

**HYBRIDIZING STRUCTURAL TIME
SERIES WITH DYNAMIC NONLINEAR
AUTOREGRESSIVE NEURAL NETWORKS
TO IMPROVE CRYPTOCURRENCY PRICE
PREDICTION**

NURAZLINA BINTI ABDUL RASHID

UNIVERSITI SAINS MALAYSIA

2025

**HYBRIDIZING STRUCTURAL TIME SERIES
WITH DYNAMIC NONLINEAR
AUTOREGRESSIVE NEURAL NETWORKS TO
IMPROVE CRYPTOCURRENCY PRICE
PREDICTION**

by

NURAZLINA BINTI ABDUL RASHID

**Thesis submitted in fulfilment of the requirements
for the degree of
Doctor of Philosophy**

March 2025

ACKNOWLEDGEMENT

First and foremost, praise be to Allah the Almighty, who has bestowed upon me knowledge, strength, smoothness, and determination to finally complete my thesis. The success achieved would not have been possible without the guidance and assistance of others.

I extend my sincere gratitude to my supervisor, Associate Professor Dr. Mohd Tahir Ismail, for his invaluable guidance, support, and encouragement throughout the course of this research. His expertise, patience, and unwavering commitment have played a pivotal role in shaping this thesis.

A heartfelt thanks go to MARA and Universiti Teknologi MARA for their assistance and funding of my study. I am also grateful for the FRGS funding provided to my supervisor and his team members, which supported several conference fees during my study period.

Special thanks are due to my family members, my mother, father, husband, daughters, and son, for their dua, unwavering love, understanding, and encouragement. Their support has been the cornerstone of my academic pursuits.

Lastly, I express my gratitude to all my friends for their encouragement and assistance during this journey.

Thank you for all your moral and emotional support throughout my academic endeavors.

TABLE OF CONTENTS

ACKNOWLEDGEMENT	ii
TABLE OF CONTENTS	iii
LIST OF TABLES	viii
LIST OF FIGURES	x
LIST OF ABBREVIATIONS	xii
LIST OF APPENDICES	xv
ABSTRAK	xvi
ABSTRACT	xvii
CHAPTER 1 INTRODUCTION	1
1.1 Background of the Study	1
1.2 Problem Statement and Motivation of the Study	5
1.3 Research Questions of the Study.....	9
1.4 Research Objectives of the Study.....	9
1.5 Scope of the Study.....	10
1.6 Significance and Contribution of the Study	12
1.7 Thesis Organization.....	13
CHAPTER 2 LITERATURE REVIEW	14
2.1 Introduction	14
2.2 Motivation of Study Hybrid Time Series Model Forecasting.....	14
2.3 Linear Structural Time Series (STS)	15
2.3.1 Application of Linear Structural Time Series	17
2.4 Dynamic Nonlinear Autoregressive Neural Network	18
2.4.1 Advantages of Dynamic Nonlinear Autoregressive Neural Network.....	21
2.4.2 Application of Dynamic Nonlinear Autoregressive Neural Network.....	22

2.5	Behavior and Predictive Models in Cryptocurrency	26
2.5.1	Behavior of Cryptocurrency.....	29
2.5.1(a)	Volatility.....	29
2.5.1(b)	Trend.....	31
2.5.1(c)	Seasonal Anomalies.....	32
2.6	Factors Affecting Cryptocurrency Price.....	34
2.6.1	Macroeconomic.....	36
2.6.2	Supply and Demand.....	36
2.6.3	Sentiment.....	37
2.6.4	Political and Others.....	38
2.7	Existing Hybrid Model in Forecasting Cryptocurrency.....	39
2.8	Gaps in Literature.....	42
2.9	Summary	44
CHAPTER 3 RESEARCH METHODOLOGY		46
3.1	Introduction	46
3.2	Overview of Research Methodology.....	46
3.3	Data Collection.....	54
3.4	Data Analysis: Stage 1	55
3.4.1	Descriptive Statistics.....	55
3.4.2	Test for Non-Stationarity (Unit Root Test).....	57
3.4.3	Time Series Plot.....	57
3.4.4	Regression Modeling Trend.....	58
3.4.4(a)	t-Statistic.....	59
3.4.4(b)	Goodness of Fit.....	61
3.4.4(c)	Durbin Watson Statistic.....	61
3.4.4(d)	Akaike Information Criteria (AIC).....	62
3.4.4(e)	Schwarz Criterion Information Criteria (SIC).....	62

3.5	Data Analysis: Stage 2	63
3.5.1	Structural Time Series (STS) Model.....	64
3.5.2	Trend Model.....	65
3.5.3	Seasonal Model	67
3.5.4	Incorporating Explanatory and Intervention Variable	70
3.5.5	State Space Form.....	72
3.5.6	Kalman Filter Estimation	73
3.5.7	Model Diagnostic Checking.....	76
3.5.8	Test of Nonlinearity (Brock-Dechert-Sheinkman (BDS) Test).....	79
3.6	Data Analysis: Stage 3	80
3.6.1	The Proposed Hybrid STS with Dynamic Nonlinear Autoregressive Neural Network.....	80
3.6.2	Dynamic Nonlinear Autoregressive Neural Network	82
3.6.2(a)	Model Development	82
3.6.2(b)	Nonlinear Autoregressive with Exogenous Input (NARX) Neural Network Framework.....	86
3.6.2(c)	Nonlinear Autoregressive (NAR) Neural Network Framework.....	93
3.7	Data Analysis: Stage 4	93
3.7.1	Forecasting Performance.....	94
3.8	Summary	95
	CHAPTER 4 PRELIMINARY STUDY	96
4.1	Introduction	96
4.2	Descriptive Statistics	96
4.3	Fitting the Trend of Top Five Cryptocurrency.....	101
4.4	Diagnostic Checking the Trend Model	113
4.5	Summary	114

CHAPTER 5	MODELING HIDDEN FACTORS VIA SINGLE LINEAR STRUCTURAL TIME SERIES MODEL IN ESTIMATING CRYPTOCURRENCIES PRICE	117
5.1	Introduction	117
5.2	Model Estimation Without Explanatory Variables	118
5.2.1	Estimating the Closing Price of Top Five Cryptocurrency Without Explanatory Variables.....	118
5.3	Understanding Estimated Closing Price of Top Five Cryptocurrency Without Explanatory Variables.....	124
5.3.1	Trend Pattern of Closing Price Top Five Cryptocurrency	125
5.3.2	Seasonal Pattern of Closing Price Top Five Cryptocurrency.....	134
5.4	Explanatory Variables	139
5.4.1	Descriptive Statistics.....	139
5.4.2	Time Series Plot	144
5.5	Model Estimation and Understanding Cryptocurrency Price with Explanatory Variables	151
5.5.1	Estimating Top Five Cryptocurrency Prices with Explanatory Variables.....	151
5.5.2	Error Estimate	153
5.5.3	Estimation of Trend, Seasonal Component, and Explanatory with Significant Intervention Variables	157
5.5.4	Observing Structural Breaks and Outliers.....	175
5.6	Test of Nonlinearity	187
5.7	Summary	189
CHAPTER 6	HYBRID STS-NARX AND STS-NAR IN PREDICTING THE PRICES OF THE TOP FIVE CRYPTOCURRENCIES.	193
6.1	Introduction	193
6.2	Network Architecture	193
6.3	The Best Integrating of Hybrid STS-NARX Model	196
6.4	The Best Fitting of the Hybrid STS-NAR Model	209

6.5	Evaluation Performance of Single and Hybrid STS Models in Predicting Weekly Cryptocurrency Price: January 2022 – December 2022	223
6.6	Summary	235
CHAPTER 7 CONCLUSION AND RECOMMENDATIONS		237
7.1	Main Findings	237
7.2	Limitation of the Study	242
7.3	Recommendations of the Study.....	243
7.4	Summary	245
REFERENCES.....		249
APPENDICES		
LIST OF PUBLICATIONS		

LIST OF TABLES

		Page
Table 1.1	Hybrid versus single model	4
Table 1.2	Sample of top five cryptocurrency.....	11
Table 2.1	Application of STS	18
Table 2.2	Model comparison	23
Table 2.3	Application of hybrid model.....	25
Table 2.4	List of anomalies.....	33
Table 2.5	Common factors affecting cryptocurrency price	35
Table 2.6	Contribution of this Study.....	43
Table 3.1	Trend specification	66
Table 3.2	Combination of various specifications of trend and seasonal components	68
Table 3.3	Explanatory description	71
Table 3.4	Sample of Explanatory Variables	72
Table 4.1	Descriptive analysis of cryptocurrency close price	97
Table 4.2	Close price, linear trend regression.....	102
Table 4.3	Close price, quadratic trend regression.....	106
Table 4.4	Close price, exponential trend regression.....	110
Table 4.5	Model selection criteria	114
Table 5.1	Estimation STS for BTC (without explanatory variables).....	119
Table 5.2	Estimation of linear STS for ETH (without explanatory variables).....	120
Table 5.3	Estimation linear STS for USDT (without explanatory variables).....	121
Table 5.4	Estimation of linear STS for BNB (without explanatory	

	variables).....	123
Table 5.5	Estimation linear STS for USDC (without explanatory variables).....	124
Table 5.6	The best single linear STS model	128
Table 5.7	Descriptive statistics (supply and demand)	142
Table 5.8	Descriptive statistics (macroeconomic variable)	143
Table 5.9	Summary estimation of single linear STS (without and with explanatory variables).....	153
Table 5.10	Linear STS (without and with explanatory variables)	159
Table 5.11	The best final estimation performance.....	170
Table 5.12	Brock Dechert and Scheinkman (BDS) test	187
Table 6.1	Summary of the best training network architecture of the Hybrid STS-NARX model.....	197
Table 6.2	Summary of the best training of the Hybrid STS-NAR model.....	209
Table 6.3	Performance of weekly closing price for January 2022 – December 2022	224

LIST OF FIGURES

	Page
Figure 2.1 Distribution by category	26
Figure 2.2 Overview of common factors contributing to cryptocurrency price	34
Figure 3.1 Flowchart overview of the research methodology.....	47
Figure 3.2 Gap of knowledge.....	53
Figure 3.3 NARX network in series-parallel (open loop) model.....	87
Figure 3.4 NARX network in parallel (close loop) model.....	88
Figure 4.1 Time series plot price.....	99
Figure 4.2 Close price, linear trend residual plot.....	103
Figure 4.3 Close price, quadratic trend residual plot	107
Figure 4.4 Close price, exponential trend residual plot.....	111
Figure 5.1 Trend pattern of top five cryptocurrency	132
Figure 5.2 Deterministic Seasonal	137
Figure 5.3 Velocity.....	145
Figure 5.4 Trading volume.....	146
Figure 5.5 Transaction volume.....	148
Figure 5.6 Number of whale transactions more than 100k	149
Figure 5.7 Consumer price index	150
Figure 5.8 Smoothed estimates of the irregular and level disturbances.....	155
Figure 5.9 Trend pattern of top five cryptocurrencies	161
Figure 5.10 Seasonal pattern of top five cryptocurrencies.....	165
Figure 5.11 Zoom in significant structural breaks and outliers.....	176
Figure 6.1 The best training performance for Hybrid STS-NARX.....	200

Figure 6.2	Error histogram for hybrid STS-NARX	203
Figure 6.3	Autocorrelation plot for hybrid STS-NARX	206
Figure 6.4	The best training performance for Hybrid STS-NAR	213
Figure 6.5	Error histogram for hybrid STS-NAR	217
Figure 6.6	Autocorrelation plot for hybrid STS-NAR	220
Figure 6.7	Weekly closing price forecast for January 2022 – December 2022	230

LIST OF ABBREVIATIONS

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criteria
ANN	Artificial Neural Network
ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARIMA	Autoregressive Integrated Moving Average
ARX	Autoregressive with Exogenous inputs
BCH	Bitcoin Cash
BDS	Brock-Dechert-Sheinkman
BNB	Binance Coin
BP-ANN	Back Propagation Artificial Neural Network
BPNN-PSO	Back Propagation Neural Network Based On Particle Swarm Optimization
BTC	Bitcoin
CBOE	Chicago Board Options Exchange
COVID	Coronavirus Disease
CPI	Consumer Price Index
DFNNs	Deep Feedforward Neural Networks
DL	Deep Learning
DNNs	Dynamic Neural Networks
DW	Durbin-Watson
DWT	Discrete Wavelet Transform
EEMD	Ensemble Empirical Mode Decomposition
EPU	Economic Policy Uncertainty
ERNN	Elman Recurrent Neural Network
ES	Exponential Smoothing
ESN	Echo State Network
ETH	Ethereum
EW	Empirical Wavelet
FF	Feedforward Neural Networks
FNM	Fuzzy Neighbourhood Model
FOMO	Fear Of Missing Out

GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
GQ	Goldfeld-Quandt
GRU	Gated Recurrent Unit
HAR	Heterogeneous Autoregressive
ICEEMDAN	Improved Complete Ensemble Empirical Mode Decomposition With Adaptive Noise
IR	Inflation Rates
JB	Jarque-Bera
LASSO	Least Absolute Shrinkage And Selection Operator
LLWNN	Local Linear Wavelet Neural Network
LM	Levenberg-Marquardt
LSTM	Long Short-Term Memory
LTC	Litecoin
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MARMA	Monthly Autoregressive Moving Average
MIDAS	Mixed Data Sampling
ML	Machine Learning
MLP	Multilayer Perceptron
MSE	Mean Square Error
NAR	Nonlinear Autoregressive
NARX	Nonlinear Autoregressive With Exogenous Input
NLP	Natural Language Processing
OLS	Ordinary Least Squares
RF	Random Forest
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RR	Ridge Regression
SARFIMA	Seasonal Autoregressive Fractionally Integrated Moving Average
SEC	Securities and Exchange Commission
SIC	Schwarz Information Criterion
STS	Structural Time Series
SVM	Support Vector Machine
UK	United Kingdom

US	United States
USDC	USD Coin
USDT	Tether
VAR	Vector Autoregressive
XRP	Ripple

LIST OF APPENDICES

Appendix A	Summary of Previous Study
Appendix B	GARCH Model
Appendix C	Close Price, Linear Trend Regression
Appendix D	Close Price, Quadratic Trend Regression
Appendix E	Close Price, Exponential Trend Regression
Appendix F	Estimation of Single Linear STS for BTC (Without Explanatory Variables)
Appendix G	Estimation of Single Linear STS for ETH (Without Explanatory Variables)
Appendix H	Estimation of Single Linear STS for USDT (Without Explanatory Variables)
Appendix I	Estimation of Single Linear STS for BNB (Without Explanatory Variables)
Appendix J	Estimation of Single Linear STS for USDC (Without Explanatory Variables)

**PENGHIBRIDAN SIRI MASA STRUKTURAL DENGAN RANGKAIAN
NEURAL AUTOREGRESIF BUKAN LINEAR DINAMIK BAGI
MENINGKATKAN RAMALAN HARGA MATA WANG KRIPTO**

ABSTRAK

Kajian ini mencadangkan model hibrid alternatif yang menggabungkan Siri Masa Struktur (STS) dengan Rangkaian Neural Autoregresif Bukan Linear Dinamik (NAR dan NARX) bagi meningkatkan ramalan harga mata wang kripto. Memandangkan pergerakan pasaran mata wang kripto adalah kompleks, disebabkan oleh turun naik, tidak pegun, tidak linear, serta dipengaruhi oleh faktor tersembunyi, dan luaran ramalan yang tepat memberikan cabaran, kerana model tradisional sering gagal untuk menangkap dinamik kompleks pasaran. Mengatasi kekangan ini, penyelidikan ini mengintegrasikan model STS, yang terkenal dengan keupayaannya mengendalikan ketidakstabilan dan memodelkan faktor tersembunyi, termasuk trend, musim, dan komponen tidak teratur bersama faktor luaran, dengan model Rangkaian Neural Autoregresif Bukan Linear Dinamik yang mampu menguruskan corak bukan linear. Dengan menganalisis terperinci lima mata wang kripto dipilih berdasarkan saiz pemodalan pasarannya pada Disember 2022, kajian ini mengambil pendekatan metodologi pelbagai peringkat untuk mencapai objektif kajian. Ia bermula dengan mengenal pasti tingkah laku trend awal melalui model regresi, diikuti dengan memodelkan faktor tersembunyi menggunakan STS. Inovasi kajian ini terletak dalam meningkatkan model-model ini dengan kerangka kerja hibrid STS-NARX dan STS-NAR, meningkatkan ketepatan ramalan secara signifikan. Hasil menunjukkan bahawa model hibrid secara signifikan mengungguli pendekatan model STS tunggal tradisional dalam meramalkan harga mata wang kripto.

HYBRIDIZING STRUCTURAL TIME SERIES WITH DYNAMIC NONLINEAR AUTOREGRESSIVE NEURAL NETWORKS TO IMPROVE CRYPTOCURRENCY PRICE PREDICTION

ABSTRACT

This study proposes an alternative hybrid model that combines Structural Time Series (STS) with Dynamic Nonlinear Autoregressive Neural Networks (NAR and NARX) to improve cryptocurrency price predictions. Given that cryptocurrency market movements are complex, caused by volatility, nonstationarity, and nonlinearity, as well as being influenced by hidden and external factors, accurate forecasting presents a challenge, as traditional models often fail to capture the market's complex dynamics. Addressing these limitations, this research integrates STS models, renowned for their ability to handle nonstationarity and modeling hidden factors, including trends, seasonality, irregular components, and external factors, with Dynamic Nonlinear Autoregressive Neural Network models capable of managing nonlinear patterns. Utilizing a detailed analysis of the top five cryptocurrencies by their market capitalization as of December 2022, the study adopts a multi-stage methodology in order to achieve the research objectives. It begins with identifying initial trend behaviors through regression model, followed by modeling hidden factors using STS. The innovation of this study lies in enhancing these models with hybrid STS-NARX and STS-NAR frameworks, significantly improving predictive accuracy. The results indicate that the hybrid models significantly outperform traditional single STS model approaches in predicting cryptocurrency prices.

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Cryptocurrencies are new types of money that work on blockchain technology, making transactions safe and direct without needing banks (Nakamoto, 2008). The fast growth of cryptocurrencies, led by Bitcoin (BTC) and including over 10,000 others, suggests a big shift toward using digital money (Kozlovskiy et al., 2022). These digital coins have become popular for their ability to make big profits (Ho et al., 2024), cut down costs, and be accepted as real payment methods (Garcia et al., 2014; Gowda & Chakravorty, 2021). Their potential for significant profits has made accurate predictive models crucial for investors.

For instance, Bitcoin, which had no value in 2013, soared to \$65,000 by November 2021. The rapid rise of BTC's demonstrates significant profitability potential while also highlighting its unpredictability and volatility. Accurately predicting these trends is challenging due to the volatile nature of the cryptocurrency market, which can be influenced by many factors. These include economic crises, the gradual acceptance and adoption of cryptocurrencies worldwide, market supply and demand, as well as global political and macroeconomic news (Cavalli & Amoretti, 2021; Gurrib et al., 2019; Smutny et al., 2021). As cryptocurrency is still in its infancy, further exploration is needed in forecasting models.

Given the dynamic and highly volatile nature of cryptocurrency data (Roy et al., 2024), many statistical methods and Machine Learning (ML) algorithms have been proposed to forecast the cryptocurrency's price accurately (Cheng et al., 2024; Mittal & Geetha, 2022; Mtiraoui et al., 2023; Saheed et al., 2022; Tripathy et al., 2024). One of the popular statistical techniques used in predicting cryptocurrency prices is time

series forecasting techniques such as Autoregressive Integrated Moving Average (ARIMA) (Adineh et al., 2020; Zhao et al., 2018; Zolghadr-Asli et al., 2021) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) are employed to capture time series components and volatility clustering (Christopher et al., 2022; Tong et al., 2022), respectively. Furthermore, Vector Autoregressive (VAR) (Dimpfl & Elshiaty, 2021; Omri, 2023) and Heterogeneous Autoregressive (HAR) (Chen, 2024; Ftiti et al., 2023) models work to analyze multiple factors affecting and modeling volatility and capturing the long memory, respectively.

Meanwhile, ML models, such as Dynamic Neural Networks (DNNs) (Al-Haija, 2022; Patra & Mohanty, 2023), leverage temporal dependencies for predicting prices based on historical patterns. Ensemble methods like Random Forests (RF) and Gradient Boosting are adept at capturing intricate relationships for regression and classification tasks (Iliev & Panwar, 2023; Rathi et al., 2024). However, despite the wide range of available models, there is lack of research exploring and modelling hidden factors within cryptocurrency data, such as trends, seasonal, irregular components, internal and external factors.

Most existing models tend to overlook or eliminate hidden components in an effort to achieve stationarity, leading to potential inaccuracies and the loss of valuable data insights. This omission often hinders the ability to generate precise predictions in cryptocurrency markets. Hence, a more comprehensive approach, which includes the hidden components, is essential for a deeper understanding and more accurate forecasting of cryptocurrency price movements. Khedr et al. (2021) stated that traditional statistical methods find it challenging to predict the price of a cryptocurrency. It requires meeting a lot of statistical assumptions, which is unrealistic, although it is simple to implement and interpret.

Moreover, the statistical model approaches can provide reliable models as long as the assumptions related to the model's residuals are met (Ali & Shatabda, 2020). However, these statistical models come with stringent assumptions that must be satisfied. One such assumption is that the data should be stationary. If these model assumptions are not met, it becomes necessary to apply differentiation or transformation to the data. Unfortunately, this process, typically utilizing aggregating or averaging, might change the pattern of the actual data. This has indirectly caused the loss of valuable information and makes accurate predictions impossible.

On the other hand, the state of the art agrees that Deep Learning (DL) or ML is effective in prediction. These algorithms provide a solid solution to the instability of nonlinear patterns in time series data and have been suggested and widely employed. However, while computational intelligence models have the unique benefit of universal approximation and optimal precision, the downside of ML is that it removes the linear constraint of traditional statistical techniques. This can lead to unfavorable outcomes in some cases. For example, ML models also ignore the importance of the observable features of the time series data. Moreover, it is only stable for pure nonlinearity, avoiding identifying hidden market components and the absence of stationarity (Livieris et al., 2020a; Reichl, 2016). Other than that, Murray et al. (2023) applied a DL model to make cryptocurrency predictions, overcoming the high fluctuation and volatility of cryptocurrency prices by applying detrending to transform non-stationary time series into stationary. This indicates that these approaches are unable to accurately or completely represent all patterns and features in the data, particularly data with numerous connected features and patterns.

However, since cryptocurrency datasets are complex in nature, a single model may not be sufficient to effectively meet all data characteristics (Chakraborty et al.,

2019; Vogl, 2022). To make predictions better, past research has proven that integrating different models to work together is a good idea (Aijaz & Agarwal, 2020). Thus, by combining the advantages of each method in a combined model, the risk of using an inappropriate method is reduced, and more accurate results are obtained (Büyükşahin & Ertekin, 2019; Huang et al., 2021; Mandrikova et al., 2021). Furthermore, there has been a recent growing trend toward hybrid models that integrate time series and neural network techniques in the cryptocurrency field, specifically preferred forecasting methods, as indicated in Table 1.1. All these previous results suggest that the ability of the hybrid model is superior to that of the single model. However, selecting a model for a study depends on the research's specific objectives and requirements. Note that different statistical or ML models have strengths and weaknesses, and selecting the appropriate model is crucial for obtaining accurate and meaningful results.

Table 1.1 Hybrid versus single model

Author(s)	Method	Field/Objective	Result
Miraoui et al. (2023)	Autoregressive Fractionally Integrated Moving Average (ARFIMA), Empirical Wavelet (EW) transform, and Local Linear Wavelet Neural Network (LLWNN)	Predict Bitcoin	The hybrid ARFIMA-EWLLWNN approach outperforms.
Amirshahi and Lahmiri (2023)	GARCH LSTM	Forecast cryptocurrencies	A combination of parametric models like GARCH with deep neural networks may produce better results in cryptocurrency price forecasting, especially in the case of highly volatile data.

Table 1.1 Continued

Author(s)	Method	Field/Objective	Result
Toai et al. (2023)	Long Short-Term Memory (LSTM). Hybrid ARIMA-SVM	Daily Bitcoin Prediction	Hybrid ARIMA-SVM improves the performance.
Borrero and Mariscal (2023)	NAR-SVR hybrid model	Predict Bitcoin Prices	Hybrid model outperforms.
García et al. (2023)	ARIMA model and LSTM	Foreign Exchange Forecasting	Hybrid model outperforms.
Shu et al. (2023)	ARIMA and LSTM	Predict Bitcoin price movement	Hybrid gives the best model.
Smyl et al. (2023)	Exponential Smoothing (ES) and Recurrent Neural Network (RNN)	Forecast Cryptocurrency price	Hybrid ES-RNN outperforms.
Zahid et al. (2022)	GARCH, LSTM, GRU	Forecast Bitcoin Volatility	Hybrid models (GARCH and ML) can generate accurate forecasts of Bitcoin's price.
Saqware and Ismail (2024)	Individual LSTM, CNN, and hybrid CNN-LSTM model	To predict close prices of Bitcoin and Ethereum.	The hybrid CNN-LSTM model produced better results for both BTC and ETH close prices compared to individual models.

1.2 Problem Statement and Motivation of the Study

Given the dynamic and high volatile of cryptocurrency data (Mishra et al., 2024; Sudhakarana et al., 2024), using a single model to make accurate predictions is a significant challenge, especially when the data exhibit various behavior such as linear, nonstationary and nonlinear (Abarghouie et al., 2024; García-Medina & Aguayo-Moreno, 2024; Rathore et al., 2022; Sheraz et al., 2022; Tabe et al., 2024; Tong et al., 2022). These behaviors are affected by hidden components such as trends, seasonal, and irregular fluctuations. Additionally, external factors like supply and demand—including trading volume (de Araujo et al., 2023), transaction volume

(Bakhtiar et al., 2023), velocity (Benlagha and Hemrit, 2023) and the number of whales—as well as macroeconomic indicators such as the consumer price index (Wang et al., 2023) contribute to cryptocurrency price volatility.

Numerous studies have been conducted to determine the best predictive model. However, these studies often fall short in terms of accuracy, as they did not consider the critical hidden components within the data. According to Fama (1965), the time series pattern is assumed to be a repetition of past price behavior. This provides insights into future price patterns or trends, indicating whether prices are likely to increase or decrease. However, trend and seasonal components rarely simplify the modeling process. Consequently, most researchers isolate or remove these components from the actual series in both linear and nonlinear time series models. Furthermore, Kourentzes and Crone (2010) suggested that deterministic seasonality makes deseasonalizing the time series inadvisable, as deseasonalizing can prevent the model from making precise estimations and affect forecasting accuracy.

Therefore, in order to preserve the information of the data, literature discovered that the Structural Time Series (STS) could handle nonstationary series (Abdul Rashid et al., 2023; Andrews, 1994; Azman et al., 2022; Md Junus & Ismail, 2014; Murthy & Kumar, 2021) by decomposing and modeling the hidden components. It also allows them to vary over time rather than remove them compared to other models, eliminating the components using differencing and transformation. This condition indicated that STS does not easily remove vital information from the original data series. Moreover, hidden components, including trend, seasonal, and irregular components, are easily built into linear STS models.

The STS model can be put in state space form, where it involves an observed series and an unobserved (state) series evolving over time. The Kalman filter is used

to estimate the state variables in a recursive manner as new observations become available (Harvey & Durbin, 1986). The formulation of the Kalman filter and state space model together provide a very powerful tool for the recursive treatment of dynamic systems (Anderson & Moore, 1979). In addition, the STS forecasting results are quite reliable and accurate compared to other forecasting methods (Wirtgen et al., 2022). Furthermore, it is easy to handle missing values and outliers once they are in state space form (Pelagatti, 2015). The missing values were estimated via the Kalman filter approach, while outliers were handled by including intervention variables.

Additionally, STS models offer insightful interpretations of time series components and explanatory variables (Harvey et al., 1997). They perform well in forecasting at different time scales, including weekly, monthly, quarterly, and yearly predictions. Despite its advantages, research on using STS models for cryptocurrency price prediction remains limited. Therefore, this study aims to explore two structural time series modeling approaches: 1) STS without explanatory variables and 2) STS with explanatory variables (trading volume, transaction volume, velocity, number of whales, and consumer price index) alongside significant intervention variables. By including these external factors, this study seeks to examine their impact on model performance and assess whether their inclusion improves cryptocurrency price prediction accuracy.

However, no single model can consistently excel in capturing the nonstationary and nonlinear behavior present in the data. Both standalone linear and nonlinear models encounter limitations in their predictive capabilities (Vogl, 2022). The literature has discovered that the STS model may not be appropriate for strong nonlinear problems (Shi et al., 2022; Wan & van der Merwe, 2000).

Therefore, to address this limitation, this study proposes a hybrid modeling approach that enhances STS efficiency in cryptocurrency price prediction by integrating it with a Dynamic Nonlinear Autoregressive Neural Network to better capture nonlinear behavior. Specifically, the first approach (linear STS without explanatory variables) is proposed to be integrated with the Nonlinear Autoregressive Model with Exogenous Input (STS-NARX). The second approach (STS with explanatory variables and intervention variables) is intended to be integrated with the Nonlinear Autoregressive Neural Network (STS-NAR) to avoid redundant input information.

This study combines with a Dynamic Nonlinear Autoregressive Neural Network since it comes from the same branch of STS, allowing it to utilize time series data by applying an autoregressive basis and handling nonlinear autoregressive behavior. This model excels in scenarios where it aims to capture the relationship between past input-output pairs and current/future output values in a nonlinear function for the forecasting model (Cheng et al., 2011; Telli et al., 2023). It utilizes the Levenberg-Marquardt (LM) training algorithm, which addresses nonlinearity issues and minimize prediction errors (Louzazni et al., 2020).

By integrating STS with Dynamic Nonlinear Autoregressive Neural Networks (STS-NARX and STS-NAR), a more accurate prediction of cryptocurrency prices can potentially be achieved. Accordingly, it leverages the strengths of both linear and nonlinear modeling techniques to navigate the complexities of the cryptocurrency market better.

1.3 Research Questions of the Study

The research questions of this study are as follows:

- a) What are the trend behaviors of the price data for the top five cryptocurrencies?
- b) How can hidden and external factors be effectively modeled using a single linear STS model for cryptocurrency price estimation?
- c) How can a hybrid STS model integrated with Dynamic Nonlinear Autoregressive Neural Networks (STS-NARX and STS-NAR) improve the accuracy of cryptocurrency price prediction?
- d) How does the predictive accuracy of the proposed STS-NARX and STS-NAR models compare to benchmark models (single linear STS) in forecasting the prices of the top five cryptocurrencies?

1.4 Research Objectives of the Study

The main objective of this study is to propose an alternative hybrid STS model approach with a Dynamic Nonlinear Autoregressive Neural Networks (NARX and NAR) to improve the predictive accuracy of cryptocurrency prices. Specifically, this study attempts:

- a) To identify the trend behaviors of the price data for the top five cryptocurrencies.
- b) To model the hidden and external factors via a single linear STS model in estimating the price of the top five cryptocurrencies.
- c) To develop STS-NARX and STS-NAR models with the aim of improving the accuracy in predicting the prices of the top five cryptocurrencies.

- d) To validate the predictive accuracy of hybrid STS-NARX and STS-NAR models by comparing them with benchmark models (single linear STS) in predicting the prices of the top five cryptocurrencies.

1.5 Scope of the Study

This research focuses on a detailed analysis of the top five cryptocurrencies by market capitalization as of December 2022. These cryptocurrencies exhibit varying levels of volatility: Bitcoin (BTC) and Ethereum (ETH) are highly volatile, Binance Coin (BNB) is moderately volatile, and Tether (USDT) and USD Coin (USDC) are stablecoins. By including this diverse range of cryptocurrencies, the study aims to evaluate the ability of the proposed model to handle different types of data, from highly volatile to stable price movements. The selection of these cryptocurrencies is based on data from santiment.net, which reported over 10,000 cryptocurrencies in circulation at that time. Given the dynamic nature of the cryptocurrency market, where rankings and valuations frequently fluctuate, December 2022 was chosen as a benchmark to ensure consistent and reliable data collection.

The timespan history data this study takes of each cryptocurrency are different due to the availability of data on the system based on the existence of cryptocurrency mines. Notably, BTC is the oldest cryptocurrency currently in existence. That is why it has the largest market capitalization compared to other cryptocurrencies. The sample data of the top five cryptocurrencies vary in terms of the start and end date for all cryptocurrencies on 26 December 2022. This study focuses on weekly historical data. The detailed samples and recent market capitalization for 2023 are provided in Table 1.2.

Table 1.2 Sample of top five cryptocurrency

Cryptocurrency	Sample Period	Total Sample	Market Capitalization (2023)
Bitcoin (BTC)	23/12/2013 – 26/12/ 2022	470	\$800 billion
	Estimation: 23/12/2013 -27/12/2021	418	
	Evaluation: 03/01/2022 – 26/12/2022	52	
Ethereum (ETH)	04/01/2016 – 26/12/2022	364	\$280 billion
	Estimation: 04/01/2016-27/12/2021	312	
	Evaluation: 03/01/2022- 26/12/2022	52	
Tether (USDT)	22/01/2018 – 26/12/2022	258	\$91 billion
	Estimation: 22/01/2018-27/12/2021	206	
	Evaluation: 03/01/2022- 26/12/2022	52	
Binance (BNB)	15/04/2019– 26/12/2022	194	\$48 billion
	Estimation: 15/04/2019-27/12/2021	142	
	Evaluation: 03/01/2022 – 26/12/2022	52	
USD Coin (USDC)	15/10/2018 – 26/12/2022	220	\$24 billion
	Estimation: 15/10/2018-27/12/2021	168	
	Evaluation: 03/01/2022- 26/12/2022	52	

This study focuses on the linear STS model, which encompasses two approaches. The first approach analyzes the model without explanatory variables. In contrast, the second, known as the linear STS model with explanatory variables, integrates these variables with significant intervention variables to estimate cryptocurrency prices. The significance of this study lies in investigating how the inclusion of explanatory and intervention variables can enhance the model. However, the selection of explanatory variables is limited due to data availability constraints.

1.6 Significance and Contribution of the Study

The proposed hybrid models that combine linear STS and Dynamic Nonlinear Autoregressive Neural Networks (STS-NARX and STS-NAR) can offer several significant advantages in time series forecasting. One of the main advantages is the ability to capture both linear and nonlinear patterns in time series data. STS models are well-suited for capturing the underlying trend and seasonality as well as intervention variables, while NARX models excel at capturing complex, nonlinear relationships between variables. Therefore, by combining these two approaches, the model can handle various hidden patterns without removing any data information, potentially enhancing prediction accuracy.

The information from the results of this study will indirectly help traders and investors interested in predicting weekly cryptocurrency prices. This study will help traders and investors understand the trend and hidden behaviors of the price of the top five cryptocurrencies and thus choose the appropriate model to predict cryptocurrency prices. This can minimize risk and increase returns. Moreover, good measurement and prediction save investors from losing their investments.

The contribution and novelty of this study are as follows: (1) The presence of hidden components in the price of the top five cryptocurrencies can be easily identified and interpreted by linear STS. (2) A two-novel hybrid prediction model approach combining linear STS with Dynamic Nonlinear Autoregressive Neural Network has been proposed. It will improve the accuracy of the prediction of cryptocurrency prices. In addition, this approach can potentially provide valuable insights and improvements in various areas not limited to cryptocurrency price prediction. Hence, it is hoped that the information from this study will add to the body of knowledge.

1.7 Thesis Organization

This study is organized into seven chapters. Chapter 1 introduces the research background, problem statement, research questions and objectives, scope, and contributions of the study. Chapter 2 presents a review of related literature on linear STS, Dynamic Nonlinear Autoregressive time series models, the motivation for studying hybrid time series model forecasting, and modeling and forecasting in cryptocurrency. Chapter 3 describes the study's methodology, detailing the approaches used to achieve the research objectives. To achieve the study's objectives, the analysis begins with a preliminary study, with the results explained in Chapter 4. Chapter 5 then analyzes the modeling of the hidden factors via single linear STS in estimating cryptocurrency price. Meanwhile, Chapter 6 discusses the results of the proposed hybrid model and compares its performance with that of the single linear STS. Finally, Chapter 7 discusses the conclusions and recommendations of the study for future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter consists of nine sections. The second section presents the motivation for studying a hybrid time series model for forecasting. The next section describes the linear Structural Time Series (STS). This section also discusses the developments in the field of STS described in the literature and their application in various fields. The fourth section reviews the Dynamic Nonlinear Autoregressive Neural Network model in the literature. The fifth section reviews the literature on behavioral insights and presents a list of recent models for cryptocurrencies. The sixth section presents the factors that affect the price of cryptocurrencies. The seventh and eighth sections present existing hybrid models in cryptocurrency forecasting and gaps in literature, respectively. Finally, this section discusses a summary of the chapter.

2.2 Motivation of Study Hybrid Time Series Model Forecasting

Time series forecasting methods are typically categorized as linear or nonlinear models. Single linear or nonlinear time series models find applications across diverse fields like medicine, engineering, social sciences, economics, and finance. However, real-world data often comprises both linear and nonlinear patterns, and no single model works universally. However, combining linear and nonlinear models has emerged as a promising approach to enhance forecast accuracy. Several pioneers and subsequent researchers have explored hybrid time series models (Bates & Granger, 1969; Bunn, 1989; Clemen, 1989; Granger & Ramanathan, 1984; Hibon & Evgeniou, 2005; Timmermann, 2006; Winkler & Makridakis, 1983). They have demonstrated that

combining multiple forecasts, whether linear or nonlinear, can yield better results than individually using these models.

Hybrid models, particularly those combining linear and Machine Learning (ML) approaches, have gained prominence by Zhang (2003). According to Zhang et al. (2023b), these models have been applied in various domains, consistently demonstrating improved accuracy in time series predictions. The motivation for hybrid models is threefold: (1) Real-world time series often exhibit mixed linear and nonlinear behaviors, making model selection challenging. (2) Combining linear and nonlinear models can effectively address the presence of both types of patterns in data. (3) It is almost universally agreed in the forecasting literature that no single model is the best in every situation since a real-world problem is often complex, and a single model may not capture different patterns in the data. This can be improved by combining different models.

2.3 Linear Structural Time Series (STS)

The development of structural models for time series analysis dates back to the pioneering work of Harvey and Durbin in 1986, focusing on the traditional decomposition of time series components. These initial models, simplistic and deterministic in their linear approach, were enhanced in 1964 by Theil and Wage, who evolved the time series components to adapt over time in a random walk. Building on this, Schweppe demonstrated in 1968 the use of a likelihood function, assessed through a Kalman filter and error decomposition, for evaluating these models. However, due to the computational limitations of the 1960s, the full potential of these results could not be realized.

In the 1970s, the structural approach gained prominence in control engineering, particularly with the Kalman filter introduced by Kalman in 1960. This filter, as described by Welch and Bishop in 2006, consists of mathematical equations that recursively estimate state parameters by minimizing Mean Square Error (MSE). It enabled the development of more complex models, like those applied by Roseberg in 1973 for statistical time-varying parameters. Since then, research on the Kalman filter has expanded across various fields.

The advantages of the STS model are that it incorporates hidden components like trends, seasonal, and irregular elements and is structured in state space form. This form involves an observed series and an unobserved (state) series evolving, with the Kalman filter recursively estimating state variables as new observations become available. Anderson and Moore, in 1979, noted the robustness of combining the Kalman filter and state space model for dynamic system analysis. Wirtgen et al. (2022) affirmed the reliability and accuracy of this approach's forecasting results, while Pelagatti (2015) emphasized its ability to handle missing values and outliers effectively.

This state-space model, representing time series data through equations that describe the system's states over time, leverages the Kalman filter to estimate these states recursively. It is particularly effective in managing noisy or incomplete data, making it suitable for handling the volatility of cryptocurrencies and other related behaviors. This includes non-stationarity, time-variation, and outliers, as highlighted by Koopman and Commandeur (2015). However, a significant limitation of linear STS models is their ineffectiveness in handling strongly nonlinear systems. Despite attempts to adapt nonlinear filters and estimators for more complex nonlinear challenges in STS, as explored by Shi et al. (2022), Auger-Méthé et al. (2021), Wan

and van der Merwe (2000), significant challenges remain, especially with extreme nonlinearities, as noted by Deka et al. (2022).

2.3.1 Application of Linear Structural Time Series

Recently, numerous contributions to STS have been made in various fields. This section will present recent applications of STS in various disciplines. Table 2.1 indicates the tabulations of various disciplines that applied the STS approach. In Ezike et al. (2022), authors discovered that STS was more effective than Autoregressive Integrated Moving Average (ARIMA) in predicting daily commercial tweets about e-cigarettes. This suggests that STS is a valuable tool for analyzing and predicting social media data related to discussions about e-cigarettes. Then, Wirtgen et al. (2022) developed an STS to predict monthly rentals of a bike-sharing system. This STS model decomposed the time series into various components, including trend, seasonal, cyclical, and irregular components. It also considered external factors such as weather, user behavior, school vacations, and COVID-19-related factors. The study suggested that the STS provided accurate forecasts and outperformed traditional time-series models, highlighting its effectiveness in predicting demand for bike-sharing systems.

Meanwhile, Bian et al. (2019) applied an STS to predict monthly traffic volume. They compared it to other models such as linear regression, ARIMA, Support Vector Machine (SVM), and Artificial Neural Network (ANN). The ability of the STS to decompose the time series into trend, seasonal, and irregular components made it superior for modeling traffic data with seasonal variations. The results revealed that the STS outperformed all other models and provided quite accurate predictions of traffic volumes. The power of STS was also demonstrated in the study by Petrova et al. (2017). Their results presented a novel method for predicting energy consumption using time series models with unobserved components. In this method, the time series

data were decomposed into various stochastic time-varying components. This includes level, seasonal, cycles of different frequency, irregular, and regression effects. In addition, the study highlighted the effectiveness of this approach, which uses state-space methods and the Kalman filter to predict energy consumption accurately.

Overall, these studies demonstrate the effectiveness of STS in several areas, including climate change analysis, stock market prediction, transportation, public health, and energy consumption prediction, to name a few. The ability of STS to decompose time series data into its underlying components and incorporate external factors makes it a valuable tool for accurate and robust forecasting.

Table 2.1 Application of STS

References	Field of study
Li et al. (2024)	Electricity
Maddanu and Proietti (2023)	Climate Change
Kalinina et al. (2022)	Stock price
Lee (2022)	death counts after World War II
de Nailly et al. (2022)	Transportation
Ezike et al. (2022)	Public Health
Wirtgen et al. (Wirtgen et al., 2022)	Engineering
Agarwal et al. (2021)	Sustainable and development
Bian et al. (2019)	Transportation
Monteiro and Costa (2018)	Water quality
Petrova et al. (2017)	Environment

2.4 Dynamic Nonlinear Autoregressive Neural Network

The ANN is one of the most frequently used ML models for nonlinear prediction, as noted by Malekian and Chitsaz (2021) and Kristjanpoller and Minutolo (2018). It is based on the way the human brain processes information through learning.

ANN, an ML technology, is designed to analyze processes with high complexity using a limited dataset for prediction. The advantage of ANN is that it requires no assumptions about the underlying process of functional form of dependence and is capable of handling complex nonlinear relational data problems and noise (Otchere et al., 2021; Taye, 2023). Furthermore, ANN is a tool for modeling systems when the exact relationship between input-output data is unknown. However, the disadvantages of this model are that it avoids identifying hidden components such as trends, seasonal, and the absence of stationarity (Livieris et al., 2020a; Reichl, 2016).

In general, as mentioned in Malekian and Chitsaz (2021), ANNs are classified as static or dynamic. A static neural network is a type of neural network with fixed-size input data that maintains a constant shape and size throughout training. Information flows unidirectionally, from input to output, and the output of each neuron is determined solely by the input and associated weights. There are no loops or feedback connections. Fixed weights and biases process the input data to produce the output as a function of the input size. They are suitable for structured data such as images and tables. However, once training is complete, the model parameters remain fixed, limiting efficiency and interpretability. Examples of static neural networks are Feedforward (FF), consisting of an input layer, one or more hidden layers, and output layers. The network architecture is fixed, meaning that the number of neurons and hidden layers in each layer remain constant throughout training.

Meanwhile, Dynamic Neural Networks (DNNs) represent an enhancement over static networks, offering the capability to dynamically learn from input and provide higher-quality outcomes throughout the learning process. This is achieved by adjusting and modifying their structure (Han et al., 2021). Furthermore, they can modify their network by adding or subtracting neurons connections, or layers, in

contrast to static neural networks, which possess fixed structures. This flexibility allows DNNs to learn from and adapt to new data and tasks more effectively.

Dynamic Nonlinear Autoregressive Neural Networks encompass various architectures designed to capture the dynamic and nonlinear dependencies present in time series data (Abounoori et al., 2012; Massaoudi et al., 2021). They are well-suited for sequential data modeling due to their ability to retain the memory of past observations and effectively capture temporal dependencies. One prominent type is the Nonlinear Autoregressive with Exogenous Inputs (NARX) Neural Network model, which extends the traditional autoregressive framework by incorporating exogenous variables into the prediction process. This allows the model to consider additional factors that may influence the time series behavior, thereby enhancing its predictive capabilities.

The NARX concept is a nonlinear generalization of the Autoregressive with Exogenous inputs (ARX) model, a standard instrument in linear black-box system identification (Chen et al., 1990). In the ARX model, the current output of a system is predicted based on its past outputs and inputs, assuming a linear relationship between them. The NARX model extends this concept by accommodating nonlinear dependencies between past outputs and inputs. It incorporates exogenous variables into the prediction process, considering the past outputs and inputs and their nonlinear interactions when predicting the current output (Boussaada et al., 2018). Furthermore, the NARX model is capable of capturing more complex relationships and dynamics present in the data than the linear ARX model. Essentially, it enhances the ARX model's capabilities by introducing nonlinear transformations to the input-output relationships, making it a more powerful tool for modeling systems with nonlinear behavior (Chetouani, 2008; Ouyang et al., 2017).

Meanwhile, the Nonlinear Autoregressive (NAR) model also enables the capture of nonlinear dependencies, making it particularly valuable in time series analysis where linear relationships may not suffice. Although simpler than the NARX model, its functionality is similar. However, unlike NARX, this model does not account for exogenous inputs (Abounoori et al., 2012; Massaoudi et al., 2021).

2.4.1 Advantages of Dynamic Nonlinear Autoregressive Neural Network

The NARX Neural Network model represents a significant development in the field of time series forecasting, primarily due to its sophisticated approach to modeling complex systems. One of the most notable advantages of the NARX model is its unparalleled ability to capture and analyze complex nonlinear relationships within data. Unlike conventional models that may struggle with the intricacies of nonlinear dynamics, the NARX framework, through its integration of autoregressive components and exogenous variables, offers a more detailed and comprehensive understanding of the factors driving time series behavior (Bucci, 2020; Tian et al., 2018). This capability is particularly beneficial in applications where the data exhibit nonlinear patterns influenced by historical values and external factors.

Another key strength of the NARX model is its expertise in handling long-term dependencies in time series data. The model's feedback loop mechanism plays a crucial role here, enabling it to effectively utilize information from past outputs as part of its input for future predictions (AlAlaween et al., 2022). This feature ensures that the NARX model can consider the long-term temporal structure of the data, enhancing its forecasting accuracy over extended periods. Notably, such an ability is invaluable in fields where understanding long-term trends and patterns is essential for accurate prediction and decision-making.

The NARX model also offers extensive flexibility in terms of its architecture, which can be customized to suit specific data characteristics and forecasting needs. This adaptability allows for adjustments in the model's structure. This includes the number of layers, the number of neurons within those layers, and the choice of activation functions, making it a versatile tool capable of addressing various forecasting challenges (Alsumaiei, 2020).

Moreover, the NARX model effectively addresses the vanishing gradient problem, a common obstacle in the training of deep neural networks. The strategic use of nonlinear activation functions and architectural adjustments ensures that the gradient values remain conducive to learning, thus enabling the successful training of Deep Learning (DL) models (Sarkar et al., 2019). This mitigation of the vanishing gradient problem is crucial for maintaining the model's learning efficiency and ensuring its ability to learn from complex data.

The versatility and robust performance of the NARX model have led to its successful application across various domains, including finance, meteorology, and economics. Its ability to deliver accurate predictions by comprehensively analyzing complex relationships and dynamics within time series data makes it an invaluable asset for both researchers and industry practitioners (Mahmoud et al., 2013). Moreover, the model's combination of DL flexibility, long-term memory, and nonlinear modeling capabilities position it as a superior choice for tackling the challenges inherent in forecasting time series events.

2.4.2 Application of Dynamic Nonlinear Autoregressive Neural Network

This section will highlight a range of applications of Dynamic Nonlinear Autoregressive Neural Networks across different fields, such as environmental. Rahman et al. (2023) proposed NARX-based prediction models in wind-speed

forecasting, while Dharshan et al. (2023) utilized NAR and NARX to neutralize the pH of wastewater using intelligent controllers. At the same time, Chreng et al. (2022a) applied this model to predict electricity demand. Table 2.2 provides a tabulation of the various disciplines that have implemented the Dynamic Nonlinear Autoregressive Neural Network approach. Ren et al. (2023) predicted indoor particle concentration using neural networks: a BP-ANN, a NARX Neural Network, and a LSTM Neural Network. For the prediction of outdoor particle matter concentrations, the best performance was achieved by the NARX model with the smallest MAPE and RMSE. In summary, Table 2.2 presents the recent study of different domains comparing the performance of NARX, LSTM, and other neural network models. Much of the literature has proven that NARX is able to successfully make predictions and represent the best model in different domains. This means that NARX has the ability to handle nonlinear, dynamic, and complex time series data.

Table 2.2 Model comparison

References	Model Comparison	Data Category	Result / The best model
Son and Van Cuong (2023)	ARIMA, NARX, GRU, LSTM	Canadian lynx and the Wolf sunspot	NARX
Ren et al. (2023)	LSTM, back propagation artificial neural network (BP-ANN), NARX	Indoor particle concentration	NARX
Sadeghian Broujeny et al. (2023)	NARX, LSTM, (GRU), decision tree, and XGBoost	Energy consumption	LSTM and GRU
Zhao et al. (2023)	CNN-BLSTM, Gaussian process (GP-NARX)	Simulation data	GP-NARX
Dai et al. (2023)	ensemble empirical mode decomposition (EEMD), LSTM, EEMD-NARX	Wind power	EEMD-NARX
Tcheumchoua et al. (2022)	LSTM, NARX, LSTM-NARX		LSTM-NARX

Table 2.2 Continued

References	Model Comparison	Data Category	Result / The best model
Paudel et al. (2022)	LSTM, NAR and NARX	Rainfall	LSTM
Xu and Zhang (2021)	LSTM, NARX, LSTM+NARX	Wind power	LSTM+NARX
Abi Akl et al. (2021)	LSTM, NARX	Vehicle velocity	LSTM
Bakhoday-Paskyabi (2020)	LSTM, NARX	Wind speed	NARX - short-term forecasting LSTM - long-term forecasting
Jung et al. (2020)	ANN, NARX, RNN-LSTM	Environmental changes	RNN-LSTM
Wei et al. (2020)	standard back propagation neural network based on particle swarm optimization (BPNN-PSO), the least squares support vector machine (LS-SVM), NARX-LSTM	Lithium-ion batteries	NARX-LSTM
Jeong and Park (2019)	NARX, LSTM, GRU, ARX	Water table	NARX and LSTM models are superior
Tian et al. (2018)	Elman recurrent neural network (ERNN), echo state network (ESN), (NARX), and (LSTM)	Stream flow	LSTM and NARX captured the time-series dynamics better than the other RNNs.

Table 2.3 presents the performance of hybrid model-based NAR, and NARX applied in various fields. Most of the results demonstrate the effectiveness of the hybrid approach in improving the accuracy of time series predictions compared to traditional models or single models. It is difficult for a single model to capture all kinds of data characteristics simultaneously in prediction. Hence, most utilized the hybrid model, the result giving the best outcomes when integrating the model (Alsuwaylimi, 2023; Bukhari et al., 2022; Chou & Truong, 2021; Swaraj et al., 2021; Xu et al., 2023).