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To predict military spending in China based on ARIMA and artificial neural networks models

***Abstract**. This study takes the initiative to forecast China's military spending based on autoregressive integrated moving average (ARIMA) models and artificial neural networks (ANNs) models. The mean absolute percentage error (MAPE) approach is applied to measure prediction accuracy. The results indicate that these single variable ARIMA models show higher accuracy and stability than those made by the single variable ANNs models across the four time periods, namely the short term (1 year), the medium term (3 years), the medium-long term (5 years), and the long term (10 years). As to multiple variable ANNs models, the prediction accuracy of each model with different variables has advantages in different time periods. The highest accuracy for the long term predictions among all of the multivariate models is made by ANN2 including China's military spending and GDP. ANN3 including variables of China's military spending, GDP, and inflation rates illustrates the most accurate prediction for the short term and medium-long term, while ANN4 including China's military spending, GDP, inflation rates, and Taiwan's military spending shows the highest accuracy for the medium term prediction. This concludes the contributions of this study.*

***Streszczenie.** W artykule przedstawiono wyniki analizy dotyczącej przewidywanych wydatków Chin na militaria, opracowanej na podstawie modelu autoregresji (ang. ARIMA) oraz sztucznych sieci neuronowych (ANN). Dokładność predykcji oparta została na funkcji średniej wartości absolutnej procentowego uchybu. Badania wykazują, że model ARIMA ma wyższą dokładność i stabilność niż model oparty na ANN w odniesieniu do czterech, różnych okresów (1, 3, 5, 10 lat), przy czym dla ANN badanie wykonano dla czterech wartości dokładności predykcji. (**Przewidywania wydatków militarnych Chin na podstawie modeli ARIMA i sztucznych sieci neuronowych**).*

Keywords: Artificial neural networks (ANNs), Autoregressive integrated moving average (ARIMA), Forecasting, Military spending
Słowa kluczowe: sztuczne sieci neuronowe (ang. ANNs), autoregresja, przewidywanie, wydatki militarne.

1. Introduction

The fact that China's active diplomatic and business activities with other countries has led to a substantial growth of its economy in recent years have drawn much more attention for China's "peaceful rise" and its great-power status [1]. The increasing military spending of China reflects its general economic growth. Indeed, China will become a global partner or military superpower relying on its military spending [2]. Its military spending growth had shot up to 189 percent over the period 2001 through 2010 before it became the fastest growing country in the world, while that of the USA's was 81 percent and European NATO countries remained flat or even declined over the same period. China's military spending, about $119 billion In 2010, was approximately twice as much as the United Kingdom, $59.6 billion, France, $59.3 billion, Russia, $58.7 billion, and Japan, $54.5 billion [3].

Many researchers have been dedicated to develop and improve time series forecasting models over the past several years [4]. Being as an active research method, time series prediction has drawn significant attention for applications in variety of studies [5]. Autoregressive integrated moving average (ARIMA) model is one of the most principal and widely used time series models [6]. ARIMA models can be used to forecast water quality [7], air quality [8], epidemiology [9], [10], consumers' expenditure [11], sales forecasting [12], energy price [13], ozone levels [14], ammonia concentration [15], etc. ARIMA models are applicable when the time series are stationary without missing data [16]. However, they have limited accuracy due to its failure to forecast extreme cases or nonlinear relationship. On the other hand, artificial neural networks (ANNs) have been suggested as an alternative method for nonlinear models [17]. ANNs models are an interconnected group of natural or artificial neurons that use mathematical or computational models for information processing based on a correlated method for calculation.These models also can change their structure based on internal or external information that flow through the network or system. As noticed, when data have shown more non-linear orientation, ANNs models are more accurate than ARIMA models [14]. These advantages make them attractive in predicting nonparametric nonlinear time series models [4], [5], [8], [18], [19], [20], [21], [22], [23], [24], [25], [26].

Although these two models have the above advantages in prediction for some specific situations, the forecasting results are out of expectation under some conditions. For example, as function approximators, the application of ANNs showed significantly non-accurate predictions than those made by linear regression [27] and ARIMA models failed to forecast extreme concentrations of respirable suspended particulate matter (RSPM) in urban Delhi and Hong Kong [28]. When the data are linear without much disturbance, predictions conducted by ANNs are worse than those obtained by linear models [5]. In addition, a research applied auto regressive (AR) model and BP neural network for the Dissolved Oxygen (DO) outperforms in short interval prediction, while BP neural network illustrates better performance in longer interval prediction [29]. Furthermore, Taskaya & Casey [30] operated autoregressive linear and time-delay neural networks models with nine data sets for predicting and learned that the former achieve higher accuracy than that made by the later in some cases. Denton [31] indicated that under ideal states, with all regression assumptions, there was little variance in the forecasting between ANNs and linear regression, and only under less ideal states, such as outliers, multicollinearity, and model misspecification, ANNs models illustrated better results. Certainly, both ARIMA and ANNs models have their success in prediction for linear or nonlinear patterns. Therefore, no general models exist to fit for all circumstances.

There is a considerable literature to discuss the Granger causality relationship between military spending and economic growth [32], [33], [34], [35], [36], [37], [38], [39], [40]. Besides, Wanger & Brauer [41] employed dynamic forecasting genetic programming (DFGP) to predict the US's gross domestic product (GDP) with its military spending as one of the GDP's determinants and the results were compared with the prediction made by a regression-based prediction. The results revealed that unlike regression-based model, DFGP did not generate any prior assumption regarding any functional form or produced the time-span for prediction. In addition, Andreou & Zombanakis [42] applied ANNs models to predict the future behavior of relative security between Greece and Turkey and concluded that high forecasting performance permitted the application of alternative scenarios to predict the impact of the Greek-Turkish arms race on the relative security of the Greek-Cypriot alliance. Moreover, Andreou & Zombanakis [43] predicted the burden on the Greek economy resulting from the arms race against Turkey based on ANNs models to measure the pressure on the military debt and the GDP share of defense expenditure on Greece. The results exhibited highly satisfactory accurate prediction on both military debt and defense expenditure. Furthermore, military spending and economic growth are correlated and economic growth will not be the single determinant of military spending. The research completed by Starr et al [44]. showed that the relationship between defense spending and inflation was mutually related in France and Germany. Chan's [45] study proved that military spending tended to be more import-demanding in the developing countries and was possible to generate domestic inflation. Military spending might cause inflation and further hinder economic growth [46], [33]. China is emerging rapidly as the next global superpower based on its economic and political development. It is reasonable for Taiwan to deliberate the issue of military spending due to the hostile relationship between Taiwan and China in the past [38]. However, little study has dedicated to predict China's military spending based on ARIMA and ANNs models. Therefore, the aim of this paper is to apply these two methods for predicting China's military spending trying to understand and compare the accuracy obtained by both methods in different time period.

The rest of the paper is organized as follows. In the next section, the basic concepts of ARIMA and ANNs are introduced. The third section presents the prediction results from the empirical investigation. Concluding remarks are provided in the final section.

2. Methodology

To analyze time series data and make accurate forecasting are motivated many researchers in several fields, ranging from the natural sciences, economics, and management related disciplines. It is well noticed that ARIMA models are designed for predicting linear data,16 while ANNs models are suitable for data with nonparametric and nonlinear patterns [5], [8], [17], [18], [22], [26]. Obviously each model possesses its own strength and has different applications. Based on single variable ARIMA models and single variable as well as multivariate ANNs models to conduct forecasting, this study applies the mean absolute percentage error (MAPE) approach to evaluate prediction accuracy.

2.1 Research period

This study extrapolates predictions into separates periods of time, namely the short term (1 year), the medium term (3 years), the medium-long term (5 years), and the long term (10 years). items of data provided by Stockholm International Peace Research Institute (SIPRI) and International Monetary Fund (IMF) for the period of 1953 to 2006 are used for prediction analysis. Out-of-sample forecast tests based on the 54 yearly data are conducted for predicting military spending for the four different time periods. Of those, the first 53 items, dating from 1953 to 2005, are used to establish the short-term model and the result is compared to the data in 2006 to determine the accuracy of that model. In the same fashion, the medium-term model uses 51 items of data from 1953 to 2003 testing against the data from 2004 to 2006. The medium-long-term model uses 49 items of data up to 2001 testing against the data from 2002 to 2006; and the long-term model uses 44 items of data up to 1996 testing against the data from 1997 and onward.

2.2 Autoregressive integrated moving average (ARIMA) models

For more than three decades, ARIMA linear models have dominated many fields of time series prediction. In an ARIMA (p, d, q) model, the future value of a variable is supposed to be a linear function of several past observations and random errors. The general form is shown as follows:

(1) $$ø(B)\nabla^d(y_t-u) = \Theta(B)a_t ,$$

where y_t and at are the actual value and random error at time period t, respectively.

$ø(B) = 1-\sum_{i=1}^{p}\varphi_i B^i$, $\Theta(B)= 1-\sum_{j=1}^{q}\theta_j B^j$ are polynomials in B of degree p and q, $ø_i$(i=1, 2, . ., p), ∇=(1−B), B is the backward shift operator, p and q are integers and the orders of the model, and d is an integer and the number of regular differencing. Random errors, at, are the noise components of the stochastic model assumed to be independent, identically distributed (iid) with a mean of zero and a constant variance of σ2, NID(0, σ2). The ARIMA modeling method includes three steps: model identification, parameter estimation, diagnostic checking. Stationary is necessary for an ARIMA model to predict. Data transformation is required to generate the stationarity of these time series. The first step in model identification is that if a time series is generated from an ARIMA process, it should have some autocorrelation properties. It is likely to identify one or more feasible models for the given time series. The temporal correlation structure of the sample data is proposed to use the autocorrelation function (ACF) and partial autocorrelation function (PACF) to identify the order of the ARIMA model1 [16], [47]. The model that gets the minimum Akaike Information Criterion (AIC) is chosen as the optimal model. After the functions of the ARIMA model have been specified, estimation of the model parameters is forward. When the fitting model is chosen and its parameters are estimated, the Box-Jenkins methodology requires to examine the residuals of the model is minimized. It can be achieved using a nonlinear optimization process. The last step is diagnostic checking of the model. Several tests are operated for diagnostic check to determine whether the residuals of the ARIMA models from the ACF and PACF graphs are independent and identically distributed [7]. As a good prediction model, the residuals are used to examine the goodness of fit of the model that meets the requirements of a white noise process. If the model is not suitable, a new model should be identified. The steps of parameter estimation and diagnostic checking are repeated many times until an optimal model is selected [5]. The last selected model is used to forecast the value.

2.3 Artificial neural networks (ANNs) models

ANNs can be classified as a kind of artificial intelligence with self-learning function. ANNs models are a vast parallel processing of the information from the data and has a natural tendency for storing experiential information and making it available for the later use [48]. They can be widely used in many fields related to classification and forecasting. Users of ANNs do not need to design a complex program to solve problems. ANNs models are capable to estimate a large class of functions with high accuracy [5] without any prior assumption and identify patterns or trends and learn from the environment. The most commonly used form of ANNs models are the three layer feed-forward back-propagation neural network [49]. The basic principle of calculation applies the concept of the gradient steepest descent method to minimize the average squared error between the network's outputs. In other words, take the desired output value to minus the inference output value to get the error signal, then it can be returned to the network. After repeated amendments, a minimum error can be reached. This network model characterizes as part of multi-layer, feed-forward network with supervised learning. The network includes three basic frameworks, namely input layer, hidden layer and output layer. In order to calculate the precise output value under repeated learning processes, the information provided to the network must have the input values and target output values. And in the processes of unceasing endeavors, the gap between the output inference value of network and target output values can be narrow down and reach convergent effect. In general, if there are many uncertainties, and non-linear complex relationships existed between the output and input, the back-propagation neural network can be applied to solve such problems. The model is illustrated by a network of three layers of simple processing units linked by acyclic connections. The relationship between the output (y_t) and the inputs ($y_{t-1}, \ldots, y_{t-P}$) has the following algorithmic illustration:

(2) $y_t = w_0 + \sum_{j=1}^{Q} w_i g\,(w_{Qj} + \sum_{i=1}^{p} w_{i,j}\, y_{t-i}) + e_t$,

where $w_{i,j}$ ($i = 1, 2, \ldots, P$, $j = 1, 2, \ldots, Q$) and w_j ($j = 1, 2, \ldots, Q$) are model parameters often called linking weights; P is the number of input points; and Q is the number of hidden points. The sigmoid function is often used as the hidden layer transfer function, that is,

(3) $Sig(x) = 1/\{1 + \exp(-x)\}$

Hence, the ANNs model executes a nonlinear operative mapping from the previous observations to the future value yt, where W is a vector of all parameters and $f(\cdot)$ is a function defined by the network formation and correlation weights.

(4) $y_t = f\,(y_{t-1}, \ldots, y_{t-P}, W) + e_t$,

Thus, the neural network is equal to a nonlinear autoregressive model. Expression (2) indicates one output point in the output layer, which is normally used for one-step-ahead prediction. The simple network given by (2) is amazing effective. It can estimate random function as the number of hidden points Q is adequately large.[4] Simple network framework that has a small number of hidden points often performs well in out-of-sample prediction. The generalization ability begins to worsen when the network starts to match the noise of the training data and the data trained is more than needed [50].

2.4 Measurement of prediction

MAPE approach is frequently adopted as the measurement criteria of prediction accuracy in a fitted time series. MAPE is mainly used to measure the percentage of unexplained part of a model constructed. Therefore, the smaller the MAPE value obtained may indicate that more accuracy of the model will be. Also, it means that a better match exists between the historical data and the estimation result of the forecasting model. MAPE equation is shown as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{F_t - A_t}{A_t}\right| \times 100\%$$

Where At is the actual value and Ft is the value predicted. The difference between At and Ft is divided by the actual value At again. The absolute value of this computation is summed for every prediction point in time and divided again by the number of fitted points n. This makes it a percentage error, so one can evaluate the error of matched time series that differ in levels. Lewis [51] categorizes the value of MAPE into 4 levels illustrated. Lewis's explanation of MAPE results is a means to assess the accuracy of the prediction--less than 10% is a highly accurate prediction, 11% to 20% is a good prediction, 21% to 50% is a reasonable prediction, and 51% or more is an inaccurate prediction.

3. Empirical analysis

3.1 Single variable ARIMA models

This study employs single variable ARIMA models and single variable as well as multivariable ANNs models. Before beginning empirical analysis, data must be verified as stationary in order to yield more significant results. This is accomplished by using the Augmented Dickey-Fuller (ADF) test, the widespread unit root test. If the test shows the data to be non-stationary, they will be made stationary using finite-difference methodology. The unit root test consists of three types: trends and intercepts, only intercepts, and none; these three types are compared one-by-one. Analysis of the raw data for China's military spending is shown in Table I.

Table 1. The results of unit root tests of China's military spending.

Prediction periods	Excluding intercept and time trend		Including intercept but excluding time trend		Including intercept and time trend	
	t value	p value	t value	p value	t value	p value
Short term	-0.169	0.620	-1.433	0.559	-1.831	0.675
Medium term	-0.453	0.5136	-1.678	0.436	-1.910	0.634
Medium-long term	-0.740	0.390	-1.844	0.355	-1.901	0.638
Long term	-0.919	0.313	-1.786	0.382	-1.690	0.738

***,**,* indicate 1%, 5%, 10% significance level respectively

As illustrated by Table I, none of the predictions for military spending over the different time periods are particularly outstanding. This indicates that the raw data consist of simple roots are not stationary, necessitating approximations through the first-order differential. Results of this method can be seen in Table II. As can be seen from the results of Table II, the various predictions are now stationary, while the results of the three unit root tests are highly consistent. Next, modeling of the research is based on the differentials data.

Table 2. The results of unit root tests of the first-order Differential for China's military spending.

Prediction Period	Without intercept and time trend		With intercept but without time trend		With intercept and time trend	
	t value	*p* value	*t* value	*p* value	*t* value	*p* value
Short term	-7.033 ***	0.000	-7.066 ***	0.000	-7.003 ***	0.000
Medium term	-6.979 ***	0.000	-6.976 ***	0.000	-6.899 ***	0.000
Medium -long	-6.983 ***	0.000	-6.943 ***	0.000	-6.874 ***	0.000
Long term	-6.638 ***	0.000	-6.569 ***	0.000	-6.544 ***	0.000

***,**,* indicate 1%, 5%, 10% significance level respectively

The first-order differentials are used to make the sequence of military spending become stationary. The sequence is then rendered and analyzed using autocorrelation and partial autocorrelation functions (ACF and PACF) to determine the possible number of periods for processes AR(p) and MA(q). From ACF graph, we realize that lag 6 protrudes to double the range of the standard deviation, while the PACF graph illustrates an exponential drop, thus being the MA(1) model. Since this is the result of differentiation, the preliminary model is determined as ARIMA (6, 1, 1), with a formula expression $China\ \mathrm{DE}_{-1}$ represents the China's military spending for the previous period, while $(1-\theta_1 B)e_{-1}$ represents the white noise of e_{-1}.

$$(1-B)China\ \mathrm{DE}_{-1} = (1-\theta_1 B)e_{-1}$$

The Q statistics of the residuals indicate that the coefficients of difference between the different periods are within twice the range of standard deviation. Q's value of 7.9508 is below$\chi_{0.05}$ (23.685), indicating the stochastic error without autocorrelation. Table III lists the results and analysis for each period. Based on the above data, these ARIMA models show the best results for medium term (3 years), followed by short term (1 year), then long term (10 years), and lastly medium-long term (5 years). Medium, short, and long term results reach high levels of accuracy, while the result of medium-long term shows good accuracy only. Due to the national security considerations as well as the major military weapon system procurement procedures, establishment of one-generation military force may last for decades. Empirically, the results revealed that these single variable ARIMA models based on data obtained from 1953-2006 provides consistently "highly accurate" and "good" results to predict China's military spending over the various periods. This also demonstrates that China's military spending based on national security has been considerable stable over the past decades. Therefore, long-term military budget planning is normally consistent and stable in China. However, the prediction results of short and medium term outperform those made by medium-long and long term.

Table 3. The prediction results of ARIMA models.

Prediction Period	Mean Absolute Percentage Error (MAPE)	Results of Prediction
Short term (1 year)	8.76%	Highly accurate
Medium term (3 years)	8.63%	Highly accurate
Medium-long term (5 years)	10.79%	Good
Long term (10 years)	9.32%	Highly accurate

Table 4. Explanatory of variables under different ANNs models.

Model	Input Layer	Output Layer
ANN1	X1: China's military spending in the previous period	Y: China's military spending in the current period
ANN2	X1: China's military spending in the previous period X2: China's GDP in the previous period	Y: China's military spending in the current period
ANN3	X1: China's military spending in the previous period X2: China's GDP in the previous period X3: China's inflation rates in the previous period	Y: China's military spending in the current period
ANN4	X1: China's military spending in the previous period X2: China's GDP in the previous period X3: China's inflation rates in the previous period X4: Taiwan's military spending in the previous period	Y: China's military spending in the current period

3.2 Artificial neural networks (ANNs) model

This section uses back-propagation neural networks as a means to predict China's military spending. For this research, the best model decided finally is a synthesis of one to four separates input variables, hidden layers and learning rates. Both one-on-one and one-on-many are compared in order to determine the optimal combination (normalized mean square error and mean absolute error being the smallest, and the prediction value being the best). Variables are firstly divided into four model types (see Table IV). ANN1 uses the historical data of China's military spending to predict its future spending. ANN2 applies China's military spending and GDP as variable. ANN3 includes China's military spending, GDP, and inflation rates as variables. Lastly, ANN4 includes variables such as China's military spending, GDP, inflation rates, and military spending in Taiwan.

Network structures are separated into processing units 1, 2, 3, and 4 input layer types. The output layer has one processing unit, while the hidden layers are set one layer. Under different networks and different settings, a model's learning results are better when the mean squared error (MSE), normalized mean squared error (NMSE), and mean absolute error (MAE) are smaller and the related coefficients are larger. These criteria will be used to select the optimal model for back-propagation network (BPN).

3.3 Empirical analysis

Following the above-mentioned methodology, the BPN models show the best results for the long term, followed by medium-long term, then medium term, and lastly short term. The two shorter time periods, 1 and 3 years, achieve a "reasonable" level of accuracy, while the two longer periods, 5 and 10 years, indicate "good" level of accuracy (as in Table V). In other words, the longer time periods, the better prediction accuracy achieves.

Table 5. Prediction results of ANN1 for China's military spending.

Prediction Period	Mean Absolute Percentage Error (MAPE)	Results of Prediction
Short term (1 year)	21.21%	Reasonable
Medium term (3 years)	20.03%	Reasonable
Medium-long term (5 years)	18.21%	Good
Long term (10 years)	11.79%	Good

Table 6. Prediction results of ANN2 for China's military spending.

Prediction Period	Mean Absolute Percentage Error (MAPE)	Results of Prediction
Short term (1 year)	3.26%	Highly accurate
Medium term (3 years)	7.61%	Highly accurate
Medium-long term (5 years)	2.78%	Highly accurate
Long term (10 years)	7.32%	Highly accurate

ANN2 model including military spending and GDP performs the best resulted in medium-long term prediction, then short term, followed by long term, with medium term coming in the last place. All of these periods reach levels of "highly accurate" (as in Table VI). Meanwhile, ANN2 reflects that China's GDP for the given period has an important effect on military spending. It also shows that this BPN model has a high level of accuracy in predicting China's military spending, and could thus be a valuable reference for policymakers.

When military spending, GDP, and inflation rates are used as variables, the medium term predicting is the best, then medium-long term, followed by short term, with long term coming in the last place. In this model, short, medium, and medium-long predictions all reach “high” levels of accuracy, while the long-term predicting resulted in “incorrect” data (see Table VII). The prediction results of this model with inflation rates are highly accurate in the short, medium, and medium-long terms. However, the result of the long term prediction shows “inaccurate” indicating that the central government and defense department will consider inflation rates for planning military budget within one to five years of time periods, but inflation rates are not suitable for predicting China’s military spending for more than five years.

Lastly, military spending, GDP, inflation rates, and Taiwan’s military spending are used as variables. In ANN4 model, the best accurate result came for the medium term, followed by the short term, then the medium-long term, and the long term coming for the least accurate. The medium term prediction exhibits a “high” accuracy level, while short and medium-long term predictions achieve “good” levels. Long term prediction results are “reasonable.” (see Table VIII). Based on the mutual long hostile relationship between China and Taiwan, the results show that China’s military spending has been significantly influenced by Taiwan’s medium-term (3 years) military expenditures.

Table 7. Prediction results of ANN3 for China’s military spending.

Prediction Period	Mean Absolute Percentage Error (MAPE)	Results of Prediction
Short term (1 year)	2.97%	Highly accurate
Medium term (3 years)	2.10%	Highly accurate
Medium-long term (5 years)	2.75%	Highly accurate
Long term (10 years)	50.18%	Inaccurate

Table 8. Prediction results of ANN4 for China’s military spending.

Prediction Period	Mean Absolute Percentage Error (MAPE)	Results of Prediction
Short term (1 year)	10.58%	Good
Medium term (3 years)	1.2%	Highly accurate
Medium-long term (5 years)	11.22%	Good
Long term (10 years)	28.95%	Reasonable

Table 9. Comparison of prediction accuracy of ARIMA and ANN models.

Model / Period	ARIMA (MAPE)	ANNs (MAPE)			
		ANN1	ANN2	ANN3	ANN4
Short term (1 year)	8.76%	21.21%	3.26%	**2.97%**	10.58%
Medium term (3 years)	8.63%	20.03%	7.61%	2.10%	**1.2%**
Medium-long term (5 years)	10.79%	18.21%	2.78%	**2.75%**	11.22%
Long term (10 years)	9.32%	11.79%	**7.32%**	50.18%	28.95%

In general, data shown in Table IX, single variable ARIMA model can achieve “highly accurate” results for short (8.76%), medium (8.63%), and long (9.32%) term predictions, and “good” results for medium-long (10.79%) term predictions. On the other hand, ANN1 shows only “reasonable” accuracy for short (21.21%) and medium-long (20.03%) term, and “good” accuracy for medium-long (18.21%) and long term (11.79%) predictions.

The prediction performance of these single variable ARIMA models show three “highly accurate” results with only one “good” result, while the single variable ANN1 models show only “good” or “reasonable” accuracy for the four different periods. In comparison of the prediction results made by ARIMA models and ANN1 models, the ARIMA models are superior to those conducted by ANN1 due to the characteristics of the time series in this research. As for multiple variable models, ANN3 shows the most accurate results for both short term (2.97%) and medium-long term (2.75%) predictions, while ANN4 shows the highest accuracy for medium term predictions (1.2%). Meanwhile, ANN2 had the most accuracy for the long term (7.32%).

4. Conclusions

China has, in the past decade, seen immense economic strides, and with its military budget growing by the multiples. This has led to something of a threat in the military stability of Asia, and even of the whole world. These various factors add up to mean that an accurate prediction and analysis of China’s military spending are critical to Taiwan, Japan, USA and other Asian countries.

For single variable models, the ARIMA models show more stability and high accuracy across all four time periods, while ANNs models show only “good” accuracy. The results reveal that the single variable ARIMA models based on data obtained from 1953-2006 provide consistently highly accurate and good results to predict China’s military spending over the various periods. This also demonstrates that China’s military spending based on national security has been considerable stable over the past decades. For multiple variable models, ANN2 including China’s military spending and GDP indicate the highest accuracy for the long term predictions among all of the multivariate models. ANN3 including variables of China’s military spending, GDP, and inflation rates shows the most accurate prediction for the short term and medium-long term, while ANN4 including China’s military spending, GDP, inflation rates, and Taiwan’s military spending reaches the highest accuracy for the medium term prediction. This concludes the contributions of this study.

Based on the national security considerations as well as the major military weapon system procurement features, establishment of one-generation military force may last for decades. The drawing up of military spending budgets is intertwined with many factors; military, political, and economic elements will all inevitably have their impacts. Further studies are needed to use more variables with various research methods trying to compare the prediction accuracy made by different approaches for policymakers as references.

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