

A HYBRID APPROACH BASED ON ARIMA AND ARTIFICIAL NEURAL  
NETWORKS FOR CRIME SERIES FORECASTING

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This dissertation is dedicated to my late father Mohd Zaki bin Hasan, my mother Rusni binti Siking and my sisters Suhaila, Suhanim and Suhanom for their endless support and encouragement.

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## **ABSTRACT**

Crime forecasting is an interesting application area of research with ARIMA and ANN models offer a good technique for predicting time series. Time series data often contain both linear and nonlinear patterns. Therefore, neither ARIMA nor neural networks can be adequate in modeling and predicting time series data. In this study, a hybrid ARIMA and neural network model is proposed to predict crime series data. The hybrid approach for the crime series prediction is tested using 216-month observations of four crime category that are Non-Domestic Violence Related Assault, Break and Enter Non Dwelling, Steal from Retail Store and Steal from Person. Specifically, the results from the hybrid model provide a good modeling framework capable of capturing the nonlinear nature of the complex time series and thus producing more accurate predictions. The accuracy results from the hybrid models for the four case studies are 92.08%, 91.78%, 93.62 and 94.13%, respectively, which are satisfactory in common model applications. Predicted crime data from the hybrid model are compared with those from the ARIMA and neural network using the performance measures. As the result, the hybrid model provides a better accuracy over the ARIMA and neural network models for crime series forecasting.

## ABSTRAK

Peramalan jenayah merupakan bidang kajian yang sangat menarik dengan teknik pemodelan ARIMA dan rangkaian neural menawarkan penyelesaian yang baik dalam meramalkan siri masa. Data siri masa lazimnya bercorak lurus dan tidak lurus. Oleh yang demikian ARIMA dan rangkaian neural masing-masing tidak berkeupayaan untuk memodel dan meramal data siri masa secara bersendirian. Di dalam kajian ini, model gabungan di antara ARIMA dan rangkaian neural dicadangkan untuk meramal data siri jenayah. Pemodelan secara gabungan ini diuji terhadap empat set data yang masing-masing dikategorikan sebagai Serangan Berkaitan Keganasan Bukan Kediaman, Pecah Masuk Kediaman Mewah, Mencuri dari Kedai Runcit dan Mencuri dari Seseorang yang kesemua set tersebut mengandungi 216 data. Secara khususnya hasil yang diperolehi daripada gabungan tersebut menunjukkan kerangka pemodelan yang dibangunkan itu boleh dipercayai dan berupaya mengenalpasti kerumitan corak tidak lurus data siri masa yang seterusnya dapat menjana ramalan yang lebih tepat. Peratus ketepatan ramalan yang diperolehi daripada pendekatan gabungan tersebut bagi keempat-empat kajian kes adalah 92.08%, 91.78%, 93.62% dan 94.13% di mana peratusan yang terhasil itu cukup memuaskan berdasarkan penilaian biasa. Data ramalan yang terhasil daripada pemodelan gabungan telah dibuat perbandingan dengan yang terhasil daripada pemodelan ARIMA dan rangkaian neural dengan menggunakan beberapa pengukur prestasi. Secara keseluruhannya, pendekatan gabungan telah menunjukkan prestasi peramalan yang lebih baik berbanding ARIMA dan rangkaian neural untuk peramalan siri jenayah di dalam kajian yang dibuat ini.

## TABLE OF CONTENTS

<b>CHAPTER</b>	<b>TITLE</b>	<b>PAGE</b>
	<b>DECLARATION</b>	ii
	<b>DEDICATION</b>	iii
	<b>ACKNOWLEDGEMENT</b>	iv
	<b>ABSTRACT</b>	v
	<b>ABSTRAK</b>	vi
	<b>TABLE OF CONTENTS</b>	vii
	<b>LIST OF TABLES</b>	x
	<b>LIST OF FIGURES</b>	xii
	<b>LIST OF ABBREVIATIONS</b>	xv
	<b>LIST OF APPENDICES</b>	xvi
<b>1</b>	<b>INTRODUCTION</b>	
	1.1 Introduction	1
	1.2 Problem Background	2
	1.3 Research Objective	4
	1.4 Research Scope	4
	1.5 Thesis Outline	5
<b>2</b>	<b>LITERATURE REVIEW</b>	
	2.1 Introduction	6
	2.2 Study of Crime	6
	2.2 Forecasting Methods	8
	2.2.1 Quantitative Forecasting Models	8
	2.2.2 Qualitative Forecasting Models	9
	2.3 Box-Jenkins Methodology	9

2.4.1	Model Identification	10
2.4.2	Parameter Estimation	15
2.4.3	Diagnostic Checking	16
2.5	Artificial Neural Network Methodology	18
2.5.1	Basic Concept of Neural Networks	19
2.5.2	Layer Architecture	23
2.5.3	Backpropagation Approach	25
2.5.4	Artificial Neural Network Modeling Procedure	26
2.6	Study of Hybrid Methodology	29
2.7	Performance Evaluation	30
<b>3</b>	<b>RESEARCH METHODOLOGY</b>	
3.1	Introduction	31
3.2	Research Framework	31
3.3	Data Collection	32
3.4	Model Development Tools	33
3.4.1	Statistica	33
3.4.2	Matlab	34
3.5	Box-Jenkins Forecasting Model	35
3.5.1	Statistica Model Development	35
3.5.1.1	Non Domestic Violence Related Assault	36
3.5.1.2	Break and Enter Non Dwelling	40
3.5.1.3	Steal from Retail Store	43
3.5.1.4	Steal from Person	46
3.6	Artificial Neural Network Forecasting Model	49
3.6.1	Matlab Model Development	50
3.6.1.1	Hybrid Non Domestic Violence Related Assault	51
3.6.1.2	Hybrid Break and Enter Non Dwelling	52
3.6.1.3	Hybrid Steal from Retail Store	53
3.6.1.4	Hybrid Steal from Person	54
<b>4</b>	<b>RESULTS AND DISCUSSIONS</b>	
4.1	Introduction	55

4.2	Hybrid Modeling Result	55
4.2.1	Non Domestic Violence Related Assault	56
4.2.2	Break and Enter Non-Dwelling	59
4.2.3	Steal from Retail Store	62
4.2.4	Steal from Person	65
4.3	Box-Jenkins Modeling Result	68
4.2.1	Non Domestic Violence Related Assault	68
4.2.2	Break and Enter Non-Dwelling	69
4.2.3	Steal from Retail Store	71
4.2.4	Steal from Person	72
4.4	Artificial Neural Network Modeling Result	74
4.2.1	Non Domestic Violence Related Assault	74
4.2.2	Break and Enter Non-Dwelling	77
4.2.3	Steal from Retail Store	80
4.2.4	Steal from Person	82
4.5	Future Predictive Result	85
4.6	Discussions	88
<b>5</b>	<b>CONCLUSION</b>	
4.1	Conclusion	90
4.2	Future Works	91
	<b>REFERENCES</b>	92
	<b>APPENDICES A-E</b>	95



## LIST OF TABLES

<b>TABLE NO.</b>	<b>TITLE</b>	<b>PAGE</b>
2.1	Data partition	27
2.2	Hidden nodes specification	27
2.3	Proposed network architecture	28
3.1	Summary of ARIMA (2,1,1)(2,1,0) for NDVRA	39
3.2	Summary of ARIMA (1,1,1) for BEND	42
3.3	Summary of ARIMA (1,1,1) for SFRS	45
3.4	Summary of ARIMA (1,1,1) for SFP	48
3.5	Validation MSE result for NDVRA	51
3.6	Validation MSE result for BEND	52
3.7	Validation MSE result for SFRS	53
3.8	Validation MSE result for SFP	54
4.1	Network models for hybrid NDVRA	56
4.2	The best network model for hybrid NDVRA	57
4.3	Performance measure for hybrid NDVRA modeling	58
4.4	Network models for hybrid BEND	59
4.5	The best network model for hybrid BEND	60
4.6	Performance measure for hybrid BEND modeling	61
4.7	Network models for hybrid SFRS	62
4.8	The best network model for hybrid SFRS	63
4.9	Performance measure for hybrid SFRS modeling	64
4.10	Network models for hybrid SFP	65
4.11	The best network model for hybrid SFP	66
4.12	Performance measure for hybrid SFP modeling	67
4.13	Future values predicted from the best ARIMA model for NDVRA	69

4.14	Performance measure for ARIMA NDVRA modeling	69
4.15	Future values predicted from the best ARIMA model for BEND	70
4.16	Performance measure for ARIMA BEND modeling	71
4.17	Future values predicted from the best ARIMA model for SFRS	71
4.18	Performance measure for ARIMA SFRS modeling	72
4.19	Future values predicted from the best ARIMA model for SFP	73
4.20	Performance measure for ARIMA SFP modeling	74
4.21	Network models for ANN NDVRA	75
4.22	The best network model for ANN NDVRA	76
4.23	Performance measure for ANN NDVRA modeling	77
4.24	Network models for ANN BEND	77
4.25	The best network model for ANN BEND	78
4.26	Performance measure for ANN BEND modeling	79
4.27	Network models for ANN SFRS	80
4.28	The best network model for ANN SFRS	81
4.29	Performance measure for ANN SFRS modeling	82
4.30	Network models for ANN SFP	83
4.31	The best network model for ANN SFP	84
4.32	Performance measure for ANN SFP modeling	85
4.33	Statistical comparison of errors from hybrid, ARIMA and ANN	88

## LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
2.1	Original time series plot	11
2.2	Autocorrelation function (ACF) and partial autocorrelation function (PACF)	11
2.3	Biological neuron	20
2.4	Artificial neuron	21
2.5	Activation functions	22
2.6	Multilayer perceptron network	24
3.1	Research framework	31
3.2	Statistica workspace	34
3.3	Matlab workspace	35
3.4	Original data series plot for NDVRA	36
3.5	First difference plot for NDVRA	37
3.6	First seasonal difference plot for NDVRA	38
3.7	Residuals plot for NDVRA	40
3.8	Original data series plot for BEND	41
3.9	First difference plot for BEND	41
3.10	Residuals plot for BEND	43
3.11	Original data series plot for SFRS	44
3.12	First difference plot for SFRS	44
3.13	Residuals plot for SFRS	46
3.14	Original data series plot for SFP	47
3.15	First difference plot for SFP	47
3.16	Residuals plot for SFP	49
3.17	Training iterations graph met performance goal for NDVRA	51

3.18	Training iterations graph met performance goal for BEND	52
3.19	Training iterations graph met performance goal for SFRS	53
3.20	Training iterations graph met performance goal for SFP	54
4.1	Comparison graph between actual and predicted data for hybrid NDVRA	58
4.2	Comparison graph between actual and predicted data for hybrid BEND	61
4.3	Comparison graph between actual and predicted data for hybrid SFRS	64
4.4	Comparison graph between actual and predicted data for hybrid SFP	67
4.5	Comparison graph between actual and predicted data for ARIMA NDVRA	68
4.6	Comparison graph between actual and predicted data for ARIMA BEND	70
4.7	Comparison graph between actual and predicted data for ARIMA SFRS	71
4.8	Comparison graph between actual and predicted data for ARIMA SFP	73
4.9	Comparison graph between actual and predicted data for ANN NDVRA	76
4.10	Comparison graph between actual and predicted data for ANN BEND	79
4.11	Comparison graph between actual and predicted data for ANN SFRS	82
4.12	Comparison graph between actual and predicted data for ANN SFP	84
4.13	Comparison of future values from hybrid, ARIMA and ANN for NDVRA	85
4.14	Comparison of future values from hybrid, ARIMA and ANN for BEND	86

4.15	Comparison of future values from hybrid, ARIMA and ANN for SFRS	87
4.16	Comparison of future values from hybrid, ARIMA and ANN for SFP	87

**LIST OF ABBREVIATIONS**

<b>SYMBOL</b>	<b>TITLE</b>
ACF	Autocorrelation Function
ANN	Artificial Neural Network
ARCH	Autoregressive Conditional Heteroscedatic
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
BEND	Break and Enter Non Dwelling
Lr	Learning rate
Mc	Momentum rate
MSE	Mean Squared Error
NARX	Non Linear Autoregressive Neural Network with External Input
NDVRA	Non-Domestic Violence Related Assault
PACF	Partial Autocorrelation Function
SFP	Steal from Person
SFRS	Steal from Retail Store
SVR	Support Vector Regression
TAR	Threshold Autoregressive

**LIST OF APPENDICES**

<b>APPENDIX</b>	<b>TITLE</b>	<b>PAGE</b>
A	Time series data	95
B	Time series descriptive statistics	99
C	Box-Jenkins model estimation	103
D	Residuals data generated from Box-Jenkins	107
E	Hybrid training results	111

## **CHAPTER 1**

### **INTRODUCTION**

#### **1.1 Introduction**

Forecasting is a process of predicting or estimating the future events by referring to historical data. The information provided about the potential future events and their consequences is able to make important decisions confidently. Forecasting can be carried out by using the availability of time series data. The type of data is time-oriented or a sequence of observations regarding to the variable of interest. This kind of forecasting is known as time series forecasting.

Time series forecasting is an active domain of research that has become increasingly important in various fields of research, such as business, economics, finance, science and engineering. With time series forecasting, the data that consists historical observations are analyzed in a way to develop an appropriate model which describes the inherent structure of the series. It is obvious that a successful time series forecasting depends on an appropriate model fitting. This model is then used to generate future values for the series. A lot of efforts have been spent over the decades in developing efficient models to improve the forecasting accuracy. As the result, currently various important time series forecasting models have been evolved.

Study in crime has its importance. Obviously crime is an omnipresent challenge to societies. The study of Harrendorf et al. (2010) gives some broad



comparable international crime cases in homicide, assault, rape, robbery, burglary, motor vehicle theft and kidnapping but generally crime can be divided into two major categories which are violent crime and property crime. Ehrlich and Saito (2010) examine various aspects of criminal activity such as its determinants, different types of crime, policy responses and methods to face criminal activity. One of the methods is time series forecasting and it will be conducted in this study. The ability to predict can serve as a valuable source of knowledge for law enforcement agencies, both from tactical as well strategic perspectives. Forecasting can help a police department's performance by strategic deployment efforts and efficient investigation direction.

## **1.2 Problem Background**

In recent times, there is the growing manifestation among stake holders that crime cannot be controlled exclusively through the action of the police and criminal justice administrators. Always the primary target of the police had been the persons and their criminality, for example, examining the modus operandi of serial criminals, and arresting them (Gorr and Harries, 2003). A motivating factor in the shift of focus from the offender to the offence is the reality that brought the idea of new forms of approach on crime prevention against the backdrop of the apparent failure of the police, courts and prisons to stem the rising crime rates in many societies.

In spite of many limitations of criminal statistics in the current societies, data generated from the case gathered are used in dealing with the problem of crime both in developed and developing countries. For example Australia, the modern trends of criminological studies are that police, executives, judiciaries, prison administrators, parole authorities, social workers and researchers in the various multi disciplinary which subjects relating to crime and crime control spend resources in terms of money and time in assembling, quantifying and analyzing criminality. Empirical data on crime rate serves as a veritable source of information on the rate of crimes in the

society. The implications of these data or specifically time series data will enable us to know the pattern and trend of crimes in the country and further assist us to be able to plan for the prevention and curtailment of crime. Crime forecasting is of recent development. As a follow up to the successful crime mapping in the 1990s, the US National Institute for Justice (NIJ) awarded some grants to study crime forecasting for police as an extension of crime mapping with the objective forecasting crime one period ahead (Gorr and Harries, 2003).

In term of forecasting, there are two types of time series modeling known as linear and nonlinear models. Currently there are no single models which able to model both linear and nonlinear pattern of time series data. There are many studies shown that nonlinear models such as ANN are significantly better in forecast than the conventional linear models. ARIMA is one of the conventional linear models and mostly used in time series forecasting (Shahwan and Odening, 2007). But the major limitation of these models is the pre-assumed linear form of the associated time series which becomes inadequate in many practical situations. ARIMA model assumed that in a time series the future values have a linear relationship with current and past values as well as with white noise, thus estimations by ARIMA model may not be adequate for nonlinear time series that inherited a complex real-world problems that often nonlinear (Chen, et al., 2005).

Nevertheless, with a major progress in model combination or hybrid has given a way out in improving the forecasting performance. Both theoretical and empirical findings agreed that by combining different models together is effectively improve the forecasting performance, particularly when the hybrid is a combination of different models from each other (Berardi and Zhang, 2003). Many different techniques have been combined and proposed in order to overcome the deficiencies of a single model and hoping to produce more accurate results. Hybrid models can either be homogeneous, such as using differently configured neural networks or heterogeneous, such as using ARIMA and ANN models (Balkin and Ford, 2000).

Furthermore, a hybridization of ARIMA and ANN models as linear and nonlinear model is extensively studied by researchers since it produces promising results (Alwee, Shamsuddin and Sallehuddin, 2013). Further discussions about the literature of the hybrid between ARIMA and ANN are given in Section 2.6. In conducting this study, we are using a medium size of data and tried to control the training results from over fitting. Many factors will surely influenced the results from selected architecture and parameters of ANN model but the motivation behind this hybrid approach is largely due to the fact that the crime rates is often complex to predict. The selection of architecture and parameters of ANN model is made due to the limitation of study period and exploration efforts of this new domain personally.

### **1.3 Research Objective**

The objectives of the research are:

- To obtain a forecasting model by using ARIMA.
- To obtain a forecasting model by using ANN with the correspond residuals as input data into the model.
- To implement a hybrid approach by using the results from ARIMA and ANN.

### **1.4 Research Scope**

The delimitation of the research noted as the following:

- The dataset been used is a univariate historical time series.
- The actual data from the dataset are presented by month, offense type and area.
- The dataset is obtained from NSW Police of Australia website.

## **1.5 Thesis Outline**

The organization of this thesis is summarized as follows. In Chapter 2, the concept of ARIMA, ANN and the hybrid models are reviewed. In Chapter 3, the methodology of each modeling process has been described. In Chapter 4, the results from the methodology are discussed and finally Chapter 5 will conclude the discussions.

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