is the predicted input. These networks have been used in a number of applications including novelty detection, feature selection, and data compression. In this book, we propose to use auto-associative networks to construct a missing data estimation technique predictive system, which was described by Marwala (2009). Auto-associative networks have been applied successfully in many diverse areas such as HIV modelling (Leke et al. 2006), damage detection in structures (Zhou et al. 2011), and for predicting internet stability (Marais and Marwala 2004).

1.4.4 Rough Sets

Rough set theory, which was proposed by Pawlak (1991), is a mathematical method which models vagueness and uncertainty. It allows one to approximate sets that are difficult to explain even with accessible information (Marwala 2012). As observed by many researchers in the past, the advantages of rough sets, as with many other artificial intelligence methods, are that they do not require inflexible *a priori* assumptions about the mathematical characteristics of such complex relationships, as generally required for the multivariate statistical methods (Machowski and Marwala 2005; Crossingham et al. 2009; Marwala and Lagazio 2011a). Rough set theory is premised on the assumption that the information of interest is associated with some information from its universe of discourse (Crossingham and Marwala 2007, 2009; Marwala and Crossingham 2008, 2009; Marwala 2012). This technique is useful in that unlike neural networks, for example where the identified model is a strictly mathematical concept, in rough sets method the identified model that describes the data is in terms of natural language. Because of this reason, rough sets are useful in economics because they in a sense represent a formal technique for knowledge extraction from data.

1.4.5 Incremental Learning

Incremental learning methods are approaches that are able to learn incrementally. Incremental learning is suitable for modelling dynamically time-varying systems where the operating conditions change with time (Pang et al. 2012; Clemente et al. 2012; Khreich et al. 2012). It is also suitable when the data set accessible is inadequate and does not completely characterize the system (Marwala

2012; Cavalin et al. 2012; Martínez-Rego et al. 2012; Li et al. 2012a). Another advantage of incremental learning is that it can take into account the new conditions that may be presented by the newly acquired data. For example, suppose a model for predicting inflation is built, the concept of incremental learning can be applied so that every month when new inflation data set comes out, the model is updated without having to reconstruct it entirely. In this book we apply incremental learning techniques that are based on ensemble methods.

Ensemble learning is a method where multiple models are identified and combined to solve a specific problem (Rogova 1994; Polikar 2006). Ensemble learning is usually applied to increase the performance of a model (Zhang et al. 2012a; Li et al. 2012b; Hu et al. 2012; Ñanculef et al. 2012). In this book, ensemble based methods are applied for incremental learning in the modeling of economic data.

1.4.6 Multi-agent Systems

Agents are computer systems that are located in specific environments and are capable of *autonomous action* in this environment with the aim of meeting its objectives (Marivate et al. 2008; Wooldridge 2004; Baig 2012; Hu 2012). Intelligent agents are agents that are capable of *reacting* to changes in their environment and they possess *social ability* such as communication, as well as interaction and the ability to use artificial intelligence to achieve their objectives by being *proactive* (Wooldridge 2004; Rudowsky 2004; Zhang et al. 2012b). Agents are active, modeled to achieve specific tasks, and are able to autonomously act and take decisions (Hu 2012; Chen and Wang 2012). In an object oriented framework, objects are passive, non-oriented and modeled to represent things (Weisfeld 2009; Schach 2006; Abadi and Cardelli 1998). Consequently, the agent modeling method can be viewed as a more powerful manifestation of localized computational units that execute definite tasks while objects model real-world "things" with particular characteristics. A multi-agent system (MAS) is a combination of multiple agents in one system to solve a problem (Baig 2012). These systems have agents that are able to solve problems that are simpler than the total system. They can communicate with one another and support each other in realizing larger and more complex objectives (Hurwitz and Marwala 2007; van Aardt and Marwala 2005). Multi-agent systems have been applied in simulating trading systems (Mariano et al. 2001) and industrial automation (Wagner 2002).

1.4.7 Genetic Algorithms

The genetic algorithm approach is a population-based, probabilistic method that is intended to identify a solution to a problem from a population of possible solutions

(Velascoa et al. 2012; Goyal and Aggarwal 2012). It is inspired by Darwin's theory of natural evolution where the principle of 'the survival of the fittest' applies and members of the population compete to survive and reproduce while the weaker ones disappear from the population (Darwin 1859). Each individual is allocated a fitness value in accordance to how well it achieves the aim of solving the problem. New and more evolutionary fit individual solutions are created during a cycle of generations, where selection and re-combination operations, analogous to gene transfer are applied to the current individuals. This continues until a termination condition is satisfied. Genetic algorithms have been applied successfully in many areas such as engineering (Marwala 2002), control systems (Marwala 2004), and condition monitoring of buildings (Marwala and Chakraverty 2006).

1.4.8 Particle Swarm Optimization

The particle swarm optimization (PSO) method was proposed by Kennedy and Eberhart (1995). This technique was inspired by algorithms that model the "flocking behavior" seen in birds. Researchers in artificial life (Reynolds 1987; Heppner and Grenander 1990) developed simulations of bird flocking. In the context of optimization, the concept of birds finding a roost is analogous to a process of finding an optimal solution. PSO is a stochastic, population-based evolutionary algorithm that is extensively used for the optimization of complex problems (Marwala 2010). It is based on socio-psychological principles that are inspired by swarm intelligence, which gives understanding into social behavior and has contributed to engineering applications. Society enables an individual to influence and learn to solve problems by communicating and interacting with other individuals and, in that way, develop similar approach of solving problems. Thus, swarm intelligence is driven by two factors (Kennedy and Eberhart 1995; Marwala 2009, 2010, 2012):

1. Group knowledge.
2. Individual knowledge.

Each member of a swarm always behaves by balancing between its individual knowledge and the group knowledge.

1.4.9 Control Systems

A control system is essentially a procedure where the input of a system is manipulated to obtain a particular desired outcome (Marwala and Lagazio 2004; Boesack et al. 2010; Zhu et al. 2012). To realize this, a model that describes the relationship between the input and the outcome needs to be identified. For example, suppose we have a model that describes the relationship between the growth domestic product (GDP) and the interest rate to the inflation rate. Such a relationship can be identified using various methods such as neural networks. After this model that predicts inflation rate given the interest rate and GDP has been identified, the following stage is to apply a control system to identify the interest rate that gives the desired inflation rate. This involves an optimization procedure such as genetic algorithms or particle swarm optimization. In economics, this process is called inflation targeting. Control techniques have been applied successfully in many diverse fields such as brewing (Marwala 2004), water supply systems (Wu et al. 2012), and political science (Marwala et al. 2009).

1.5 Common Mistakes in Data Modeling

The prospect of artificial intelligence for application in economic modeling has been apparent to virtually everyone to have even experimented in the fields since their inception. Efforts to make such artificial intelligence applications accepted within the economic modeling space have generally been unsuccessful, and not without justifications. Mistakes have continued to give knowledge and theories that have passed superficial academic enquiry, but have demonstrated to be unsuccessful when applied to actual real world data. As identified by Hurwitz and Marwala (2012), a number of common mistakes will be probed, demonstrating how they frequently slip past cursory academic inquiry, and then displaying how they fail when applied to actual real data and why. It is intended that with attention paid to common shortcomings, researchers can circumvent these drawbacks and improve the uses of these methods within the economic modeling arena. Even though many of these errors overlap in individual implementations, this chapter intends to tackle them on an individual basis in order to more easily circumvent these mistakes in the future.

1.5.1 Insufficient Datasets

According to Hurwitz and Marwala (2012), conventional trading strategies are complicated systems, usually entailing a cycle of prediction, evaluation, feedback, and recalibration when designed. The cycle contains a feedback element but not necessarily the predictive technique. This cycle comprises the designer predicting price movements then evaluating trades based on price movements. The intention for recalibration feedback going into both prediction and evaluation instruments is that in many more complex systems the actual trading based on the predictions will be updated, as well as the predictions themselves. Because of this cycle, it becomes essential to have a strictly unseen set of data to evaluate performance. Normally, trading systems use a training data set and a verification data set (de Oliveira et al. 2011; Lam 2004; Kim 2002; Bao and Yang 2008) and this is not adequate, as neither the predictive system nor the evaluation system ever see the second set of data during the optimization phase. This is nevertheless inadequate, as the calibration of the training system is conducted with the results of the verification set taken into account, necessitating a totally unseen validation set to be used so as to validate if the system is truly generalizing. Overlooking this critical phase can give a system result that has merely been tweaked by the designer to fit the specific data, without essentially being able to function correctly in a general setting. The results will obviously appear satisfactory as the system has been calibrated precisely to fit the data being used even while the designer has not planned this to be the case. In the case that the trading mechanism is revisited after the validation set has been utilized, a new set of unseen validation data must be achieved.

1.5.2 Inappropriate Scaling

As identified by Hurwitz and Marwala (2012), this error is characterized by expressing the normally large target values of the predicted variable as its actual value (Kaastra and Boyd 1996), instead of scaling the data to some appropriate level within (or near) the range of the training data. The justification is to offer a precise understanding of the actual target values.

The actual data and the predicted data will appear to be close in the initial prediction, but experience difficulty to reach the higher values in the range for the later values. The actual errors in this initial prediction will obviously be very low, being underestimated by the scale of the data, despite their being fairly clearly unusable for any undertaking that necessitates the prediction. Actually, the errors characteristic of the system are frequently hidden by using unsuitable measures of accuracy or performance. It is actually far more risky to commit this error if the target data is reasonably bounded, as the evident lack of fit will not be obvious, and what is in effect an unusable prediction can certainly be confused for a performing predictive system, and leads to all the dangers characteristic in trading upon poor information.

The reason for this discrepancy is the high quantitative value of the predictive results, which offer a low registered error for what is really a large trading error. Considering a prediction for a given input–output set with the correct value being 1,025 and the system's predicted value being 1,010. The actual error in root mean squares (RMS) terms is small, while the effect on predictions is actually quite high, considering a daily expected fluctuation of approximately 15 cents, which explains why an error that appears so small is actually significant enough to render a predictive system unusable. The clear recommendation is to first pre-process the data and as part of that process to scale the data. Depending on the nature of the historical share price fluctuations, a scaling factor of anything from the maximum historical price recorded to a fractional amount larger than the maximum historical price can be applied. It is recommended, even though not necessarily relevant to this particular error that one also scales input data for ease of training and convergence.

1.5.3 Time-Series Tracking

This error occurs in time series modeling where the predictive system predicts the previous day's price as the present price which satisfies the error minimization function's requirement (Hurwitz and Marwala 2012). This error emanates when an attempt is made to do an exact price prediction based upon the time-series data of historical prices of the self-same share. Unfortunately, any trading based upon such a system is completely unusable as it cannot ever predict an accurate price movement unless by some coincidence every single day's new close is the same as that of the day before. To avoid this error, it is then necessary for the user to reconsider the input–output pairs for the system to learn from and consider change in prices as an output rather than the price itself. When trading, the direction of price movement is actually far more important than the precise amount, and this distinction is critical if a trading system is to be successful.

1.5.4 Inappropriate Measures of Performance

The problem here lies not with the measurements themselves, but rather on the reliance on them for validating the success of a trading system. These methods often obscure problems in the system design by looking like successful computational intelligence systems by the standard computational measures (Hurwitz and Marwala 2012). This includes graphs of receiver operating characteristics (ROC) curve and other typical computational measures of performance. If any of the preceding errors had been made, they would not be detected by the usual performance measures since they only measure the performance of the system based on the given input and output values. This is a dangerous error to commit, as the system is still concealing any mistakes made, but the user is satisfied to carry on, secure in the success of the system, verified by an inappropriate measure of performance. Dependence on these measures arises naturally to users in this field as they form the benchmark of most computational intelligence and machine learning approaches, and are, therefore, likely to be utilized almost out of practice.

Instead of the above, the user should set up a trading simulator, and apply the designed predictor to simulate trading based on its predictions. By performing actual trades based upon the predictions, many of the errors described will be quickly identified, as the actual trading results will be poor, or at best highly erratic. The nature of the errors will often become apparent when measuring performance in this manner, matching those described within each section, making it a much more useful measure of performance both during and after the system design process.

1.6 Data Handling

There are many ways in which economic data can be handled when used in economic modeling. The choices on how economic data are handled sometimes have effects which artificial intelligence modeling method to be used. In this section, we describe three domains that could be used to model economic data and these are time, frequency and time-frequency domains.

1.6.1 Time Domain Analysis

Time domain data is un-processed data taken over a time history. For example, if we consider GDP data as a function of time, this will be said to be in the time domain. From this data in the time domain, essential statistical features such as means, variance, Kurtosis can be extracted (Marwala 2012). Normally when these data are used, some of the statistical analysis such as variance and means are used. Lima and Xiao (2007) used economic data in the time domain to evaluate whether shocks last forever while Kling and Bessler (1985) compared multivariate forecasting procedures for economic time series analysis. Bittencourt (2012) studied the inflation and economic growth in Latin America in the time domain, while Greasley and Oxley (1998) compared British and American economic and industrial performance between years 1860 and 1993 in the time domain. Even though studying economic phenomena in the time domain is useful, it is sometimes necessary to study economic data in the frequency domain which is described in the next section.

1.6.2 Frequency Domain

The measured economic data in the time domain (time series) can be transformed into the frequency domain using Fourier transforms (Fourier 1822). As an example, the GDP versus time data can be transformed into the frequency domain using the Fourier transform and then this signal can be represented in magnitude and phase versus frequency data. The data in the frequency domain will have a series of peaks and troughs with each peak corresponding to the frequency of each cycle that makes the data. McAdam and Mestre (2008) evaluated macro-economic models in the frequency domain, while Tiwari (2012) conducted an empirical investigation of causality between producers 'price and consumers' price indices in Australia in the frequency domain. Gradojevic (2012) applied frequency domain analysis to study foreign exchange order flows while Grossmann and Orlov (2012) studied the exchange rate misalignments in the frequency domain.

1.6.3 Time-Frequency Domain

Most economic data are highly non-linear and non-stationary signals. None stationary signals are those whose frequency components change as a function of time (Larson 2007; Marwala 2012). To analyze non-stationary signals, the application of the Fast Fourier Transform method is not satisfactory. Consequently, time-frequency methods that concurrently display the time and frequency components of the signals are essential. Some of the time-frequency methods that have been used are: the Short-Time Fourier Transform (STFT), Wavelet Transform (WT) and Wigner-Ville Distribution (WVD). Gallegati (2008) applied wavelet analysis in stock market analysis, while Yogo (2008) applied wavelet analysis for measuring business cycles. Furthermore, Benhmad (2012) applied wavelet analysis for modeling nonlinear Granger causality between the oil price and the U.S. dollar.

1.7 Outline of the Book

In Chap. 2, data modeling techniques in economic modeling are studied. These methods include concepts such as mean, variance and fractals and how these vital concepts are applied to economics. Frequency and time-frequency analysis techniques are also studied.

Chapter 3 introduces the Bayesian and the evidence frameworks to construct an automatic relevance determination method. These techniques are described in detail, relevant literature reviews are conducted and their use is justified. The automatic relevance determination technique is then applied to determine the relevance of economic variables that are essential for driving inflation rate. Conclusions are drawn and are explained within the context of economic sciences.

Chapter 4 describes the multi-layered perceptron, radial basis functions, and support vector machines and apply these to economic modeling. The maximum-likelihood techniques are implemented to train these networks.

Chapter 5 introduces Bayesian support vector machines and multi-layer pereceptron for option pricing. European styled options can be priced using the Black-Scholes equation and are only exercised at the end of the period but American options can be exercised at any time during the period and are, therefore, more complex due to the second random process they introduce. These techniques are implemented using a Bayesian approach to model American options and the results are compared.

Chapter 6 introduces a rough set approach to economic modeling. A rough set theory based predictive model is implemented for the financial markets. The theory can be used to extract a set of reducts and a set of trading rules based on trading data.

Chapter 7 introduces an autoassociative network, with optimization methods, for modeling economic data. The autoassociative network is created using the multi-layered perceptron network while the optimization techniques which are implemented are genetic algorithms, particle swarm optimization, and simulated annealing. The results obtained for modeling inflation are then compared.

Chapter 8 explores the issue of treating a predictive system as a missing data problem, that is, correlation exercise and compares it to treating it as a cause and effect exercise, that is, feed-forward network. An auto-associative neural network is combined with a genetic algorithm and then applied to missing economic data estimation. The results of the missing data imputation approach are compared to those from a feed-forward neural network.

Chapter 9 examines the use of a genetic algorithm in order to perform the task of constantly rebalancing a portfolio targeting specific risk and return characteristics. Results of targeting both the risk and return are investigated and are compared as well as optimizing the non-targeted variable in order to create efficient portfolios.

Chapter 10 introduces real-time approaches to economic modeling. This chapter assumes that a complete model is the one that is able to continuously self-adapt to the changing environment. In this chapter, an incremental algorithm that is created to classify the direction of movement of the stock market is proposed and applied.

Chapter 11 introduces multi-agent approaches within game theoretic framework and applies this to model a sock market. This multi-agent system learns by using neural networks and adapts using genetic programming.

Chapter 12 applies control approaches to economic modeling and applies this to inflation targeting. In this chapter, a control system approach that is based on artificial intelligence is adopted to analyze the inflation targeting strategy.

Chapter 13 explores the role of trade in maintaining peace and, therefore, healthy economic activities. This is done by constructing the relationship between independent variables Allies, Contingency, Distance, Major Power, Capability, Democracy as well as Dependency which indicates inter-country trade and the dependent variable Interstate Conflict.

In Chap. 14 conclusions are drawn and future and emerging areas in economic modeling are identified and emerging opportunities are drawn.

1.8 Conclusions

This chapter introduced economic modeling based on artificial intelligence methods. It introduced issues such as economic data handling and modeling as well as prediction, knowledge discovery including data mining, and causality versus correlation. It also outlined some of the common problems in economic modeling with regards to data handling, modeling, and data interpretation. It surveyed the relevant econometric methods and motivated for the use of artificial intelligence methods.

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