

ISTANBUL TECHNICAL UNIVERSITY★ GRADUATE SCHOOL

**PORTFOLIO OPTIMIZATION WITH WAVELET ANALYSIS AND
NEURAL FUZZY NETWORKS**



Ph.D. THESIS

Ömer Zeki GÜRSOY

Department of Management

Management Programme

DECEMBER 2022

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İSTANBUL TEKNİK ÜNİVERSİTESİ★LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

**DALGACIK ANALİZİ VE BULANIK SİNİR AĞLARI MODELİ İLE
PORTFÖY OPTİMİZASYONU**



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ABBREVIATIONS

Adaline	: Applied Lineer Neuron
ANN	: Artificial Neural Networks
AR	: Autoregressive
ARIMA	: Autoregressive Integrated Moving Average
ARMA	: Autoregressive Moving Average
BPNN	: Backpropagation Neural Network
CAPM	: Capital Asset Pricing Model
CWT	: Continous Wavelet Transform
DWT	: Discrete Wavelet Transform
EMD	: Empirical Mode Sepertion
FFT	: Fast Fourier Transform
KOSPI	: South Korea Exchange Index
MA	: Moving Average
MAPE	: Mean Absulate Percent Error
MCA	: Multi Layer Sensors
MPT	: Modern Portfolio Theory
PDF	: Probability Density Function
RMSE	: Root Mean Square Error
RTSI	: Moscow Exchange Index
SHCOMP	: Shangai Stock Index
SVM	: Support Vector Machine



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PORTFOLIO OPTIMIZATION WITH WAVELET ANALYSIS AND NEURAL FUZZY NETWORKS

SUMMARY

Recently, Robo-advisors have come to the fore in the investment management business both in the world and in Turkey. Robo-advisors can be defined as financial algorithms that generate trading signals and optimize financial assets with machine learning. Robo-advisors, who perform asset management by analyzing data without human intervention, have the potential to provide better returns than traditional portfolio management.

Assets under management in the Robo-Advisors segment are projected to reach US\$3.2 tn in 2027. According to latest surveys, 63% of Americans are open to using a robo-advisor to manage their investments, with millennials being the most open (75%).

Financial asset forecasts are of great importance in portfolio management and the performance of forecasts plays a key role in the success of portfolio managers. This situation has led to an increased interest in models. While most of the models were based on statistical techniques in the past, new modeling techniques have been used recently. The most notable of these are artificial intelligence models such as artificial neural networks and fuzzy logic.

In this study, the daily values of Borsa İstanbul 30 Index, Gold and USD / TL exchange rate are tried to be estimated by using Wavelet Analysis and Neural Fuzzy Networks method. Buy / Sell signals are generated from the estimates created by the model. The performance of the portfolio was analyzed assuming that the underlying asset was invested on the days when the model predicted an increase and the investment was not made on the days when it predicted a decrease, and it was evaluated in overnight risk-free interest when not invested.

In addition, the model has been tested in artificial indices and stock market indices of other developing countries. While the model showed a successful performance in Russia and China, it remained below the index in South Korea stock exchange. Then, the optimal portfolio was created by using wavelet fuzzy network model estimates and the performance of the portfolio was examined. With the return and standard deviation values produced by the model, optimization was made to obtain the largest Sharpe ratio, and the performance of the portfolio of three assets was compared with the assets' own performances and risk-free interest by re-balancing at different time intervals.

The results show that the model created by using wavelet analysis and fuzzy neural networks together gives successful results in predicting the future values of financial assets and further research has potential. Wavelet Neural Network method, in which Artificial Neural Networks are used together with wavelet transform, can be used to

predict the future price of assets traded in financial markets such as BIST30, Gold and USD/TL exchange rate.

In the future, estimates can be made using the model in this study for financial assets other than gold, USD/TRL and BIST-30. The performance of the model in different market conditions can be tested by repeating the study at different time intervals. In the study, wavelet transform is done using Haar wavelet, financial series can be decomposed into its components by using different wavelets.



DALGACIK ANALİZİ VE BULANIK SİNİR AĞLARI MODELİ İLE PORTFÖY OPTİMİZASYONU

ÖZET

Son zamanlarda yatırım yönetimi işinde Robo-danışmanlar ön plana çıkmıştır. Robo-danışmanlar, alım satım sinyalleri üreten ve makine öğrenimi ile finansal varlıkları optimize eden finansal algoritmalar olarak tanımlanabilir. İnsan müdahalesi olmadan verileri analiz ederek varlık yönetimi gerçekleştiren Robo-danışmanların, geleneksel portföy yönetimine göre daha iyi getiri sağlama potansiyeline sahip oldukları yapılan çalışmalarla gösterilmiştir.

Robo-Danışmanlar segmentinde yönetilen varlıkların 2027'de 3,2 milyar ABD Dolarına ulaşması beklenmektedir. Son yapılan araştırmalara göre, Amerikalıların %63'ü yatırımlarını yönetmek için bir robo-danışman kullanmaya açıktır.

Portföy yönetiminde finansal varlık tahminleri büyük önem taşır ve tahminlerin performansı portföy yöneticilerinin başarısında kilit rol oynar. Bu durum modellere olan ilginin artmasına neden olmuştur. Geçmişte modellerin çoğu istatistiksel tekniklere dayalıyken, son zamanlarda yeni modelleme teknikleri kullanılmaya başlanmıştır. Bunlardan en dikkat çekenleri yapay sinir ağları ve bulanık mantık gibi yapay zeka modelleridir.

Finansal piyasalar, ekonomik, politik, kültürel ve sosyal haberlerden etkilenen karmaşık sistemlerdir. Temel analiz ve teknik analiz, geleneksel olarak finansal varlıkların performansını tahmin etmek için kullanılır. Çoğu finansal varlığın fiyat hareketi dinamik ve doğrusal olmadığı için istatistiksel modeller genellikle fiyat hareketini tahmin etmekte başarısız olur. Yapay Sinir Ağları gibi makine öğrenimi modelleri doğrusal olmayan verileri çok etkili bir şekilde modelleyebilir, ancak bu modeller parametre seçimine duyarlıdır. Bulanık mantık sistemleri insan uzmanlığı ile karar verme kapasitesini artırırken, sinir ağları farklı koşullara uyum sağlama ve öğrenme avantajına sahiptir.

İstatistiksel modellerin aksine, bu modeller çok az varsayımda bulunur ve girdiler ve çıktılar arasındaki ilişkiyi öğrenerek tahmin etmeye çalışır. Yapay zeka uygulamalarının başında gelen yapay sinir ağları ve bulanık mantık modelleri birbirini tamamlayan yapılar olduğundan son yıllarda birçok modelde birlikte kullanılmış ve başarılı sonuçlar elde edilmiştir.

Ayrıştırma modellerinin kullanılmasının tahmine dayalı modellerin başarısını artıracağı düşünülmektedir. Çalışma, hisse senetleri, döviz kurları ve altın gibi finansal varlıkları tahmin etmek için hem ayrıştırma modelinin (Dalgacık Dönüşümü) hem de makine öğrenimi modellerinin (YSA) avantajlarını birleştiren hibrit bir yaklaşım önermektedir. İlk aşamada, veriler dalgacık dönüşümü kullanılarak alt kümelerle ayrıştırılır. Ardından, her bir alt dizi, makine öğrenimi modelleri kullanılarak tahmin edilir. Son tahminleri elde etmek için tahmin edilen alt seriler eklenir. Ardından, tahminlerin başarısı istatistiksel testler ile ölçülür.

Bu çalışmada, Ocak 2016-Şubat 2019 verileri kullanılarak İstanbul Menkul Kıymetler Borsası (BİST30) Endeksi, USD/TL kuru ve Altın (TL) fiyatlarının Mart 2019-Aralık 2019 tarihleri arasındaki günlük getirileri tahmin edilmiş ve bir portföy oluşturulmuştur. bu tahminlere göre oluşturulmuştur. Ağ eğitimi yapılırken verilerin %58'i eğitim, %42'si doğrulama verisi olarak gruplandırılır.

Çalışmanın ilk bölümünde BİST-30 Endeksi, Altın ve USD/TL kuru için Neural Fuzzy Network ile tahminler yapılmıştır. İlgili varlık sınıfı için geleceğe yönelik tahminler yapılırken öncelikle varlıkların otokorelasyon fonksiyonları incelenmiş ve tahminde kullanılacak geçmiş veriler bulunmuştur. İlk olarak, zaman serisinin geçmiş değerlerden etkilenip etkilenmediğini görmek için serilerin otokorelasyonu incelenmiştir. Otokorelasyon, zaman serilerinin farklı değerleri arasındaki korelasyon olarak tanımlanır. Bu analiz ile serilerin hangi geçmiş değerlerinin gelecek değerleri üzerinde daha fazla etkiye sahip olduğu görülmektedir. Oto korelasyon fonksiyonları incelendiğinde her üç zaman serisinde de oto korelasyon olduğu görülmektedir. Altın ve USD/TL zaman serilerinin en çok son 4 veriden (T-4) ve BİST-30 endeksinin son 1 veriden (T-1) en çok etkilendiği görülmektedir.

Çalışmada öncelikle modelin başarısını artırmak için bir sinyal işleme tekniği olan Ayrık Dalgacık Dönüşümü (DCT) ile finansal varlıklar serisi 3 farklı alt seriye (a2-d2-d1) ayrılmıştır. Daha sonra yapay sinir ağları ve bulanık mantık uygulamalarının bir kombinasyonu olan bulanık sinir ağı yöntemi kullanılarak finansal seriler tahmin edilmiştir. Çalışmada ilk olarak finansal seriler dalgacık analizi ile 3 alt segmente ayrılmıştır. Sinirsel bulanık ağ modeline girdi olarak farklı frekans bilgileri verilmiş ve gelecekteki fiyatlar tahmin edilmiştir. Daha sonra yapay sinir ağları ve bulanık mantık uygulamalarının bir kombinasyonu olan bulanık sinir ağı yöntemi kullanılarak finansal seriler tahmin edilmiştir. Son olarak, bu tahminler kullanılarak oluşturulan portföylerin performansı orijinal serilerle karşılaştırılarak modelin başarısı ölçülmektedir.

Al/Sat sinyalleri, model tarafından oluşturulan tahminlerden üretilir. Portföy performansı, dayanak varlığa modelin artış öngördüğü günlerde yatırım yapıldığı, düşüş öngördüğü günlerde ise yatırım yapılmadığı varsayılarak değerlendirilmiştir.

Çalışmanın ikinci bölümünde, Dalgacık Analizi ve Bulanık Sinir Ağları ile yapılan tahminlerin farklı piyasa koşullarındaki performansını görmek için Wiener Süreci kullanılarak yapay zaman serileri üretilmiştir.

Wiener süreci ile Dalgacık Sinir Ağları modelinin farklı piyasa koşullarında nasıl performans gösterdiğini görmek için yapay zaman serileri oluşturulmuştur. Wiener Süreci formülü ile üretilen zaman serilerinin oynaklığı ve yönü değiştirilebilir, böylece düşük veya yüksek oynaklığa sahip yukarı veya aşağı yönlü seriler oluşturulabilir. Modelin bu şekilde üretilen serilerdeki performansı, ileride oluşabilecek farklı piyasa koşullarındaki başarısı hakkında fikir verecektir.

Yüksek oynaklığa sahip yükselen ve düşen trendlerde model performansının, yapay zaman serilerine pasif yatırımdan daha başarılı olduğu görülmüştür. Seriyeye rastgele sıçramalar eklendiğinde model yine başarılı olmuş fakat maliyetlerde göz önüne

alındığında modelin performansı pasif yatırımın altında kalmıştır. Sıçramaların belirli bir paterni olmadığı için modelin tahmin performansını düşürmesi beklenir.

Ayrıca model, diğer gelişmekte olan ülkelerin borsa endekslerinde de test edilmiştir. Model Rusya ve Çin'de başarılı bir performans sergilerken Güney Kore borsasında endeksin altında kalmıştır. Daha sonra dalgacık bulanık ağ modeli tahminleri kullanılarak optimal portföy oluşturulmuş ve portföyün performansı incelenmiştir. Modelin ürettiği getiri ve standart sapma değerleri ile en büyük Sharpe oranını elde etmek için optimizasyon yapılmış ve üç varlıktan oluşan portföyün performansı, varlıkların kendi performansları ve risksiz faizi ile farklı zaman aralıklarında yeniden dengeleme yapılarak karşılaştırılmıştır.

Son bölümde modelin ürettiği getiri ve standart sapma değerleri ile en büyük Sharpe oranını elde etmek için optimizasyon yapılmış ve üç varlıktan oluşan portföyün performansı, varlıkların kendi performansları ve risksiz faizi ile farklı değerlerde yeniden dengeleme yapılarak karşılaştırılmıştır. Sonuçlar, dalgacık analizi ve bulanık sinir ağlarının birlikte kullanılmasıyla oluşturulan modelin finansal varlıkların gelecekteki değerlerinin tahmin edilmesinde başarılı sonuçlar verdiğini ve daha fazla araştırma potansiyeli olduğunu göstermektedir. Hem optimal portföyün getirisinin hem de tüm zaman dilimlerinde Sharpe oranının varlıkların kendisinden daha yüksek olduğu gözlemlenmiştir. Yapay Sinir Ağlarının dalgacık dönüşümü ile birlikte kullanıldığı Dalgacık Sinir Ağı yöntemi, BIST30, Altın ve USD/TL döviz kuru gibi finansal piyasalarda işlem gören varlıkların gelecekteki fiyatını tahmin etmek için kullanılabilir.

Çalışmada nöral bulanık sistem olarak ANFIS kullanılmıştır. Sinirsel Uyarlamalı Öğrenme teknikleri, bulanık modelleme için girdi verilerini kullanarak bir öğrenme modeli geliştirmeye izin verir. Matlab Fuzzy Logic Toolbox'ta ANFIS grafik kullanıcı ara yüzü kullanılarak ağ eğitim, kontrol ve test olmak üzere üç veri seti ile eğitilmiştir.

Tüm avantajlı yönlerine ve gelişen yapılarına rağmen yapay sinir ağları ve ANFIS yöntemleri yetersiz kaldığı durumlarda mevcuttur. Bu yöntemlerde belirli veri kümesi yapıları için modeller oluşturulur, her veri kümesi için uygun değildir. Ayrıca mevcut veri seti için uygun modelin keşfi sırasında birçok deneme yapılması gerekir. Veriler için örneklem seçimi, hangi öğrenme yönteminin kullanılacağı, veri setinin büyüklüğü, kullanılacak üyelik fonksiyonunun türü çıktı değerlerinin belirleyicileridir ve bu değerler denemelerle belirlenir.

Gelecekteki çalışmalarda Altın, USD/TRL ve BİST-30 dışındaki finansal varlıklar için bu çalışmadaki model kullanılarak tahmin yapılabilir ve modelin farklı enstrümanlardaki performansı araştırılabilir. Bu çalışmada fiyat tahmini için zaman serilerinin geçmiş verileri girdi olarak kullanılmıştır, gelecekteki fiyatları etkileyen enflasyon, çeşitli risk endekleri, yurtdışı borsa endeksleri, gelişmiş ülkelerin para birimlerinin değişimi gibi başka değişkenler de olabilir. Farklı değişkenler girdi olarak kullanılarak çalışma tekrarlanabilir. Farklı zaman aralıklarında çalışma tekrarlanarak değişim piyasa koşullarında model performansı test edilebilir.

Ayrıca bu çalışmada zaman serilerini bileşenlerine ayırmak için Haar dalgacığı kullanılmıştır. Coiflet, Symlet, Daubechies, Moore gibi farklı özelliklere sahip dalgacıklar kullanılarak seriler alt katmanlarına ayrıştırılabilir ve bulanık sinir ağlarının finansal varlıkların gelecekteki fiyatlarını tahmin başarısı incelenebilir.





1. INTRODUCTION

Market players and investors try to find financial assets with the lowest risk and highest return potential when investing in financial markets. The balance between potential return and risk is one of the most important challenges when creating a portfolio. Market timing can be defined as estimating the direction of financial assets and increasing or decreasing the weight of risky assets in the portfolio in line with this forecast. In order to make these transactions successfully, it is necessary to be able to predict the direction of the markets. From this point of view, accurate estimation of the return of financial assets is of great importance in terms of asset management performance.

Statistical models often fail to predict price action because the price movement of most financial assets is dynamic and non-linear. Machine learning models such as Artificial Neural Networks (ANNs) can model nonlinear data very effectively, but these models may suffer from over fitting and are sensitive to parameter selection. While fuzzy logic systems increase the capacity to make decisions with human expertise, neural networks have the advantage of adapting and learning to different conditions.

The use of decomposition models is thought to increase the success of predictive models. The article proposes a hybrid approach that integrates the advantages of both the decomposition model (Wavelet Transform) and machine learning models (ANN) for estimating financial assets such as stocks, exchange rates, and gold. In the first stage, the data is parsed into subsets using wavelet transform. Next, each subsequence is predicted using machine learning models. Predicted subseries are added to obtain final estimates. Then, the success of the predictions is measured by statistical tests.

It has been observed that the return on investment obtained at the end of the strategy created by using the values estimated by wavelet analysis and fuzzy neural networks model is higher than the return of the buy-and-hold strategy in most cases.

Financial markets are complex systems influenced by economic, political, cultural and social news. Fundamental analysis and technical analysis are traditionally used to predict the performance of financial assets. Fundamental analysis makes use of fundamental indicators such as return on equity or price-earnings ratio.

In technical analysis, it is assumed that the future price of an asset depends on its past price. Forecasting is attempted using graphs and various technical indicators. The technical analyst's focus is to develop a model that can accurately predict stock price dynamics.

The success of various machine learning techniques such as Genetic Algorithms, Artificial Neural Networks, Support Decision Machines in modeling nonlinear data has led to their use in the prediction of time series, on the other hand, these models have the disadvantages of overfitting and being trapped in the local optimum. The accuracy of the predictions can be improved by improving the algorithms used or by preprocessing.

The decomposition of time series is done by converting time series into various components. Two different data decomposition techniques, classical and non-classical, can be applied. In classical models, the trends of the series are detected, seasonality is corrected or the series are divided into random components. There is a high probability of information loss in these methods, which reduces the prediction success.

In the category of non-classical methods, signal processing techniques such as Wavelet Transform, Empirical Mode Separation (EMD) are included in the category.

In this study, future prices of financial assets are modeled by using artificial neural network, fuzzy logic and wavelet transform techniques together. By using the wavelet transform, the historical data of the prices were split into sub-series, the future prices of the sub-series were estimated with a combination of artificial neural networks and fuzzy logic, and then the forecasts of the sub-series were collected to obtain the estimation of the main series. To measure model performance, it is assumed that investors invest in financial assets or risk-free assets according to the model's price prediction.

1.1 Portfolio Management

Portfolio, in the meaning of finance, is an investment basket created by combining multiple investment instruments with different properties. A portfolio has its own risk and return due to the relationships between the different assets it contains.

In other words, a portfolio emerges as a different financial asset, not a simple combination or sum of the values of the assets it contains. A portfolio can be structured according to parameters such as investor's risk perception, investment targets, and time interval when he wants to realize the investment.

There are some key features expected from an ideal portfolio:

- Liquidity: the portfolio can be easily converted to high liquidity values such as cash if desired.
- High return: high weighted return of its components
- Low and low variability risk value: low volatility of the portfolio's price movements
- Easy to manage: contain a reasonable number of securities
- Quantity and maturity compatibility with the market: widely used and standard maturity, quantity, etc. to facilitate disposal if desired. consist of securities with such features

“Asset diversification” underlies the traditional portfolio management. In this approach; The idea that diversification held at a certain level is sufficient to reduce the risk to a systematic risk level. In the traditional portfolio management approach, the return rate relationships of the assets within the portfolio are neglected. The more the number of these assets, the less likely that they will move at the same time and in the same direction is accepted as a fact that is valid in all cases. According to the traditional portfolio theory, the points to consider when making diversification are:

- Choice of financial assets belonging to different companies
- Selection of financial assets belonging to companies in different sectors
- Selection of financial assets in different geographic regions or countries

Modern Portfolio Theory (MPT) was created in conjunction with Harry Markowitz's article "Portfolio Selection" of 1952, and by adjusting the ratios of various assets within a portfolio, maximizing the expected return for a risk amount of data, or an

expected return with data. It is an investment theory that aims to minimize portfolio risk for its level.

This study and the diversification of investment baskets, together with the booklet that followed in 1959, were first put into a mathematical model. Later, Markowitz's student, William Forsythe Sharpe, introduced the "single index model" that he created based on the modern portfolio theory.

At the basis of the model lies the idea that the method of reducing the risk of investments through financial diversification is in relation to the correlations between the returns on the assets. Unlike the previous methods, which are the framework of combining portfolios with the highest return with the lowest risk level combination, modern portfolio theory requires investors to consider the return-risk relationships of portfolios rather than the return-risk relationships of individual assets. In traditional portfolio management strategies, which are the predecessors of the method, it was aimed to reduce the risk factor only by keeping the number of different assets in the portfolio high, regardless of the relationships between the returns on the securities in the portfolio. In this sense, the most important difference brought by the modern portfolio theory is that the concept of "correlation of the returns of assets" has entered the portfolio management area.

According to modern portfolio theory, an investor can reduce their total risk by diversifying their assets. What is important at this point is the relationship between the price changes of the assets held by the investor. While dealing with this phenomenon, the concept of correlation, which expresses the relationship between the two variables' value changes, is used.

The price of one of the two assets in positive correlation with each other changes in what ratio and in what direction, and the other changes in the same direction and in the same ratio, in this case the correlation value between the two assets becomes 1. In the case of negative full correlation, the rate of increase or decrease remains the same, but the direction is opposite this time and the correlation value is shown as -1. Another case is when there is no interest between the price changes of the assets. The correlation value may be outside these three extreme cases.

According to modern portfolio theory, in order for an investor to reduce his overall risk through diversification, his assets should not be positively correlated with each other. So the correlation value should be $-1 \leq \rho < 1$.

MPT opposes the idea that the portfolio will be shared only among the assets that yield the highest expected return, in direct proportion to the returns of those assets. According to this idea, the highest expected return rate can be achieved; In addition, diversification can be achieved only by adding as many different assets as possible to the portfolio, and the risk can be kept at the lowest point. However, according to Markowitz, the returns of assets are interdependent to the extent that this would not be possible. Therefore, the portfolio with the highest expected return is not necessarily the lowest risk.

Risk is the name of the situation that contains the possibility of a deviation from the desired or expected output.

The concept of risk can be defined and calculated in cases where possibilities exist instead of "certainty". Regarding the realization of a case, if there is a certainty of certainty, the risk of that case is zero.

Financial risk arises from the fact that the number of expected returns, impact values, realization or non-realization of future returns from an investment depend on many factors that cannot be determined today. One of the issues in which risk is handled in the broadest sense in the field of finance is the relationship between the returns and risks of investments. Generally, the high return expectation is directly proportional to the high risk amount. If the risk of a product with an investment value is considered higher than another, the return rate promised by the same product should be more than the lower risk, so there is a rationale for the rational investor to consider this option. At the basis of this idea the return is the reward or reward for a particular risk that cannot be fully insured. From another point of view, in order for an investment to promise a high return, price movements should generally take place in a wider uncertainty range, whereas this wide range of movements brings a higher amount of risk. In this respect, the risk of an investment is determined by the rate of return of that investment which has a mutual relationship in terms of both its rationale and its consequence.

There are different rates of risk in all of the investments made on stocks, bonds or currencies. The reason for these variable risk rates is that these products are exposed to different types of risk in different amounts.

Risk, in particular in the field of finance, is divided into two as systematic and non-systematic risk in terms of controllability. The CAPM model (Capital Asset Pricing Model), which was put forward by independent studies by Jack Treynor (1961), William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966), uses this classification.

Systematic risk cannot be diversified because it affects the entire market as a whole and is inherent in the market. For this reason, it is also called "market risk".

Various types are listed as follows;

- Interest Rate Risk: It is the risk that affects fixed income instruments such as bonds and bills due to the change in market rates. For example, central banks can increase or decrease interest rates.
- Market Risk: Risk involving changes in the prices of securities such as stock market, gold, instruments containing interest. An example is the stock market correction.
- Currency Risk: It shows the changes in currency prices. It is important for companies that carry out foreign exchange transactions, import and export figures, and companies or investors in these sectors.
- Political Risk: Political or economic turbulence in a country affects investors. The imposition of sanctions on a country, a state of war, or political instability may result in funds leaving the country.

Risk specific to a security is defined as non-systematic risk and can be reduced or eliminated by diversification.

An investor holding a variety of securities in his portfolio may be exposed to unsystematic risk due to the depreciation of these securities. Unsystematic risk can be reduced by diversification, but still the portfolio is vulnerable to unsystematic risk. Various risk management tools are used to manage unsystematic risk.

1.2 Measuring Risk

The Sharpe ratio subtracts the return on a risk-free asset (usually treasury bills) from the portfolio return, dividing the result by the portfolio's standard deviation, and adjusts the portfolio return for the risk ratio. Thus, it calculates the risk that the investor takes per unit of return. The formula of the ratio, first expressed by William F. Sharpe in 1966, is as follows;

$$S_a = E [R_a - R_b] / \sigma_a = E[R_a - R_b] / [\text{var} [R_a - R_b]]^{1/2} \quad (1.1)$$

In the formula, R_a represents the portfolio return and R_b represents the return of the risk-free asset. σ_a is the standard deviation of the portion of the portfolio return over the risk-free asset return.

The Sharpe Ratio shows the performance of the portfolio or financial asset against the risk taken. When comparing two portfolios, the portfolio with a higher ratio is interpreted as more successful in terms of risk-return balance. Sharpe Ratio has had many uses, as it first brought up the risk-adjusted return perspective. However, it may not involve all risks. While some strategies have a high sharpe ratio in the short term, different risks may arise in the long term. While ponzi schemes provide high returns to investors for a long time, when new investors do not come, the system collapses and all investment disappears. Similarly, high sharpe ratio rates can be obtained when trading derivative products such as options, but high losses may occur at some point. Therefore, when using the Sharpe ratio to examine portfolio performance, analysis over a sufficiently long timeframe is necessary. In addition, caution should be exercised against rare events that are very unlikely to occur, and how resilient portfolios are to such events.

In the literature, different ratios such as Treynor Ratio, Jensen Alpha, and Information Ratio are frequently used in addition to the Sharpe ratio to examine the performance of investments.

Arthur D. Roy, in his 1952 article, suggested using the "minimum acceptable return" instead of the sharpe rate risk-free return. In addition, instead of the standard deviation of excess returns in the denominator, he only used the standard deviation of returns. Similarly, Sortino proposed a new ratio using "minimum acceptable return" in the numerator and the standard deviation of negative returns only in the denominator.

In 1994, Sharpe changed the original formula and brought it to the following form;

$$S_a = E [R - R_b] / \sigma_a = E[R - R_b] / [\text{var} [R - R_b]]^{1/2} \quad (1.2)$$

If R_f is a constant risk-free return, then the formula becomes;

$$[\text{var} [R - R_f]]^{1/2} = \text{var} [R]^{1/2} \quad (1.3)$$

The use of the Sharpe ratio to measure performance in declining markets is subject to criticism. A ratio below zero indicates poor portfolio performance. On the other hand, when the ratio is below zero, portfolio managers can increase volatility, that is, risk, approaching zero. Therefore, Sharpe Ratio is not significant for negative returns.

Another weakness of the Sharpe ratio is that it assumes that returns are normally distributed. Kurtosis, skewness, or thick tail indicates that the series does not have a normal distribution. In non-normally distributed series, the standard deviation does not have the same efficiency, so it may not be correct to use the Sharpe ratio. Therefore, the accuracy of the ratio depends on the statistical properties of the series. Also, it is difficult to interpret how much better a return with a high Sharpe ratio is than a return with a low rate.

Sharpe Ratio has become popular because it can be calculated using only the portfolio returns and the risk-free return on assets without the need for any additional information. One of the most important advantages of the Sharpe Ratio is that it includes both systematic and specific risks. There are studies that show that the volatility observed in the literature recently does not fully show the risk involved in a time series.

In the literature, there are many studies on the prediction of financial asset prices with artificial neural networks. Successful results have been achieved in studies that have been used and continued to be developed since the 1990s. The originality of this study is that it proposes a hybrid model by combining the prediction mechanisms of different models. This study is unique in terms of predicting the future prices of 3 basic financial assets traded in Turkish markets by using wavelet transform and fuzzy neural network methods together. The proposed hybrid forecasting model has been tested in terms of both passive investment and portfolio creation, and a detailed study has been made for Turkish financial assets.

2. LITERATURE REVIEW

There are numerous articles on the estimation of asset prices in the finance literature. In these studies, the future prices of financial assets were tried to be estimated by using asset pricing models such as fundamental analysis, technical analysis and CAPM. Especially after the 1990s, models containing artificial intelligence started to be used and successful results were obtained.

After the 2000s, models in which wavelet analysis and artificial neural networks are used together have been developed. This hybrid model technique, which was first used in the fields of hydrology and meteorology, later found its place in the field of finance.

Wang et al.'s estimation of the prices of the Shanghai Stock Exchange Index in 2011 using wavelet transform and neural networks, and the article in which Lahmiri divided the SP index into its components with wavelet transform in 2012 and estimated the index using the Support Vector Machines method formed the basis of this study. The hybrid method used in the related studies was developed with fuzzy logic and used in the estimation of financial assets in the Turkish market. In addition, portfolio optimization was made with the predictions created by the model, and the existing studies were tried to be carried to a further point.

Kimoto et al. (1990) successfully predicted the Tokyo stock index with artificial neural networks. In the same year, Kamijo and Tanikawa worked successfully with recurrent neural networks, and Ahmadi with back propagation network. Yoon and Swales (1991) studied both quantitative and qualitative data. Choi et al. (1995) estimated the daily direction change of the S&P 500 index.

Bansal et al. (1993) compared linear regression and ANN, which are two alternative models in the field of finance and concluded that the estimates with ANN were more consistent in terms of predictive accuracy when linear regression gave better results and data reliability decreased. Schöneburg (1990) studied the data of three important

companies from the German securities market and analyzed the possibility of forecasting stock prices on a short-term or even daily basis with the help of the ANN model, and stated that the accuracy rate of the estimates could reach up to 90% within a short period of time. With the ANN method, Leigh et al. (2002) New York Stock Exchange Index; Kim and Han (2000) tried to predict the future value of the stock market index.

Donaldson and Kamstra (1997) tried to predict the volatility and volatility of stocks in London, New York, Tokyo and Toronto markets in their study using artificial neural network. Similarly, in their studies, Cao, Leggio and Schniederjans (2005) estimated the stock price movements for companies traded on the Shanghai stock exchange. Mostafa (2010), Chen, Leung, and Daouk (2003) made predictions of stock market price movements in their studies using neural network models.

Birgöl and Bertan (2009) established feed forward neural network models with various macro variables to estimate the BIST100 index. As a result, in the 127-day forecast, the direction of the index was determined as 55.1%. This rate remained above the 50.4% rate found by the moving averages method. Diler (2003) tried to estimate the daily price direction of BIST100 with 2700 days of data between 1993-2003 and achieved 60.8% success.

Akca and Eagles (2011) constituting the insurance sector index BIST 7 companies 15 days, 1 month and 2 months have tried to anticipate the subsequent artificial neural network model established by the stock price. For the 15-day forecast, change the average absolute percent error between 0.85% and 2.36%. It has been observed that the success of the estimates decreases as the estimation period increases.

Wang et al. (2011) estimated the Shanghai Stock Exchange Index with the wavelet transform and Backpropagation Neural Networks (BPNN) model. They showed that the use of BPNN together with the wavelet transform is more successful than the use of BPNN.

Lahmiri (2012) decomposed the S&P price index using wavelets with low frequency coefficients to estimate index. He used Support Vector Machines (SVM) as his prediction method. In the study where macroeconomic variables were used as input, it was shown that SVM with wavelet analysis produced more accurate predictions.

Aydın and Cavdar (2015) tried to anticipate artificial neural networks and financial crises by using 7 different economic indicators between 1994-2014. They calculated that Turkey's economy enter a high-risk period between the years 2014-2016.

Çalışkan and Deniz (2015) estimated the prices of the stocks in the BIST30 index. In their studies, they used variables such as exchange rates, gold prices, and closing prices of stocks as input variables. At the end of the study, they report that artificial neural network model can be used successfully in stock price prediction.

In 2015, Özçalıcı successfully predicted the closing prices of BIST 30 index stocks. In the study, a genetic algorithm was used to determine the number of neurons in the artificial neural network model. The study has shown that the use of artificial neural networks and genetic algorithms together gives successful results.

In Atsalakis and Valavanis' 2015 studies, a neuronal fuzzy system composed of an Adaptive Neuro Fuzzy Inference System (ANFIS) controller used short-term stock trends and the best stock trend forecast for the next day. The results showed that it is possible to make accurate forecasts of stock price trends using historical data.

Yiğiter et al. (2017) tried to predict the closing prices of stocks traded in the BIST between 2006-2016 using multiple linear regression, artificial neural networks and fuzzy logic methods. It has been stated that artificial neural networks give more successful results compared to other methods. The efficiency coefficient of the best result achieved with these models was calculated as 0.823.

Tran (2021) applied the wavelet transform method to investigate the effect of macroeconomic and technical predictors on equity premium. He used wavelet transform to decompose time series into high, medium, low frequencies and the result suggest that the macroeconomic predictors work well in medium and low frequencies.

Çetin and Metlek used artificial neural networks to forecast Turkish Sovereign Sukuk prices in 2021. They designed a multi-layer feed forward artificial networks model and defined the dollar index, volatility index, geopolitical risk index, S&P sukuk index and Eurobond prices as inputs.

Lee, Beh and Lem, in 2021, forecasted financial time series with Hybrid ARIMA-Wavelet Transform. They compare the hybrid ARIMA-CTW results with pure

ARIMA forecasting results and concluded that using wavelet transform yields better forecasting results.

Wavelet analysis is a method that has started to be used in determining the characteristic structure of data in recent years. It first started to be used for meteorological and hydrological variables, and after successful results, it took place in other fields such as finance. There are many studies showing that using wavelet transform increases the success of artificial neural networks.

One of the first studies on the use of ANN and Wavelet technique in hydrology was done by Wang and Ding (2003). In this study, a new model consisting of a combination of ANN and wavelet analysis is proposed. The original time series was separated into sub-time series ($W_1, W_2, \dots, W_p, C_p$) by wavelet transform technique, it was stated that these series gave detailed information about the original series and each decomposed series had a different behavior. Here, W_i is the detail series and C_p is the approximate series. Then, the original time series was tried to be estimated by using these dissociated series as input in the ANN model. In other words, the data were tried to be estimated by their own sub-time series. These researchers tried this method with two different applications: daily flow estimation and estimation of groundwater level. They compared the results with the ARMA model results and found that the proposed wavelet-ANN model was satisfactory and successful.

In another study, Kim and Valdes (2003) proposed a hybrid model, which is a mixture of ANN and wavelet technique, to predict drought in Mexico. In this technique, the original signal is segmented at various resolution levels with the discrete wavelet transform and these new series are inserted into the ANN model for prediction. That is, the data were estimated by their wavelet components.

3. FUZZY LOGIC AND APPLICATIONS IN FINANCE

Fuzzy logic approach is defined as one of the sub-branches of artificial intelligence. It emerged as a product of very valuable logic studies against Aristotle's two-valued logic proposition.

Fuzzy logic, which is used in many different fields today, was first used in steam engine control systems. The use of fuzzy logic in the field of finance dates back to the early 2000s. This new field is generally used as a decision support mechanism in subjects such as stock price prediction, financial risk analysis, portfolio creation.

Human experience with fuzzy logic, which emerges from the intersection of different branches of science such as mathematics, sociology, logic and medicine, gives machines abilities with various artificial intelligence techniques.

The fuzzy logic approach can be described as converting one type of thought to another and it gives machines the ability to work like humans. Fuzzy logic evolved from classical logic gains flexible working ability to automation working with precise values.

Zadeh started to think about fuzzy logic in 1965 with the idea of transferring human experience and knowledge to machines. The article "Fuzzy Sets" published in the "Information and Control" journal of Zadeh, who argues that algorithms can make decisions with a human-like way of thinking, is considered the first publication on this subject.

Lütfi Rahim Son Askerzade, known as Lütfi Zadeh, was born on February 4, 1921 in Baku. After studying Electrical Engineering at Tehran University, he completed his master's degree at Massachusetts Institute of Technology and his doctorate in Electrical Engineering from Columbia University. Continuing his research at Columbia, Princeton, and California Universities, Zadeh passed away on September 6, 2017.

In classical logic, entities can belong to only one set. It has an ownership rule consisting of 0-1 values. If an entity has the value 1, it belongs to a cluster, if it is 0, it does not belong. On the other hand, things do not always happen this way in nature, concepts may not or may partially fall into either of these categories. Therefore, the exact set notion does not represent nature. In fuzzy logic, 0 and 1 are defined as border regions, not absolute values, and there are different probabilities between these two values.

According to the classical logic, it is necessary to define grapes as either black grapes or green grapes. In fuzzy logic, although there are green and black grapes, different categories of grapes can be defined between the two. For example, 30% black grapes can be defined as "light black" and 50% black grapes as "some black".

One of the first steps taken that a machine or system capable of thinking can be built is the emergence of fuzzy logic. With this method, the possibilities are categorized in a manner similar to human thought and the “thought” system of the machine is enriched. The logic of Aristotle is different from its positive and negative duality. Due to its proximity to the Far East philosophy, it is thought to have made faster progress in Japan and China before being accepted in the Western world.

Three phases different from traditional methods are used in the operation of this logic:

- Creating fuzzy sets
- Writing rules using clusters
- Decision making process

The fact that entities can belong to different clusters instead of a single cluster gives fuzzy logic superiority in applications. Possibility of a cluster or multiple clusters and fuzzy system manifests itself.

3.1 Historical Development of Fuzzy Logic

Living in the same period as Confucius in Ancient China and believed to be the founder of the Mohist movement school, Master Mo studied the rules for correct reasoning and consequently making conclusions. These studies date back to the 4th century BC. The foundations of logic science were laid with Aristotle in ancient Greece.

Based on the conceptual mindset and knowledge derived from the mind, Zenon from Elea has dealt with the principles of reason with an overview. Parmenides, who was the teacher of Zenon from Elea, produced various paradoxes and defined compulsory asset information as information that does not exist, does not change and always remains stationary. Zenon supported these paradoxes of his teacher with various theses.

Socrates, for the first time, raised the concept issue and laid the foundations for induction logic by using similar qualities between singular examples to describe concepts. According to Plato, the concept of an entity cannot be created using inductive techniques. Reality is the world of ideals behind the experimental and sensory universe.

Many philosophers, researchers, thinkers, who formed the basis of the concept of logic, from the old period to the modern period, contributed to the field of logic. Between 350 and 1650, St. Augustine (354- 430), Severinus Boethius (470-525), Farabi (870-950), Ibni Sina (980- 1037), Ibn Rushd (1126-1189), Albertus Magnus (1193-1280), Thomas (1225) -1274), Duns Scotus (1265-1308), William from Ockham (1285-1347) and Francis Bacon (1561-1626); Between the years of 1650-1850, the thinkers named Gottfried Wilhelm Von Leibnitz (1646-1716), Immanuel Kant (1724-1804) and Bernhard Bolzano (1781-1848) prepared important grounds for the concept of logic in the modern period.

For the comparison process, John Venn (1854-1923) produced the circular shapes method. British philosopher John Stuart Mill (1806-1873) developed the Mill Method and was also closely involved with the induction method. During this period, Charles Dodgson (1832-1898) wrote the Logic Game and Symbolic Logic books. Charles S. Peirce (1839-1914) is the first logic to come to mind. Gottlob Frege (1848-1925) argued that the basis of mathematics is logic, and it aims to derive and distinguish mathematics from logic.

By 1910, Wilhelm Ackermann (1896-1962) and David Hilbert (1862-1943) wrote the book Principles of Mathematical Logic. Ludwig Wittgenstein (1819-1951) and Emil Post (1897-1954) independently developed their validity tables.

In the early 1900s, Jan Lukasiewicz (1878-1956) added a third value to the 2 values in addition to the Aristotle logic and stated it as $[0,1,2]$. Donald E. Knuth (1938) used

$[-1,0,1]$ integer values instead of $[0,1,2]$ values of Lukasiewicz. These 3 valuable methods were ignored and not accepted. Later, Zadeh, the first founder of fuzzy logic in the modern sense, prepared many scientific publications about the principles and structure of fuzzy logic and became the leader of this field.

In 1975, the concept of fuzzy logic was introduced for the first time by Assilian and Mamdani by integrating a steam engine into the control system. They realized this system with the rules, "If the acceleration of the turbine is increasing, the pressure drops too much, open the steam valve a little" (J., 2006). In 1987, Hitachi Company applied the concept of fuzzy logic to Sendai Metro. With this study, 10% energy was saved and the train was stopped 3 times better than expected. In 1988, the intelligent system based on fuzzy logic by Yamaichi Securities gave the signals of the crisis, also known as the Black Market in the Tokyo Stock Exchange, 18 days in advance. After these successful results, interest in fuzzy logic has intensified.

With all these developments, in 1989, 51 companies including IBM, Matsuhita, Toshiba, Omron, SGS, and Thomson came together and established laboratories named Laboratory for Interchange Fuzzy Engineering (LIFE).

Fuzzy logic was initially met with suspicion in the western world. The opponents were mostly those who worked on probabilities. According to them, anything that fuzzy logic expresses explains could already be explained by the theory of probabilities. One of the most important reasons for the increase of the importance of fuzzy logic is the important technological developments that have been carried out in Japan after 1970 by using fuzzy logic.

Fuzzy logic, which is suitable for the philosophical thinking structure of the Eastern world, also explains a transition and continuity. Because in classical logic, there are two opposite and limit values as 0 or 1, that is, white or black. However, in fuzzy logic, there are intermediate colors such as gray between white and black.

One of the features of fuzzy logic is that it uses principles other than some basic principles on which classical clusters are based. For example, in classical thought there is a set A and the set $\bar{A}$ that does not contain it; however, in fuzzy logic, the cluster understanding accepts these two values (ie 1 and 0 values) as boundary conditions.

In terms of classical logic understanding, if an element does not belong to set A, it will belong to set even which does not contain it. For example, if an apple is not red (that is, it does not belong to the set of red apples), it will be an element of the set $\bar{A}$. But according to the Fuzzy logic, we can consider an apple that is not red, if not exactly green, with a certain percentage of red. In this case, if the value of the full red apple is 1, the value of the non-red (green apple) will be 0. It will be possible to qualify all other apples according to their degree of redness, such as '40%, 60%, 90%, ... red'.

In this case, the classical logic also goes beyond the principle of contradiction known as “something is both A and $\bar{A}$ cannot”; because an 'a' object, for example, has to carry the 'A feature' by 40% and at the same time the 'not being A' feature by 60%. Therefore, "A and $\bar{A}$ " are true together.

This cluster understanding of fuzzy logic not only goes beyond the basic principles on which classical logic is based, it can also express and use it in a process that is completely foreign. For example, a proposition p takes values 1 and 0 for classical logic. The propositions p and q will take the values 11,10,01 and 00, respectively. Let us assume that the same p and q propositions in terms of fuzzy logic are, for example, 2/3 and 3/4 respectively. Figure 3.1 shows the scheme of fuzzy numbers.

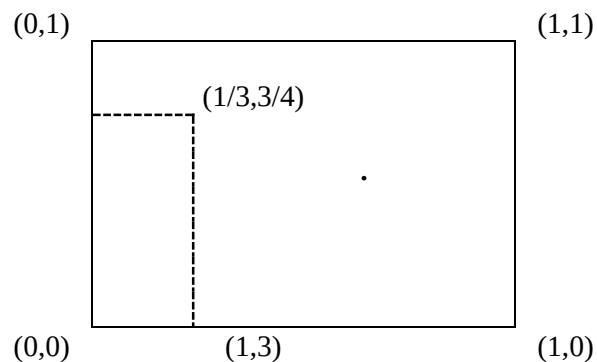


Figure 3.1 : Scheme of fuzzy numbers (Kosko, B., 1993, p.32).

Classical logic deals only with the four corners of the square represented by Figure 3.1, while fuzzy logic provides information about a large area expressed by the surface of the square. If we want to show these accuracy values of these two elements together we get a diagram as in Figure 3.2;

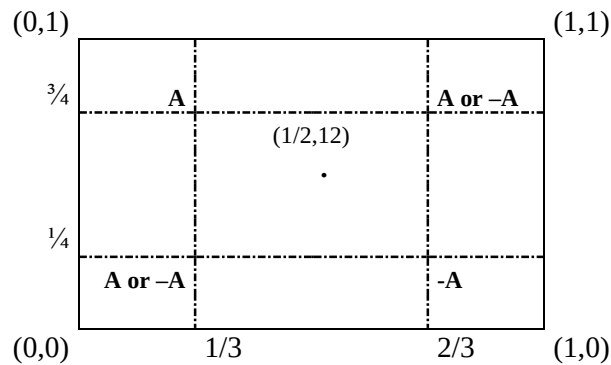


Figure 3.2 : Expression of Fuzzy Logic (Kosko, B., 1993, p.33).

In this notation, it is clearly seen that classical logic, which functions with 1 and 0 values, expresses a special form of fuzzy logic. In addition, fuzzy logic, by accepting the region between the values of 1 and 0 as an accuracy value, has a much richer and different expression than classical logic.

One of the main reasons for the concentration of attention on fuzzy logic has been its applications in technology and engineering, especially in Japan. The reason for its acceptance in Japan is the appropriateness of the mindset here. Because the fuzzy logic is in line with the philosophical worldview of the Eastern world and it also expresses a transition and continuity. Indeed, when using two boundary states, such as classical logic 1 and 0 (or true and false, or in a way black and white), there is a gray zone and a transition of gray tones for fuzzy logic. In addition, it is possible to describe this transition, continuity, the different 'states' successively using quantitative values.

According to Ali Lütüf Askerzade, fuzzy logic has three features that are unusual:

- 1) Fuzzy logic's truth values are words, not numbers!
- 2) These words contain terms such as very true, quite true, very false. The truth tables of fuzzy logic do not contain certainty.
- 3) For the validity of inference rules, absolute accuracy cannot be mentioned.

With these definitions, not only the most basic concepts used by classical logic, but also some of its very important results are avoided. Instead of defining a proposition as 1 and 0 (or true, false), defining it by staying within the properties of fuzzy sets gives the possibility to leave aside the questioning of the concepts that are always

discussed and the nature of them, such as “true and false”. Because the use of the concept of "right" in the language is "blurred". Therefore, it is possible to use concepts such as “right” (or “absolute right”) instead of “very correct”, “quite correct” - without the need to question their nature, and many successful applications can be reached from here. In addition, the qualifications such as "very beautiful, very beautiful" or "very good, very good", ultimately "what is beautiful?", "What is good?", "What is right?" It also makes questions such as unnecessary. Undoubtedly, the nature of concept pairs such as "very beautiful / very beautiful" or "very correct / quite correct" as well as the "true / false" concept couple can be questioned. However, there is no longer any need for such a discussion in terms of fuzzy logic. Because the concept pairs used by fuzzy logic express only a degree and continuity. Figure 3.3 shows the concept of “beautiful” as a scheme.



Figure 3.3 : Description of “Beautiful” in fuzzy world.

As you can see, there is no need to question the contents of the concepts such as "very beautiful", "very fast", "very sweet" and "very correct"; it is sufficient to use only values in a selected range. For example, being “very beautiful” can of course vary depending on the person, society and time. But in terms of fuzzy logic, it is sufficient to express what is desired to be described with "very beautiful", "beautiful" and "most beautiful" within a certain range with fractional values; It is not necessary to discuss the nature of the "beautiful" or how true it is to call something "beautiful". Saying that an object is beautiful, for example $\frac{3}{4}$, does not require any research on the beauty of that object nor an explanation about the "beautiful". From this perspective, A. L. Askerzade's "Fuzzy logic's truth values are words, not numbers!" view becomes clear; In this point of view, there is no need to search for a definitive and absolute definition of the "beautiful" and the aim is to convey their language

equivalents to a quantitative language and to make logical operations especially through this language without questioning the nature of the "beautiful".

3.2 Relationship between Logic and Sets

Logic, through mathematics, provides a strong link between philosophy and other sciences. Three basic views are generally considered to be effective in mathematics today: 'intuitive', 'formalist', and 'logical' views. The argument of the logical view is that mathematics is a branch of logic. Mathematical concepts can be expressed in logical concepts, and all theories of mathematics can be derived as the theories of logic.

Set theory forms the basis of arithmetic and logic, it can even be said that it constitutes the most important part of mathematics and formal causation. Therefore, there is a tight link between basic cluster operations ('merge' and 'intersection'), basic logical operations ('or' and 'and' and 'conjunctions'). It is common to express truth conditions for propositions among logicians in terms of set theory.

Fuzzy sets are the basic elements of fuzzy logic systems. It is the mathematical models we have created to transfer the verbal expressions we use to the computer. It is a cluster with elements that have the degree of belonging to a fuzzy set. In the classical set, an element is either inside (1) or outside (0) of the cluster. In fuzzy sets, an element has any membership value between 0 and 1.

Fuzzy set theory is a form of "uncertainty", its formulation. It is a kind of multi-valued set theory. But its operations differ from those of other cluster theories. Each individual in the cluster is regarded as a member to some degree, not as a 'member' or 'not a member', as in dual-value cluster theories. For some purposes, it may not be sufficient to classify them as 'members' or 'not members' of this cluster. In such cases, it may be appropriate to define their membership values gradually, by size.

Advantages of Fuzzy Logic

- Simple to control time-changing, complex systems, as in everyday life brings solutions.
- Its functioning is in human thinking style.
- It does not need a mathematical model; it gives good results in nonlinear systems.

- It is very easy to apply and enables applications to reach results faster.

Disadvantages of Fuzzy Logic

- It needs expert experience to determine the rules properly.
- It may not be easy to define rules and memberships.
- The most appropriate method is trial and error, so it may take a long time.
- Stability, observability and inability to analyze are the main problems of this method.
- There is no precise method and learning ability in determining membership functions.

Classical mathematics is simply binary, while fuzzy set theory; perception, subjectivity, attitude, ambiguities in understanding and purpose, and situations involving the human factor. Fuzzy set theory is becoming more powerful and flexible as it incorporates ambiguity and linguistics into the classical set theory. However, membership functions are vital in fuzzy set theory. Fuzzy set theory is a very general, flexible and canonical theory. Therefore, membership functions and processors do not have a single semantic interpretation. Contextual semantic interpretation can lead to different mathematical interpretations and practices.

Membership functions are functions that show the change of degrees of belonging to the fuzzy set of x elements of the universal set U . The membership function describes the information that this fuzzy set has.

Five basic concepts can be mentioned about a membership function and its form. These are core, support, boundaries, height and transition points. The elements of the fuzzy set whose membership level is greater than zero are called the fuzzy set's support. The classical cluster formed by this support is called the support cluster. The support of a fuzzy set, $\text{supp}(\check{A})$, is the crisp subset of the universal set.

The largest degree of membership of a fuzzy $\check{A}$ set gives the height of that set. The height can be seen as the validity or credibility of the information provided by the $\check{A}$ fuzzy set. The transition point of a membership function refers to elements that are members of the set defined in the universal set with a membership degree of $\text{Ma}-(x) = 0.5$.

3.3 Membership Function Assignment

Membership functions are divided into two main groups: optional membership functions and possibility distributions. While the preferential membership function is formed by revealing the desires of the decision makers, the likelihood function is formed from the possible occurrences of events as a likeness of the probability function. Likelihood is to write the results as if each of them has equal importance without making any distinction between the elements.

The determination of membership functions in a correct and overlapping manner with practice becomes important in fuzzy set theory and modeling based on this. Determining the membership function of a fuzzy set can be compared to determining the probability density function of a random variable.

While working in fuzzy sets, the processes of determining the membership function or the degree of membership of its elements can be intuitive or some algorithmically or logically based. In addition to approaches such as intuition, inference, ranking, various artificial intelligence methods can be used to determine membership functions.

Intuition requires little or no basic knowledge. This method is based on people's understanding of events and perspectives. An example of this is the 'temperature' variable, which we express linguistically in our daily lives. The word temperature can basically be divided into subsets such as 'very cold', 'cold', 'warm', 'hot' and 'very hot'. Ideas declared about a place with the same temperature can vary from person to person.

Therefore, the positions and shapes of membership functions expressed by these subsets may differ. For example, one person in the same room at 20 ° C can call it warm, while another person might call it hot. In this case, we can conclude that 20 ° C is a member of different degrees to both warm and warm subsets.

Inference, when deciding on the membership function, it is absolutely necessary to have some basic information about the event. Here, deductions are made from the knowledge acquired by deductive reasoning.

Ranking is carried out by assigning membership degrees by conducting research, questionnaires, investigations or choices about a fuzzy variable. In any case,

transactions are carried out about the two options and by scoring given to these preferences.

3.4 Membership Function Types

In the literature, while membership types are considered as function forms in some sources, geometric shape similarities are handled in terms of similarities.

Here, membership functions will be mentioned more in terms of shape similarities. Membership functions according to their forms are briefly divided into four groups in the literature:

- 1) Membership functions based on experimental decision making
 - a) Zadeh's single model (unimodal) function
 - b) Force functions of Dimitru and Luban
 - c) Sine function of Sawarowski
- 2) Reliability-based membership function specific to a particular problem
 - a. Linear function of Zimmermann (1976)
 - b. Symmetrical triangle function of Tanaka, Uejima and Asai
 - c. The partial linear function of Hannan
 - d. Hyperbolic function of Liberling
 - e. Exponential and inverse hyperbolic function of Sakawa and Yumine
 - f. The function of Dimitru and Luban
 - g. Linear random (L-R) fuzzy number of Dubois and Prade
- 3) Theoretical optional membership functions
 - a. Functions of Trussel
 - b. Functions of Sawarowski
- 4) Membership functions that suggest models for personalized concepts
 - a. Functions of Hersh and Caramazza
 - b. The functions of Zimmermann and Zysno
 - c. The function of Dombi

Although there are many different types of membership functions in terms of the relevant situation, the most common ones in practice are; triangle, trapezoid and Gaussal membership functions. However, there is also relatively rarely used sigmoidal, S type, Z type, π (pi) type membership functions.

- Triangle Membership Function

Triangular membership functions are defined by three parameters, a_1 , a_2 and a_3 . As can be seen in Figure 3.4, while a_2 is the core of the function, values between a_1 and a_3 constitute support.

$$M_A(x; a_1, a_2, a_3) = \begin{cases} 0 & , x < a_1 \text{ or } x > a_3 \\ (x - a_1) / (a_2 - a_1) & , a_1 \leq x \leq a_2 \\ (a_3 - x) / (a_3 - a_2) & , a_2 \leq x \leq a_3 \end{cases} \quad (3.1)$$

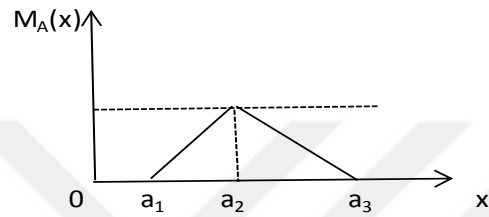


Figure 3.4 : Representation of the Triangular Membership Function.

- Trapezoid Membership Function

Trapezoid membership functions are defined by four parameters, a_1 , a_2 , a_3 and a_4 . As can be seen in Figure 3.5, the a_2 - a_3 range is the core of the function, while the values between a_1 - a_2 and a_3 - a_4 form the support of the function.

$$M_A(x; a_1, a_2, a_3, a_4) = \begin{cases} 0 & , x < a_1 \text{ or } x > a_4 \\ (x - a_1) / (a_2 - a_1) & , a_1 \leq x \leq a_2 \\ 1 & , a_2 \leq x \leq a_3 \\ (a_4 - x) / (a_4 - a_3) & , a_3 \leq x \leq a_4 \end{cases} \quad (3.2)$$

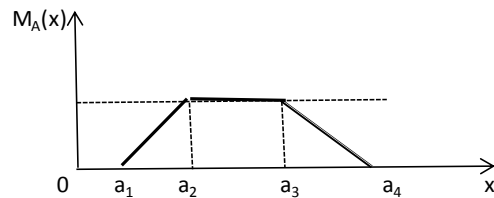


Figure 3.5 : Representation of Trapezoid Membership Function.

- Probability Density Functions and Gaussal Membership Function

The vertex of probability density functions used in statistical science is not in question, and the area under this function must be equal to 1. Since the probability density functions are convex, they can also be used as a membership function provided that the peak value is equal to 1. This is accomplished by dividing all values by the peak value, as mentioned in the normalization formula. Among the probability density functions, the most commonly used as membership function is the Gauss curve.

Gaussal membership function can be expressed with the m , σ parameters given below and shown as in Figure 3.6;

$$M_A(x; m, \sigma) = \exp(-(x-m)^2/2\sigma^2) \quad (3.3)$$

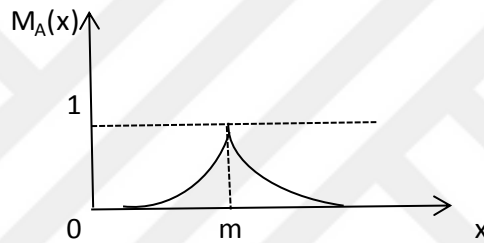


Figure 3.6 : Gaussal Membership Function (Şen, 2004, p. 55).

In this function, m determines the center of the distribution of the function and σ around the center, the width and shape of the function. As σ shrinks, the membership function becomes more pointed and thin, and as this value grows, the membership function will become more and more widespread.

The two-part Gauss membership function is a function obtained by dividing the Gauss curve into two equal parts, with more than one element (a range) with membership degrees 1.

- General Bell Curve

This membership function, shown in Figure 3.7, is defined with three parameters as a_1, a_2, a_3 ;

$$M_A(x; a_1, a_2, a_3) = 1 / (1 + \mathbf{I}(x-a_3)/a_1 \mathbf{I}_2^{2a_2}) \quad (3.4)$$

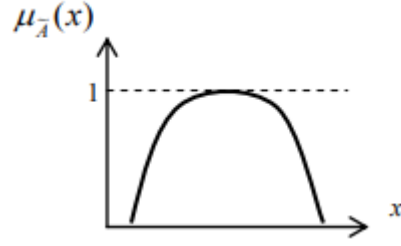


Figure 3.7 : Demonstration of the Bell Shaped Membership Function (Şen, 2004, p. 56).

- Sigmoidal Membership Function

In the sigmoidal type membership function, two parameters, β and α , are defined in Figure 3.8;

$$M_A(x; \beta, \alpha) = (1/1 + e^{-\beta(x-\alpha)}) \quad (3.5)$$

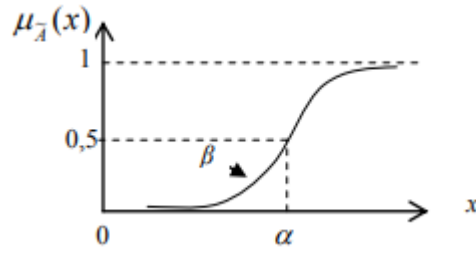


Figure 3.8 : Sigmoidal Membership Function (Dombi & Gera, 2005, p. 279).

β shows the slope of the curve, while the parameter α indicates the transition point of the function with a value of 0.5 membership.

- S Shaped Membership Function

This membership function is a regular membership function defined by a and b parameters. The name of this function comes from the shape resembling the letter S. Figure 3.9 shows the demonstration of the function.

$$M_A(x; a_1, a_2, a_3, a_4) = \begin{cases} 0 & , x < a \\ 2[(x-a) / (b-a)]^2 & , a \leq x \leq [(a+b)/2] \\ 1-2 [(x-b) / (b-a)]^2 & , [(a+b)/2] \leq x \leq b \\ 1 & , b \leq x \end{cases} \quad (3.6)$$

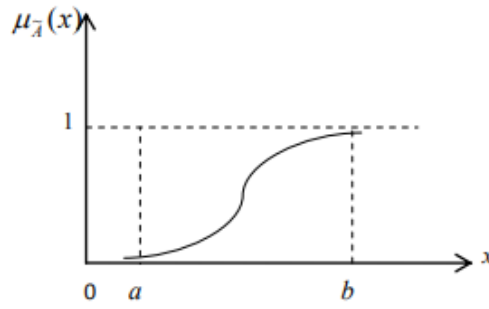


Figure 3.9 : S-shaped Membership Function (Bojadziev & Bojadsiev, 1995, p. 65).

- Fuzzy Number Definition

Fuzzy numbers are a subset of fuzzy sets and theoretical operations such as junction, intersection, α -cut and expansion rule in fuzzy sets are also valid for fuzzy numbers.

Fuzzy numbers are defined as real numbers, integers or natural numbers. Although every fuzzy number represents a fuzzy set, the opposite is not always valid. In order for a fuzzy set defined in R to be treated as a fuzzy number, it must meet the following minimum requirements:

- $\tilde{A}$ should be a normal fuzzy set
- $\tilde{A}$'s support set should be limited
- $\tilde{A}$ should be a convex fuzzy set

By defining these conditions or features, the definition of a fuzzy number can be given as follows:

If the weak α -segment of a normal and convex fuzzy set is a closed set, this fuzzy set is called a fuzzy number.

Fuzzy numbers are widely used to include inaccurate, tolerant or approximate numerical quantities in models. In this direction, fuzzy regression, fuzzy programming, fuzzy control and fuzzy decision making stand out among the usage areas of fuzzy numbers.

Fuzzy numbers, like fuzzy sets, represent approximation and for this, fuzzy numbers must have normal and convex membership functions. For example, it is clear that the membership function of numbers such as “about 5”, in other words, “roughly 5”, “around 5”, “close to 5” can be expressed as in Figure 3.10

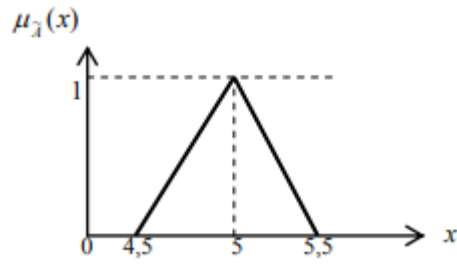


Figure 3.10 : Number of Fuzzy “Approximately 5”.

As can be seen in Figure 3.10, the number “5” has a membership level of 4.5 and 5.5, while the number 5 has a membership level of 1. Besides, the membership level of the number 5.3 belonging to the number “about 5” is also around 0.4.

Fuzzy numbers can be defined by membership functions just like fuzzy sets. Therefore, it can be said that there are as many numbers as the number of membership functions. Triangular, trapezoidal and Gaussian fuzzy numbers are the most frequently encountered in practice, but the ones with the most common usage are triangular and trapezoid.

- Triangular Fuzzy Number

In problems that can be expressed with fuzzy models, triangular fuzzy numbers are frequently used. The triangular fuzzy number (a_1, a_2, a_3) can be defined by the triplet and the membership function is shown in Figure 3.11

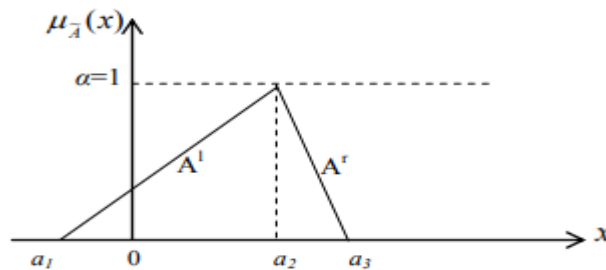


Figure 3.11 : Triangular Fuzzy Number (Chen, 2000, p. 3).

$$M_A(x; a_1, a_2, a_3) = \begin{cases} 0 & , x < a_1 \text{ or } x > a_3 \\ (x - a_1) / (a_2 - a_1) & , a_1 \leq x \leq a_2 \\ (a_3 - x) / (a_3 - a_2) & , a_2 \leq x \leq a_3 \end{cases} \quad (3.7)$$

Some important algebraic properties of triangular fuzzy numbers are:

- i. As a result of adding or subtracting two triangular fuzzy numbers, a triangular fuzzy number is obtained again.
- ii. As a result of multiplying, dividing, or taking the inverse of the triangular fuzzy numbers, a triangular fuzzy number may not always be obtained.
- iii. As a result of maximum or minimum operations of triangular fuzzy numbers, a triangular fuzzy number may not always be obtained.

Triangular fuzzy numbers, where two linear segments $(a_2, 1)$ such as A_l and A_r converge at the end point; It has membership function. This is a factor that facilitates graphical representation of triangular fuzzy numbers and trading with them. In addition, they can be easily created on the basis of a little knowledge.

- Trapezoid Fuzzy Number

Trapezoid fuzzy numbers are a special type of triangular fuzzy numbers. A trapezoidal fuzzy number (a_1, a_2, a_3, a_4) can be identified by a quadruple, and as seen in Figure 3.12, in $\alpha = 1$ there is not a single point, but a defined line in the range (a_2, a_3) . Trapezoid fuzzy numbers have the same algebraic processing properties as triangular fuzzy numbers.

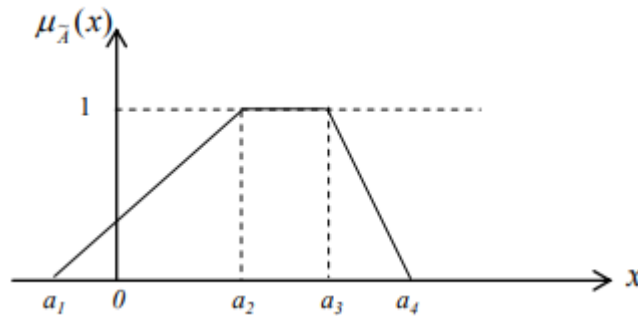


Figure 3.12 : Trapezoid Fuzzy Number.

The membership function;

$$M_A(x; a_1, a_2, a_3, a_4) = \begin{cases} 0 & , x < a_1 \text{ or } x > a_4 \\ (x - a_1) / (a_2 - a_1) & , a_1 \leq x \leq a_2 \\ 1 & , a_2 \leq x \leq a_3 \\ (a_4 - x) / (a_4 - a_3) & , a_3 \leq x \leq a_4 \end{cases} \quad (3.8)$$

- Gaussal Fuzzy Number

A gaussal fuzzy number can be expressed depending on the m and σ parameters with the membership function given in Figure 3.13. Parameter σ represents the distribution pattern of the fuzzy number in question and m indicates the distribution center. As the σ shrinks, the membership function becomes sharper, while the membership function gets more and more broad.

$$M_A(x; m, \sigma) = \exp(-(x-m)^2/2\sigma^2) \quad (3.9)$$

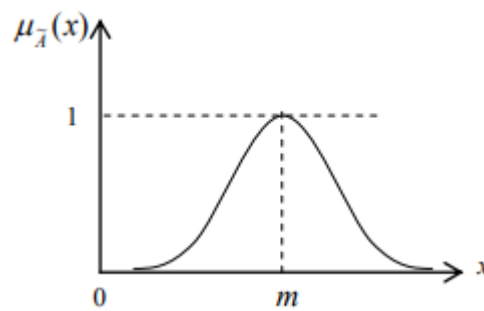


Figure 3.13 : Gaussal Fuzzy Number. (Kaya, 2007, p. 17-18)

3.5 Applications in Finance

Fuzzy logic is used especially in finance, investment management, portfolio optimization and technology systems. In some trading models, automatic buy and sell signals are generated using fuzzy logic, and fund managers' trade securities according to these signals. These systems help traders react to market volatility in multivariate financial markets.

Fuzzy logic-based models are often used in securities analysis and rule-based trading. Trading models analyze the prices of multiple securities simultaneously and offer investors the best trading potential.

Recently, fuzzy logic and neuro-fuzzy models have been used frequently for optimal portfolio creation. The reason for this is that these models give more successful results than statistical models. The ability of these models to analyze large amounts of data and the ability to learn from historical data can be shown as the reason for the successful results.

There are many factors that affect the prices of financial assets such as stocks, exchange rates, gold, commodities, and treasury bills. The large number of these factors and the fact that each factor affects asset prices in different ways makes it difficult to create an optimal portfolio. To overcome this problem, the analytic hierarchy process is used. This method tries to make the complex structure more orderly by handling numerous and complex factors in a hierarchy. Classical analytic hierarchy process and fuzzy analytic hierarchy process are used together to select the appropriate portfolio, and tried to determine which method was more effective.

There are models created to predict the stock price trend of the next day by looking at the historical data of stock prices. The basic methodology is based on artificial neural network - fuzzy logic system consisting of ANFIS control and stock market process model. If the trend prediction concluded that the stock price will be upwards, investment managers buy assets. Trading according to models signals is compared with the buy-hold strategy and it is seen that the proposed model was much superior.

As mentioned in the methodology part of the study, fuzzy logic was used as a layer in artificial neural networks in the study. In this layer, the performance of artificial neural networks has been increased by combining the advantages of fuzzy logic to make decisions like humans and to provide expert knowledge.



4. WAVELET ANALYSIS AND APPLICATIONS IN FINANCE

Wavelet transform is used for time-frequency analysis of a signal. The wavelet transform was first used to analyze seismic data, and then it was applied to different types of signals. The transformation used to detect discontinuities in signals and to remove noise is similar to the Fast Fourier Transform (FFT). In the transformation, it scales and shifts, acting as a master wavelet window. With scaling, the wave expands and contracts, and with translation, it shifts along the time axis.

The vast majority of signals in nature are non-stationary signals that change all the time. Therefore, the Fourier transform does not include frequency information. Wavelet analysis is a solution developed to solve the problem of frequency information loss. Due to all these advantages, Wavelet analysis is widely used and applied to many fields. There are many successful publications on image processing, image enhancement, noise analysis and boundary detection with wavelet transform method.

Although wavelet analysis is quite new in use, its foundations were laid in 1805 by Joseph Batista Fourier. The subject of frequency analysis, which forms the basis of the study of Fourier, has proven to be both an important and effective method. It is frequently encountered in practice today.

Considering that only frequency analysis is not enough, the transition from frequency analysis to scale analysis was made because the analysis of measured average fluctuations at different scales was less sensitive to noise.

In other words, instead of making decisions regarding the overall time series, it has come to the agenda that small fluctuations on a regional scale may be important. Therefore, wavelet analysis has been an important option for users.

With its current use, the word "wavelet" was first used in the appendices of Alfred Haar's (1909) doctoral dissertation.

Paul Levy modeled the Brownian motion (random walk of particles) and contributed to the wavelet theory (1930-1950). Levy proved that Haar's scale variable basic functions (Haar wavelet) model the random motion of particles better than the Fourier basic functions.

Details about the basics of wavelet theory were first introduced in 1985 by the Marseille Theoretical Physics Center working group under the direction of Jean Morlet and Alex Grossmann.

Wavelet analysis methods were developed by Yves Meyer and colleagues. The main algorithm is based on the work of Mallat (1988). After that, it is seen that the subject of wavelet analysis gained an international direction. In particular, researchers named Daubechies, Coifman and Wickherhouser have accelerated the subject with their important work. After this stage, it started to be heard frequently in the world literature. (1988-1989).

4.1 Introduction to Fourier analysis and Wavelet Theory

It is the Fourier Technique that is best known and used in the analysis of time series. Fourier analysis calculates different frequencies of a signal. With another point of view; converts a signal from time-based to frequency-based.

There is a disadvantage that time information is lost in analyzes made with the Fourier transform. For this reason, the Fourier transform does not tell where a particular event occurs. If the characteristic feature of the signal does not change over time, this disadvantage is not important. However, most signals contain imbalances that can be considered important or temporary features such as sudden changes or breaks. These characteristics may be the most vital part of the signal. Fourier analysis is not suitable for determining them. For this reason, transformation method to be used must be able to detect instabilities in the signal. The wavelet transform satisfies this condition. Example of sine wave and a wavelet is shown in Figure 4.1

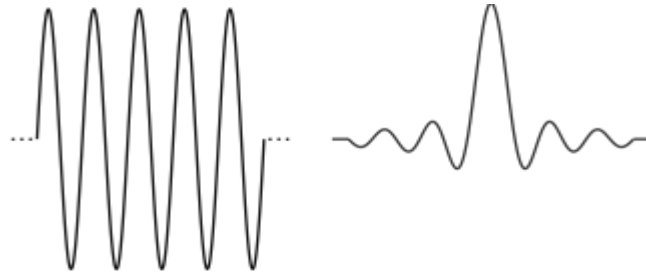


Figure 4.1 : Sine wave and a wavelet example.

- Wavelet

If we need to define roughly from the word meaning, wavelet; means small of the wave. A wavelet is an effective waveform in limited time.

For example, consider the sine wave that forms the basis of the Fourier analysis. Sine waves do not have a certain limit. It constantly repeats itself in the range from $-\infty$ to $+\infty$. In addition, sine waves have both smooth transitions and can be predicted. In contrast, wavelets tend to be irregular and asymmetrical.

In Fourier analysis, the signal can be expressed in different frequencies of the sine function, while in wavelet analysis the situation is somewhat different. The signal can be obtained by shifting the main wavelet on a certain scale and time.

Wavelet analysis allows looking at a signal from a perspective of time and scale. While the scale offers an idea about local regularity, time also refers to the moment of formation of the wavelet. In Figure 4.2, the effect of the scale factor on sinus and wavelet function is given.

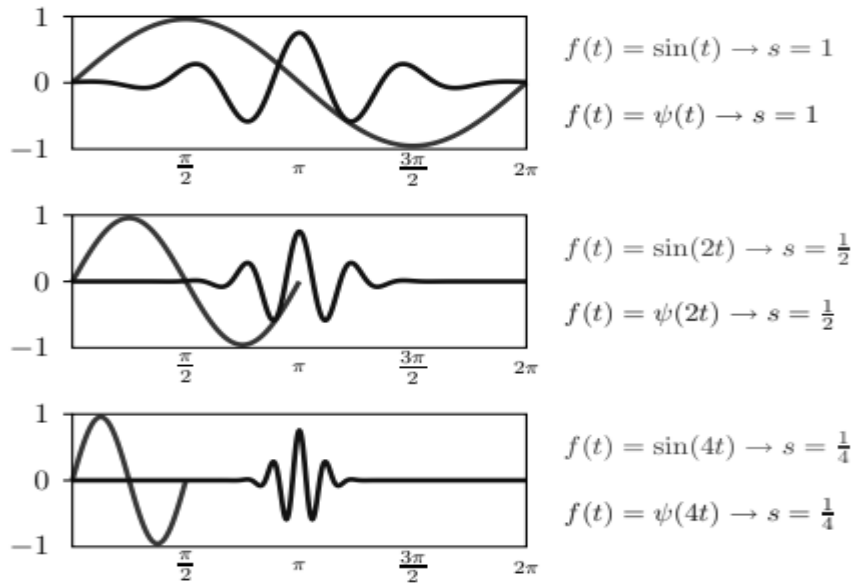


Figure 4.2 : Scale factor in sinusoidal and wavelet.

The scaling process is to stretch or shrink a function at a certain rate along the horizontal axis. The scale factor is symbolized by “s”. Briefly, as the scale factor becomes smaller, the wavelet is compressed at the same rate.

An important factor in wavelet analysis is the time that determines the sudden changes that occur. The moment of rupture, edge detection and short time formation are among the aims of wavelet analysis.

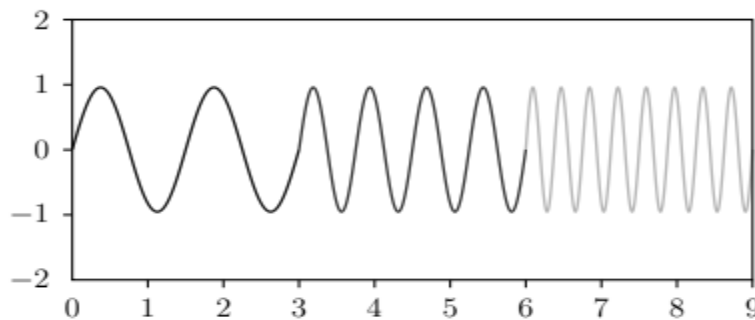


Figure 4.3 : Frequency change over time.

As seen in Figure 4.3, as time progresses, there may be changes in the frequency of the signal. In other words, the signal contains different frequencies at certain times. In this case, it turns out that the structure of the signal is not static. In the analysis of such signals, the location of frequency changes should also be determined.

In classical analysis methods, the frequency components of the signal are determined. These components are assumed to be in the entire signal. This assumption is not always true. The signal in Figure 3 is the best example of this. It should be such a mathematical tool; you can monitor the changes occurring at every moment of the signal.

- Short Time Fourier Analysis

To compensate for the timing deficiency of the Fourier analysis, Gabor (1946) put forward and successfully applied the idea that he could analyze the signal in small sections in the time domain.

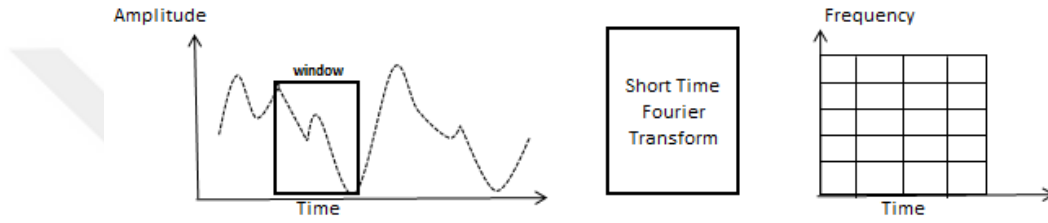


Figure 4.4 : Short Time Fourier Analysis.

As seen in Figure 4.4, the short time Fourier Analysis allows a signal to reconcile between time and frequency display. In other words, it gives information about when and at what frequency the signal occurred. However, this information cannot be obtained with certainty because accuracy depends on the size of the window. If the window size is large, the frequency resolution is good, if the window size is small, the frequency resolution is low.

The method is derived from the classical Fourier technique by multiplying the time signal by $f(t)$ and an approximate time window $w(t)$. In this way, the signal is analyzed step by step with the time window of the user choice. Placing the sliding window adds the time dimension and performs frequency analysis of time variables. Thus, unlike the standard Fourier analysis, the following equation is obtained.

$$F(\tau, \omega) = \int F(t) w(t - \tau) e^{-j\omega t} dt \quad (4.1)$$

While it is useful for the method to compromise between time and frequency information, the disadvantage is that the custom window we choose is the same for all frequencies. In other words, it is not possible to change the width of the window function for high and low frequency components in short time Fourier transform.

With just different window function widths, the short-time Fourier transform can be repeated several times, resulting in several time-frequency displays of the signal. However, this type of analysis is not useful since it causes both waste of time and unnecessary processes. Therefore, most signals require a more flexible approach. Thus, the size of the windows should change to determine the more accurate time or frequency component. For this reason, the method could not fully meet the need and another method was needed.

4.2 Wavelet Analysis

Wavelet analysis is the technique of windowing in variable-sized regions. It also enables the determination of low and high frequency information in long and short time intervals.

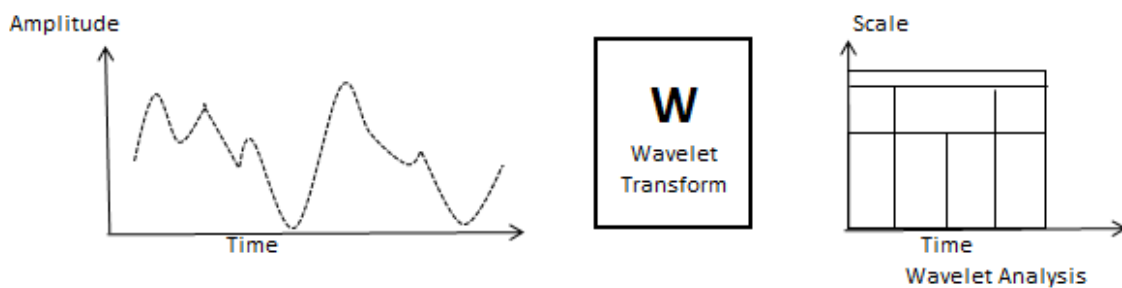


Figure 4.5 : Wavelet Analysis (Graps, 2006).

The fast Fourier Transform uses the time-frequency domain while the wavelet transform uses the time-scale domain. As can be seen in the Figure 4.5, as a result of the analysis, fields are formed, not a one-dimensional line.

Being able to analyze a large signal in a small area is the most important advantage of wavelet analysis. After the Fourier analysis of a sine signal, the spectral component graph is meaningless since it is a flat spectrum, whereas the location of the discontinuity can be shown exactly with wavelet analysis. Therefore, wavelet analysis is a successful method used in the analysis of signals with voids, inclines, breakpoints and discontinuity points. In addition, when compared to traditional methods, de-noising of a signal can be easily performed without disturbing the original of the signal with the help of wavelet analysis.

Mathematical Basics of the Wavelet

Short time Fourier analysis has a window function, while wavelet analysis uses a wavelet ($\psi(x)$) function. The analysis is performed by scaling the said wavelet function and shifting it in the time domain.

If the wavelet is considered in terms of quality, it should first be a real-valued function $\psi(x)$ that satisfies the following conditions:

- The integral of ψ is zero: $\int \psi(x) dx = 0$
- The integral of ψ square equals one: $\int \psi^2(x) dx = 1$

Any function $\psi(x)$ that satisfies these two conditions is considered a wavelet. The mathematical representation of the Haar wavelet, which is the most basic wavelet function, is as follows;

$$\Psi^{(H)}(x) = \begin{cases} -1/2^{(1/2)} & , -1 < x \leq 0 \\ 1/2^{(1/2)} & , 0 < x \leq 1 \\ 0 & , \text{otherwise} \end{cases} \quad (4.2)$$

Figure 4.6 shows the graph of the wavelet.

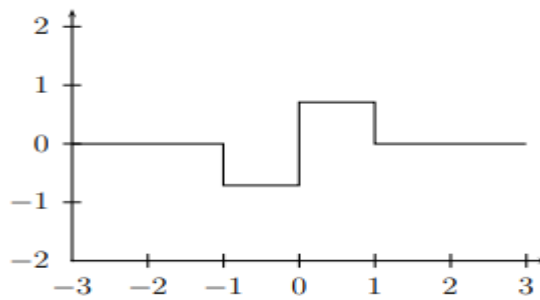


Figure 4.6 : Haar Wavelet.

To give another wavelet example, let's consider Gauss's probability density function (PDF), which we call the bell curve. The function is indicated by the following equation;

$$\phi(x) = (e^{-x^2/2\sigma^2}) / (2\pi\sigma^2)^{1/2} \quad (4.3)$$

The first derivative of this refers to a wavelet. The newly created function is as follows. The graphic representation of this statement is given in Figure 4.7.

$$\Psi^{(fdG)}(x) = (2^{1/2} x e^{-x^2/2\sigma^2}) / (\sigma^{3/2} \pi^{1/4}) \quad (4.4)$$

Then, the Mexican hat wavelet is created by derivatizing it a second time.

$$\Psi^{(MH)}(x) = (2 (1-x^2/\sigma^2) e^{-x^2/2\sigma^2}) / (\pi^{1/4} (3\sigma)^{1/2}) \quad (4.5)$$

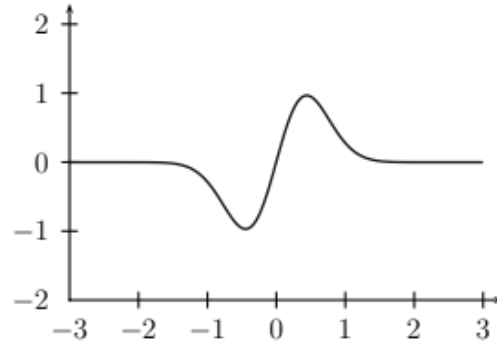


Figure 4.7 : Wavelet consisting of the first derivative of PDF.

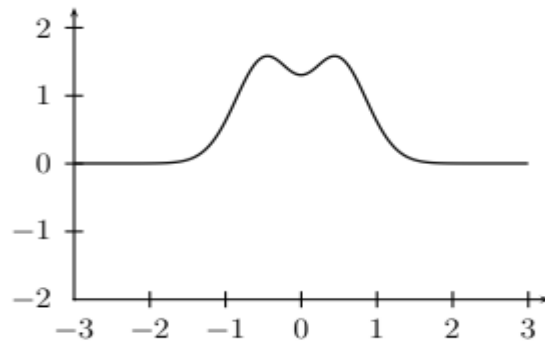


Figure 4.8 : Mexican Hat Wavelet

As can be seen in Figure 4.8, it will be possible to encounter different wavelet functions. There are different wavelets with different usage areas and the usage area differs according to the structure of the series to be analyzed.

Signals can be categorized in two structures;

- Continuous signals
- Discrete signals

Examples of continuous signals are musical recordings. Wavelet transform is used to eliminate noise in music recordings, assuming that music is formed by adding noise

to music signals. Noise contributes less to music than music signals, but it irritates the ears. With wavelet transform, coefficients smaller than a threshold value can be removed so that signals defined as noise are eliminated. The remaining coefficients represent the music itself. If there are parts of the music with coefficients as low as noise, they will also disappear with this transformation. Despite this disadvantage, the result will be better than the first case and listeners will hear smoother music.

Discrete signals consist of strings of numbers. For example, black and white photographs consist of dividing the picture into pixels. Each pixel is scaled by a value between all white or all black. These very small squares come together to form the whole picture. Mathematically, photography is the sum of the information that emerges as a result of numbering series of numbers according to the amount of light intensity.

Continuous Wavelet Transform (CWT)

Mathematically, the Fourier analysis process is represented by the Fourier transform.

$$F(\omega) = \int f(t) e^{-j\omega t} dt \quad (4.6)$$

The equation is obtained by multiplying the signal $f(t)$ by a complex exponential. The purpose of the transformation is to calculate these Fourier coefficients. Thus, a signal is split into its components with the help of the Fourier transform. Each component has its own amplitude and frequency. This process is shown graphically in Figure 4.9.

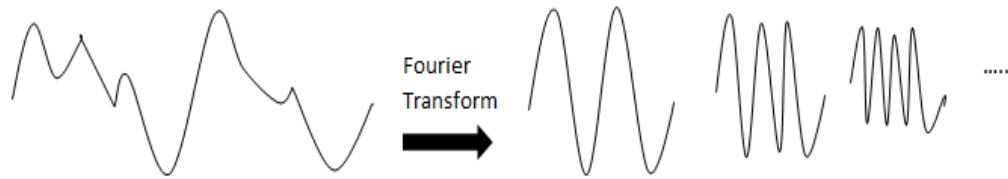


Figure 4.9 : Fourier transform

Similarly, Continuous Wavelet Transform (CWT) is the sum of the wavelet function (ψ) over the time domain after shifting and multiplying by a scale. Its mathematical expression;

$$SDD(\tau, s) = 1/IsI^{1/2} \int f(t) \Psi(t-\tau)/s dt \quad (4.7)$$

Where s represents scale and " τ " position. If we want to explain the algorithm of CWT, this process is defined in 5 steps.

These;

1. Compare the wavelet with the original signal,
2. Calculate the correlation coefficient C between the wavelet and the signal, the greater the coefficient, the more similarity will be,
3. Move the wavelet a little to the right, repeat steps 1 and 2 until it covers the entire signal,
4. Scale the wavelet and repeat steps 1, 2 and 3,
5. Repeat steps 1 to 4 for all scales.

After performing these operations, coefficients of different scales are obtained in different regions of the signal. These coefficients show the regression results of the original signal.

Discrete Wavelet Transform (DWT)

Performing wavelet analysis within certain intervals eliminates the difficulty of working with big data. The application of wavelet transform in selected intervals taking into account the scale and position values is called Discrete Wavelet transform (DWT). As a mathematical theory, there is no difference from CWT. Only the scale and position values of the account boundary in the time domain depends on the analyst's preference.

Relationship between Wavelet Scale and Fourier Frequency

While Fourier analysis separates a signal into its components at different frequencies, wavelet analysis performs the operation at different scales. Since the aim is to determine the hidden periodicity within the signal, it is necessary to establish a relationship between the scale and frequency. This relationship is $s = 1 / f$. Although there is an inverse proportion between frequency and scale, the Fourier period is not equivalent to wavelet scale. That is, when the type of the main wavelet changes, the ratio between the period and the scale changes. For example, while the scale of the Morlet wavelet is almost equal to the Fourier period, the scale in the Mexican hat is $1/4$ times the Fourier period. Therefore, the scale-period relationship should be known well before the analysis.

4.3 Application of Wavelets

Different application areas of wavelet analysis are as follows;

- Signal processing
- Data compression
- Smoothing and image noise removal
- Fingerprint verification
- DNA analysis
- Blood pressure, heart rate and ECG analysis
- Finance
- Speech recognition
- Computer graphics and multifractal analysis

4.4 Advantages of Wavelet Theory

1. With the wavelet transform, time and frequency can be analyzed simultaneously.
2. Fast wavelet transform provides convenience in calculations.
3. Wavelets can distinguish different sized components in a signal.
4. It is possible to represent a function to a large extent using a small number of coefficients.
5. Breakpoints, discontinuities and trends in a signal can be determined with wavelet analysis.
6. With wavelet transform, a signal can be compressed or noise removed without deteriorating its original state.

4.5 Wavelet Families

4.5.1 Haar

The Haar wavelet is the first and simplest type of wavelet known. It is a wavelet with compact support defined as the zero of a wavelet outside a finite range. The advantage of the Haar wavelet is that it is fast and has an efficient memory. The main wavelet function of the Haar wavelet is shown in Figure 4.10 and can be defined as:

$$\Psi(t) = \begin{cases} 1 & , 0 \leq t < 1/2 \\ -1 & , 1/2 \leq t < 1 \\ 0 & , \text{otherwise} \end{cases} \quad (4.8)$$

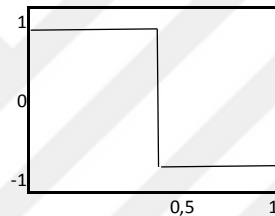


Figure 4.10 : Haar Wavelet Function.

4.5.2 Daubechies

Based on the work of Ingrid Daubechies, Daubechies wavelets are a family of orthogonal wavelets that describe a discrete wavelet transform and are characterized by the maximum number of vanishing moments for a given support. Each wavelet type of this class has a scaling function that produces orthogonal multi-analysis analysis.

The Daubechies wavelet family is expressed as DbN. Here N represents the order. The db1 wavelet is the same as the Haar wavelet. The functions of some members of the family are shown in Figure 4.11;

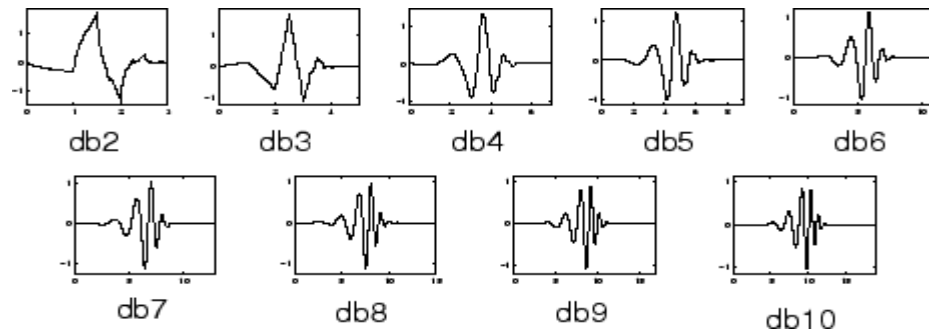


Figure 4.11 : Daubechies Family wavelets.

4.5.3 Biorthogonal

This family of wavelets is similar to orthonormal wavelets, but unlike orthonormal wavelets, they use two wavelets. The wavelet on the left is used for decomposition, and the wavelet on the right is used for reconstruction. Figure 4.12 shows some examples of this family.

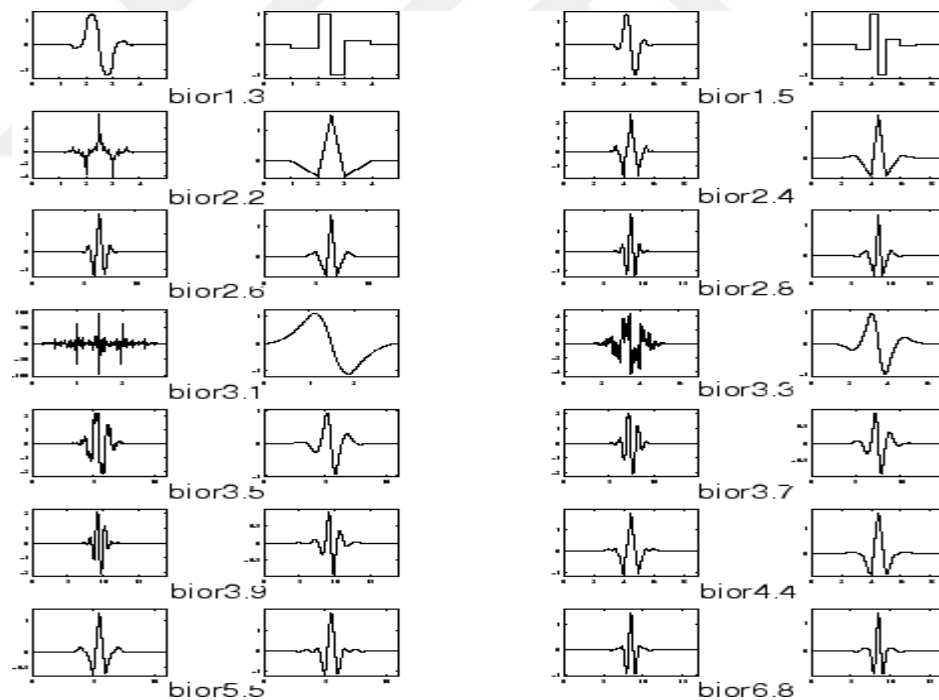


Figure 4.12 : Biorthogonal family wavelets.

4.5.4 Coiflets

Coiflets are discrete wavelets designed by Ronald Coifman and Ingrid Daubechies. In wavelets with a $2N$ vanishing moment and a $2N-1$ scaling function, the low and

high pass filters are normalized by a factor of $1/2^{1/2}$. Some examples of coiflet family wavelets are shown in Figure 4.13.

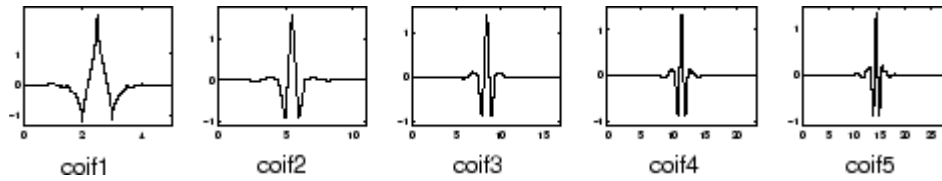


Figure 4.13 : Coiflet family wavelets.

4.5.5 Symlets

Scaling and wavelet functions in symlets, which are similar to the Daubechies family, have a $2N$ support length. SymletWavelet, also known as the "smallest asymmetrical" wavelet, belongs to the orthogonal wavelet family.

Symlet wavelet functions are as Figure 4.14;

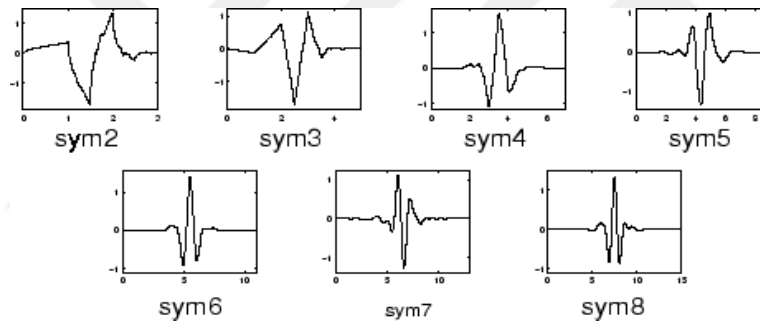


Figure 4.14 : Symlet family wavelets.

4.5.6 Morlet

Morlet wavelet, shown in Figure 4.15, also known as Gabor wavelet, has no scaling function. Although $[-4, 4]$ has an effective support range, $[-8, 8]$ support range can also be used to get more successful results in calculations.

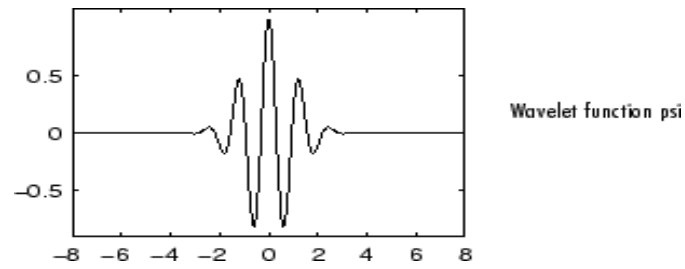


Figure 4.15 : Morlet wavelet.

4.5.7 Mexican Hat

The Mexican hat wavelet, also known as Ricker wavelet and shown in Figure 4.16, derived from the Gaussian function, has no scaling function. It is mainly used to analyze seismic data and in computational electrodynamics.

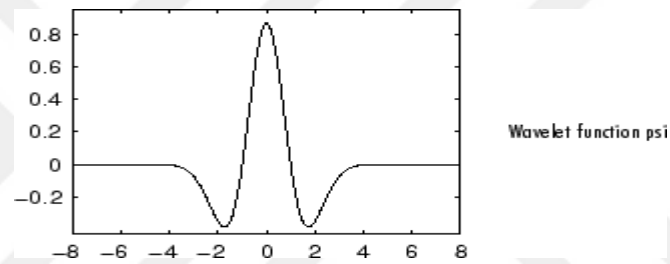


Figure 4.16 : Mexican Hat wavelet.

4.5.8 Meyer

The Meyer wavelet, shown in Figure 4.17, discovered by Yves Meyer is a continuous orthogonal wavelet. It is used in error classification, filtering and fractal field calculations.

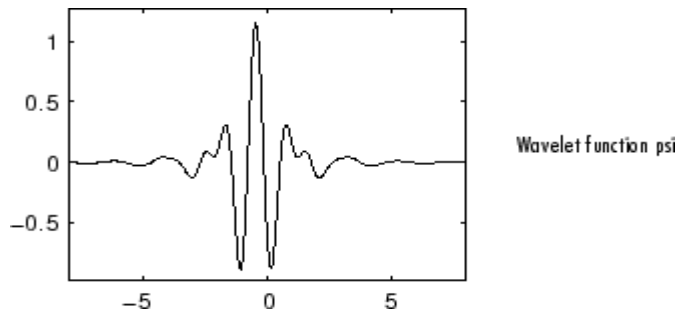


Figure 4.17 : Meyer wavelet.

4.6 Applications in Finance

Wavelet transform is a commonly used method for compressing, analyzing and separating signals. It is used to analyze images and sounds in physics, chemistry and biology as well as high frequency time series in finance and economics.

In recent years, the big data era has begun, as the values of many financial assets can be measured instantaneously with high frequency. Large datasets are large volumes, high variability and complex time series. Increasing complexity necessitates advanced data processing. Finance professionals have begun to use new and powerful methods such as wavelet analysis to make sense of information in data and make smart decisions.

Over time, the weaknesses of classical analysis methods have emerged. Time series analyzes focus only on time, spectral analyzes focus only on frequency. These traditional techniques are based on the assumption that the data is stationary. Whereas this is not the case for most financial time series, the volatility of these series often includes complex structures such as breaks, clusters and long memory. In addition, frequency separation with spectral analysis is meaningful in periods when markets are stable, in most cases market movements are high in some periods and stagnant in other periods. Wavelet analysis, on the other hand, is flexible and does not require strong assumptions, it is capable of analyzing highly complex data without the need to know the underlying causes. This is of great benefit in finance time series, as the underlying process of a dataset is not always fully known.

While time series analysis and spectral analysis provide information about time and frequency, wavelet analysis can perform both time and frequency analysis at the same time. This feature of wavelet analysis is very important for examining finance

series, as these variables can work differently and interact with each other. For example, the price of two financial assets may behave similarly in the long run but differ significantly in the short run. In addition, wavelet analysis can detect time regime changes by detecting discontinuities in series, and find shocks isolated to dynamic systems.

Knowing the correlation between assets in finance is very important for creating an investment strategy. Investors can improve returns and reduce portfolio risk by investing in assets with low correlation. In order to create an optimal portfolio, the correlation between assets must be estimated. Although the correlation coefficient can be easily calculated, the time series must be free of short-term noise in order to successfully predict the long-term correlation. Therefore, before performing the correlation analysis, it is possible to extract unwanted information from the series by separating the main signals and noise with wavelet transform.

Forecasting in finance and economy is one of the important applications with its wide usage area. Investors use forecast prices to make decisions about buying, selling or holding assets or to update their portfolios. Economists and policy makers, on the other hand, calculate GDP, inflation, house price, etc. They estimate economic variables, such as, for policy-making decisions. It has been observed that DWT produces successful results when used together with other time series estimation techniques.

As mentioned in the methodology part of the study, wavelet transform was used as a preprocessing in the study. The data to be estimated were decomposed before going to the fuzzy neural network model. Thus, it is possible to make predictions of all sub-layers of the data by using of the ability of the wavelet transform to decompose the data.



5. ARTIFICIAL NEURAL NETWORKS AND APPLICATIONS IN FINANCE

Artificial Neural Networks are a kind of artificial intelligence algorithms that imitate the perception, knowledge creation and learning features of the human brain without any outside help. It works with a model similar to the methods the brain uses when performing a function and consists of nerve cells that connect to each other. People can make predictions on many different issues and problems with the knowledge and experiences they discover by learning. However, Artificial Neural Networks can produce faster and more powerful solutions to complex problems. It offers solutions and predictions to these complex problems by mimicking the human brain. This system inspired by the human brain; In addition to forecasting, it also has classification, clustering, analysis and association features.

Although artificial neural networks are used for application, prediction, diagnosis, planning, surveillance, repair, routing and control, the most used and successfully applied areas are classification and image recognition. Classifies or identifies an object under the names disease, tissue, image, and chemical compound. Another usage area is to translate text to speech

Neural networks analyze the data, learn its characteristics, detect the patterns in data and make decisions about the new data using the information it has learned. Artificial neural networks are used in solving complex problems in many different disciplines due to their ability to learn, generalize and predict.

In other words, an artificial neural network is a mechanism inspired by the information processing structure of the human brain, consisting of interconnected nerve cells and having a memory.

The foundations of the first computational model on which artificial neural networks are based, is published by Warren McCulloch and Walter Pitts. A model that reacts to and adapts to the warnings is created by Clark in a network. 1960 was the first year of the emergence of the first neural computer. Although the first examples contain

deficiencies, successful results started to be obtained with the development of nonlinear networks after the 1970s. After the 1980s, research with artificial neural networks continued intensified.

The main areas of use are image and sound recognition, error analysis, traffic control units, estimation of time series. As seen in Table 5.1, ANN's have several advantages.

Table 5.1 : Comparison of Traditional Algorithms and ANNs (Pirim, 2006).

Traditional Algorithms	Artificial Neural Networks
Outputs are obtained by applying the inputs to the established rules.	During learning, input and output information is given and rules are set.
Information and algorithms are precise.	It benefits from experience.
Calculations are central, simultaneous and sequential.	Calculations are collective, asynchronous, and parallel after learning.
Memory is packed and literal information is stored.	The memory is allocated and spread over the network.
There is no error tolerance.	It has error tolerance.
It is relatively fast.	It is slow and hardware dependent.

Nerve cells called neurons are made up of body, dendrites, and axons. Neurons interact with other cells in biological neural networks. It is known that there are billions of neurons in the human brain. The structure of a neuron is shown in Figure 5.1;

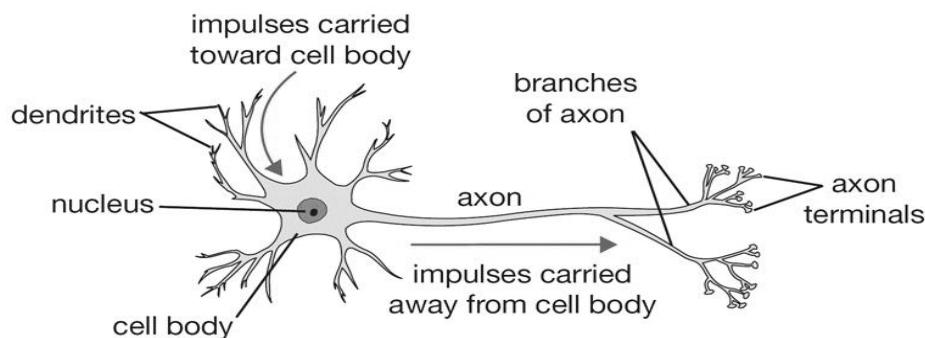


Figure 5.1 : Biological Representation of a Nerve Cell.

- Axon: It is the output of the system. It is an active region with one-way electrical conduction on the body.
- Dendrites: It is the input of the system. It consists of electrically passive arms around the nucleus.

- Synapse: They connect axons with dendrites.
- Nucleus: This is where signals are produced along the axon.

The signal reaches the cell body with dendrites, then it is transmitted to the dendrites of other nerve cells via axons. Synapses between axons and dendrites allow the transmission of the signal. The "synaptic vesicles" within the synaptic space are elements that condition the incoming stimuli to pass to other cells through dendrites. The filling of the neuroconductive substance provided by the "synaptic vesicles" into the synaptic cavity conditions the passage of impulses to other cells. The learning process of neural networks occurs with the establishment of new synaptic relationships between cells. The equivalents of the elements in the biological nerve structure are shown in the Table 5.2

Table 5.2 : Biological Neural Structure and Artificial Neural Network (Koç, 2004).

Biological Nervous System	Artificial Nervous System
Neuron	Processor element
Dendrit	Collection function
Cell body	Transfer function
Axons	Artificial neuron output
Synapse	Weights

The mathematical model of a human nerve cell can be illustrated in Figure 5.2,

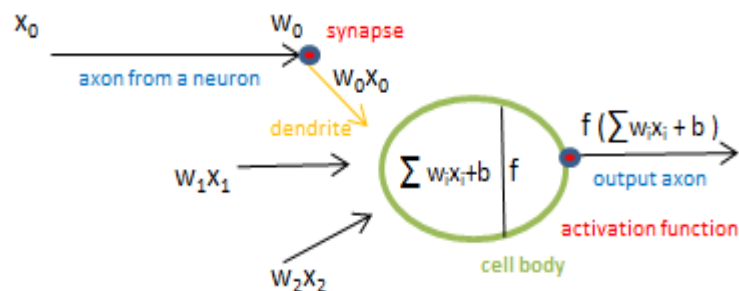


Figure 5.2 : Mathematical Model of a Nerve Cell.

Perceptron: It is the smallest part of the artificial neural network and is first described by Frank Rosenblatt in 1957.

$$Y = w * x + b \quad (5.1)$$

y: It depends on the value of x, it is a dependent variable. Returns the score for the input.

x: argument, input.

W: weight parameter

b: bias value

Artificial neural networks contain artificial nerve cells that perform the task of nerve cells in biological neural networks. General structure is shown in Figure 5.3,

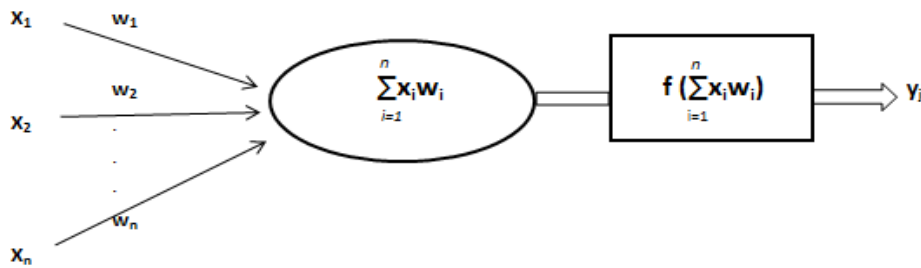


Figure 5.3 : General structure of artificial neural networks (Öztemel, 2006).

Inputs: These are the data to be used in determining the outputs. The learning process takes place over these data.

Weights: Indicates the importance of information coming into a cell. The weight w_i in the figure shows the effect of the x_i input on the cell.

Addition Function: This function is used to calculate the net input to be evaluated. All inputs are multiplied by their weights and the results are summed. Some aggregation functions are included in the Table 5.3.

Table 5.3 : Some Addition Functions (Çayıroğlu, 2015).

	N	
Sum	$\text{Net} = \sum_{i=1}^N X_i * W_i$	The weight values are multiplied by the inputs and the found values are added together to calculate the Net input.
Multiplication	$\text{Net} = \prod_{i=1}^N X_i * W_i$	The weight values are multiplied by the inputs and the found values are multiplied with each other to calculate the Net input.
Maximum	$\text{Net} = \text{Max} (X_i * W_i)$	After multiplying the weights with the inputs out of n inputs, the largest one is accepted as the net input.
Minimum	$\text{Net} = \text{Min} (X_i * W_i)$	After multiplying the weights with the inputs out of n inputs, the smallest one is accepted as the net input.
Kumulative Sum	$\text{Net} = \text{Net (ex)} + \sum X_i * W_i$	The information coming into the cell is mainly collected. The net input of the cell is calculated by adding the newly calculated input values to the information previously received in the cell.

Activation Function: This function calculates the output to be produced by processing the net input calculated by the sum function. Activation functions are usually chosen from nonlinear functions. Although choosing functions that can be easily calculated has the risk of reducing the output quality, it is advantageous in terms of making the calculation fast.

Output: This value is the output calculated with the activation function. It can be the result of the model, or it is sent to another neuron for processing in multilayer networks.

5.1 Main Components of Artificial Neural Networks

1. Architectural Structure
2. Learning Algorithm
3. Activation Function

Since these components directly affect the performance of the forecasting, it should be preferred that the structure of the data is appropriate at the decision point.

5.2 Architectural Structure

Learning Algorithm

The ability to learn from inputs and outputs defined to the network is critical to the success of artificial neural networks. How the weights are determined is important because the information is held in weights. Training the network is the process of dynamically changing these weights and determining the most appropriate values by comparing the performances of the results.

Activation Function

The activation function provides the matching between inputs and outputs. Therefore, the choice of this function significantly affects the success of the network. Unipolar, linear or non-linear functions can be used.

Various models have been developed for artificial neural networks, the most used are single-layer neural networks, simple neural networks, adaline and multi-layer neural networks.

1. Single Layer

Single-layer neural networks consist of only input and output layers. All inputs have a weight and the output is found from the calculation with these weights. A single-layer neural network consisting of two inputs and one output is given in Figure 5.4.

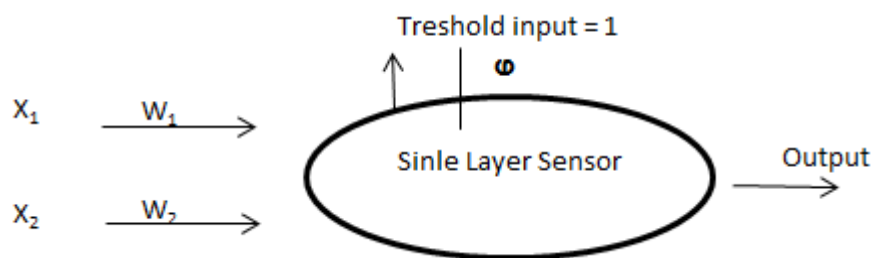


Figure 5.4 : Single Layer Model (Öztemel, 2006).

To prevent the output value from being zero, a threshold value of 1 is defined. The output is calculated by processing the inputs with the activation function. In such networks, the output value is linear, so it can take the values of 1 or -1.

2) Simple Sensors

Simple networks found by Rosenblatt in the late 1950s are the models used for classification purposes. It works on the principle of planar separation of classes. It

works in the form of an output as a result of more than one input and processing these inputs with the activation function. As shown in figure 5.5, output can be 1 or 0 and represents the class to which the inputs belong.

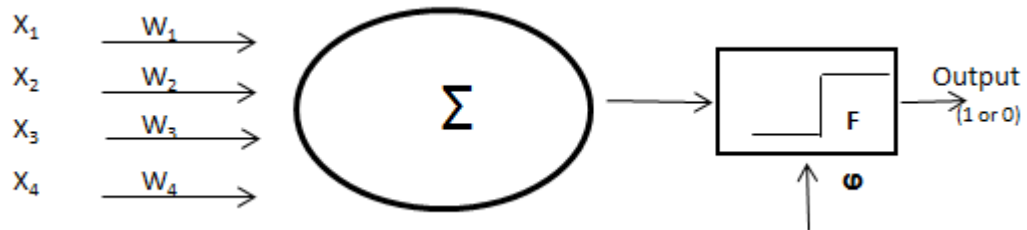


Figure 5.5 : Simple Sensor Model (Diamond, 2003).

3) Adaline

The Applied Linear Neuron (Adaline) was developed by Bernard Widrow in 1959. The two-layer model used for topics such as voice and character recognition, noise removal and weather forecasting is called madaline (Multiple Adaline). The use of Adaline to eliminate echo on telephone lines is the first time artificial neural networks have been used to solve a real-life problem. Since the linear function is used, it is insufficient in solving complex problems. Learning is performed by dividing the inputs into patterns and new inputs can be classified by the network after training.

4) Multi Layer Sensors (MCA)

Multi-Layer Networks using nonlinear functions have emerged because single-layer network and adaline models are insufficient in solving complex problems because they use linear functions. Having a structure in which many neurons with non-linear activation function in terms of architecture are hierarchically linked, MLP uses the learning system called back propagation as well as the advantages of the Sensor and Adaline methods, and in general, artificial neural networks are divided into feed forward and feedback networks.

Neurons in a layer are not related to each other and they perform the task of transferring the information that is in the system to the next layer or output. "Learning performance increases as the number of layers increases", although it seems to be said, this is not true. Because model performance has to do with inputs and layers, but it is not determined by this. The effect of many different

hyperparameters affects the output performance. In cases where the Model Input (x) is '0', the value of $W.x = 0$ and $+ b$ shifts the output of the score function. Thus, it ensures that the model continues the learning process in the next iteration. Only this step has no effect on the learning process. Take a look at the forward and backward spread issues. W weight vector node / neuron number (cell), bias (b) values should be the number of nodes in the next layer.

Feed Forward Networks

Feed forward neural networks allow for unidirectional signal flow. Information is first processed in the hidden layers before being transmitted to the output layer after the input layer. An example of a feedforward network consisting of two hidden layers and output layers is given in Figure 5.6. These networks provide continuous learning with gradient-based training.

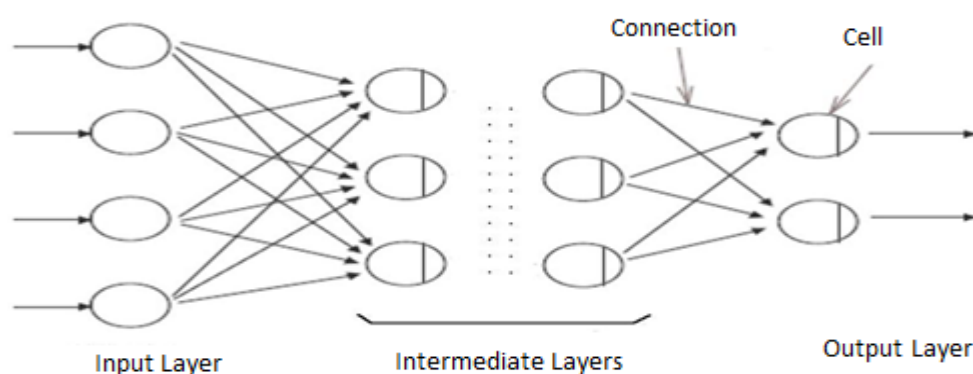


Figure 5.6 : Example of Feedforward Neural Networks (Öztemel, 2006).

Feedforward neural networks consist of input, intermediate and output layers. The output values of one layer are determined as the input value of the other layer and processed in the relevant layer. As soon as the input layer does not function, it transmits the information to the middle layer, and the output value is calculated with the information processed with the relevant functions in the middle layer and output layer. Feedforward networks operate with nonlinear functions, back propagation learning algorithm is generally used for the training function. For the learning process, sample inputs and outputs are given to the neural network, and the network that produces an appropriate transformation function based on the examples given can then give successful results for new inputs.

Feedback Neural Networks

In feedback neural networks, the output of at least one cell is given as input to the previous cells. This operation is done with a delay element and can be between cells in the same layer or between cells in different layers. Such networks use nonlinear functions. An exemplary bilayer feedback neural network structure is shown in Figure 5.7.

Since feedback neural networks are successful in making predictions, they are frequently used in the predictions of time series. Examples of these networks are Hopfield, Self Organizing Map, Elman and Jordan networks.

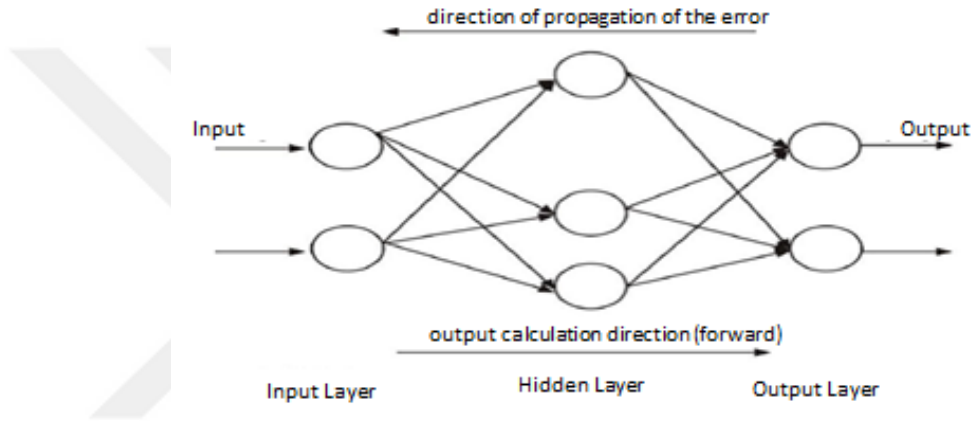


Figure 5.7 : Feedback ANN (Kabalcı, 2015).

Back Propagation Algorithm

In the back propagation algorithm, as in other algorithms, there is a relationship between the learning process and the sample input and output values. While calculating the relationship, the error term is tried to be reduced by changing the weights. The error, $e(t)$, is the difference between the desired output $t(t)$ and the output $y(t)$ of the neural network.

$$e(t) = t(t) - y(t); t = 1, \dots, m \quad (5.2)$$

The purpose of the back propagation-learning algorithm is to spread the error function to the entire network with the chain rule, thereby reducing its effect and thus reducing the error value.

$$E_{\text{Top}} = \lim_{T \rightarrow \infty} \frac{1}{T} \left(\sum_{t=1}^T E(t) \right) \quad (5.3)$$

$$\Delta w_{ji}(t) = \eta \delta_j x_i + \alpha \Delta w_{ji}(t-1) \quad (5.4)$$

With this algorithm the change of $w_{ji}(t)$ in the weights between the i and j floor process elements is calculated. In equation 5.4, η is a factor of learning coefficient, α momentum coefficient and any j neuron in the intermediate or exit floor. For the output stage, this factor is given as follows.

$$\delta_j = \epsilon f' / \epsilon_{netj} (y_{jt} - y_j) \quad (5.5)$$

Here, $y_j(t)$ is the target output of the j processor element. This factor for the Operation Elements on the intermediate floors,

$$\delta_j = (\epsilon f' / \epsilon_{netj}) \sum w_{qi} \delta_q \quad (5.6)$$

Equation 5.6 is used instead of 5.5 because there is no output target for the operation elements. The δ_j factor is calculated for the operation elements in all layers, including the output layer, and the weights are updated with equation 5.4. It will be advantageous in terms of computation that the activation function used in this algorithm is continuous and its derivative can be taken simply. A sample of feedforced multilayer neural network is shown in figure 5.8.

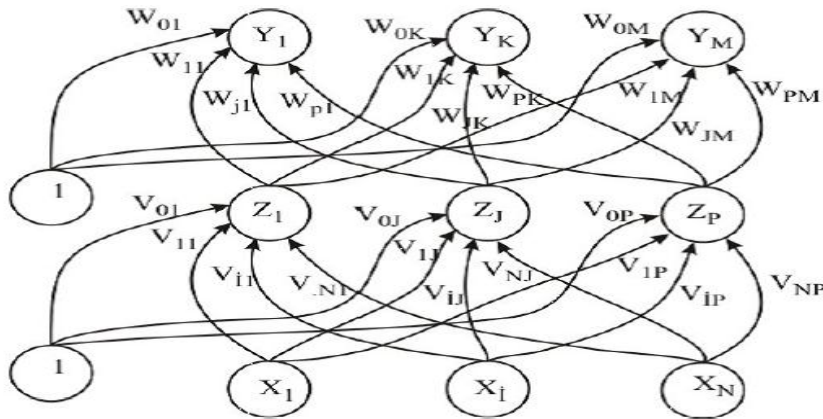


Figure 5.8 : Feedforced multilayer neural network: x, z, y vectors and V, W matrices (Yüksek vd, 2007).

5.3 Advantages of ANNs

Although ANNs display different characteristics according to the network model applied, they have several common features.

1. ANNs consist of many cells and these cells work simultaneously, performing complex functions.

In other words, complex functions are created by the simultaneous operation of many cells. Even if any of these cells lose their function in the process, the system can continue to operate safely.

2. The numerical information used during the training is to obtain the general characteristics of the problem and thus to produce meaningful answers for the inputs that are not used during the training.
3. Certain types of non-linear subunits scattered over the structure also enable the solution of non-linear problems.
4. Artificial neural networks can make the right decisions in similar situations with machine learning.
5. Information processing methods differ from traditional programming. Therefore, much negativity brought about by traditional programming can be eliminated.
6. Information is spread throughout the network and stored in network connections measured by values. Loss of function of some cells does not cause meaningful information to be lost.
7. They have distributed memory. In ANNs, information is kept scattered across the network. The connection and weight ratings of the cells show the information of the network. Therefore, a single connection has no meaning on its own.
8. Artificial neural networks perform the learning function through sample inputs and outputs. The quality of the examples given determines the success of the network, and if the examples are not sufficiently inclusive and representative, successful outputs may not be achieved.
9. They can produce information about previously unseen examples. ANNs derive generalizations from the examples given to them during their education and can produce information about these generalizations and new examples.
10. They can be used in detection oriented events. The areas where ANNs are most successful are application areas for perception. Their success has been proven in these areas.
11. They can associate and classify patterns. ANNs can relate patterns given to them with themselves or others. They can also be used to decide which cluster to include the next data by clustering the samples given to it.

12. They can complete the pattern. When the network contains patterns containing missing information, they are successful in completing this missing information.
13. They have the ability to learn and organize on their own. ANNs can learn online and educate themselves.
14. They can work with missing information. Unlike traditional systems, ANNs can produce output after training even if the data contains incomplete information. This situation does not cause a loss of performance, loss of performance depends on the importance of missing information. The importance of information is learned during education.
15. They have fault tolerance. The ability of ANNs to work with missing information and even if some of their cells are damaged makes them tolerant of errors.
16. They show graceful degradation. A network suffers from a slow and relative deterioration over time. Networks do not immediately fail as soon as the problem occurs.

5.4 Disadvantages of ANNs

ANNs have some disadvantages besides many advantages. The main disadvantages are;

1. Hardware dependent. The most important problem of ANNs is that they are hardware dependent. One of the most important features of ANNs and the reason for its existence is its ability to perform parallel operations, it performs with parallel processors.
2. There are no predetermined rules to determine the most suitable network structure, the appropriate network structure is determined by trial and error method or according to the studies done for solving similar problems.
3. There is no specific rule in the determination of parameters such as learning coefficient, number of cells, and number of layers in ANNs. Although there is no specific standard for determining these values, there may be a different approach for each problem.

4. Since Artificial Neural Networks are mathematical models, they work with numerical information. Problems must be converted to numeric values when introducing them to the network, which is limited by the user's ability.
5. In order for the network training to be completed, the error term must fall below a certain threshold. This threshold value may vary from person to person. There is no mechanism for optimum results here yet and forms an important branch of ANN-related research.

5.5 Training Artificial Neural Networks

The human brain interprets the behaviors it perceives with the sense organs from its environment in the development process after birth and uses this information in other behaviors. As we live, the brain develops and experiences. Now he often knows how to react to events. But in the face of an event he has never encountered, he may still be inexperienced. In the learning process, the inputs are processed with the activation function and the outputs are calculated. The calculated outputs are compared with the samples given to the network and the error rates are found. It is tried to approach the real output by reducing the error with various learning algorithms. It is the weights of the artificial neural network renewed during the study. Weights are renewed in each cycle and the aim is tried to be reached. The measure of achieving or approaching the goal is an external value. If the network starts producing outputs with a low error rate, the used weights are kept in memory.

The time that passes until the desired result is achieved by constantly renewing the weights is called learning. After the learning process is completed, new inputs are given to the network and the outputs are examined. If it approaches the new examples correctly, neural network has learned the job. If the number of samples given to the neural network is more than the optimum value, it means that the neural network has not learned and memorized the work. In general, 80% of the data set is used for learning and the remaining 20% for testing.

1. Collection of samples: It is the process of collecting historical data for the learning process of the network. Historical data is used to train and test the network. The examples in the training set are shown one by one, so that the network can learn the event. After the learning process, new inputs are

defined to the network and outputs are calculated. The accuracy of the outputs produced against the new inputs indicates the performance of the network.

2. Determining the network structure: It is the step in which the topological structure of the network such as the number of inputs, the number of middle layers, the number of processing elements and the number of outputs are determined.
3. Determining the properties of the learning function: This is the step in which properties such as learning coefficient, activation function, and addition function is determined.
4. Assignment of the initial values of the weights: The initial weight values and the weights of the threshold unit are determined. The start is usually assigned random values. The network then determines the appropriate values during learning.
5. Selecting samples from the learning set and displaying them to the network: Examples of the network are displayed according to a certain arrangement so that the network starts learning and changes weights in accordance with the Learning rule.
6. Learning calculations: In this step, output values are calculated for the input values given to the network.
7. Calculation of the network error value: The error value is calculated by comparing the actual outputs with the outputs produced by the network.
8. Changing the weights: Weights are changed to reduce the error produced by applying the recalculation method.
9. Completion of learning: The feed forward neural network continues until it completes learning, that is, the errors between actual and expected outputs decrease to an acceptable level.

The weights of the input values are initially randomly generated. By analyzing the sample inputs and outputs given to it, that is, by learning, the network changes the weights and reaches the ideal values.

In some cases, the place where the network is attached may remain above the error level. In this case, in order for the network to learn the event, some changes must be made and retrained. These are;

- Changes to the initial values can be made.
- Changes can be made to the network topology.
- Changes can be made to the parameters of the network.
- A new set of samples can be created by changing the display of the data presented to the network and the formulation of the samples.
- The number of data used for learning can be changed.

Momentum coefficient has been developed to ensure that the feed forward neural network does not get caught in local optimum. If the weight values determined at the beginning are chosen in a large range, the probability of falling into the local optima is high. If it is selected in a small range, it may have the disadvantage that the learning time is too long. Some problems only take 200 iterations, while others take 5-10 million iterations.

When the error graph is drawn as a result of iterations, it is seen that the error gradually decreases. At some point, the increase in the number of iterations does not decrease the error value. This means that the network stops learning and a better result cannot be found. If the solution obtained is unacceptable then the network is stuck in a local solution.

- Determination of Coefficients

In the feed forward neural network, determining the weight values of the connections at the beginning is closely related to the performance of the network. Initial weights are usually randomly assigned. It has been observed that if the intervals in assignments are kept large, learning takes longer, and if narrow intervals are taken, the risk of local optima increases. Previous studies have shown that assigning weights between 0.1 and 1.0 produces successful results. But this depends entirely on the nature of the problem to be learned.

The initial values of the learning coefficients affect the performance of the network, just like the weights. The learning coefficients determine the change of the weights. If large values are chosen, then there is a network roaming and oscillation among

local solutions. Choosing small values increases the learning time. Experience has shown that values between 0.2-0.4 are generally used. Some applications have shown that when the learning coefficient gets 0.6, it gives the most successful results. This situation is completely dependent on the problem.

Similarly, the momentum coefficient affects the performance of learning. Momentum coefficient is the addition of a certain rate of change in the previous iteration to the new change amount. This is especially recommended with the aim of ensuring that networks attached to local solutions find better results with bounce. Small values may make it difficult to get rid of local solutions. Very high values may cause problems in reaching a solution. Experience has shown that it would be appropriate to select the momentum coefficient between 0.6-0.8. It is useful to take the user according to the nature of the problem.

5.6 Applications in Finance

Artificial Neural Networks have recently been used frequently in financial applications such as financial asset estimation, loan application evaluation, credit card spending profile, investment consultancy. Financial applications often try to predict future events based on historical data. Neural networks are more successful in handling uncertainty than expert systems in predictive events.

Another area where Artificial Neural Networks are used is handwriting recognition. This is used in banking to recognize handwriting on documents in credit card transactions. The image recognition capabilities of neural networks are used in check transactions to read handwriting and the amount entered into the system by a human system check.

Similarly, artificial neural networks have been found to be quite successful in subjects such as credit evaluation and scoring system, futures prediction, currency estimation, debt transaction evaluations.

It has been seen that neural networks give successful results for the prediction of stock indices. Network teaching is done with historical data. Prediction success can be increased by increasing the information used for variable selection and training. The daily closing price prediction of the Nasdaq index was estimated with 94%

accuracy by a neural network with three hidden cores: 20 neurons in the first layer, 40 neurons in the second layer, and 20 neurons in the third layer.

Neural networks are also used in banks to decide whether to approve loan applications. Financial institutions want to increase their income by keeping the default rate of loans low. It has been shown that the rate of default in loans approved by using neural networks is lower than traditional methods.

In order for credit card transactions to be valid, customers must spend using the card and use their credit limits. Otherwise, the revenue per card will be lower than the cost. In an application carried out by a bank, 14 different features were determined to predict the ideal credit card customer with artificial neural networks. Thus, giving cards to customers who would not use the card actively was prevented and credit card applications were concluded faster.

As mentioned in the methodology part of the study, artificial neural networks were used as the main model in the study. Neural networks consist of a structure that works in parallel with each other, transmits information to each other and receives information. Learning is performed by adjusting the connection weights between the artificial nerve cells and neurons, which are connected to each other in the form of a network. The prediction ability of artificial neural networks powered by fuzzy logic is used in the prediction of financial assets.



6. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM - ANFIS

ANFIS (Adaptive Neuro Fuzzy Inference System) is an artificial intelligence application that has been frequently preferred in recent years because it gives successful results in different data types.

ANFIS was developed in the early 1990s to model nonlinear functions such as random time series. In the data set consisting of sample inputs and outputs, a connection is established between the learning function and the inputs and outputs with fuzzy rules. In the learning process, the difference between the outputs produced by the model and the outputs in the sample data set is tried to be minimized. In this study, price estimation of financial assets such as USD/TL, Gold, BIST index was applied with ANFIS, which is a model that provides the integration of fuzzy logic and artificial neural networks.

Fuzzy logic uses verbal expressions that can be understood by a person to explain system information. Thus, interaction between the human and the algorithm is ensured. On the other hand, the lack of learning feature is the most important disadvantage of the system.

Artificial neural networks can provide fuzzy logic learning ability. Neural-fuzzy systems aim to combine the successful features of both methods.

Fuzzy logic and Artificial Neural Networks (ANNs) can be combined in two ways;

- Fuzzy Neural Networks
- Neural Fuzzy Systems

Fuzzy Neural Networks are neural networks that can work with fuzzy information, while Neural Fuzzy Systems are fuzzy systems with neural networks feature.

More specifically, in fuzzy neural networks, the training process is fuzzy, fuzzy union sets are used instead of classical addition, and the outputs are given as fuzzy sets.

Neural networks and fuzzy logic methods are used together to eliminate each other's missing features. It is difficult to make sense of the learning function of neural networks. Contrary fuzzy systems are easily understandable because they use verbal terms and if-if rules, but there are no learning algorithms. The features of these complementary techniques are shown in Table 6.1;

Table 6.1 : The features of Fuzzy Syetems and Neural Networks (Baykal and Beyan, 2004).

Capabilities		Fuzzy Systems	Neural Networks
Knowledge Acquisition	Inputs	Human Experts	Sample Sets
	Tools	Interaction	Algorithms
Uncertainty	Information	Quantitative and Qualitative	Quantitative
	Cognition	Decision Making	Perception
Reasoning	Mechanism	Experiential	Parallel Computing
	Speed	Low	High
Adaption	Error Tolerance	Low	Very high
	Learning	Induction	Adjusted Weights
Natural Language	Performing	Open	Hidden
	Flexibility	High	Low

According to Beyan and Baykal (2004), it is possible to talk about five different categories in fuzzy logic and synthesis of artificial neural networks. These; putting the blur on the neural network roof, designing the neural network with fuzzy logic formality, changing the basic properties of nerve cells, using the measurement of turbidity as the instability or error of a network, making each nerve cell blurred.

In neural fuzzy systems, features such as flexibility, speed and adaptability are added to the fuzzy system with neural networks.

6.1 Advantages of Neural-Fuzzy Systems;

- Function of learning with education
- Incorporating expert opinions into the model
- Flexibility and speed
- Parallel computing capability

The ANFIS model includes a Sugeno-like fuzzy system and uses back propagation learning. GARIC, NEFCON (neural-fuzzy controller), NEFCLASS (neurosurgical classifier) and NEFPROX (neural-fuzzy prediction model) models also use Mamdani type fuzzy systems.

Considering the RMSE error criterion, Although Sugeno fuzzy inference systems require more calculation, they give better results than Mamdani fuzzy systems.

Each model has its strengths and weaknesses. While evaluating the models, different criteria such as time, flexibility, speed, performance can be taken into account.

6.2 ANFIS Structure

ANFIS is a system that has been developed to increase the success of fuzzy-based models and performs the learning process using sample data with an adaptive network structure. Adaptive network structure tries to increase the performance of the network by constantly updating itself in the learning process. Different layers, each with a different task, come together to form the network structure. In fact, the ANFIS model is an advanced version of Sugeno fuzzy systems with the ability to learn with neural networks.

The selection of membership functions in the Fuzzy Inference System is arbitrary, it depends on the user. Although the choice of membership functions also depends on the data, it is not always easy to understand how it should be.

Neural adaptive networks are based on learning the connections by analyzing the data set consisting of inputs and outputs. While the back propagation algorithm provides the learning function with fuzzy modeling, the membership function parameters are created with the least squares method.

In this way, the fuzzy system learns the model by using the data given to it, that is, it adapts to the sample data. Therefore, the system is described as adaptive.

ANFIS can assign the rules needed by the network for the problem to be solved, or it allows the rules to be assigned by experts. Thus, the system creates rules by utilizing expert experience instead of mechanical analysis. This feature of ANFIS makes it possible to obtain better results by combining the learning capability of artificial neural networks with expert opinions.

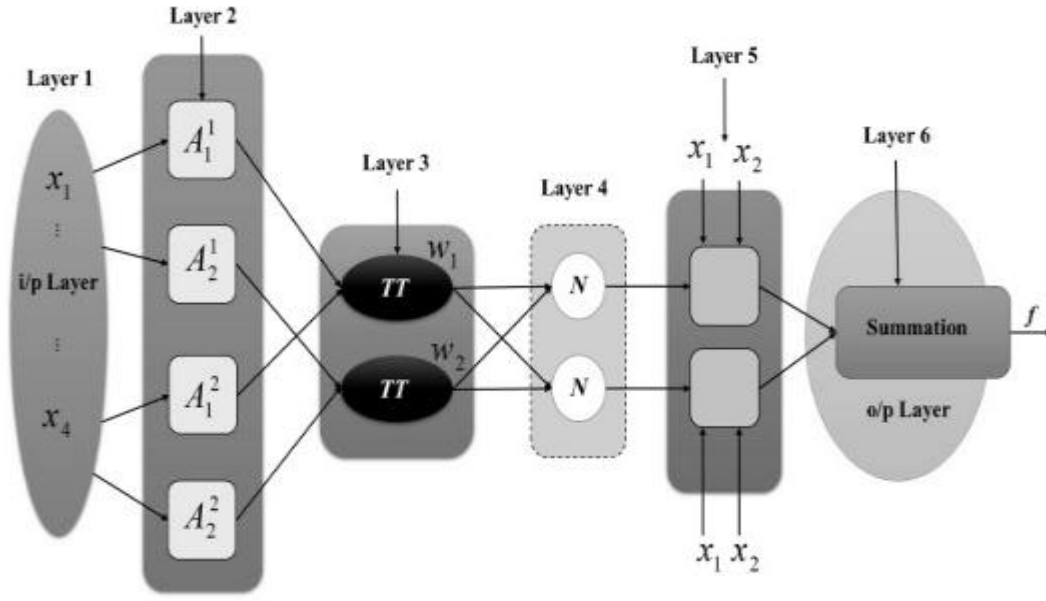


Figure 6.1 : ANFIS Structure.

As shown in Figure 6.1, ANFIS consists of 6 layers.

The tasks of the layers in the ANFIS structure are as follows;

Layer 1: Inputs coming to this layer, which is defined as the input layer, are transferred to other layers. Output of each i node:

$$O = \mu_A(x), i = 1, 2, \dots, I \quad (6.1)$$

$$O = \mu_B(x), i = 1, 2, \dots, I-2 \quad (6.2)$$

Layer 2: It is the blur layer. Input values in this layer transformed into fuzzy sets. With the Bell activation function, the output of each node i consists of membership degrees.

Layer 3: It is the rule layer. The output (μ_i) of each rule node is the product of the membership degrees from the blur layer.

The μ_i values are calculated as follows;

$$Y_i^3 = \prod I = \mu_{Ai}(x) \times \mu_{Bi}(y) = \mu_i \quad (6.3)$$

Layer 4 : It is the normalization layer. Nodes in this layer accept the output values of the rule layer as input and normalize the rules. Calculation of normalized firing level μ_i ,

$$y_i^4 = N_i = \mu_i / \sum M_i = \mu_i \quad (i=1, n) \quad (6.4)$$

Layer 5: It is the purification layer. Weighted result values of a rule given in each node in the purification layer are calculated. In layer 5 i. the exit value of the node is as follows. Here (p_i, q_i, r_i) variables, i. is the result parameters of the rule.

$$y_i^5 = \mu_i[p_i x_1 + q_i x_2 + r_i] \quad (i=1, n) \quad (6.5)$$

Layer 6: It is the total layer. It contains a single node and this node is denoted by $\sum$. The output values of the nodes in the defuzzification layer are summed and the net output value (y) of ANFIS is calculated. y is calculated as follows;

$$y = \sum \mu_i[p_i x_1 + q_i x_2 + r_i] \quad (6.6)$$

6.3 Learning Algorithm

In ANFIS, the learning process is performed using the back propagation learning algorithm. It is also supported by the least squares method. With error backpropagation, the weights in the network are updated so that the ANFIS output is close to the actual output. For this purpose, gradient descent optimization algorithm is used. First, the least squares method is used with sample data and initial parameters, and new parameters are generated. Then the input samples are regenerated and the first parameters are replaced with the final parameters.

- Fuzzy Logic and Neural Networks Integration

Artificial Neural Networks are artificial intelligence algorithms that imitate the processes of the human brain to learn, interpret and produce new information. Successfully applies human brain features such as learning, classification, recognition, grouping, and forecasting.

Artificial nerve cells have two processes as learning and practice. Artificial nerve cells are trained to learn the relationship between inputs and outputs defined in current historical data. This training is related to the learning function of the artificial nerve cell. The definition of output through the structure learned with current inputs is related to the application function of the cell.

Artificial learning is the programming of computers to improve their performance using sample data or past experience. For the analysis, a model defined based on parameters and a criterion that can be used to measure the performance of the model must be defined. The aim is to find the parameter values that make the model's

parameters best according to this performance criterion. The model may be a predictor that can be used to make relevant forecasts in the future or an explanatory model that provides information.

Artificial learning rules can be divided into three classes: supervised learning, unsupervised learning and reinforcement learning. Consultant learning rules require weights to be adapted to reduce the output error to achieve the desired network throughput. In this learning type, each input value and output value are introduced to the system. In consultant or reinforcing learning rules, the desired output value is not introduced to the system.

If the error that occurs in each iteration is plotted for a learning network, an error graph similar to that of Figure 6.2 occurs.

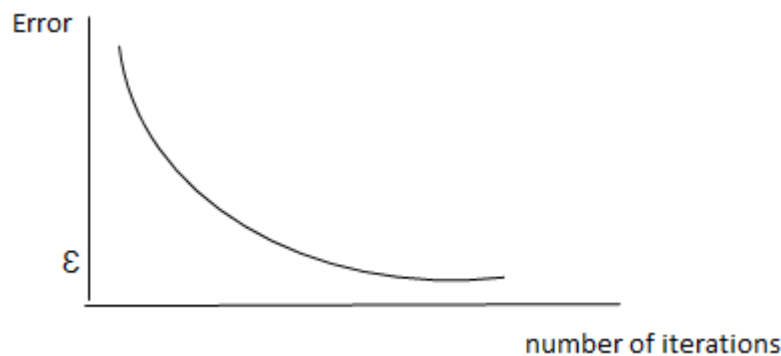


Figure 6.2 : Networks learning curve.

6.4 ANFIS Training Process

The training process of the ANFIS algorithm is shown in Figure 6.3. The input vector and the output vector are used to train the system. The parameters of the membership functions are estimated with the sample data. It is desired that the error term, which is the difference between the outputs produced by the model and the actual outputs, is lower than a specified threshold value.

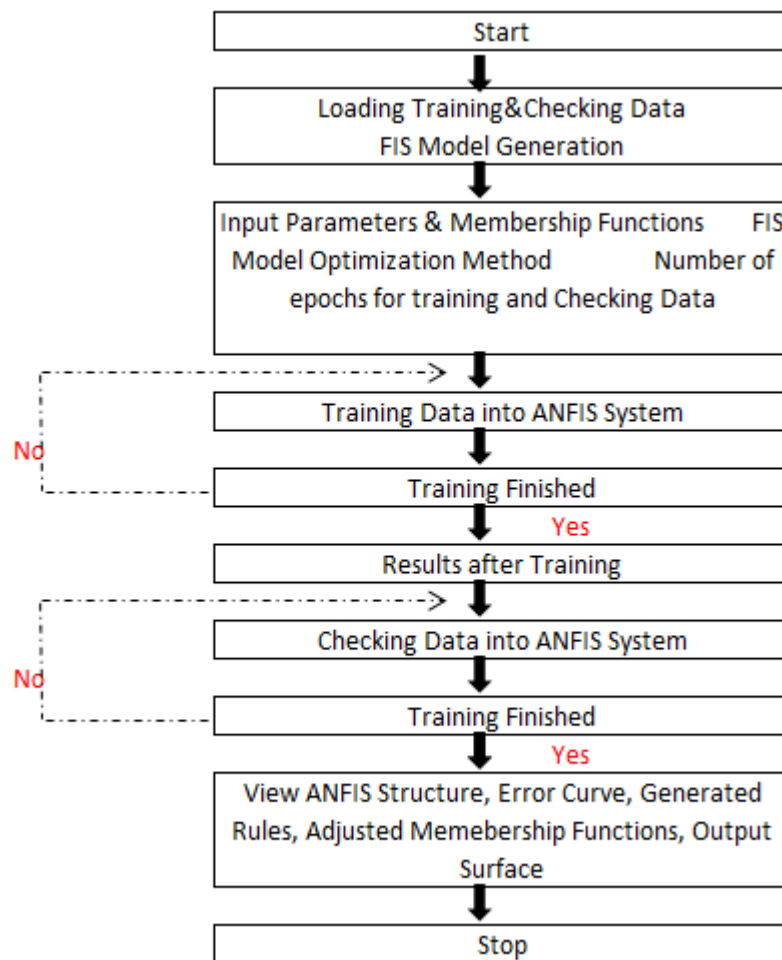


Figure 6.3 : ANFIS training system.

After the result parameters are found with the least squares method, the error value is checked, if the value is above the threshold value, the result parameters are changed and the same operations are repeated. When the error value is below the threshold value, the outputs of the model are compared with the outputs of the control set.

In the training process, the least squares method is used to calculate the error value, and the gradient descent method is used when changing the parameters. The best performance is tried to be obtained by using these two techniques together. The more different situations the training data defined in the model includes, the more successful the parameters calculated at the end of the training will be.

The parameters of the first membership functions are created by the user with MATLAB's `genfis1` command. After the first membership functions are created, the training process is started by giving the `amps` command to MATLAB. Defined

training data is entered to produce the membership functions and the most acceptable output generated using the fismat command.

After processing the data used for training, the final membership functions and error values are found. The data used for control and the parameters found after the training are checked, the control data increases the effectiveness of the model.

After the training and control processes, ANFIS goes to the evaluation stage. The process of analyzing system performance begins with the input of input datasets into the fuzzy data system without output values. The output of the evaluation function represents the final output of the ANFIS system. The correlation between this final output and the desired outputs is measured.

In ANFIS network training, input and output values are matched with membership functions. The parameters of the membership functions change during the learning period.

The ANFIS training process begins by determining the fuzzy sets and the number of clusters of each input variable and the form of membership functions. RMSE is the function used to track exercise errors. RMSE is used and is defined as:

$$RMSE = (1/N \sum_{j=1}^N (y_j - \hat{y}_j)^2)^{1/2} \quad (6.7)$$

Mean Average Error (MAE) is used and defined as

$$MAE = 1/N \sum_{j=1}^N |y_j - \hat{y}_j| \quad (6.8)$$

where N is the total number of prediction, $\hat{y}_j$ is the predicted time series, and y_j is the original series.

7. METHODOLOGY

In this section, different artificial intelligence methods such as Fuzzy Logic, Artificial Neural Networks, and Wavelet Analysis were combined into a single model, and future price predictions of 3 basic financial assets in the Turkish markets were made. The time series of financial assets were decomposed by wavelet analysis and separated into their components, then future price predictions were made for each component using fuzzy neural networks. In the first part, the performance of portfolios created based on model estimates of USD/TL, Gold and BIST30 indexes and the comparison of passive investment in underlying assets are shown. Then, artificial series were created with the Brownian stochastic process and the performance of the model was measured under different conditions. In the third part, a similar study was conducted with the stock market indices of China, South Korea and Russia and the success of the model performance in developing countries was observed. In the last section, the performance of portfolios created by using 3 assets together instead of a single asset is examined. In addition, the effect of rebalancing the portfolios at different time intervals on the performance was examined. At the end of the study, it was seen that the buy-sell decisions made according to the signals produced by the artificial intelligence-based model gave more successful results than the passive investment.

In this study, using the data between January 2016 and February 2019, the daily returns of the Istanbul Stock Exchange (BIST30) Index, USD/TL exchange rate and Gold (TL) prices between March 2019 and December 2019 were estimated and a portfolio was created according to these estimates.

In the study, which includes 1023 working days data between 29.01.2016 - 31.12.2019, the first 470 data were used for training and the next 335 data were used for validation. The model produced daily price predictions for the remaining 218 days.

In the first part of the study, estimates were made with Neural Fuzzy Network for BIST-30 Index, Gold and USD/TL rate. While making predictions about the future for the related asset class, the auto correlation functions of the assets were first examined and historical data to be used in the prediction was found. First, the autocorrelation of the series was examined to see if the time series was affected by the past values. Autocorrelation is defined as the correlation between different values of time series. With this analysis, it is seen which past values of the series have more effect on the future values. When auto correlation functions are analyzed, it is observed that there is auto correlation in all three time series. Gold and USD/TL time series appear to be affected most by the past 4 data (T-4) and the BIST-30 index affected most by the past 1 data (T-1). Figure 7.1 shows the results of autocorrelation analysis for BIST30, Gold and USD/TL time series.

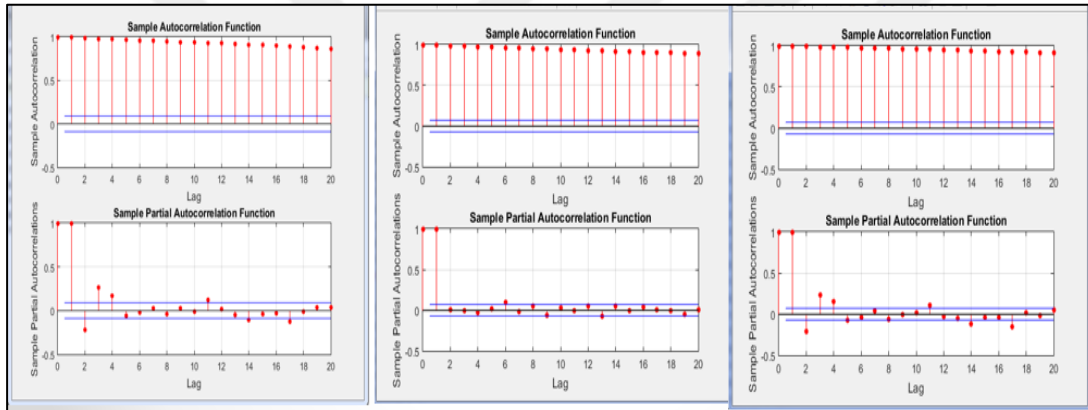


Figure 7.1 : Autocorrelation and Partial Autocorrelation functions of Gold, BIST-30 Index and USD/TL exchange rate respectively.

In this study, first, the series of financial assets are divided into 3 different sub-series (a2-d2-d1) with Discrete Wavelet Transform (DCT), a signal processing technique, to improve the success of the model. Then, using the fuzzy neural network method, which is a combination of artificial neural networks and fuzzy logic applications, the financial series are estimated. In the study, first, the financial series are divided into 3 sub-segments with wavelet analysis. Different frequency information is given as input to the neural fuzzy network model and future prices are predicted. Then, using the fuzzy neural network method, which is a combination of artificial neural networks and fuzzy logic applications, the financial series are estimated. Finally, the success of the model is measured by comparing the performance of the portfolios

created using these estimates with the original series. Figure 7.2 shows the framework of the study.

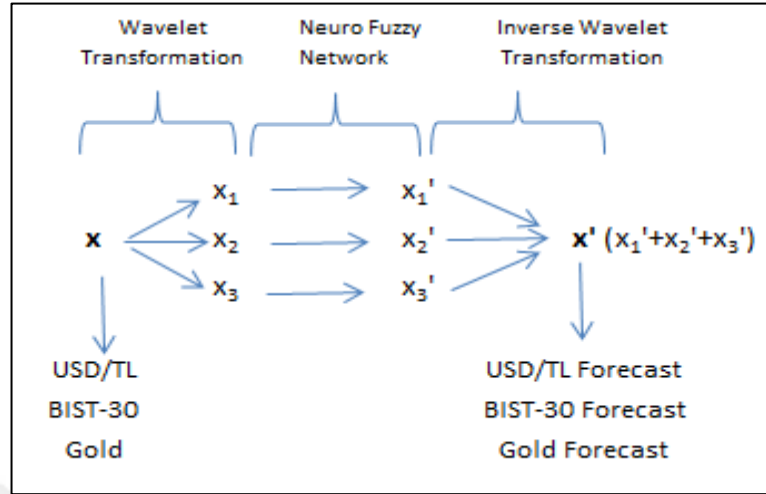


Figure 7.2: Framework of study.

With wavelet analysis, a signal can be divided into subseries of different frequencies. The $O(t)$ signal can be divided into two as the smooth coefficient $A(t)$ and the detail coefficient $D(t)$ with the following formulas;

$$A_{i,j} = \int o(t) \Phi_{i,j}(t) dt \quad (7.1)$$

$$D_{i,j} = \int o(t) \Psi_{i,j}(t) dt \quad (7.2)$$

where j represents the scaling parameter, k is the translation parameter, Φ is the father wavelet, that is, the low-frequency part of the signal, and Ψ is the main wavelet, the high-frequency part of the signal. Φ and Ψ are defined as follows:

$$\Phi_{i,j}(t) = 2^{-i/2} \Phi(2^{-i}j - j) \quad (7.3)$$

$$\Psi_{i,j}(t) = 2^{-i/2} \Psi(2^{-i}j - j) \quad (7.4)$$

As a result, the orthogonal wavelet representation of the original signal $o(t)$, which is shown in Figure 7.3, is defined by

$$o(t) = \sum a_{i,j} \Phi_{i,j}(t) + \sum d_{i,j} \Psi_{i,j}(t) + \sum d_{i-1,j} \Psi_{i-1,j}(t) + \dots + \sum d_{i,j} \Psi_{i,j}(t) \quad (7.5)$$

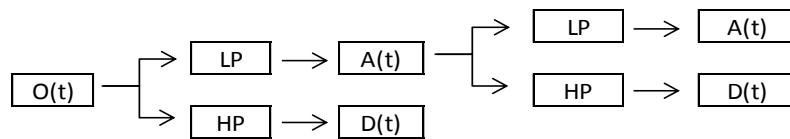


Figure 7.3 : The two-level decomposition of signal $o(t)$.

Different types of wavelets can be used for financial time series estimates such as Daubechies, Haar, Morlet, and Mexican Hat wavelets. In this paper, the Haar wavelet has been applied to decompose the original signal $O(t)$. Daubechies, Mexican Hat wavelets, and Morlet wavelets have the advantage of better resolution to change time series smoothly. However, they have the disadvantage of more expensive computation than Haar wavelets. The decomposition level is set to three. The wavelet transform results of the financial series are shown in appendix 1.

To specify model structure, FIS model is generated using subtractive clustering with 3 membership functions. The activation function plays a critical role in neural networks as it learns the data structure and creates a meaningful result between inputs and outputs. Without the activation function, the learning power of the neural network will be limited and the neural network will look like a linear regression. In order to obtain a good output performance, a function suitable for the data should be selected. In the study, while choosing the activation function, attention was paid to the non-linearity of the function and its easy derivation. Easy derivation reduces the computational load.

The lowest error rate was found to be 3,5648% for the Sigmoid Activation Function, as experiments were made with different activation functions for the feedforward backpropagation algorithm and the neural network (6-6-4-2) using 2 hidden layers. In addition, the mean square error (M.S.E) was used as a performance measure. Gradient descent with momentum weight and bias learning function (learnrngdm) was preferred as the learning function because it is momentum based.

7.1 Model Performance in BIST-30, USDTL, Gold

The model correctly predicted the direction of the BIST-30 index for 123 days (60%) in 206 working days between 01.03.2019 and 31.12.2019. While the return of the BIST-30 Index was 7.28%, the return on the portfolio created according to the estimates made with fuzzy wavelet neural networks was 19.9%. Considering the liquidity premium and brokerage commissions, the portfolio's return was 14.3%.

Figure 7.4 shows the comparative performance of the BIST30 index, which is the underlying asset, and the portfolio created according to the estimates made by the wavelet neural network technique for the test period. The model predicts the closing

price of the BIST30 index on day T+1. If the closing price is higher than the T price, the index is invested, and if it is low, a portfolio is created by investing in a risk-free asset. Performance comparisons were made by indexing the index and portfolio initial values to 100. The portfolio that also reflects the commission costs arising from the trading transactions between the underlying asset and the risk-free asset is defined as the Model Portfolio +. Brokerage houses collect commissions for the purchase and sale transactions made in the underlying asset. In addition, trading spreads on prices can negatively affect performance. While calculating the Model + performance, 0.04% liquidity premium and 0.01% brokerage commission were applied for trading transactions. Model - shows the result of the modeling using only fuzzy neural networks without using the wavelet analysis preprocess.

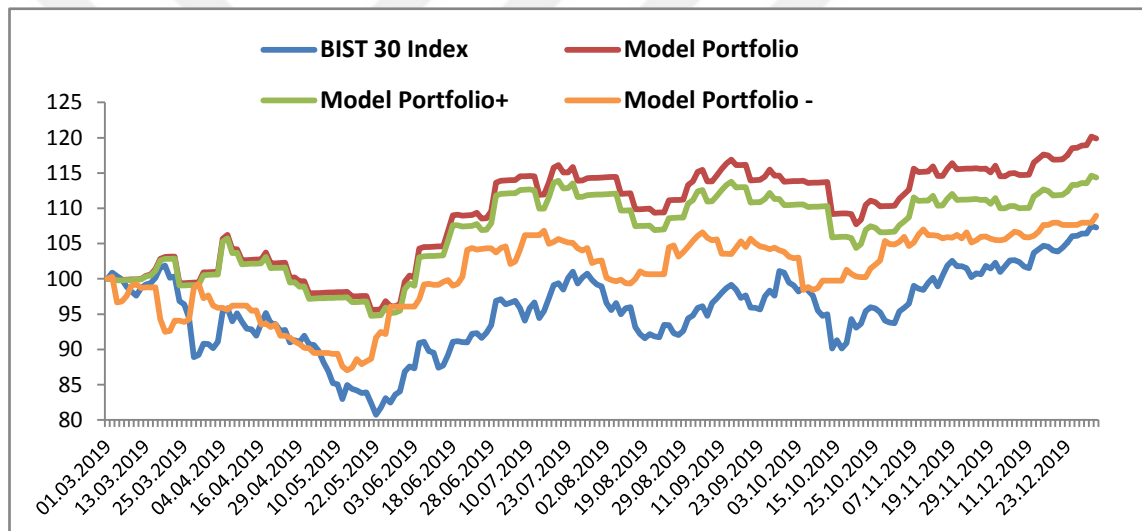


Figure 7.4 : Performance of BIST 30 portfolio which is constructed BUY/SELL signals from the model.

Figure 7.5 similarly shows the performance of the portfolio created according to gold prices and the gold forecast of the Wavelet Neural Networks model. The model portfolio was created by investing in gold in periods when the model predicts an increase and in risk-free assets in periods when it is predicted to decrease.

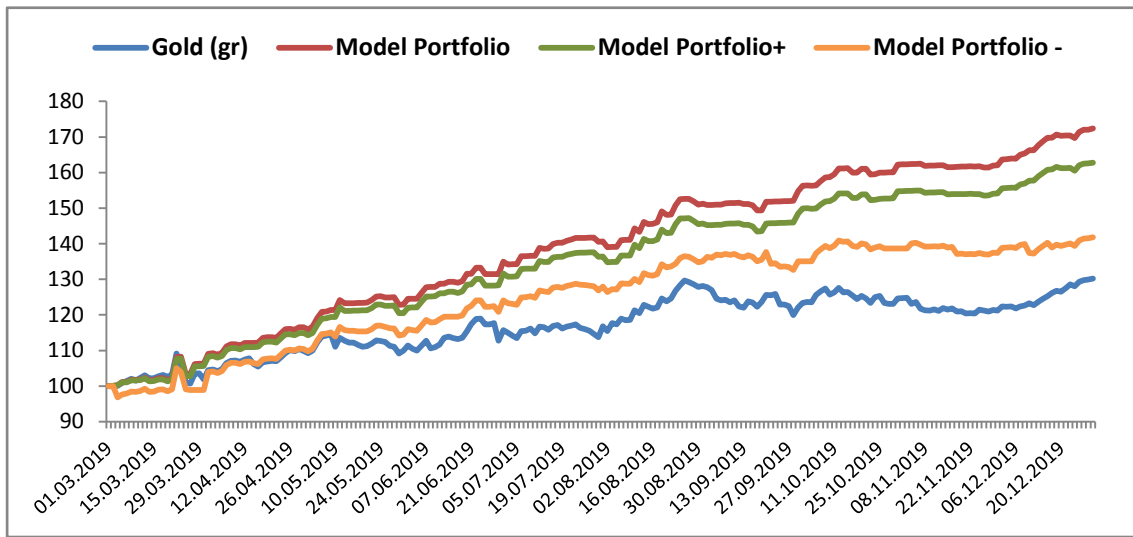


Figure 7.5 : Performance of Gold portfolio which is constructed BUY/SELL signals from the model.

Figure 7.6 shows the performance of the portfolio created according to USD/TL prices and forecast of the Wavelet Neural Networks model. The model portfolio was created by investing in USD/TL in periods when the model predicts an increase and in risk-free assets in periods when it is predicted to decrease.

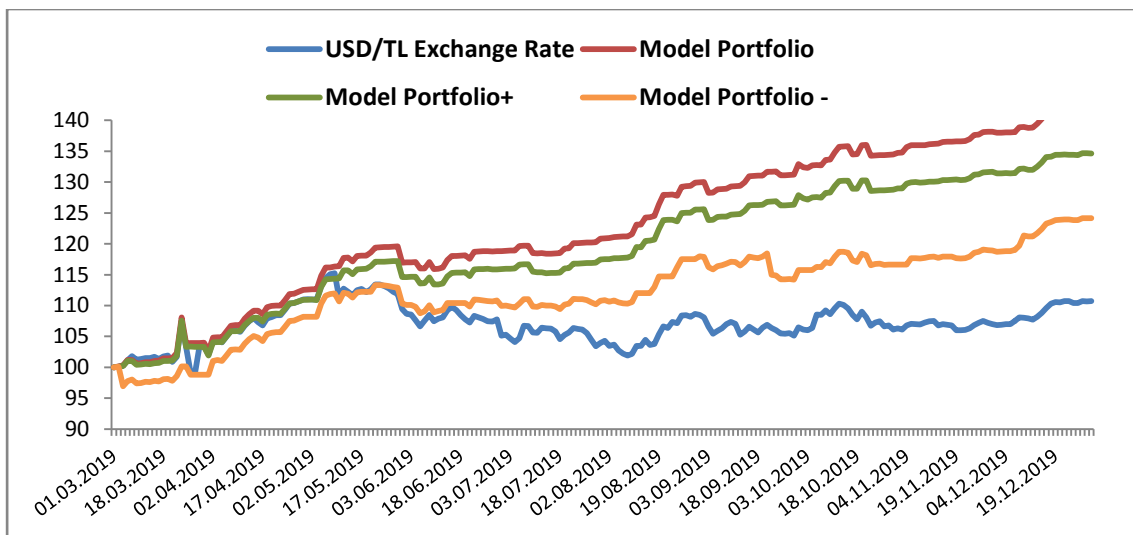


Figure 7.6 : Performance of USD/TL portfolio which is constructed BUY/SELL signals from the model.

BIST-30 Index, Gold (TL-gr) and USD / TL exchange rate model estimate performances are shown in the Table 7.1

Table 7.1 : Performance of Wavelet Analysis and Neuro Fuzzy Network models.

	Index Return	Model Portfolio -	Model Portfolio+	Sharpe Ratio	Model Portfolio -	Model Portfolio+
BIST- 30	7.28%	8.98%	14.34%	1,31	1,64	2,59
Gold (Gr)	30.02%	41.81%	52.51%	3,75	3,04	3,26
USD/TL	20.70%	24.20%	34.80%	3,51	3,5	3,54

7.2 Model Performance in Artificial Time Series

In the second part of the study, artificial time series were produced by using the wiener process (Geometric Brownian Motion) to see the performance of the predictions made with Wavelet Analysis and Fuzzy Neural Networks in different market conditions.

Geometric Brownian Motion is a stochastic process and is expressed as in Figure 7.6;

$$dS_t = \mu S_t dt + \sigma S_t dW_t \quad (7.6)$$

where W_t is a Wiener process, and μ and σ are constants. μ is used to model deterministic trends while σ is used to model unpredictable random movements.

Solution of the stochastic differential equation above for the interval $[t-1, t]$ under the risk neutral measure Q is;

$$S_t = S_{t-1} \exp(\mu - \sigma^2/2 + \sigma W_t^Q) \quad (7.7)$$

When jumps are included in the Weiner process, equation and its solution take the following forms;

$$d\log S_t = \mu dt + \sigma dW_t + dj_t \quad (7.8)$$

$$S_t = S_0 \exp\{(\mu - \sigma^2/2)T + \sigma W_t\} \prod_j \log Y_j \quad (7.9)$$

The performance of portfolios created by estimating time series which are artificially created by the Wiener process is shown in Figure 7.7. Artificial time series have been created to see how the Wavelet Neural Networks model performs in different market conditions. The volatility and direction of the time series produced with the Geometric Brownian formula can be changed, so that upward or downward series with low or high volatility can be formed. The performance of the model in the series produced in this way will give an idea about its success in different market conditions that may occur in the future.

As seen in Figure 7.7, model performance in rising and falling trends with high volatility was better than passive investment in the artificial time series. When random jumps were added to the series, the performance of the model remained below the passive investment considering the costs.

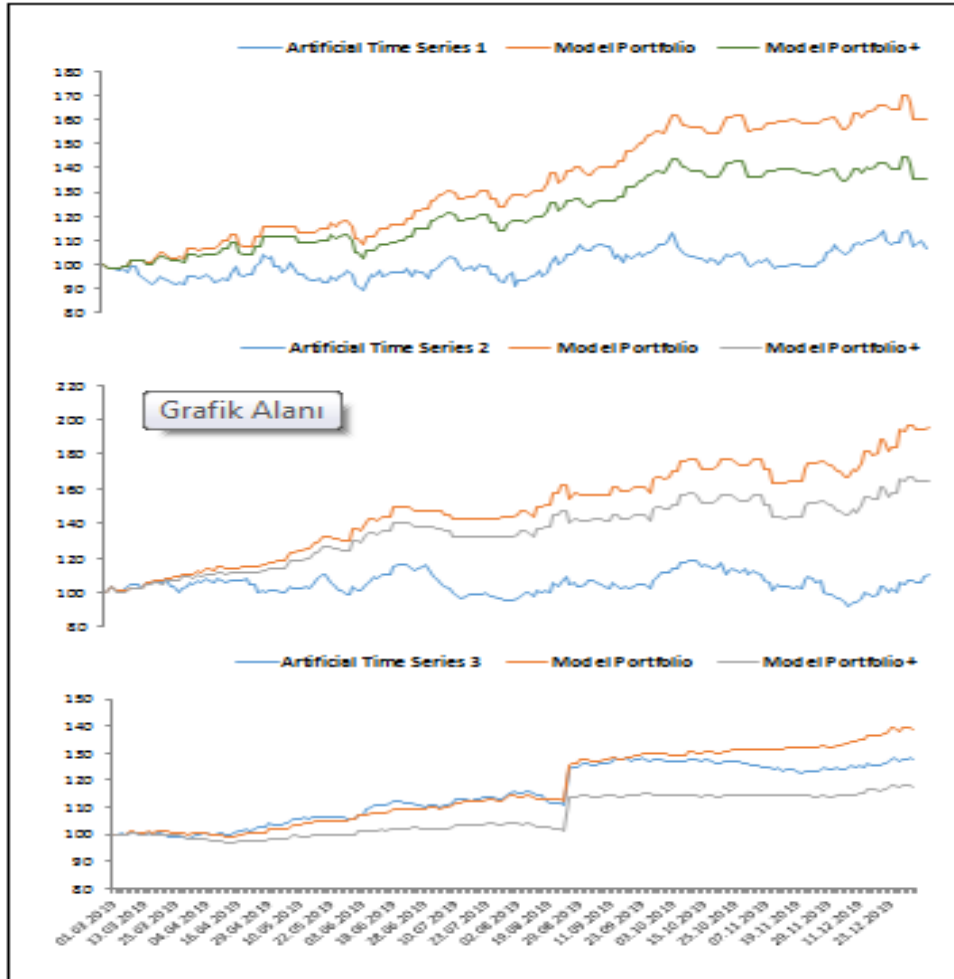


Figure 7.7 : Model Performance – Artificial Time Series with different volatility and trend.

As seen in Table 7.2, the performance of the model is quite good in up and down series with high volatility. In both cases, the return on the portfolio invested according to the model estimation yielded a much higher return than the series itself, that is, the passive investment. When random jumps were added to the artificial series (Synthetic Time Series 3), the performance of the model decreased and remained below the original series. Since jumps do not have a specific pattern, it is expected that they will decrease the prediction performance of the model.

Table 7.2 : Performance of the portfolio created by wavelet analysis and neural fuzzy network in artificial time series.

	Series Return	Model Portfolio+	Sharpe Ratio	Model Portfolio+
Artificial Time Series 1	6,70%	39,14%	1,22	2,52
Artificial Time Series 2	10,45%	69,23%	1,87	3,68
Artificial Time Series 3	27,89%	20,46%	2,67	2,53

7.3 Model Performance in Selected Developing Stock Markets

In the third part of the study, the model was tested on the stock exchanges of selected developing countries such as South Korea (KOSPI), Shanghai Stock Exchange Composite Index (SHCOMP) and Moscow Exchange Index (RTSI). First, the autocorrelation function was tested to see if the time series were affected by historical data. All 3 time series were found to be correlated with the T-1 value. Figure 7.8, Figure 7.9 and Figure 7.10 show the autocorrelation analysis of the KOSPI, SHCOMP and RTSI indices. The gradual decrease of the Sample Autocorrelation Function indicates that there is autocorrelation, while the Sample Partial Autocorrelation Function approaches zero after the first lag, indicating that the series is highly affected by the T-1st data.

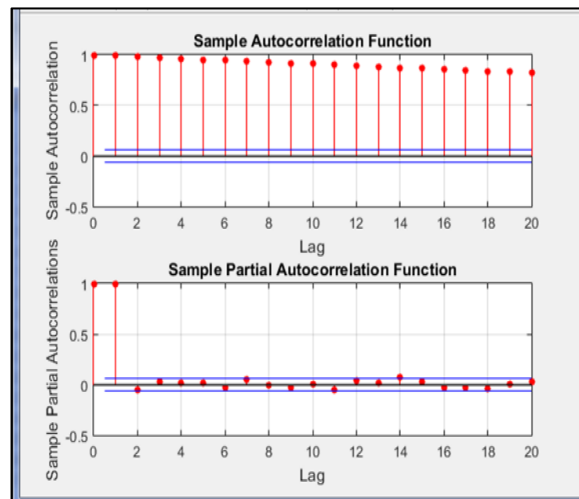


Figure 7. 8 : Autocorrelation and Partial Autocorrelation functions of RTSI.

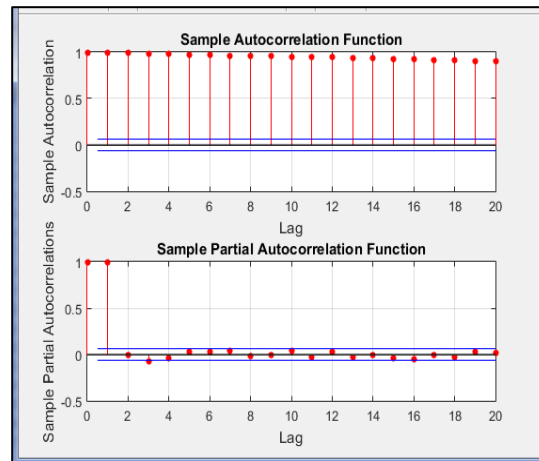


Figure 7.9 : Autocorrelation and Partial Autocorrelation functions of RTSI.

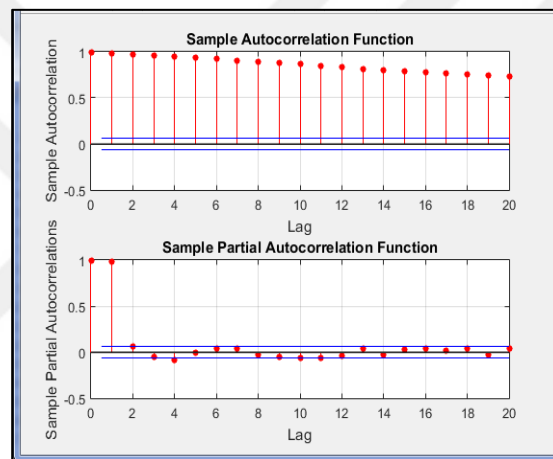


Figure 7.10 : Autocorrelation and Partial Autocorrelation functions of SHCOMP.

RTSI, KOSPI and SHCOMP indices were divided into subgroups by wavelet analysis method using Haar wavelet. For the subsegments, predictions were made using the neuro fuzzy network model. Then, the index estimates were obtained by summing up the estimates made for each subsegments.

Figure 7.11 shows the performance of the portfolio created according to RTSI index and forecast of the Wavelet Neural Networks model. The model portfolio was created by investing in index in periods when the model predicts an increase and in risk-free assets in periods when it is predicted to decrease. Model- shows the result of the modeling using only fuzzy neural networks without using the wavelet analysis preprocess.

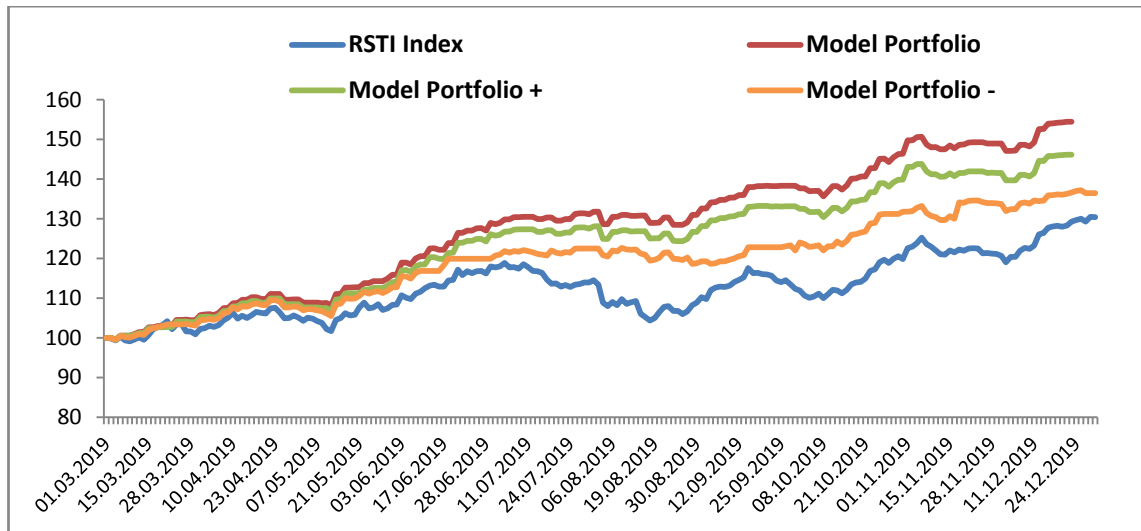


Figure 7.11 : Performance of RTSI portfolio which is constructed BUY/SELL signals from the wavelet fuzzy model.

In Figure 7.12, the same process is repeated for the KOSPI index and the performance of the model portfolio relative to the original index is shown in the graph.

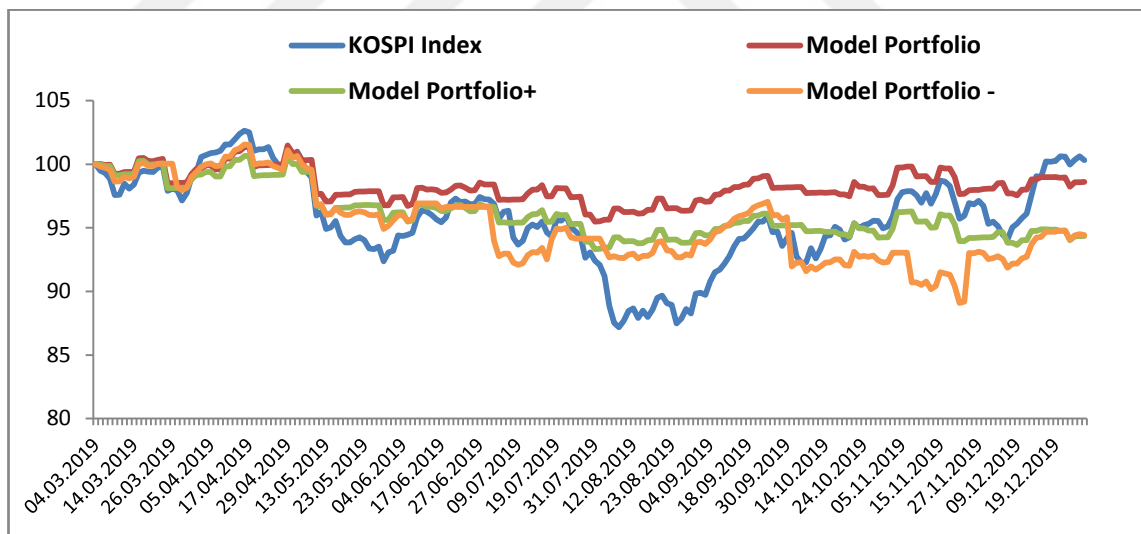


Figure 7.12 : Performance of KOSPI portfolio which is constructed BUY/SELL signals from the wavelet fuzzy model.

In Figure 7.13, the same process is repeated for the SHCOMP index and the performance of the model portfolio relative to the original index is shown in the graph.

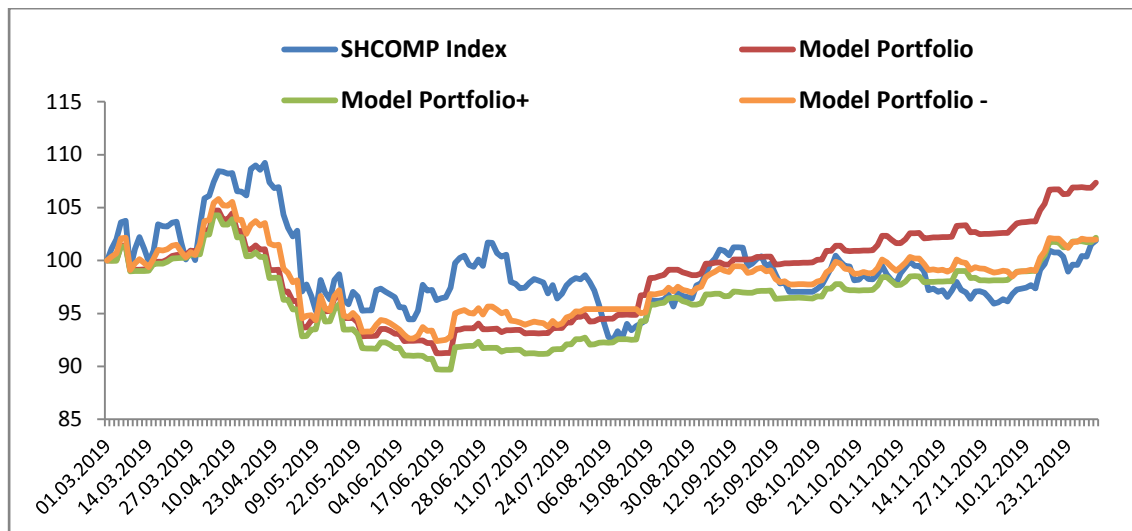


Figure 7.13 : Performance of SHCOMP portfolio which is constructed BUY/SELL signals from the wavelet fuzzy model.

South Korea (KOSPI), Shanghai Stock Exchange Composite Index (SHCOMP) and Moscow Exchange Index (RTSI) model estimate performances are shown in the Table 7.3. Based on the wavelet analysis and fuzzy neural network model, the portfolio outperformed the Russian and Chinese stock market indices, but fell behind the South Korean index.

Table 7.3 : Comparison of the performance with the portfolio created by wavelet analysis and neural fuzzy network and original indexes.

	Index Return	Model Portfolio-	Model Portfolio+
RTSI	30,45%	36,49%	47,05%
KOSPI	0,32%	-5,57%	-5,64%
SHCOMP	1,87%	1,99%	2,16%

7.4 Portfolio Optimization

In the last part of the study, the performance of the portfolio consisting of three assets estimated by wavelet analysis and fuzzy neural network model was tested.

Using model estimates at different period intervals, optimization was made for the portfolio consisting of Gold, BIST-30 and USD / TL exchange rate and the optimal asset distribution was determined. In case of investment in this asset distribution, portfolio performance is calculated.

2 weeks, 1 month, 2 months and 3 months have been selected for the re-balance period for the portfolio. With the returns and variances of the estimates by the model, optimization was made so that the sharpe ratio of the portfolio was maximized.

Table 7.4 shows the asset distribution ratios updated with 2-week intervals in the 40-week investment period. The portfolio distribution was updated with the ratios shown in the table every two weeks, and the performance of the portfolio created with the Wavelet Neural Networks technique was examined.



Table 7.4 : Asset distributions as a result of optimization according to expected return and risk estimates of the wavelet fuzzy model (updated every 2 weeks).

2 weeks	Asset Allocation		
	Gold	BIST-30	USD/TL
period 1	24.44%	6.17%	69.39%
period 2	0.00%	0.00%	100.0%
period 3	85.25%	0.00%	14.75%
period 4	32.79%	0.00%	67.21%
period 5	100.00%	0.00%	0.00%
period 6	0.00%	0.00%	100.00%
period 7	20.07%	67.86%	12.07%
period 8	0.00%	100.00%	0.00%
period 9	0.00%	100.00%	0.00%
period 10	0.00%	100.00%	0.00%
period 11	100.00%	0.00%	0.00%
period 12	8.25%	0.00%	91.75%
period 13	0.00%	96.94%	3.06%
period 14	100.00%	0.00%	0.00%
period 15	13.93%	0.00%	86.07%
period 16	0.00%	100.00%	0.00%
period 17	16.92%	59.29%	23.78%
period 18	0.00%	100.00%	0.00%
period 19	60.62%	30.77%	8.60%
period 20	9.06%	67.22%	23.72%
period 21	2.90%	23.76%	73.33%

Figure 7.14 shows the performance of the financial instruments used with the portfolio distribution optimized with the two-week forecasts of the model. The portfolio created with 3 different assets yielded returns above the singular performance of all of the assets.

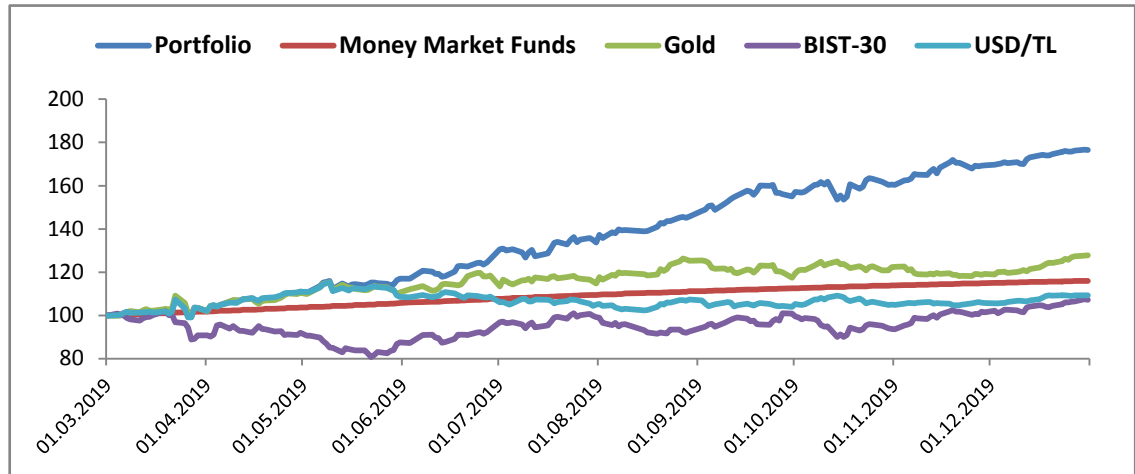


Figure 7. 14 : The performance of the portfolio, which is created according to the expected return and risk estimates of the wavelet fuzzy model and updated every 2 weeks.

As can be seen in Table 7.5, the portfolio's return and sharpe ratio are over gold, BIST30 index and USD/TL rate. This shows that the asset distribution created using the model is successful.

Table 7.5 : Return, Standart Deviation and Sharpe ratio of the portfolio, which is created according to the expected return and risk estimates of the wavelet fuzzy model and updated every 2 weeks.

	Portfolio	Money Market Funds	Gold	BIST-30	USD/TL
Return	76.57%	15.78%	27.86%	7.28%	9.39%
St.Dev.	2492%	487%	702%	558%	305%
Sharpe	0,0244	0	0,0172	-0,01524	-0,02091

Table 7.6 shows the asset distribution ratios updated with 1 month intervals in the 40-week investment period. The portfolio distribution was updated with the ratios shown in the table every month, and the performance of the portfolio created with the Wavelet Neural Networks technique was examined.

Table 7.6 : Asset distributions as a result of optimization according to expected return and risk estimates of the wavelet fuzzy model (updated every month).

Asset Allocation			
1 Month	Gold	BIST-30	USD/TL
period 1	0.00%	0.00%	100.00%
period 2	81.81%	0.00%	18.19%
period 3	100.00%	0.00%	0.00%
period 4	3.07%	66.89%	30.05%
period 5	0.00%	100.00%	0.00%
period 6	0.21%	0.00%	99.79%
period 7	0.00%	100.00%	0.00%
period 8	28.53%	0.00%	71.47%
period 9	18.30%	81.70%	0.00%
period 10	8.10%	63.08%	28.82%

Figure 7.15 shows the performance of the financial instruments used with the portfolio distribution optimized with 1 month forecasts of the model. The portfolio created with 3 different assets yielded returns above the singular performance of all of the assets.

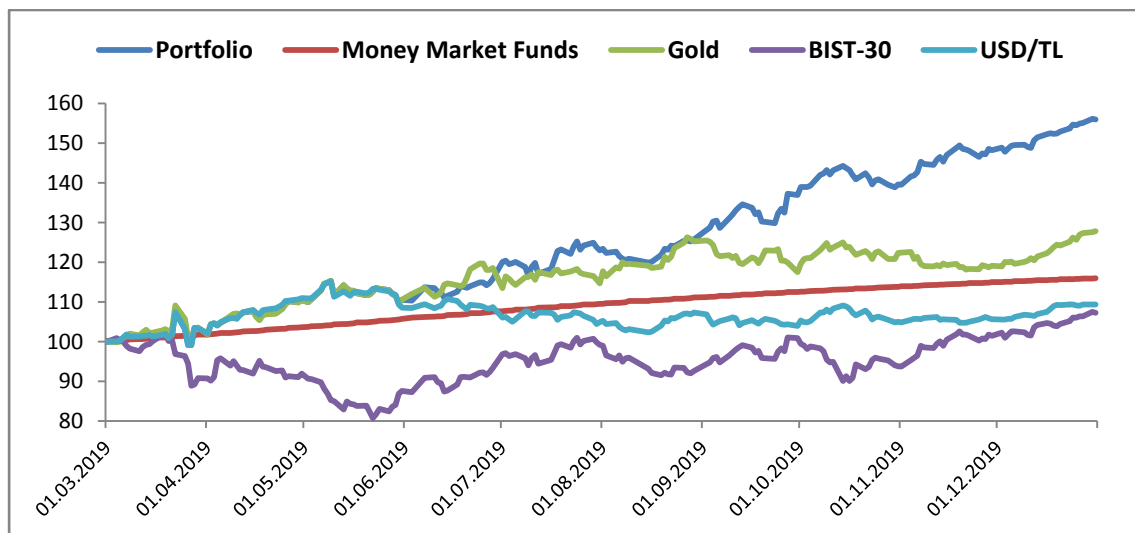


Figure 7.15 : The performance of the portfolio, which is created according to the expected return and risk estimates of the wavelet fuzzy model and updated every month.

As can be seen in Table 7.7, the portfolio's return and sharpe ratio are over gold, BIST30 index and USD/TL rate.

Table 7.7 : Return, Standart Deviation and Sharpe ratio of the portfolio, which is created according to the expected return and risk estimates of the wavelet fuzzy model and updated every month.

	Portfolio	Money Market Funds	Gold	BIST-30	USD/TL
Return	55.97%	15.78%	27.86%	7.28%	9.39%
St.Dev.	1670%	487%	702%	558%	305%
Sharpe Ratio	0.02407	0.000	0.0172	-0.01524	-0.02091

Table 7.8 shows the asset distribution ratios updated with 2 month intervals in the 40-week investment period. The portfolio distribution was updated with the ratios shown in the table every 2 months, and the performance of the portfolio created with the Wavelet Neural Networks technique was examined.

Table 7.8 : Asset distributions as a result of optimization according to the wavelet fuzzy model (updated every 2 months).

	Asset Allocation		
2 Months	Gold	BIST-30	USD/TL
period 1	78.02%	0.00%	21.98%
period 2	44.97%	55.03%	0.00%
period 3	5.30%	94.70%	0.00%
period 4	0.00%	100.00%	0.00%
period 5	18.11%	62.85%	19.04%

Figure 7.16 shows the performance of the financial instruments used with the portfolio distribution optimized with 2 month forecasts of the model.

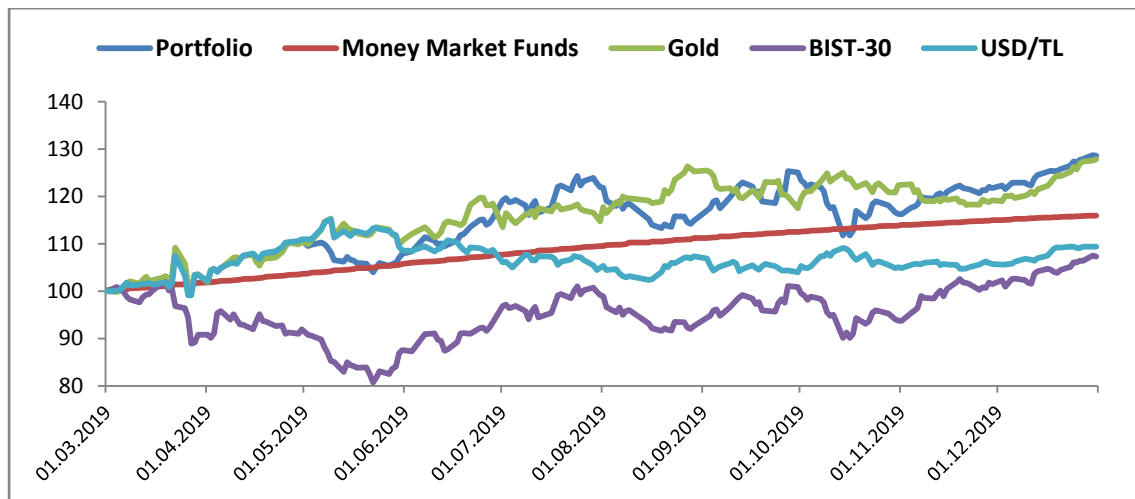


Figure 7.16 : The performance of the portfolio, which is created according to the wavelet fuzzy model and updated every 2 months

As can be seen in Table 7.9, the portfolio's return is over gold, BIST30 index and USD/TL rate. Portfolio's sharpe ratio is the second best ratio after gold.

Table 7.9 : Return, Standart Deviation and Sharpe ratio of the portfolio, which is created according to the expected return and risk estimates of the wavelet fuzzy model and updated every 2 months.

	Portfolio	Money Market Funds	Gold	BIST-30	USD/TL
Return	28.61%	15.78%	27.86%	7.28%	9.39%
St.Dev.	754%	487%	702%	558%	305%
Sharpe Ratio	0.01702	0.000	0.017201	-0.01524	-0.02091

Table 7.10 shows the asset distribution ratios updated with 3 month intervals in the 40-week investment period. The portfolio distribution was updated with the ratios shown in the table every 3 months, and the performance of the portfolio created with the Wavelet Neural Networks technique was examined.

Table 7.10 : Asset distributions as a result of optimization according to expected return and risk estimates of the wavelet fuzzy model (updated every 3 months).

Asset Allocation			
3 Months	Gold	BIST-30	USD/TL
period 1	80.64%	0.00%	19.36%
period 2	0.00%	94.24%	5.76%
period 3	0.00%	100.00%	0.00%
period 4	8.10%	63.08%	28.82%

Figure 7.17 shows the performance of the financial instruments used with the portfolio distribution optimized with 2 month forecasts of the model.

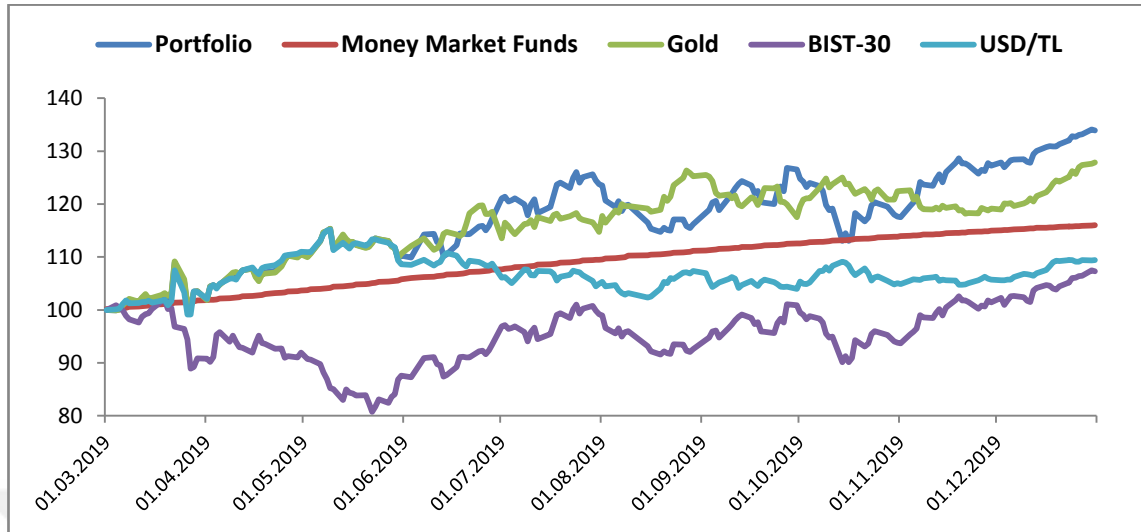


Figure 7.17 : The performance of the portfolio, which is created according to the expected return and risk estimates of the wavelet fuzzy model and updated every 3 months.

As can be seen in Table 7.11, the portfolio's return and sharpe ratio are over gold, BIST30 index and USD/TL rate.

Table 7.11 : Return, Standart Deviation and Sharpe ratio of the portfolio, which is created according to the expected return and risk estimates of the wavelet fuzzy model and updated every 2 months.

	Portfolio	Money Market Funds	Gold	BIST-30	USD/TL
Return	33.92%	15.78%	27.86%	7.28%	9.39%
St.Dev.	853%	487%	702%	558%	305%
Sharpe Ratio	0.02127	0.00	0.017201	-0.01524	-0.02091

In the last part of the study, the performance of the proposed wavelet transform and fuzzy neural networks model is specifically measured in the stock asset class. For this, AKBNK, ARCLK, GARAN, ASELS, KCHOL, KRDMD, KOZAL, SAHOL, THYAO and TUPRS stocks in the BIST-30 index were selected. In order to create the most efficient portfolio with the selected stocks, the return estimates made with the proposed hybrid model were used and the weight of each stock in the portfolio was calculated by maximizing the portfolio's sharpe ratio. The shares were invested at the recommended weights as a result of optimization, and asset allocation was updated every month.

The performance of the portfolio of stocks selected from the BIST-30 index, which was created according to the return estimates of the hybrid model, was compared with the basket in which the BIST-30 index and the related stocks are equally weighted (10%).

Table 7.12 shows the asset distributions, and Figure 7.18 shows the performance of the portfolio created with the hybrid model, the BIST-30 index and the basket that makes equal weighted investments in selected 10 stocks.

Table 7.12 : Asset distribution as a result of stock optimization according to wavelet fuzzy model (updated every month)

Asset Allocation										
1 Month	AKBNK	ARCLK	GARAN	ASELS	KCHOL	KRDMD	KOZAL	SAHOL	THYAO	TUPRS
period 1	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
period 2	0.0%	26.2%	5.7%	18.1%	23.4%	7.4%	19.1%	0.0%	0.0%	0.0%
period 3	33.5%	12.2%	0.0%	0.0%	1.1%	13.2%	3.9%	16.5%	19.5%	0.0%
period 4	0.8%	1.1%	11.7%	24.1%	0.0%	7.5%	11.2%	0.0%	18.4%	25.3%
period 5	0.0%	0.6%	23.6%	22.3%	0.4%	29.5%	0.0%	8.0%	15.7%	0.0%
period 6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%
period 7	23.9%	7.1%	0.0%	15.7%	0.0%	16.1%	7.1%	20.1%	7.5%	2.4%
period 8	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
period 9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%
period 10	0.0%	0.0%	76.3%	0.0%	0.0%	0.0%	0.0%	23.7%	0.0%	0.0%

Figure 7.18 shows the performance of the model portfolio, BIST-30 Index and equally weighted 10 selected stocks basket.

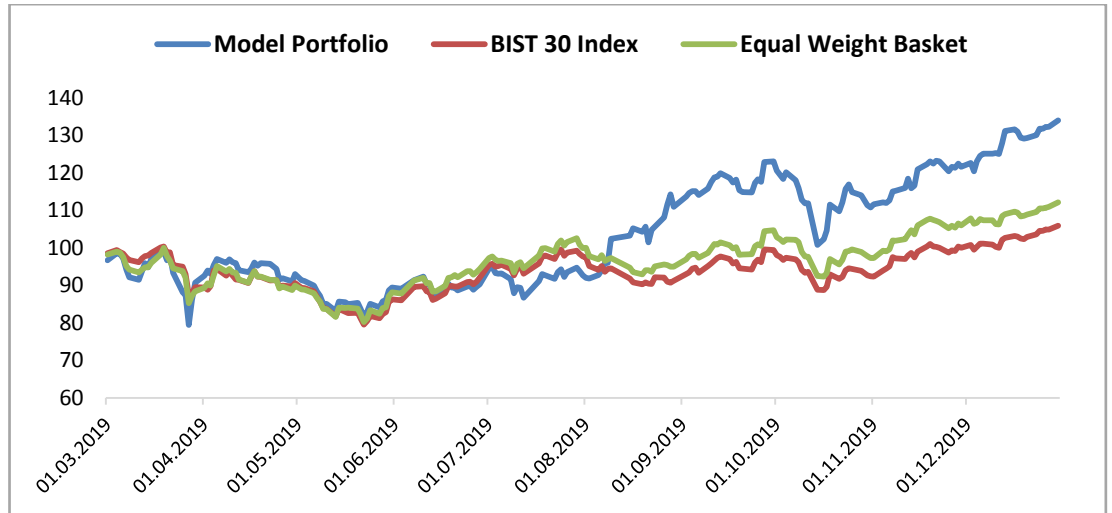


Figure 7.18 : The performance of the stock portfolio, which is created according to the expected return and risk estimates of the wavelet fuzzy model and updated every months.

As can be seen in the Table 7.13, the return and sharpe ratio of the portfolio suggested by the hybrid model were better than the index and the equally weighted basket.

Table 7.13 : Return, Standart Deviation and Sharpe ratio of the stock portfolio, which is created according to the expected return and risk estimates of the wavelet fuzzy model and updated every month.

	Portfolio	BIST-30 Index	Equal Weighted Basket
Return	33.93%	5.94%	12.14%
St.Dev.	1447.7%	542.7%	701.4%
Sharpe Ratio	0.02343	0.01094	0.01730



8. CONCLUSION

Forecasting models for the future are widely used in many fields, especially in economy and finance. Financial asset forecasts are of great importance in portfolio management and the performance of forecasts plays a key role in the success of portfolio managers. This situation has led to an increased interest in models. While most of the models were based on statistical techniques in the past, new modeling techniques have been used recently. The most notable of these are artificial intelligence models such as artificial neural networks and fuzzy logic.

Unlike statistical models, these models make few assumptions and try to predict by learning the relationship between inputs and outputs. Since artificial neural networks and fuzzy logic models, which are among the leading artificial intelligence applications, are complementary structures, they have been used together in many models in recent years and successful results have been achieved.

ANFIS was used as neural fuzzy system in the study. Neural Adaptive Learning techniques allow developing a learning model using input data for fuzzy modeling. Using the ANFIS graphical user interface in Matlab Fuzzy Logic Toolbox, the network was trained with three datasets as training, control and testing.

In this study, the daily values of Borsa İstanbul 30 Index, Gold and USD / TL exchange rate are tried to be estimated by using Wavelet Analysis and Neural Fuzzy Networks method. Buy / Sell signals are generated from the estimates created by the model. The performance of the portfolio was analyzed assuming that the underlying asset was invested on the days when the model predicted an increase and the investment was not made on the days when it predicted a decrease, and it was evaluated in overnight risk-free interest when not invested.

In addition, the model has been tested in artificial indices and stock market indices of other developing countries. While the model showed a successful performance in Russia and China, it remained below the index in South Korea stock exchange.

Then, the optimal portfolio was created by using wavelet fuzzy network model estimates and the performance of the portfolio was examined.

With the return and standard deviation values produced by the model, optimization was made to obtain the largest Sharpe ratio, and the performance of the portfolio of three assets was compared with the assets' own performances and risk-free interest by re-balancing at different time intervals. The performance of the proposed wavelet transform and fuzzy neural networks model was also tested in the stock asset class. For this, 10 stocks in the BIST-30 index were selected. In order to create the most efficient portfolio with the selected stocks, the return estimates made with the proposed hybrid model were used and the weight of each stock in the portfolio was calculated by maximizing the portfolio's Sharpe ratio.

The highlights of the thesis can be summarized as follows;

- The results show that the model created by using wavelet analysis and fuzzy neural networks together gives successful results in predicting the future values of financial assets and further research has potential.
- It has been observed that both the return of the optimal portfolio and the Sharpe ratio of all time periods are higher than the assets themselves.
- Wavelet Neural Network method, in which Artificial Neural Networks are used together with wavelet transform, can be used to predict the future price of assets traded in financial markets such as BIST30, Gold and USD/TL exchange rate.
- Despite all its advantageous sides and developing structures, artificial neural networks and ANFIS methods are handicapped. In these methods, models are created for certain dataset structures and are not suitable for every dataset.
- In addition, many attempts should be made during the discovery of the appropriate model for the available data set. The choice of sample for the data, which learning method to use, the size of the data set, the type of membership function to be used are the determinants of the output values and these values are determined by trials.

In the future, the performance of the model can be examined and developed by working on the following issues;

- Estimates can be made using the model in this study for financial assets other than gold, USD/TRL and BIST-30.
- A similar study of the stock portfolio for BIST-30 index stocks can be done in the BIST-100 index. In addition, the performance can be tested by creating an effective portfolio with the proposed model for the stocks selected from the stock market indices of other developing countries.
- For the estimations of the financial assets used in the study, estimations can be made by using different variables.
- The performance of the model in different market conditions can be tested by repeating the study at different time intervals.
- The effectiveness of the model can be measured in other developed and developing country markets.
- In the study, wavelet transform is done using Haar wavelet, financial series can be decomposed into its components by using different wavelets.
- Model can be developed using a different ANFIS structure



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APPENDICES

APPENDIX A: Decomposition of BIST-30/USD/TL/Gold Time Series with Wavelets

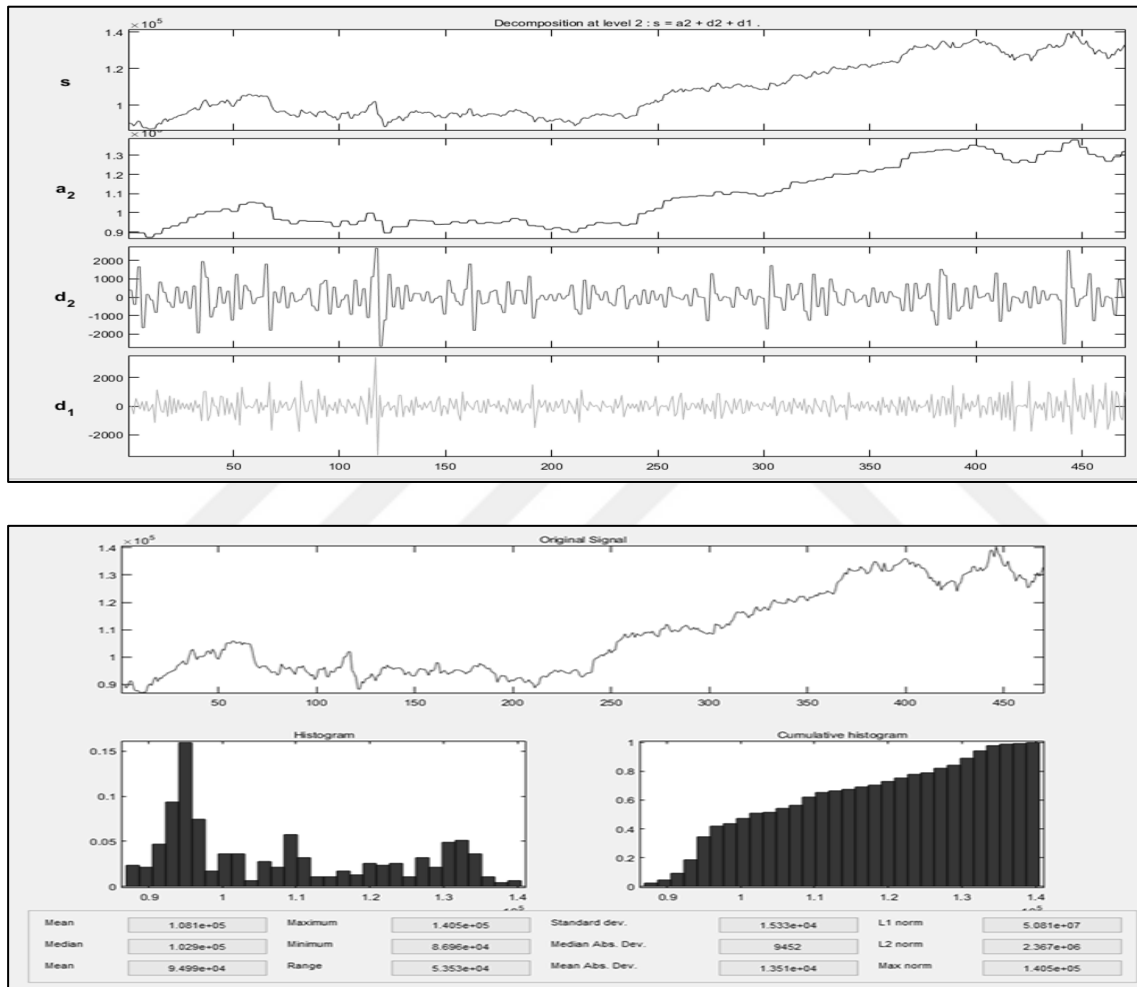


Figure A.1 : Decomposition of BIST-30 Index training data with Haar wavelet and descriptive statistics

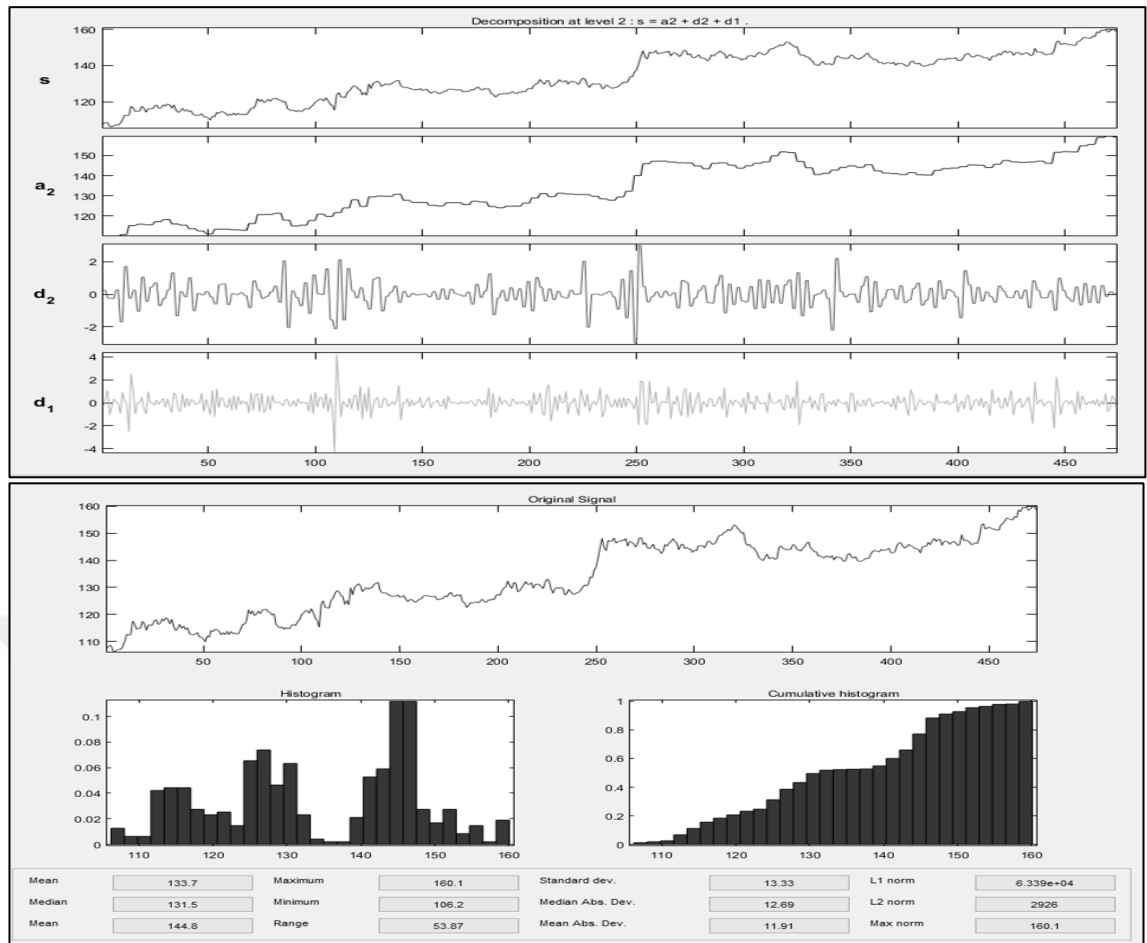


Figure A.2 : Decomposition of Gold training data with Haar wavelet and descriptive statistics

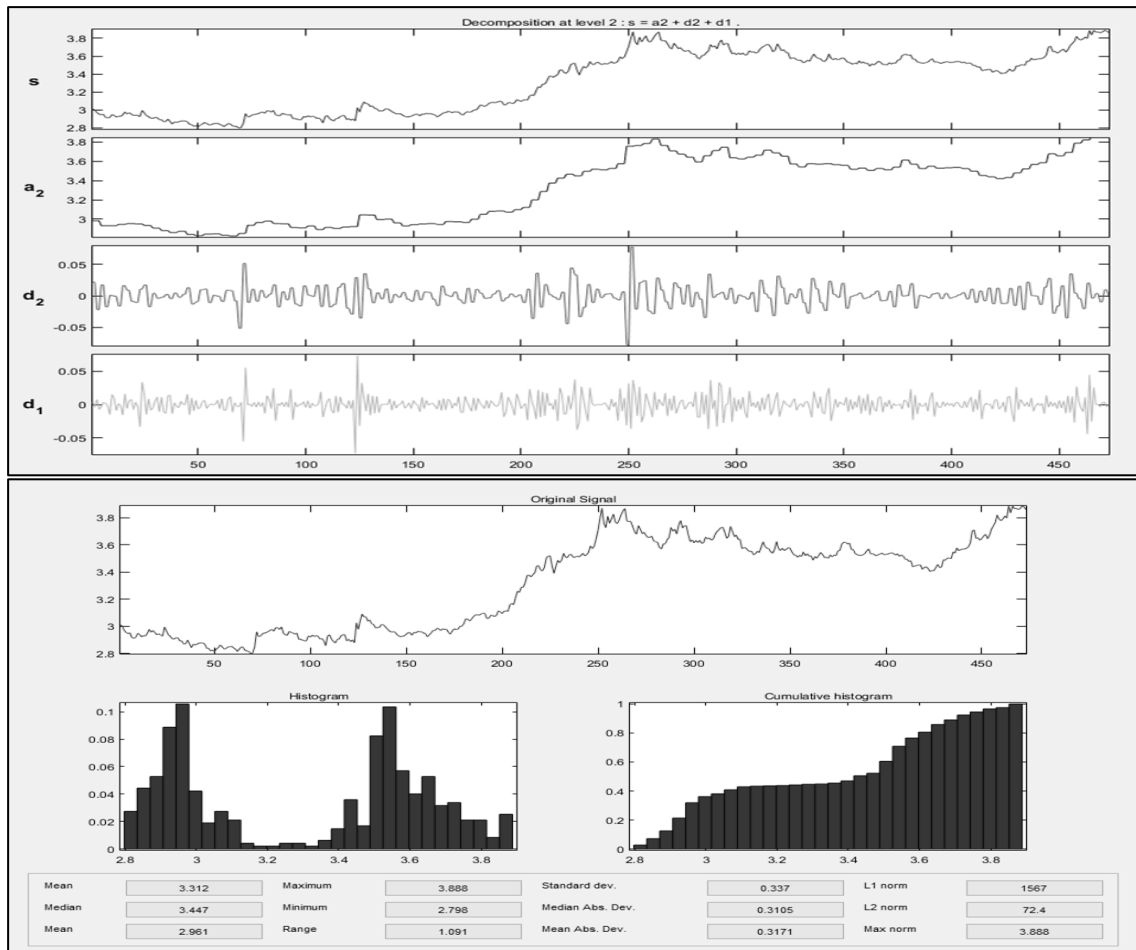


Figure A.3 : Decomposition of USD/TL training data with Haar wavelet and descriptive statistics

APPENDIX B: Training and Checking data in ANFIS

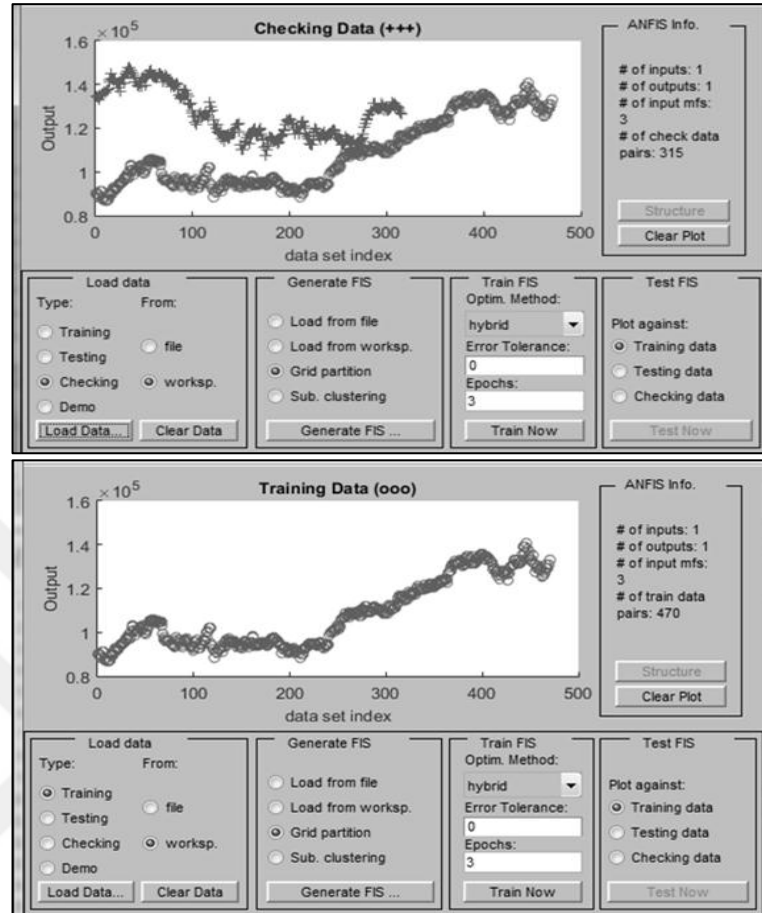


Figure B.1 : Training and Checking data set of BIST-30 first subset (a2)

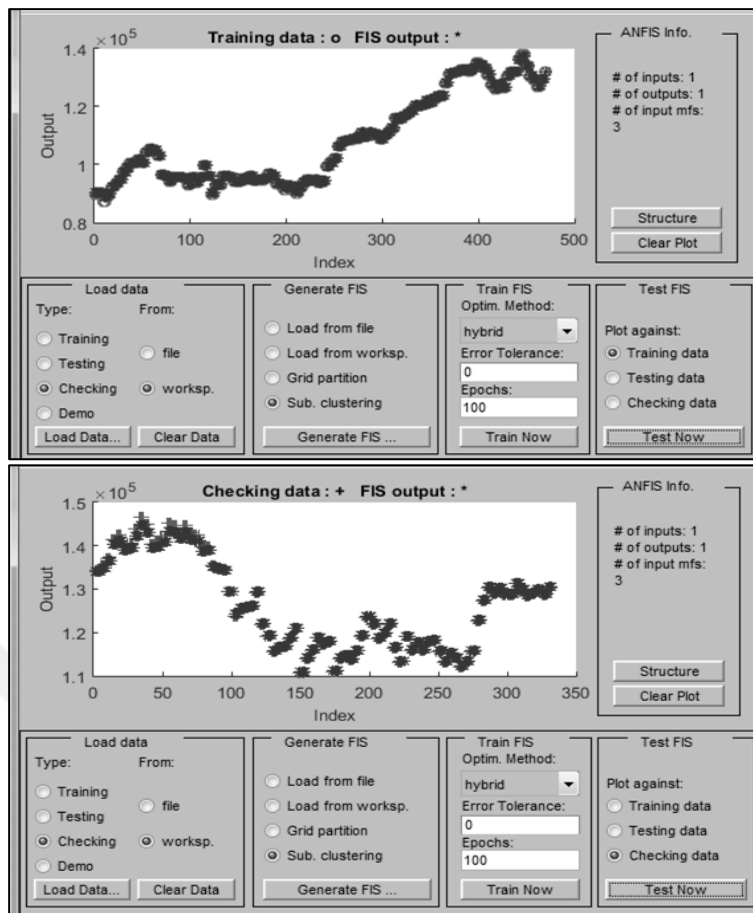


Figure B.2 : Validation of the model for checking data set.

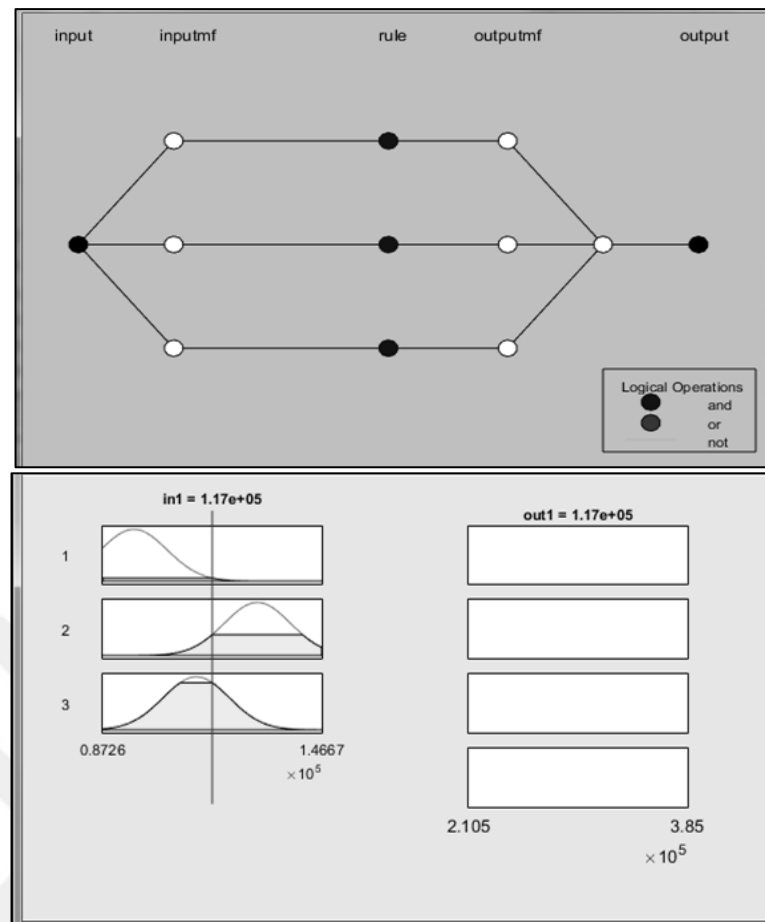


Figure B.3 : Model Structure and fuzzy rules of BIST-30 first subset (a2)

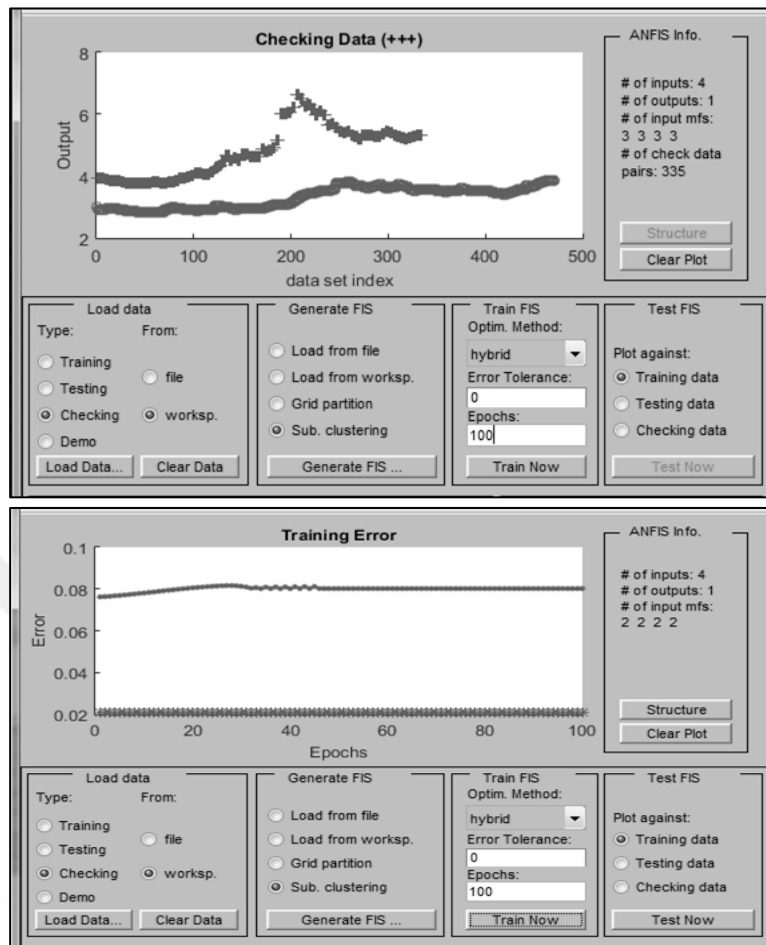


Figure B.4 : Training and Checking data set of USD/TL first subset (a2)

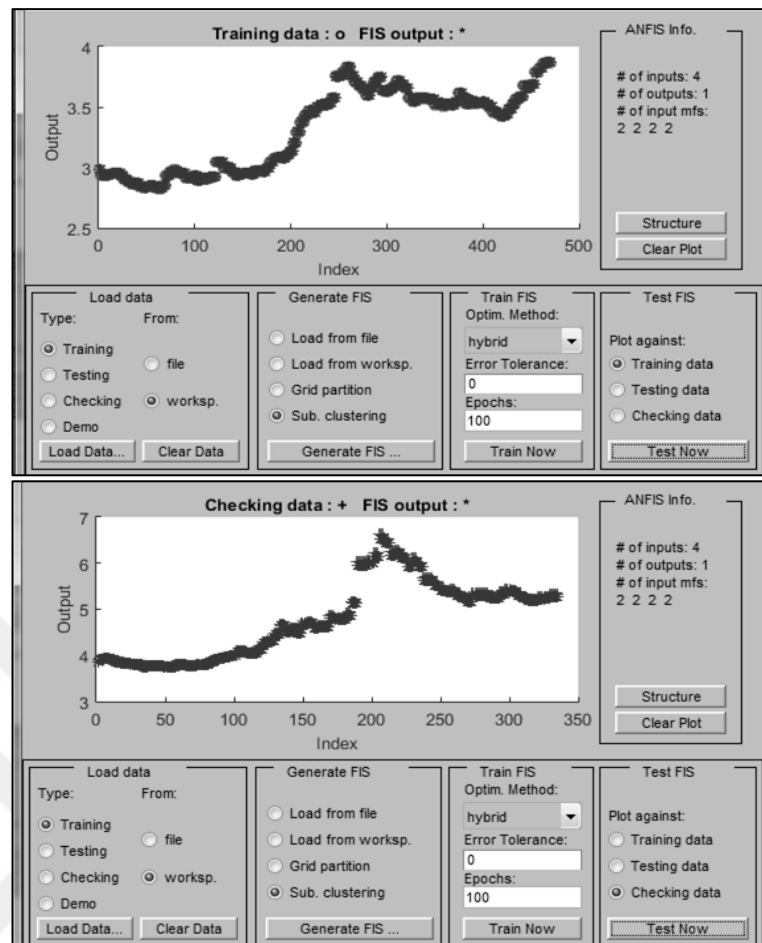


Figure B.5 : Validation of the model for checking data set.

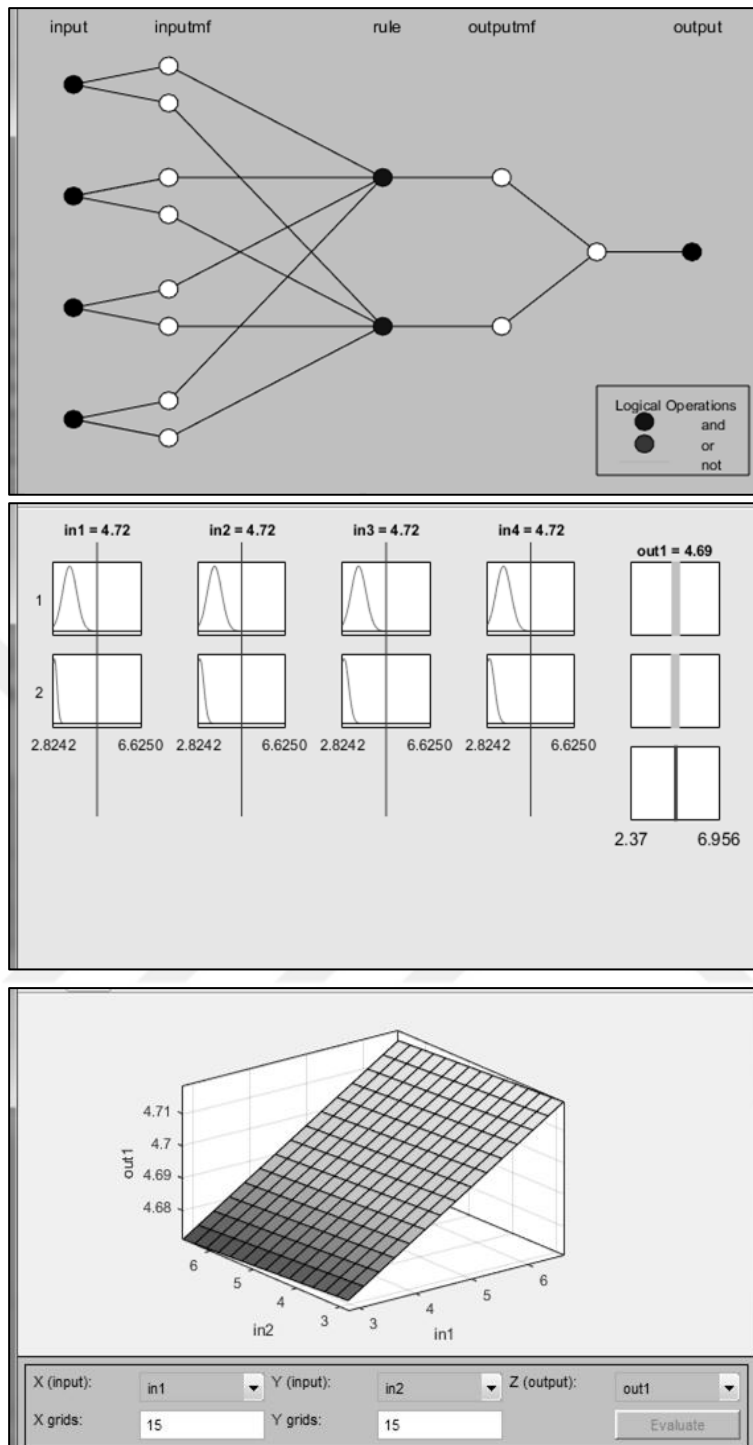


Figure B.6 : Model Structure and fuzzy rules of USD/TL first subset (a2)

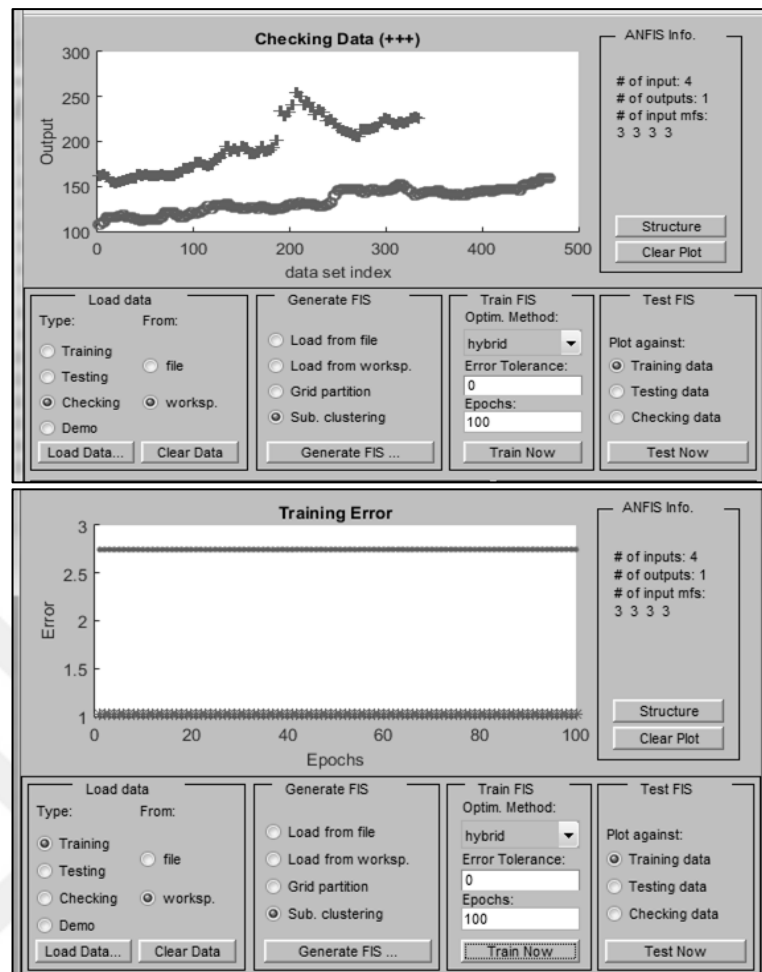


Figure B.7 : Training and Checking data set of USD/TL first subset (a2)

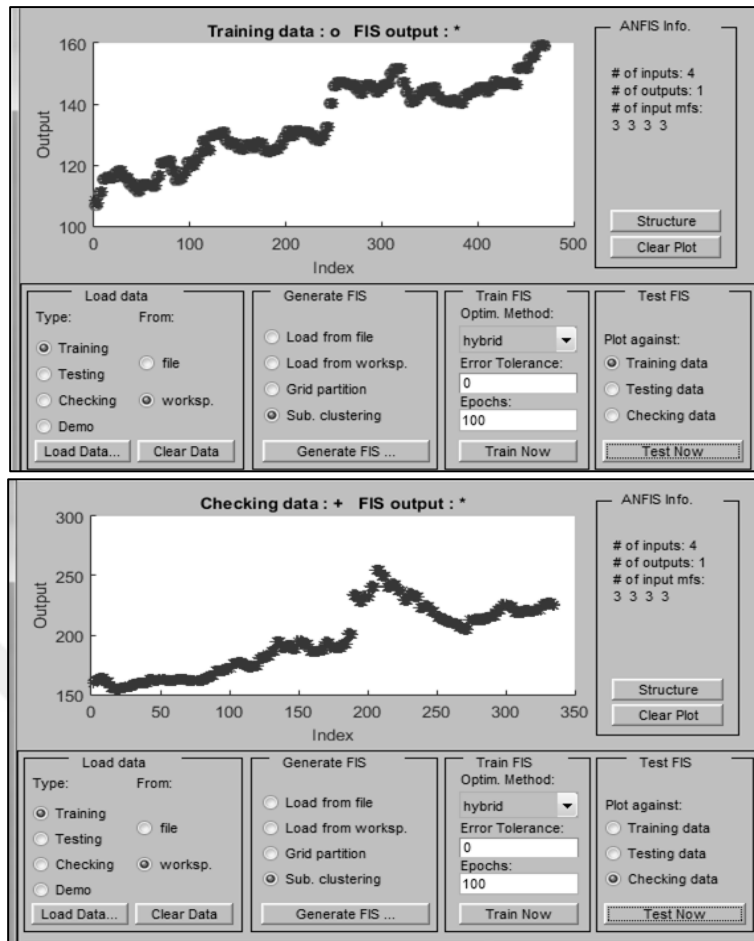


Figure B.8 : Training and Checking data set of Gold first subset (a2)

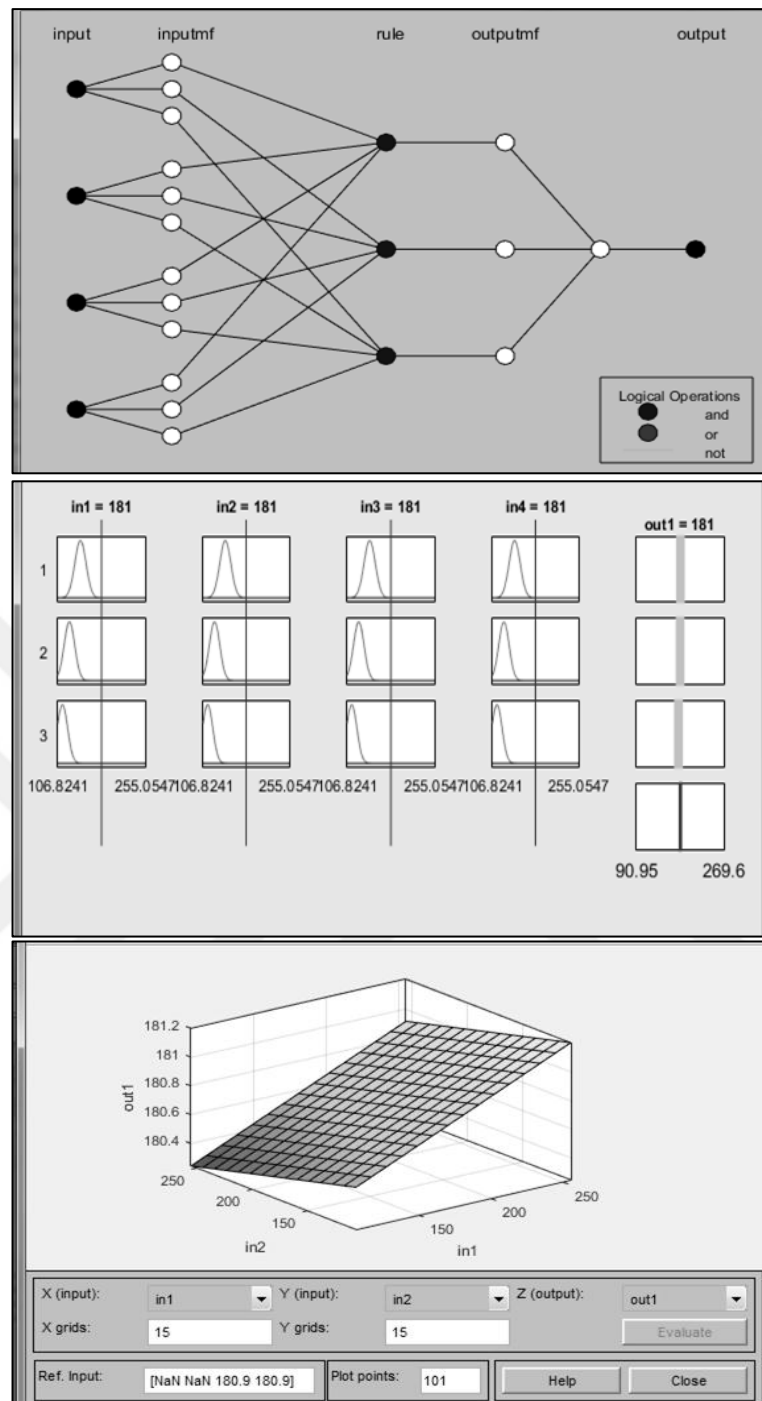


Figure B.9 : Model Structure and fuzzy rules of Gold first subset (a2)



APPENDIX C: Decomposition of RTSI Index Training/Checking/Testing Data with Wavelets

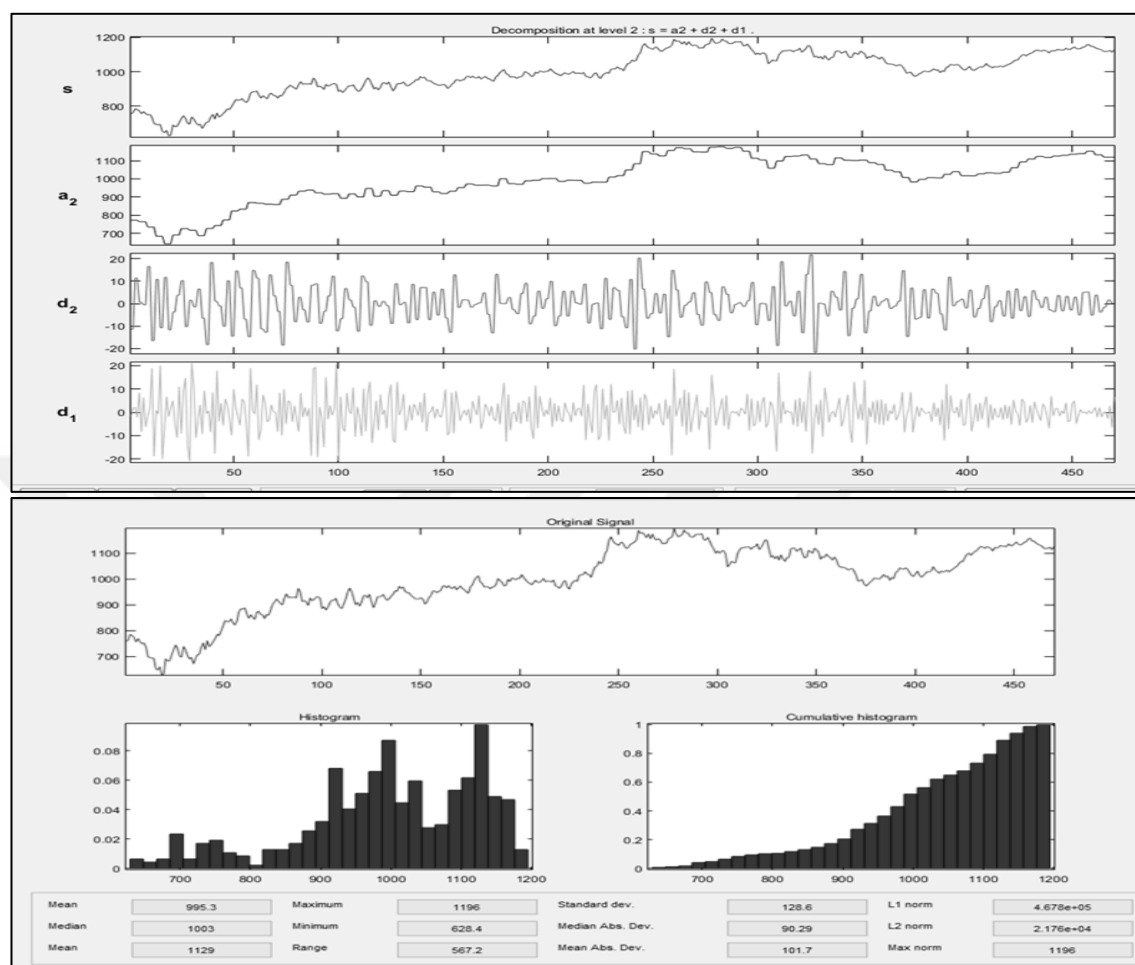


Figure C.1 : Decomposition of RTSI Index training data with Haar wavelet and descriptive statistics

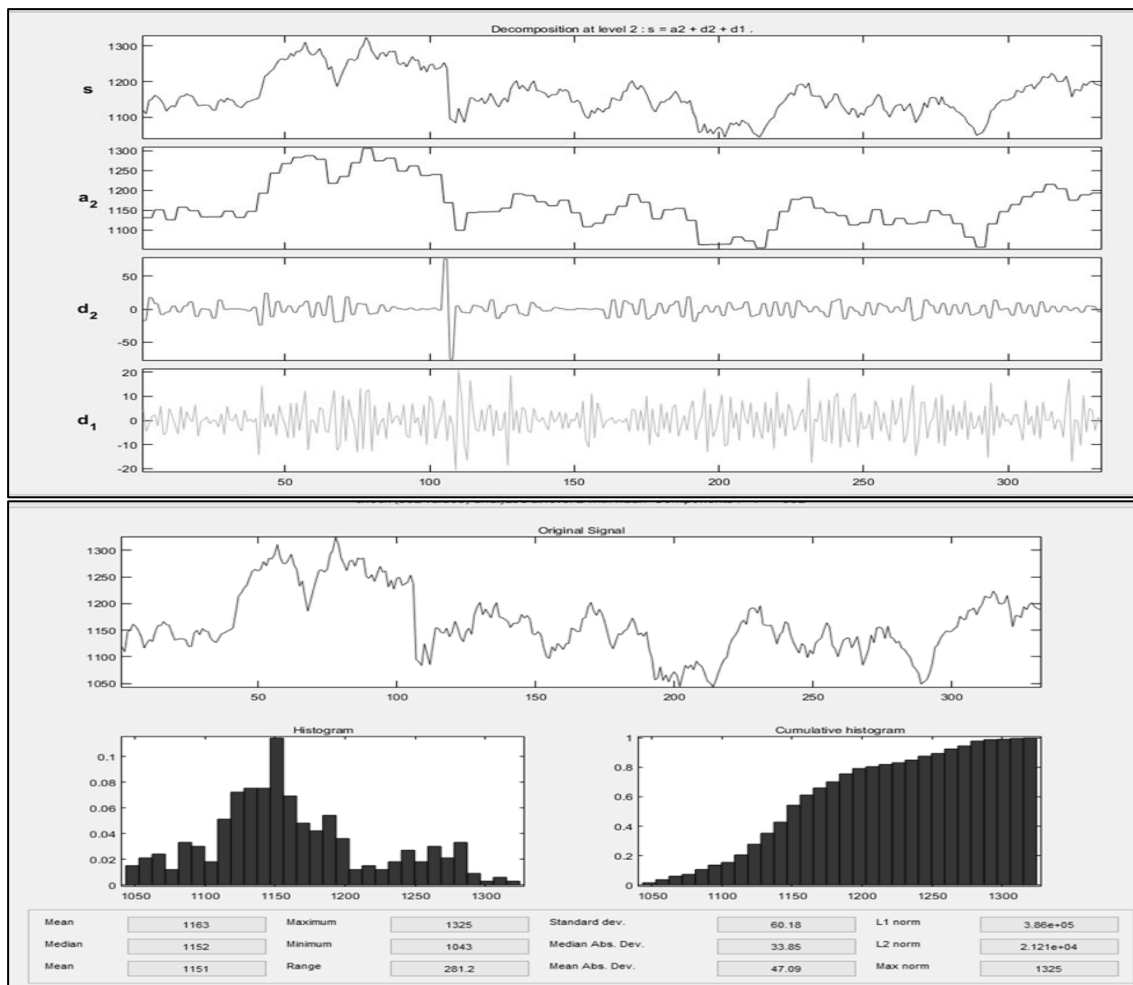


Figure C.2 : Decomposition of RTSI Index checking data with Haar wavelet and descriptive statistics

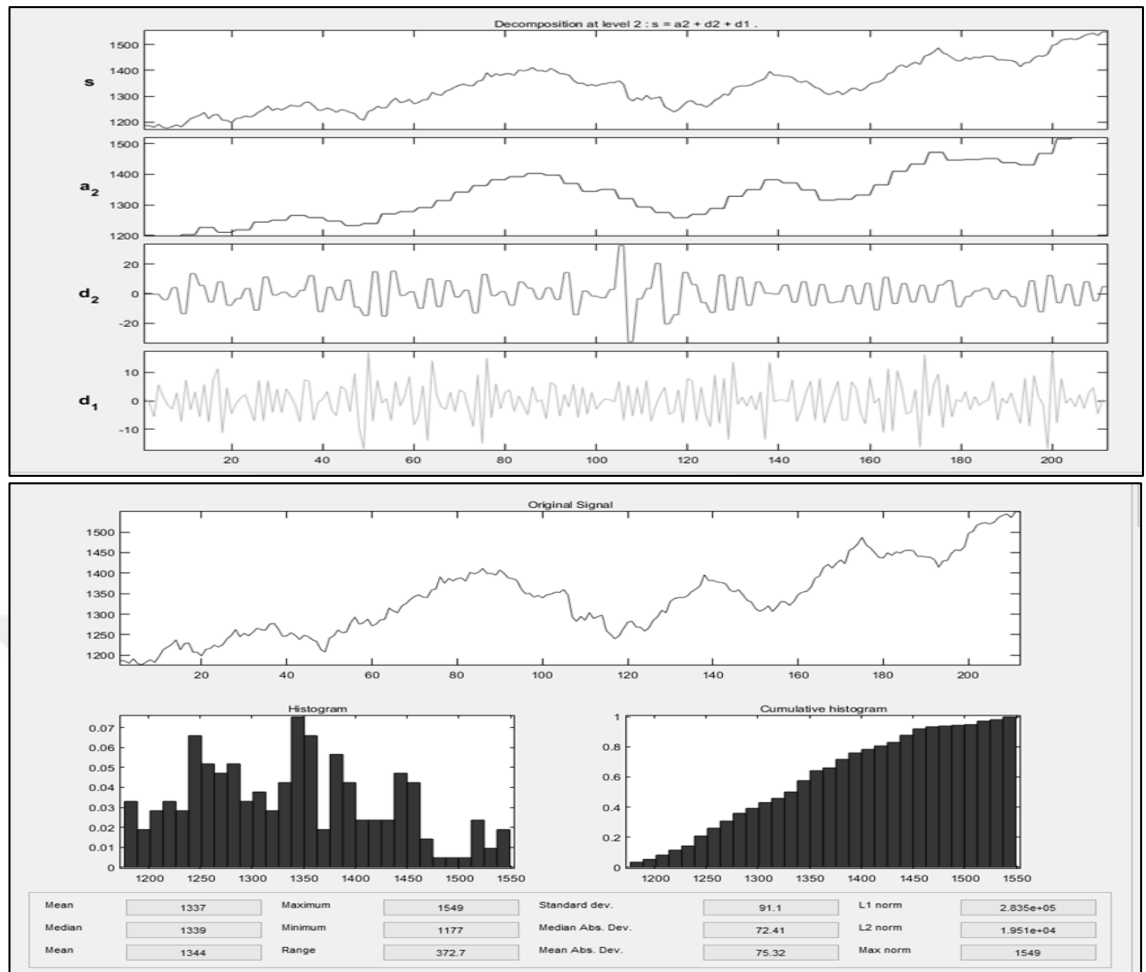


Figure C.3 : Decomposition of RTSI Index testing data with Haar wavelet and descriptive statistics



Appendix D: Modelling RTSI Training and Checking data in ANFIS

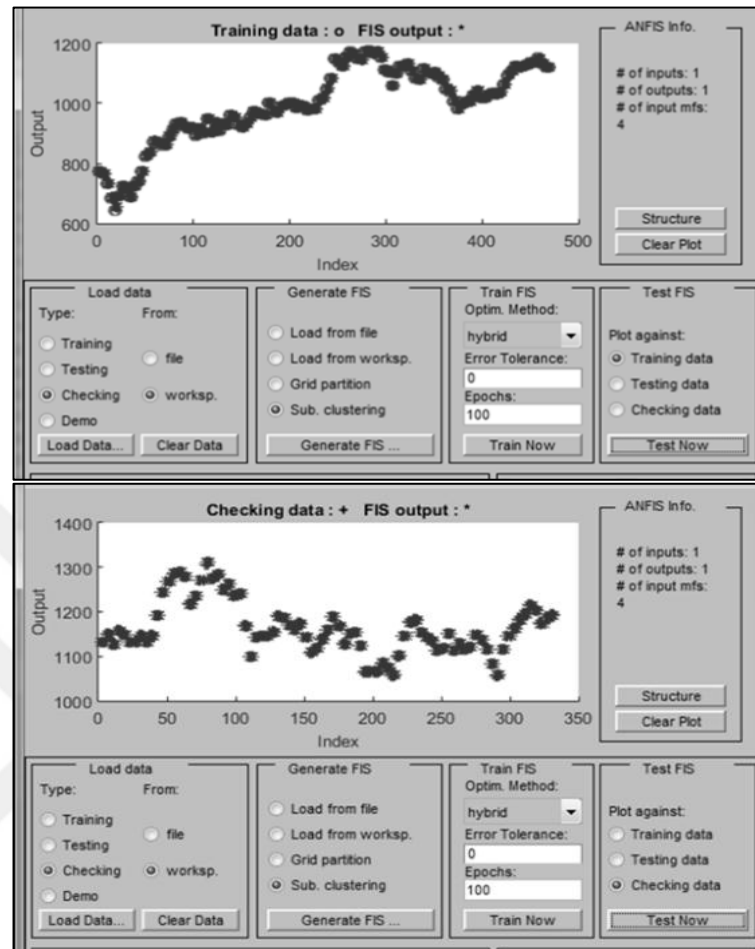


Figure D.1 : Validation of the model for firs subset of RTSI (a2)

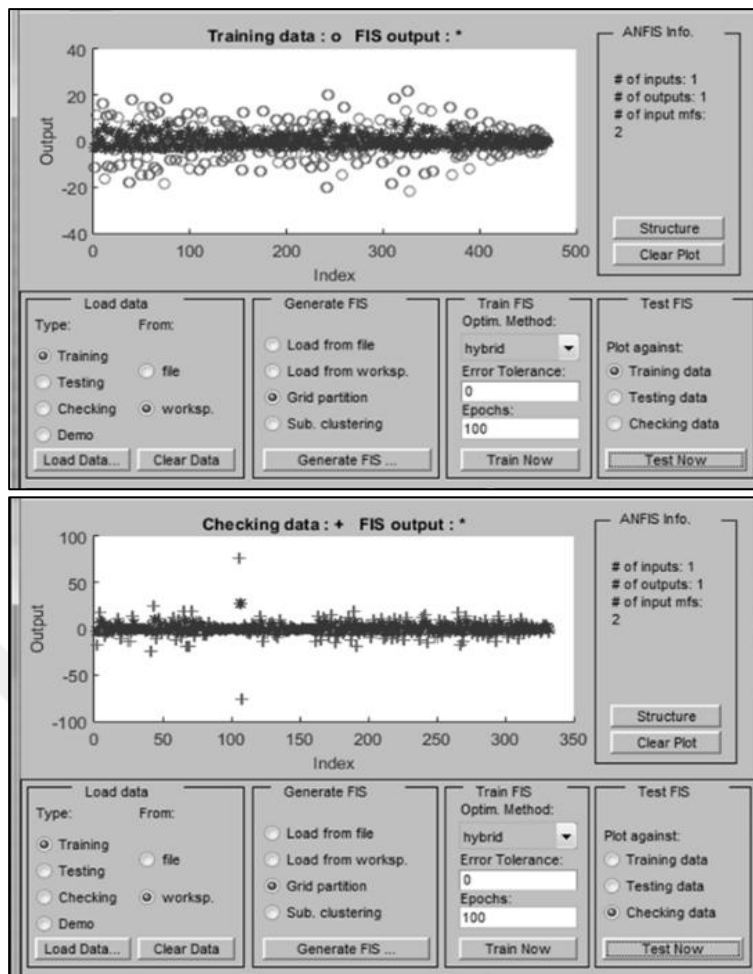


Figure D.2 : Validation of the model for second subset of RTSI (d1)

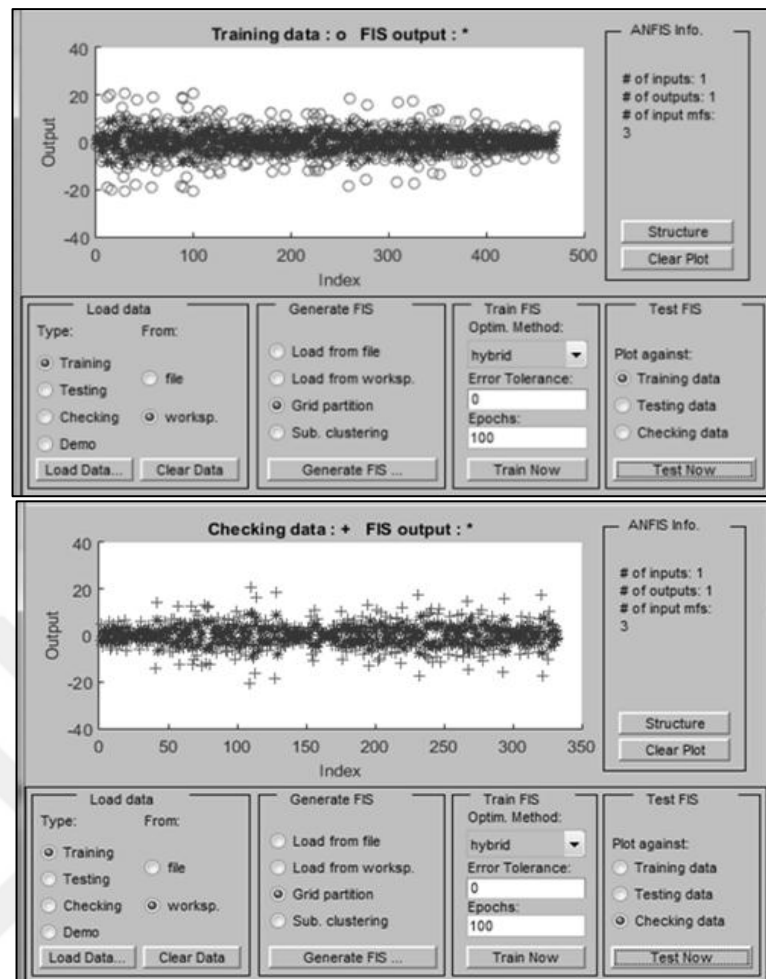


Figure D.3 : Validation of the model for third subset of RTSI (d2)



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- **Gursoy Ö.Z., & Taş O.** 2021. Dynamic Multiplier CPPI Strategy with Wavelets and Neural-Fuzzy Systems. Intelligent and Fuzzy Systems Conference (INFUS) 2021.
- **Gursoy Ö.Z., & Taş O.** Forthcoming. Portfolio Optimization with Wavelet Analysis and Neural Fuzzy Networks. The journal of Multiple-Valued Logic and Soft Computing