



Enhancing Predictive Accuracy of Insurance Stock Market in Jordan using Hybrid GFS.Thrift Model: A Genetic Fuzzy System-based Fintech Approach

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Abstract

This study focuses on improving the predicting accuracy of the daily ASE's weighted price index of the insurance sector (ICI) using a nonlinear spectral model called maximum overlapping discrete wavelet transform (MODWT) with five mathematical functions, namely, Haar, Daubechies (d4), least square (la8), best localization (bl14), and Coiflet (c6). Using a nonlinear spectral model called maximum overlapping discrete wavelet transform (MODWT) with five mathematical functions—Haar, Daubechies (d4), least square (la8), best localization (bl14), and Coiflet (c6)—this study aims to increase the daily ASE's weighted price index of the insurance sector's (ICI) prediction accuracy. The model utilizes a genetic fuzzy system based on Thrift's methodology (GFS.Thrift). The Amman Stock Exchange (ASE) supplied a dataset with 4,478 observations for the purpose of the study. The dataset represented daily data from January 2, 2006, to March 24, 2024. The adaptive GFS.THIFT model was trained with 90% of the dataset, while the remaining 10% was used to test its prediction performance. Multiple egressions and multicollinearity tests were used to select input variables such as standardized foreign direct investment (FDI), standardized value traded (VT) and consumer price index (CPI). Insights from this study indicate that all input variables are positively related to the output variable. Secondly, the proposed model (MODWT-Haar-GFS. Thrift) significantly outperforms other existing models including the GFS. Thrift model.

Keywords: wavelet transform; FDI; GFS.Thrift model; fuzzy logic; fuzzy genetic algorithm.

1. Introduction

Jordan's Amman Stock Exchange (ASE) has suffered times of crisis and volatility, with significant economic ramifications. On November 8, 2005, the ASE reached an all-time high of 9,348 points. The index completed the year at 8,192 points, up 93 percent over the previous year. The banking index grew by 134%, services rose by 78%, insurance grew by 98%, and industry increased by 15% throughout this time [1]. Following the 2008 global financial crisis, the ASE suffered significant falls in index with many other stock markets. The ASE weighted price index peaked at 7519.3 in 2007, later decreasing to 5520.1 in 2009, reaching to 4593.9 in 2012, and 4336.7 by the end of 2013. This greatly affects the finance and liquidity cost of Jordanian listed companies [2]. The COVID-19 pandemic has caused considerable volatility in the Jordanian ASE market. The stock market index was 1,867.90 points in January 2020, a significant difference from 1,573.46 in November 2020, indicating the period's volatility and unpredictability. However, a slow recovery took place, with a peak of 2,472.51 points in May 2022 [3].

Fintech is the term used to describe financial innovations that use advanced computational methodologies which include big data analytics, and machine learning [4, 5]. Faced with the global economic uncertainty, there has been

increasing pressure on the insurance sector to predict future events [6]. The presence of volatility and economic instability in Jordan's insurance industry points to reflect emerging markets [6, 7].

The stock market is influenced by a large number of economic and political events [8]. Investors, as well as financial practitioners, face a great deal of trouble in forecasting stock market prices. It is important to accurately make predictions of stock market prices, which is important in making wise investment decisions, and managing risks [9]. Researchers are interested in predicting the stock prices with various studies that using different methods. In a study conducted by [10], that analyzed predicting stock trends for major stocks in the United States, Turkey, Pakistan, and Hong Kong using three machine learning algorithms; linear regression, support vector regression, and deep learning algorithms. The results of this study showed that some events did not directly relate to stock market prediction but if there is a critical local event, the current algorithms for predicting stocks may be affected. [11] used the Empirical Mode Decomposition (EMD) in conjunction with ARIMA and EWMA methods in an effort to enhance the accuracy in Toronto stock Exchange to predict stock prices, and [12] utilized the WT to predict stock trends for the banking sector in ASE of Jordan. [13] employ the Multi-Layer Perceptron (MLP) algorithm to detect outliers in the daily stock price indices in the Saudi Arabia stock exchange, Tadawul.

In this study, we have two main goals. The first one is to model ICI time series data using a hybrid approach of GFS.THRIFT and MODWT models. In our analysis, we will also look at how FDI, VT, and CPI impact the insurance stock market. Our second aim is to delve into the fluctuations of historical data from the insurance stock market between 2006 and 2024— especially during the COVID-19 period. We will be blending MODWT functions with a GFS.THRIFT model; not only does it enhance forecast accuracy but it also takes into account the impacts of the pandemic. This study does not only work to enhance future price predictions but is also geared towards assessing COVID-19's effect on the insurance stock market and consequently offering an elaborate picture of its behavior. A structured format is adopted in the paper: Section 2 reviews the literature, Section 3 provides a research design, Section 4 explains the methodology, Section 5 presents the experimental results, and Section 6 concludes the paper.

2. Literature Review

Use of computational models such as artificial neural networks (ANN) and genetic algorithms has revolutionized stock market prediction and enhanced predictive accuracy. Many researchers have employed artificial neural networks in various economic fields such as [14-16]. The ANN can capture complex relationships within the stock market data environment. Genetic algorithms can explore the dynamic of the market landscape. Integration of ANN and genetic algorithms with traditional techniques has improved the accuracy of forecasts. In predicting stock market indices and prices, researchers have demonstrated the superiority of these models by outperforming market averages, generating higher profits by using technical indicators as predictors in stock markets [17]. Various models have been developed, such as the Support Vector Machine (SVM), Convolutional Neural Networks (CNN), regression-based models, and Long Short-Term Memory (LSTM), to predict stock market prices [18]. [19] have developed a hybrid using neural networks and genetic algorithms, which predicted stock market prices in the Palestinian market. The MLPNNs-GAs model performed better than other models. This model had a low mean square error and for the Al-Quds Index. This highlights the effect of the MLPNNs-GAs model in prediction stock market prices accurately. Particularly for predicting nonlinear financial time series.

[20] conducted a study on the effects of insurance firms and pension funds on stock markets in fifteen developing countries between 2004 and 2019. For this research, they employed the panel cointegration and causality tests. The findings indicate a two-way short-term interaction between insurance companies, pension funds, and stock market development. They note that in South Africa, Brazil, Chile, Hungary, Mexico, Peru, and other countries, pension funds and stock market growth have historically been positively correlated. [21] examine factors that impact the liquidity of the Indian stock market using different macroeconomic variables. They find that foreign investment and gold prices have a negative effect on liquidity, while money supply has a positive effect. [22] demonstrate the effect of inflation, exchange rate, and Return on Equity (ROE) on the composite stock price index in Indonesia. [13] use the MLP algorithm to identify outliers in the daily stock price index of the Saudi Stock Exchange (Tadawul) and highlight the existence of three different inputs influencing stock prices, namely the inflation rate, oil price, and repo rate.

3. Research Design

In our research, we concentrate on hybrid GFS.THRIFT versions which integrate input as well as output variables. We comply with a multi-stage procedure beginning with information collection on the Weighted Price supply insurance coverage Index from the ASE in Jordan. We perform examinations to analyze multicollinearity as well as OLS regression to pick appropriate input variables. We after that make use of MODWT a decomposition strategy, to simplify the information right into details as well as approximate coefficients. The approximate coefficients function as the outcome variable for our hybrid model. In the third stage we consist of extra input variables such as VT, FDI, as well as CPI to improve design precision. With precision examinations as well as efficiency analysis, we identify one of the most reliable projecting version. Fig. 1. shows the phases along with their links in our research.

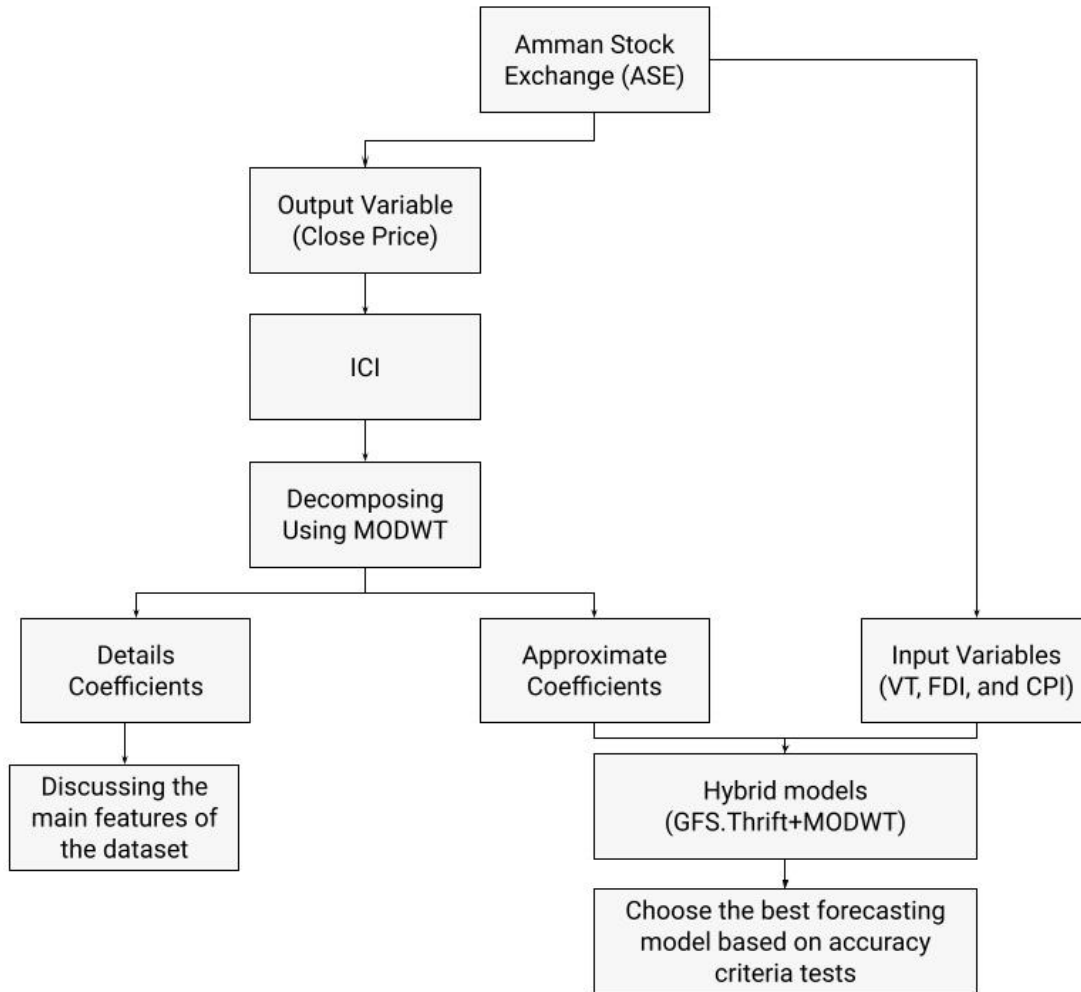


Figure 1: The flowchart of MODWT with GFS.Thrift.

4. Methodology and Mathematical Models

This section presents an introduction to the mathematical models incorporated in our study

4.1 Wavelet transform (WT)

This research study checks out the utility of time series evaluation for understanding trends, determining patterns with making accurate forecasts. Fourier evaluation presented by Joseph Fourier in 1807, changed signal evaluation by unwinding the patterns right into sinusoidal parts. The Fourier change stood for by Equation (1) permits the decomposition of a signal right into its sine as well as cosine features. cosine Fourier coefficients, specifically with

$$f(x) = \frac{1}{2}\alpha_0 + \sum_{n=1}^{\infty} \alpha_n \cos nx + \sum_{n=1}^{\infty} b_n \sin nx, \quad (1)$$

where $\alpha_n = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos nx \, dx$ and $b_n = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \sin nx \, dx$. The α_n and b_n are the sine and cosine Fourier coefficients, respectively with $n \in \{1, 2, 3, \dots\}$. These sine and cosine coefficients were changed to restore the signals referred to as deterministic [23, 24].

In the recent decades, WT has come up as a stronger substitute for other traditional models such as Fourier analysis when analyzing time series. Three main types of WT are there; the Discrete Wavelet Transform (DWT), the Continuous Wavelet Transform (CWT) and the Maximal Overlap Discrete Wavelet Transform (MODWT), which have some common features. The distinction between DWT and MODWT is that only limited number of observations for DWT can be used whereas any amount of data may be subjected to MODWT. WT involves two types of wavelets: the father wavelet $\varphi(t)$, which indicates smooth coefficients or the low-frequency components, and as the mother wavelet $\phi(t)$, which represents detailed coefficients or captures the high-frequency components, indicated in equations (2) [12].

$$S_{j,k} = \int \phi_{j,k} f(x) dt \text{ and } d_{j,k} = \int \varphi_{j,k} f(x) dt, \quad (2)$$

$$\text{where } \phi_{j,k} = 2^{\frac{-j}{2}} \phi\left(x - \frac{2^j k}{2^j}\right) \text{ and } \varphi_{j,k} = 2^{\frac{-j}{2}} \varphi\left(x - \frac{2^j k}{2^j}\right).$$

where $S_{j,k}$ represents smooth coefficients and $d_{j,k}$ represents detailed coefficients, the maximum scale sustainable by the number of data points is denoted by J . Both the father wavelets and mother wavelets must fulfill the specific requirements of $\int \phi(t) dt = 1$ and $\int \varphi(t) dt = 0$. The MODWT offers a range of valuable transform functions, such as Haar, Daubechies (d4), Coiflet (C6), least asymmetric (LA8), and best-localized (bl14), which have proven to be highly useful in various applications [25].

4.2 GFS.Thrift model

The GFS.Thrift model is a Thrift's technique-based genetic fuzzy system [26]. It comprises of different layers and components that are interconnected to solve regression problems using fuzzy logic and genetic algorithms. This model encompasses an Input Layer; a Fuzzifier Layer; an Inference Engine Layer and an Output Layer. The Input Layer typically takes normalized data for regression analysis contained in a matrix of size $m*n$ where m denotes the number of observations, n represents the number of variables with the last column being the output variable. The most important thing to note here is that normalization should be done between 0 and 1. On the other hand, the Fuzzifier Layer contains membership functions that map input variables to linguistic terms using fuzzy sets. The Inference Engine Layer exploits rules that define how input variables impact upon output through linguistic terms intersection. At this layer, it uses genetic algorithm for optimizing fuzzy rules along with linguistic terms which improve performance efficiency of the model. Lastly, there is an Output Layer that applies defuzzification methods to change a fuzzy output into a crisp value or decision as well as representing what was predicted for the whole process of regression task.

The dataset we employed in the study contained historical price of stock and values for VT, FDI, CPI pairs that are relevant to each time period. Therefore, our aim is to come up with a regression model that will predict future stock prices on the basis of these factors. The decision table has been represented as genotype using GFS.Thrift model whereby each row represents rule. For example "IF VT is high AND FDI is increasing AND CPI is stable, THEN predicted stock price is high." Here fuzzy set indicators have designation such as 'high', 'increasing' and 'stable'. After fuzzification the model forms phenotype where input variables (VT, FDI, CPI) are applied membership functions to map them into fuzzy sets. For instance a share VT value may belong to a set "high" with a membership degree of 0.8. Later on the model aggregates those fuzzy sets applying max-* composition by summing all fuzzy sets from rules into one aggregated fuzzy set. In determining degree of membership of each linguistic situation (for example "high") in the output domain (stock prices), there was an intersection between their corresponding fuzzy sets. Furthermore in this layer genetic algorithm optimizes these rules and linguistic terms by use of crossover and mutation operations that also optimize linguistic term as well through GA. Finally, the defuzzification operation is

employed to obtain a crisp output. The centroid technique, a commonly used defuzzification method, calculates the center of gravity of the aggregated fuzzy set, representing the predicted stock price. See (Fig. 2)

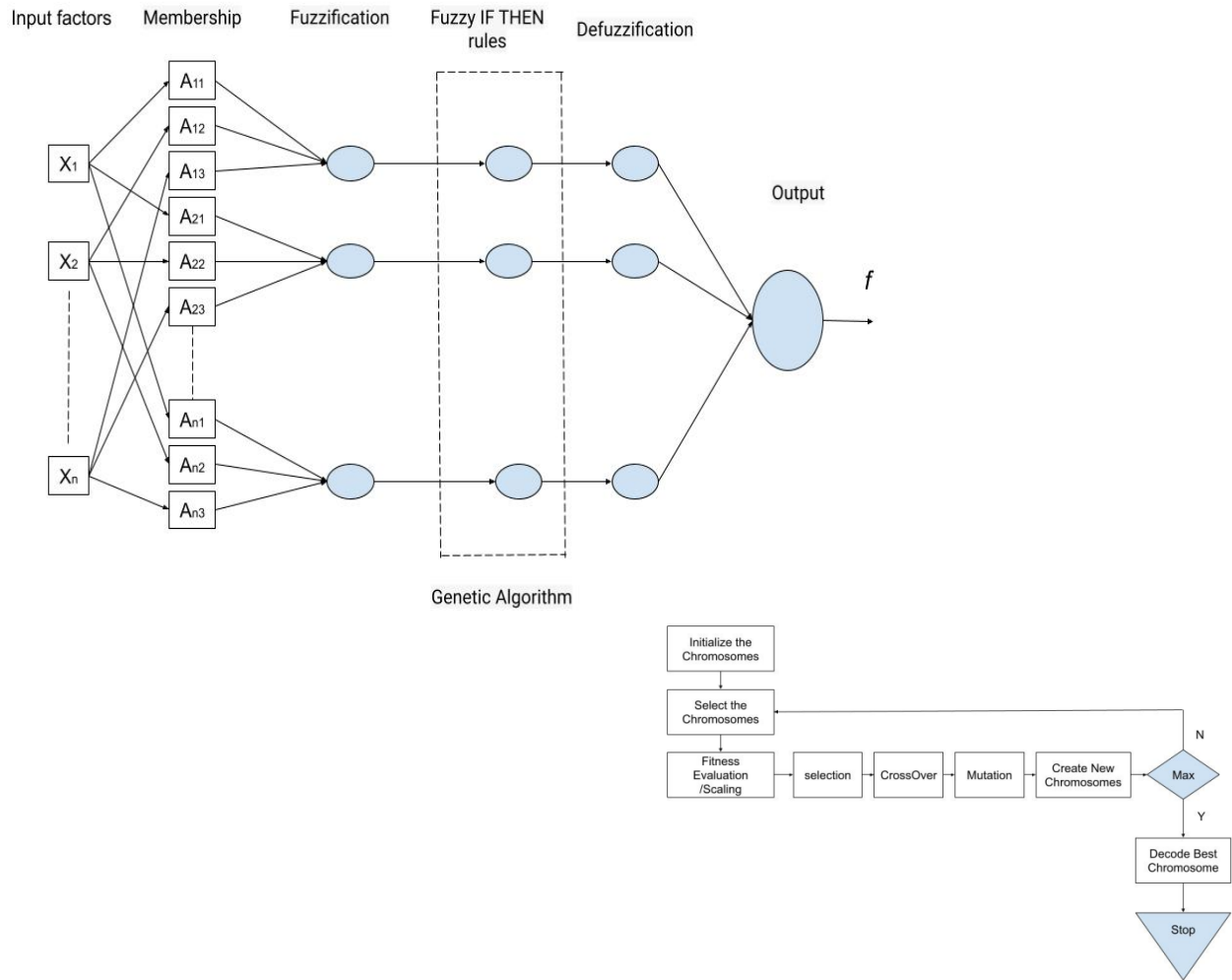


Figure 2: GFS.Thrift architecture of n -inputs and one output.

4.3 Error criteria test

In our evaluation, we apply many error metrics to assess the performance and the accuracy of the models such as the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Scaled Error (MASE), Autocorrelation Function 1 (ACF1), Akaike Information Criterion (AIC), Corrected Akaike Information Criterion (AICC), Bayesian Information Criterion (BIC), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE).

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{X_t - F_t}{X_t} \right|, \tag{3}$$

$$MAE = \frac{1}{n} \sum_{t=1}^n |X_t - F_t|, \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (X_t - F_t)^2}. \quad (5)$$

$$MASE = \frac{\sum_{t=1}^n |X_t - F_t|}{\frac{n}{n-1} \sum_{t=2}^n |X_t - X_{t-1}|} \quad (6)$$

$$AIC = -2 * \log(\text{likelihood}) + 2 * npar \quad (7)$$

$$BIC = -2 * \log - \text{likelihood} + \text{LOG}(n) * npar \quad (8)$$

Where X_t is the actual value, F_t is the forecasted value, n is the sample size and, $npar$ represents the number of parameters in the fitted model. The AICC is a version of AIC corrected for small sample sizes. The RMSE and MAE provide measures of the overall forecasting error, with RMSE emphasizing larger errors due to the squared term. MASE, on the other hand, accounts for the scale of the data and provides a relative error measure. ACF1 evaluate the correlation structure of residuals, indicating the presence of any remaining patterns. AIC, AICC, and BIC aid in model selection by balancing goodness-of-fit with model complexity. MPE and MAPE are percentage based error measures that assess the accuracy of forecasts in relation to the actual values.

5. Results and Discussion

In this section, numerical results obtained through the application of our models to the dataset under consideration are given. A hybrid model providing a combination of GFS.THRIFT and MODWT-Haar is suggested for predicting insurance closing prices from January 2, 2006 to March 24, 2024. The MODWT technique employs WT like Haar, d4, LA8, C6 and bl14 performing sequential decomposition, filtering and reconstruction processes. At the time of decomposition phase wavelet coefficients are generated for different scales as well as positions in the signal. In other words, in filtering step relevant information is extracted by applying filter bank to the coefficients while during reconstruction step filtered coefficients are used to reconstruct the original signal approximately. By splitting data into detail and approximation series', MODWT effectively copes with large fluctuations in financial data. To assess how well this model performs an accuracy indicator will be used which gives a quantitative measure of its ability to predict insurance closing prices. As a prerequisite of GFS.THRIFT model it was assumed that all factors should fall within [0;1]. For this purpose we used min-max normalization method (also called min-max scaling or min-max normalization) at initial stage. With the exception of inflation, this rescaling process guarantees that the dependent and independent variables are converted to a standardized range of [0, 1] [27, 28]. The components inside the GFS.THRIFT framework that are conducive to correct analysis and modeling are those that follow this assumption.

The MODWT-GFS.THRIFT model, a proposed hybrid model, provides a new way of predicting financial time series. This consists of data collection, scaling using min-max normalization and decomposing the MODWT into approximation and details coefficients. The GFS.THRIFT hybrid model contains MODWT functions namely Haar, d4, LA8, C6 and bl14 as well as input variables such as TV, FDI and CPI. Comparative analysis shows that the hybrid model surpasses rival functions like ARIMA or any traditional models like GFS.THRIFT. The testing dataset constitutes 10% while 90% represents training dataset adopting a 90/10 approach for comprehensive forecasting ability evaluation. This research indicates how this technique may be used in various financial prediction sectors.

5.1 Dataset Description

A sample size consisting of 4478 observations was used to examine the different factors affecting the overall

insurance sector closing price index (ICI) on ASE in Jordan. The collected time-series data were composed of dependent variable ICI together with several factors that impact it; VT, FDI and CPI amongst others. These daily-generated data points provide a comprehensive perspective of those variables for the given time frame of January 2, 2006, to March 24, 2024. The World Bank and the ASE in Jordan, which are the official channels via which this data set was obtained, provided a useful tool for analyzing the connections between these variables and the ICI. A thorough review of the fundamental statistics, including measures of central tendency and dispersion, for every variable is provided in Table 1.

Table 1: Descriptive statistics of dependant and independent factors.

Factors	Mean	Standard deviation	Minimum	Maximum
ICI	2208.5757	1479.3259	1156.2617	7993.9243
VT	20671689.7700	32117829.6580	270181	801917982.0000
FDI	1212036468.6890	543206851.5562	441500000	2516244005.6418
CPI	0.0339	0.0334	-0.0088	0.1397

5.2 The Results of Multicollinearity Tests

Multicollinearity is not significant as depicted by Table 2 which indicates the connections between ICI (dependent variable) and VT, FDI and CPI (Independent Variables). The values of Tolerance and VIF substantiate this further since VIF figures for VT(1.425), FDI (1.419) and CPI (1.377) are close to one.

Table 2: multicollinearity test between factors

	ICI	VT	FDI	CPI	Collinearity Statistics	
ICI	1	0.635	0.693	0.468	Tolerance	VIF
VT		1	0.477	0.452	0.702	1.425
FDI			1	0.448	0.705	1.419
CPI				1	0.726	1.377

5.3 Results of Multiple Regression

Table 4 presents ICI as a dependent variable in a multiple regression analysis that used three independent variables: VT, FDI, and CPI. The intercept estimate (-0.1136) represents an expected value of ICI when all independent variables are zero. These estimates for VT, FDI, and CPI (1.9860, 0.3807, and 0.5686) indicate how much we expect the ICI to change if each of these independent factors increases by one unit while keeping other factors constant. Smaller standard errors imply more precise and confident estimates about the impact of independent factors on the ICI. The absolute t-values are very large and p-values less than 5% indicating that all Independent Variable (VT, FDI, CPI) have a significant effect on the Index Composite Indicator Algebraically speaking. An R-square adjusted R-square figure reveals that approximately 60.64% variability in ICI can be explained by the regression model under study. The statistical significance of this model in relation to explaining variations in ICI is confirmed by F-statistic whose associated p-value (<2.2e-16).

Table 3: The multiple regression

Intercepte	VT	FDI	CPI	R-square	Adjusted R-square	F-statistic	p-value

Estimate	-0.1136	1.9860	0.3807	0.5686				
Std. Error	0.0045	0.0605	0.0089	0.0714	0.6064	0.6061	2298	<2.2e-16
t value	-25.483	32.848	42.832	7.966				
Pr(> t)	<2e-16	<2e-16	<2e-16	2.06e-15				

5.4 Results of GFS.THRIFT model

A dataset was divided into two distinct groups for analysis purposes. The first group consisted of 90% of the data which was then used to train the adaptive GFS.THRIFT model. In this training phase, the majority of the dataset were used to allow the model learn and establish patterns and relationships. On the other hand, a test population made up of 10% of this dataset was created for evaluating how well an already trained predictive model can forecast. This process tested whether or not adaptive GFS.THRIFT could accurately predict outcomes as a result of what it had learned during its training period. Thus, through testing on a separate group, researchers were able to rate how good a job their models did in predicting future market behavior at both aggregate and individual levels. The dependent variable (ICI) in forecasting models included four independent variables (TV, FDI, CPI). These variables were selected as they consider various factors affecting insurance market hence improving prediction accuracy. The step size employed in these models was 0.01 during 10 iterations allowing for continued refinement with progressions involving minor upward changes being overemphasized so that convergence becomes imminent with proper forecasting methods being determined by small increments or steps taken over time.

Table 4 illustrates the WT function’s output variable for a data set with 90% coverage. In the table, different WT functions are compared with various ARIMA models with regard to their performances. Seven error metrics were applied in assessing the results of this experiment: RMSE , MAE , MASE, ACF1, AIC, AICC , and BIC. According to these tests’ scores, Haar model is superior to other models. It has lower RMSE values which imply that it captures data variations more accurately and also has a smaller value of MAE that shows greater precision in predicting values. The Haar model also exhibits the lowest MASE among all models indicating better relative performance as opposed to a baseline model and the least ACF1 value implying its superior ability to capture autocorrelation patterns. On top of this, Haar model has lesser AIC, AICC and BIC figures suggesting a closer fit without complexity unlike other models Overall, these two sets of results demonstrate that the Haar model emerges as the best among several statistics across various metrics.

Table 4: Comparative Analysis of Wavelet Transform Functions for ICI using 90% Dataset

WT function ARIMA(p,d,q)	RMSE	MAE	MASE	ACF1	Aic	AICC	BIC
Haar (5,1,0) with drift	0.0126533	0.003237049	0.07995005	0.6462565	27300.87	27300.84	27256.76
Db4 (5,1,0) with drift	0.01404156	0.00343392	0.11019884	0.6903013	29179.05	29179.03	29134.95
LA-8 (1,1,3) with drift	0.0273385	0.005817931	0.70291893	4.3250275	34483.87	34483.85	34446.07

BL-14 (0,1,2) with drift 0.03557675 0.007826197 0.82869192 2.2750491 33143.14 33143.13 33117.94

C6 (3,1,2) with drift 0.02810339 0.006043033 0.71421657 1.1655715 30570.72 30570.69 30526.61

Fig. 2 displays a WT analysis of a time series dataset that is most probably the historical closing prices for an insurance index. It has three sub-plots, the top one being the original time series data, which indicates a significant drop and subsequent stability; the middle one is high frequency components or noise with some periods exhibiting greater fluctuations while the last one represents low frequency components or long-term trend showing immediate fall followed by constant state. Using MODWT-based decomposition gives us an idea about how noisy our signals are at different levels of rendering them visible to human eye. It involves functional representation of input signal using formula $X = TV1 + TW1$, where X is defined as initial signal itself. Component $TV1$ on the right corresponds to single level approximation coefficient designed to capture general behaviour in transformed data. Also, component $TW1$ on the left stands for level one detail coefficient only. It's interesting to note that 4030 samples out of a total of 4478 are used to represent 90 percent of the data.

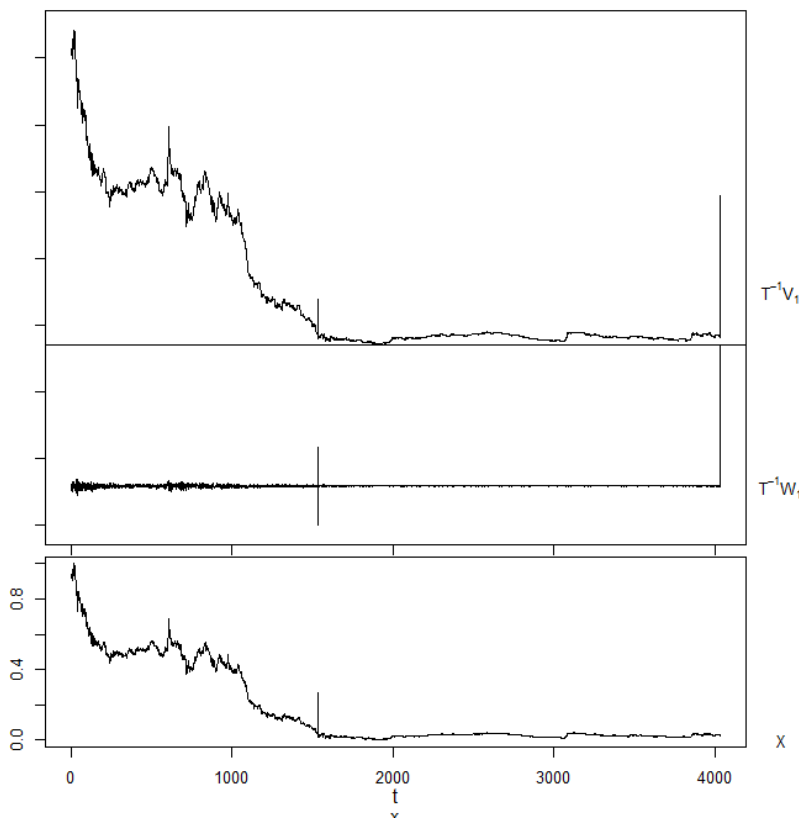


Figure 2: Decomposing the data using MODWT based on Haar function

In Table 6, a comparison is made between predictions for a dataset with 10% by utilizing the WT function on output variables (ICI). By using the RMSE metric, average size of forecast errors has been measured and where lower values indicate better accuracy. The model GFS.THRIFT+WT(Haar) shows that it performs better than other models since it has an RMSE value of 0.2306 implying that it captures data variability. On MAE metric, the model GFS.THRIFT+WT(Haar) has a minimum value of 0.2305 which calculates the mean absolute deviation from true

data set. For this reason, this model is preferred. MPE and MAPE indicators are evaluated using forecast accuracy in percentage errors terms. In terms of MPE and MAPE percentages over all data points at 91.61%, however, GFS.THRIFT+WT(Haar) performs better compared to others in this area of study. Based on these metrics therefore, GFS.THRIFT+WT(Haar) seems to be more accurate and dependable among other models for forecasting the output variable (ICI) in this dataset.

Table 6: The WT function of output variable for 10% dataset.

Hybrid Models	RMSE	MAE	MPE	MAPE
GFS.THRIFT+WT(Haar)	0.230605469	0.230462282	91.606528	91.60653
GFS.THRIFT+WT(d4)	0.506683124	0.505359422	96.003356	96.00336
GFS.THRIFT+WT(La8)	0.379691652	0.334446292	115.312208	115.31221
GFS.THRIFT+WT(b114)	0.714158743	0.714138574	97.128582	97.12858
GFS.THRIFT+WT(c6)	0.30492434	0.264337466	120.671857	120.67186
GFS.THRIFT	0.5360993	0.530868866	96.166514	96.16651
ARIMA (1,2,0) direct	0.368552178	0.319841782	141.59679	153.91991

6. Conclusions

This study is aimed to provide insights about the price performance of stocks listed on ASE using closing prices for insurance stocks during 2006 and 2024. The dataset consists of 4478 observations while the statistical summary for ICI, TV, FDI and CPI are shown in Table 1. The study also proposes a hybrid model that combines MODWT models with GFS.THRIFT to predict the closing prices of insurance stock market. Gathering ICI data, calculating ICI, decomposing ICI by MODWT function, applying input variables and hybrid models on approximation coefficient are all included in hybrid model. Comparative study compares best-performing model (MODWT-Haar-GFS.Thrift) with alternative WT functions and conventional approaches such as ARIMA and GFS.THRIFT. The results indicate notable impacts of VT, FDI and CPI as input variables on ICI. The collinearity statistics indicate no significant multicollinearity problem exists. Combining wavelet functions with GFS.THRIFT enhances forecast accuracy as shown by RMSE, MAE, MPE and MAPE values being lowest for MODWT-Haar-GFS.Thrift model. These hybrid models recommended for investors and financial analysts assist them to make informed decisions when it comes to insurance stock markets in Jordan. The study sheds light on the performance of the Amman stock market (ASE) and identifies trends and patterns in its behavior.

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