

Wavelet Neural Networks

With Applications in Financial Engineering,
Chaos, and Classification

Antonios K. Alexandridis • Achilles D. Zaprakis



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***With Applications in Financial
Engineering, Chaos, and
Classification***

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Preface

Wavelet networks are a new class of networks that combine classic sigmoid neural networks and wavelet analysis.

Wavelet networks were proposed as an alternative to feedforward neural networks, which would alleviate the weaknesses associated with wavelet analysis and neural networks while preserving the advantages of each method.

Recently, wavelet networks have gained a lot of attention and have been used with great success in a wide range of applications: financial modeling; engineering; system control; short-term load forecasting; time-series prediction; signal classification and compression; signal denoising; static, dynamic, and nonlinear modeling; and nonlinear static function approximation—to mention some of the most important.

However, a major weakness of wavelet neural modeling is the lack of a generally accepted framework for applying wavelet networks. The purpose of this book is to present a step-by-step guide for model identification for wavelet networks. We describe a complete statistical model identification framework for applying wavelet networks in a variety of ways. Although vast literature on wavelet networks exists, to our knowledge this is the first study that presents a step-by-step guide for model identification for wavelet networks. Model identification can be separated into two parts: model selection and variable significance testing.

A concise and rigorous treatment for constructing optimal wavelet networks is provided. More precisely, the following subjects are examined thoroughly: the structure of a wavelet network; training methods; initialization

algorithms; variable significance and variable selection algorithms; model selection methods; and methods to construct confidence and prediction intervals. The book links the mathematical aspects of the construction of wavelet network to modeling and forecasting applications in finance, chaos, and classification. Wavelet networks can constitute a valuable tool in financial engineering since they make no a priori assumptions about the nature of the dynamics that govern financial time series. Although we employ wavelet networks primarily in financial applications, it is clear that they can be utilized in modeling any nonlinear function. Hence, researchers can apply wavelet networks in any discipline to model any nonlinear problem.

Our goal has been to make the material accessible and readable without excessive mathematical requirements: for example, at the level of advanced M.B.A. or Ph.D. students. There is an introduction or tutorial to acquaint nonstatisticians with the basic principles of wavelet analysis, and a similar but more extensive introduction to neural networks for noncomputer scientists: first introducing them as regression models and gradually building up to more complex frameworks.

Familiarity with wavelet analysis, neural wavelets, or wavelet networks will help, but it is not a prerequisite. The book will take the reader to the level where he or she is expected to be able to utilize the proposed methodologies in applying wavelet networks to model various applications.

The book is meant to be used by a wide range of practitioners:

- By quantitative and technical analysts in investment institutions such as banks, insurance companies, securities houses, companies with intensive

international activities, and financial consultancy firms, as well as fund managers and institutional investors.

- By those in such fields as engineering, chemistry, and biomedicine.
- By students in advanced postgraduate programs in finance, M.B.A., and mathematical modeling courses, as well as in computational economics, informatics, decision science, finance, artificial intelligence, and computational finance. It is anticipated that a considerable segment of the readership will originate from within the neural network application community as well as from students in the mathematical, physical, and engineering sciences seeking employment in the mathematical modeling services.
- By researchers in identification and modeling for complex nonlinear systems, wavelet neural networks, artificial intelligence, mathematical modeling, and relevant Ph.D. programs.

Supplementary material for this book may be found by entering ISBN 9781118592526 at booksupport.wiley.com.

During the preparation of the book, the help of my (A.K.A.) wife, Christina Ioannidou, was significant, and we would like to thank her for her careful reading of the manuscript.

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October 2013

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Machine Learning and Financial Engineering

Wavelet networks are a new class of networks that combine the classic sigmoid neural networks and wavelet analysis. Wavelet networks were proposed by Zhang and Benveniste (1992) as an alternative to feedforward neural networks which would alleviate the weaknesses associated with wavelet analysis and neural networks while preserving the advantages of each method.

Recently, wavelet networks have gained a lot of attention and have been used with great success in a wide range of applications, ranging from engineering; control; financial modeling; short-term load forecasting; time-series prediction; signal classification and compression; signal denoising; static, dynamic, and nonlinear modeling; to nonlinear static function approximation.

Wavelet networks are a generalization of radial basis function networks (RBFNs). Wavelet networks are hidden layer networks that use a wavelet for activation instead of the classic sigmoidal family. It is important to mention here that multidimensional wavelets preserve the “universal approximation” property that characterizes neural networks. The nodes (or *wavelons*) of wavelet networks are wavelet coefficients of the function expansion that have a significant value. In Bernard et al. (1998), various reasons were presented for why wavelets should be used instead of other transfer functions. In particular, first, wavelets have high compression abilities, and second, computing the value at a single point or updating a function estimate from

a new local measure involves only a small subset of coefficients.

In statistical terms, wavelet networks are nonlinear nonparametric estimators. Moreover, the universal approximation property states that wavelet networks can approximate, to any degree of accuracy, any nonlinear function and its derivatives. The useful properties of wavelet networks make them an excellent nonlinear estimator for modeling, interpreting, and forecasting complex financial problems and phenomena when only speculation is available regarding the underlying mechanism that generates possible observations.

In the context of a globalized economy, companies that offer financial services try to establish and maintain their competitiveness. To do so, they develop and apply advanced quantitative methodologies. Neural networks represent a new and exciting technology with a wide range of potential financial applications, ranging from simple tasks of assessing credit risk to strategic portfolio management. The fact that neural and wavelet networks avoid a priori assumptions about the evolution in time of the various financial variables makes them a valuable tool.

The purpose of this book is to present a step-by-step guide for model identification of wavelet networks. A generally accepted framework for applying wavelet networks is missing from the literature. In this book we present a complete statistical model identification framework to utilize wavelet networks in various applications. More precisely, wavelet networks are utilized for time-series prediction, construction of confidence and prediction intervals, classification and modeling, and forecasting of chaotic time series in the context of financial engineering. Although our proposed framework is examined primarily for its use in financial applications, it is not limited to

finance. It is clear that it can be adopted and used in any discipline in the context of modeling any nonlinear problem or function.

The basic introductory notions are presented below. First, financial engineering and its relationship to machine learning and wavelet networks are discussed. Next, research areas related to financial engineering and its function and applications are presented. The basic notions of wavelet analysis and of neural and wavelet networks are also presented. More precisely, the basic mathematical notions that will be needed in later chapters are presented briefly. Also, applications of wavelet networks in finance are presented. Finally, the basic aspects of the framework proposed for the construction of optimal wavelet networks are discussed. More precisely, model selection, variable selection, and model adequacy testing stages are introduced.

Financial Engineering

The most comprehensive definition of financial engineering is the following: *Financial engineering* involves the design, development, and implementation of innovative financial instruments and processes, and the formulation of creative solutions to problems of finance (Finnerty, 1988). From the definition it is clear that financial engineering is linked to innovation. A general definition of financial innovation includes not only the creation of new types of financial instruments, but the development and evolution of new financial institutions (Mason et al., 1995). Financial innovation is the driving force behind the financial system in fulfilling its primary function: the most efficient possible allocation of financial resources (Ζαπράνης, 2005).

Investors, organizations, and companies in the financial sector benefit from financial innovation. These benefits are

reflected in lower funding costs, improved yields, better management of various risks, and effective operation within changing regulations.

In recent decades the use of mathematical techniques and processes, derived from operational research, has increased significantly. These methods are used in various aspects of financial engineering. Methods such as decision analysis, statistical estimation, simulation, stochastic processes, optimization, decision support systems, neural networks, wavelet networks, and machine learning in general have become indispensable in several domains of financial operations (Mulvey et al., 1997).

According to Marshall and Bansal (1992), many factors have contributed to the development of financial engineering, including technological advances, globalization of financial markets, increased competition, changing regulations, the increasing ability to solve complex financial models, and the increased volatility of financial markets. For example, the operation of the derivatives markets and risk management systems is supported decisively by continuous advances in the theory of the valuation of derivatives and their use in hedging financial risks. In addition, the continuous increase in computational power while its cost is being reduced makes it possible to monitor thousands of market positions in real time to take advantage of short-term anomalies in the market.

In addition to their knowledge of economic and financial theory, financial engineers are required to possess the quantitative and technical skills necessary to implement engineering methods to solve financial problems. Financial engineering is a unique field of finance that does not necessarily focus on people with advanced technical backgrounds who wish to move into the financial area but,

is addressed to those who wish to get involved in investment banking, investment management, or risk management.

There is a mistaken point of view that financial engineering is accessible only by people who have a strong mathematical and technical background. The usefulness of a financial innovation should be measured on the basis of its effect on the efficiency of the financial system, not on the degree of novelty that introduces. Similarly, the power of financial engineering should not be considered in the light of the complexity of the models that are used but from the additional administrative and financial flexibility that it offers its users. Hence, financial engineering is addressed to a large audience and should be considered within the broader context of the administrative decision-making system that it supports.

Financial Engineering and Related Research Areas

Financial engineering is a very large multidisciplinary field of research. As a result, researchers are often focused on smaller subfields of financial engineering. There are two main branches of financial engineering: *quantitative finance* and *financial econometrics*. Quantitative finance is a combination of two very important and popular subfields of finance: *mathematical finance* and *computational finance*. On the other hand, financial econometrics arises from *financial economics*. Research areas related to financial engineering are illustrated in [Figure 1.1](#).

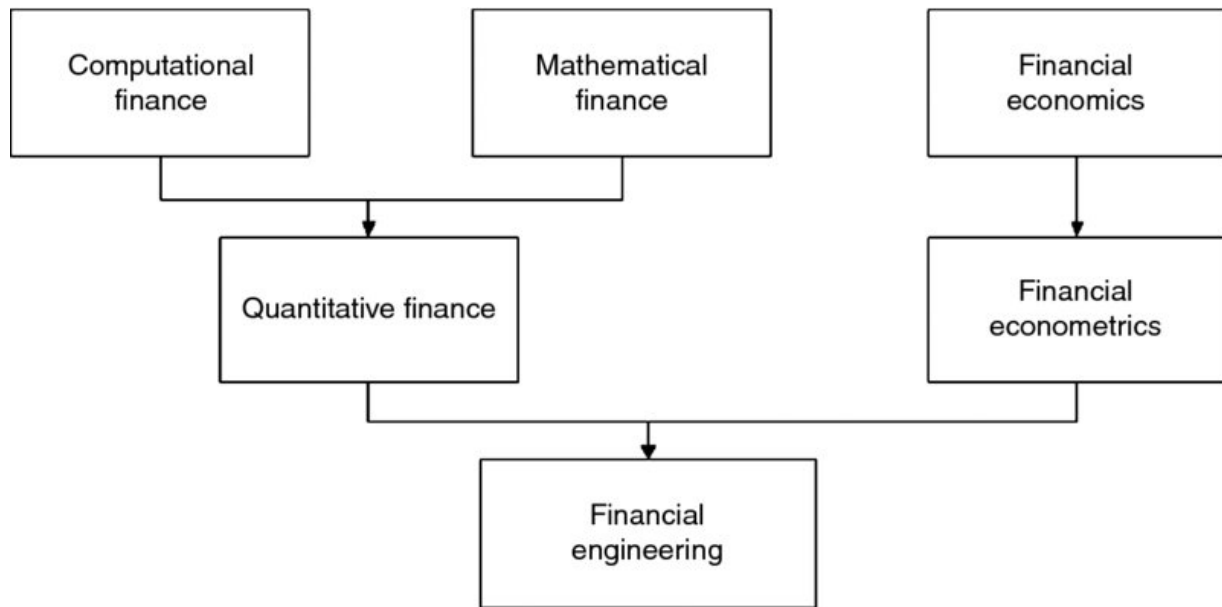


Figure 1.1 Research areas related to financial engineering.

The scientific field of financial engineering is closely related to the relevant disciplinary areas of mathematical finance and computational finance, as all focus on the use of mathematics, algorithms, and computers to solve financial problems. It can be said that financial engineering is a multidisciplinary field involving financial theory, the methods of engineering, the tools of mathematics, and the practice of programming. However, financial engineering is focused on applications, whereas mathematical finance has a more theoretical perspective.

Mathematical finance, a field of applied mathematics concerned with financial markets, began in the 1970s. Its primary focus was the study of mathematics applied to financial concerns. Today, mathematical finance is an established and very important autonomous field of knowledge. In general, financial mathematicians study a problem and try to derive a mathematical or numerical model by observing the output values: for example, market prices. Their analysis does not necessarily have a link back

to financial theory. More precisely, mathematical consistency is required, but not necessarily compatibility with economic theory.

Mathematical finance is closely related to computational finance. More precisely, the two fields overlap.

Mathematical finance deals with the development of financial models, and computational finance is concerned with their application in practice. Computational finance emphasizes practical numerical methods rather than mathematical proofs, and focuses on techniques that apply directly to economic analyses. In addition to a good knowledge of financial theory, the background of people working in the field of computational finance combines fluency in fields such as algorithms, networks, databases, and programming languages (e.g., C/C++, Java, Fortran).

Today, the disciplinary area of mathematical finance and computational finance constitutes part of a larger, established, and more general area of finance called *quantitative finance*. In general, there are two main areas in which advanced mathematical and computational techniques are used in finance. One tries to derive mathematical formulas for the prices of derivatives, the other one deals with risk and portfolio management.

Financial econometrics is another field of knowledge closely related (although more remote) to financial engineering. Financial econometrics is the basic method of inference in the branch of economics termed financial economics. More precisely, the focus is on decisions made under uncertainty in the context of portfolio management and their implications to the valuation of securities (Huang and Litzenberger, 1988). The objective is to analyze financial models empirically under the assumption of uncertainty in the decisions of investors and hence in market prices. For example, the martingale model for