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The development of a government cash forecasting model

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Abstract

Purpose – Government cash forecasting is central to achieving effective government cash management but research in this area is scarce. The purpose of this paper is to address this shortcoming by developing a government cash forecasting model with an accuracy acceptable to the cash manager in emerging economies.
Design/methodology/approach – The paper follows "top-down" approach to develop a government cash forecasting model. It uses the Indonesian Government expenditure data from 2008 to 2015 as an illustration. The study utilises ARIMA, neural network and hybrid models to investigate the best procedure for predicting government expenditure.
Findings – The results show that the best method to build a government cash forecasting model is subject to forecasting performance measurement tool and the data used.
Research limitations/implications – The study uses the data from one government only as its sample, which may limit the ability to generalise the results to a wider population.
Originality/value – This paper is novel in developing a government cash forecasting model in the context of emerging economies.

Keywords Developing countries, Neural networks, Hybrid models, ARIMA model, Government cash forecasting, Public expenditure management

Paper type Research paper

Introduction

The role of the national budget in economic performance has been a subject of research for many decades. Allen and Tommasi (2001) consider the national budget to be the primary instrument used by governments to manage the economy. Prior research has analysed the relationship between government expenditure and economic performance in various settings. Current research such as Chipaumire *et al.* (2014), Abrishami *et al.* (2013) and Tang (2010) model government expenditures totals, while Magazzino (2012), Oluwatobi and Ogunrinola (2011) and Ogujiuba and Ehigiamusoe (2014) disaggregate their data in an attempt to determine the effects of each type of government expenditure on economic performance. Some researchers (e.g. Chude and Chude (2013), Menyah and Wolde-Rufael (2013), Alshahrani and Alsadiq (2014), Chipaumire *et al.* (2014)) focus their attention on a specific country, whereas others undertake comparative research among both developed and developing economies (e.g. Lamartina and Zaghini, 2011; Magazzino, 2011; Kuckuck, 2012).

There are two alternative economic theories of public spending. One is based on the work of Adolph Wagner, the other is due to John Maynard Keynes. According to Wagner (1883), government spending is an endogenous variable in the macro-economy. On this view, public expenditure is determined by the growth of national income. Keynes (1936) in contrast treats public expenditure as an exogenous variable that can affect economic development in the short-run (Tang, 2010). The Greek crisis of 2010 shows that, whichever theory is correct, sustainable economic growth relies on the way in which government

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manages its cash resources. In this regard, reliable, real-time government cash forecasting models are clearly important.

Government cash management (GCM) is a set of strategies, and associated policies, such that an appropriate amount of cash is available to meet the government's obligations in the most cost-effective way (Storkey, 2003). This requires collaboration both within government, and between the government and other sectors of the economy. Hence, government policy with regard to GCM and other financial matters should be consistent (Williams, 2010). The increasingly important role of governments in promoting and delivering public services has made the cash management function central in the economic development of all nations (Widodo *et al.*, 2014). Failure to fulfil government responsibilities due to cash shortages interferes with governments' ability to provide public services. Unanticipated borrowing to cover government spending leads to increased costs and may affect a government's credibility. The Greek crisis in 2010 is an example of a government failing to manage cash effectively, leading to increases in the cost of borrowing to cover government spending. This has the potential for contagion in the wider financial system illustrating the importance of an effective GCM (Arghyrou and Tsoukalas, 2011; Kouretas and Vlamis, 2010).

Studies of GCM (e.g. Storkey, 2003; Mu, 2006; Lienert, 2009; Williams, 2009) stress the importance of projecting the cash needed by the government to meet their obligations as an essential feature of effective GCM. However, while sharing the objective of enhancing GCM quality, each study differs in its focus of interest. Storkey (2003) points out the advantages of technology as a tool for developing cash management and forecasting systems. Mu (2006) emphasises the importance of a cash forecasting system as a building block of an effective GCM. Lienert (2009) and Williams (2009) propose steps in sequence to improve cash management, with cash forecasting being one of the steps. Williams (2010) focusses on the synergy between GCM and other financial policies to achieve an effective GCM.

This paper focusses on developing a model for improved government cash forecasting as part of the broad field of public expenditure management. According to Potter and Diamond (1999), there are three main features of public expenditure management: budget preparation, budget execution and cash management. While budget preparation mostly deals with macroeconomic indicators (e.g. inflation, exchange rate, economic growth) and budget execution is mainly about expenditure procedures (e.g. commitment and procurement processes), cash management focusses on ensuring the availability of government money to deliver public services in the most effective way (Allen and Tommasi, 2001). This study therefore focusses on the last area, namely, cash disbursement forecasts of spending units' data.

Notwithstanding its importance in GCM, Mu (2006) argued that cash predicting capacity is poor in most developing countries. To strengthen their cash management systems, such countries should analyse the patterns of their cash flows and develop reliable cash forecasting models (Mu, 2006). Most government cash forecasting systems utilise "bottom-up" information collected individually from all spending units and a "top-down" analysis based on historical data stored in databases (Williams, 2009, 2010). Although research has been carried out on government cash forecasting, it is mostly complementary to the main topic of GCM. There is no single study which focusses on the development of a government cash forecasting model *per se*. The present study is thus motivated to develop a model of cash forecasting for the public sector in developing economies using Indonesia as an illustration.

One of the most frequently used techniques in time series forecasting is autoregressive integrated moving average (ARIMA). ARIMA represents a generalisation of autoregressive moving average (ARMA) models introduced by Box and Jenkins (1976). Recent studies such as Mondal *et al.* (2014), Ariyo *et al.* (2014), and Iqbal and Naveed (2016) show that ARIMA models can provide relatively accurate forecasts by processing time series data. Ariyo *et al.* (2014) find that ARIMA models compete well with other forecasting techniques in short-term prediction.

Despite their flexibility in forecasting time series data, ARIMA models do not capture non-linear patterns that may appear in time series data (Zhang, 2003). An experimental study by Zhang *et al.* (2001) suggested that artificial neural network (ANN) models can provide improved predictions in the presence of non-linear variations in time series data. A number of recent studies, e.g. Acuna *et al.* (2012), Dandekar and Ranade (2015), Mishra and Dehuri (2014), Venkatesh *et al.* (2014), utilise ANN models as a cash forecasting tool. These studies support the superiority of ANN models as forecasting tools. However, when both linear and non-linear patterns exist together in a time series, ARIMA is usually better for handling linear patterns, while ANN is better for handling non-linear patterns.

Addressing this issue, Zhang (2003) proposes a hybrid model combining both ARIMA and ANN models. The ARIMA part of the hybrid model is used to analyse the linear component of the data, while the ANN part analyses the non-linear component. Current studies, such as Adhikari (2015), Cadenas *et al.* (2016), Chaâbane (2014), de Oliveira and Ludermir (2016), Moretti *et al.* (2015), Wang *et al.* (2013) and Yu *et al.* (2014), tend to find in favour of the hybrid model. However, some, including Taskaya-Temizel and Casey (2005), argue that the hybrid model does not always deliver better forecasts.

This paper compares all three types of models, namely, ARIMA, ANN and Hybrid models, for their ability to forecast government cash expenditures so that the "best" model can be identified. A specific objective of this study is to develop a government cash disbursement forecasting model, which provides an accuracy that meets an acceptable level of materiality for the cash manager. To achieve this goal, we use the top-down approach proposed by (Williams, 2009, 2010) and employ information from historic time series expenditure data provided by Indonesian Government spending units from 2008 to 2015. We split the data into training (2009–2013) and testing (2014–2015) sets to avoid overfitting. The results show that building a government cash forecasting model depends on adopting a flexible method suitable to the type of data used. Combining ARIMA and ANN models into a Hybrid model does not always provide the best performance, which is consistent with the findings of Taskaya-Temizel and Casey (2005). The results also show how different evaluation criteria affect the ability of different forecasting models to detect structures of the data.

The Indonesian Government is focussed on improving the accuracy of its government cash forecasting models (Widodo *et al.*, 2014). It is intended that the findings of this research will make a useful contribution to improving GCM, in Indonesia and possibly other developing countries. An enhanced ability of the Indonesian Government to more accurately project its cash requirement into the future will improve the ability to manage cash effectively and avoid unnecessary borrowing.

In order to better understand the context of the data used in this paper, a brief outline of the government expenditure system in Indonesia is given in the second section. The third section describes the methods we use for modelling. The fourth section presents the model results. The fifth section contains some concluding remarks.

Government expenditure in Indonesia

Government expenditures in Indonesia are classified into various types: personnel expenditures, goods expenditures, capital expenditure, interest, subsidies, grants, social aids and other expenditures (Minister of Finance, 2015). Personnel expenditures are compensation to government employees, such as salary and other personnel costs. Goods expenditures cover operational costs of spending units. Capital expenditures are used to acquire new assets or improve existing assets for operating activities. Interest expenditures are interest payment on outstanding debts and other costs related to government debts. Subsidies are given to state companies, government agencies and other parties to maintain their purchasing power over products. Grants are government transfers to other countries, international organisations, local governments and communities.

Social aid consists of transfers of money, goods and services directly to people or communities for welfare reasons. Other expenditure includes outlays natural disasters, social disasters and other unforeseen events.

The types of expenditures can be grouped into routine and intermittent. Routine expenditure, including personnel expenditure, interest, subsidies and grants, refers to expenses where the time and the amount of payment are relatively predictable. The timing is scheduled, and the funds are relatively fixed. Such information is accessible to the cash manager. In most cases, routine expenditure is determined by regulations in advance.

In contrast, with intermittent expenditure, the timing and amount of cash needed is more varied in each period. An expenditure qualifies as "intermittent" when it is fully under the control of each spending unit without intervention from the cash manager. The spending unit has the authority to spend its budget depending on the activities' time frame, which might differ between activities. It is purely at the spending unit's discretion. This type of spending includes goods and capital expenditures, and social aid. It is generally more challenging to predict intermittent expenditure due to its variability (Widodo *et al.*, 2014).

The Indonesian Government introduced reforms in 2003, marked by the enactment of a legal treasury framework with a focus on cash management (Widodo *et al.*, 2014). New arrangements were introduced following international best practice, as proposed by Lienert (2009) and Williams (2009). Government cash balances were transferred into a single account in the central bank, called treasury single account (TSA), along with the consolidation of all government accounts. All receipts and expenditures now pass though the TSA. The application of "Treasury Notional Pooling" was introduced to monitor balances in imprest accounts held by spending units and to minimise idle cash. The Indonesian Government presently uses its forecasting system to more profitably manage surplus cash balances by using various monetary instruments (Widodo *et al.*, 2014).

Studies have revealed that cash forecasts in Indonesian GCM frequently do not provide the accuracy expected at an acceptable level of materiality for the cash manager (Widodo *et al.*, 2014). Currently, the Indonesian Government uses a "bottom-up method" to predict expenditure based upon aggregating periodically updated, individual, disbursement plans submitted by spending units. The review that formed the basis of the study cited above, conducted by the cash manager, found that not only the accuracy of expenditure forecasting was poor, but also that the requirements for spending units to predict and update their disbursement plans were onerous (Widodo *et al.*, 2014). The present study proposes a top-down approach to forecasting by the cash manager using formal forecasting models that should improve cash forecasting accuracy and simplify the requirements relating to the reporting of plans by spending units. As already noted, we focus on intermittent expenditures in developing our government cash forecasting model as these are usually more difficult to predict. For comparative purposes, three models are built for each type of intermittent expenditures and total expenditure.

Methods

This section describes the data, the research design, the modelling methods and forecast evaluation criteria used in the study.

Datasets

The data were collected from the Ministry of Finance, Indonesia, based on Audited Financial Statements of the Indonesian Central Government from 2008 to 2015. Weekly data of government expenditure were allocated into a four-fold classification: goods and services expenditure, G; capital expenditure, C; social aids expenditure, S; and total intermittent expenditure, T, as shown in Table I.

All data are transformed to natural logarithms. The data are split into a training set (2008–2013) and a testing set (2014–2015). The testing set spans a two-year time period to accommodate assessing the effect of at least one lag in the data. The magnitude of the variables can be seen in Table II. In the unlogged data, the magnitude of the variables is of the order of thousands of billions of Indonesian Rupiahs.

Research design

Three different models – ARIMA, ANN, and Hybrid, described in detail below – are applied to the variables separately. The performance of each forecasting model is compared based on specific criteria described at the end of this section. A summary of the procedures employed is shown in Figure 1.

ARIMA model

The ARIMA model is a pure time series model in which past values of a variable and a "white noise" error term are used to forecast future values of the same variable. The use of ARIMA models does not necessarily require any underlying theory (Gujarati and Porter, 2009).

ARIMA is a modification of an ARMA model (Mondal *et al.*, 2014). An ARMA (p, q) has the form:

$$Y_t = \theta + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \ldots + \beta_q \varepsilon_{t-q}, \quad (1)$$

Table I.
List of variables

Variable	Description	Sample size (2008–2015)	Training size (2008–2013)	Test size (2014–2015)
G	Goods and services expenditure in logs	420	315	105
C	Capital expenditure in logs	420	315	105
S	Social aid expenditure in logs	420	315	105
T	Total intermittent expenditure in logs	420	315	105

Table II.
Descriptive statistics of the variables (in unlogged values)

Variable	Mean (Trillion Rupiah)	SD	Maximum (Trillion Rupiah)	Minimum
G	2.58	2.95	37.5	0.00
C	2.49	3.81	43.2	0.00
S	1.52	1.30	7.92	0.00
T	6.60	7.21	83.5	0.00

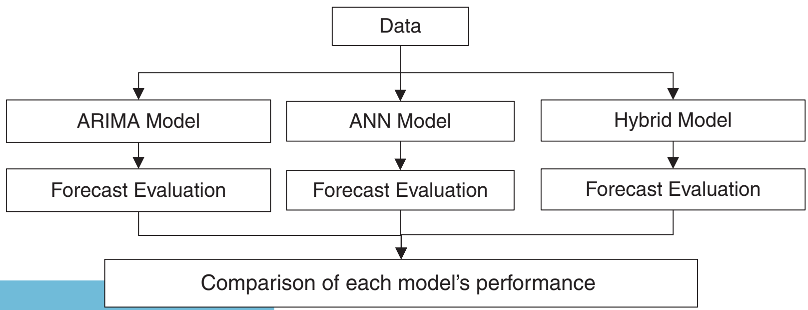


Figure 1.
Research design

where Y_t is the variable to be predicted based on its preceding p-values with constant linear coefficients α and current ε_t and previous errors for q periods with constant linear coefficients β. To ensure a robust time series analysis, the underlying data need to be stationary. If the data are not stationary, they have to be differenced d times to make them stationary – such time series are denoted $I(d)$. When a time series is $I(d)$ and applied to Equation (1), the formal ARIMA model is ARIMA(p, d, q), where p, d and q are the number of autoregressive terms, order of integration and moving average terms, respectively, and are all nonnegative integers. Consequently, an ARIMA model can be estimated once values of p, d and q are determined.

Utilising the ARIMA approach to forecasting involves four steps, as shown in Figure 2 (Gujarati and Porter, 2009). Identification utilises correlograms of autocorrelation functions (ACF) and partial autocorrelation functions (PACF) of the data to determine the most appropriate estimates of p, d and q. Diagnostic checking, employing white noise tests on residuals, verifies whether the chosen model gives the best fit for the data. When the residuals are not white noise, the process repeats from the first step iteratively. The forecasting step produces predicted future values. In this study, all variables are analysed following the same ARIMA procedure described in Figure 2.

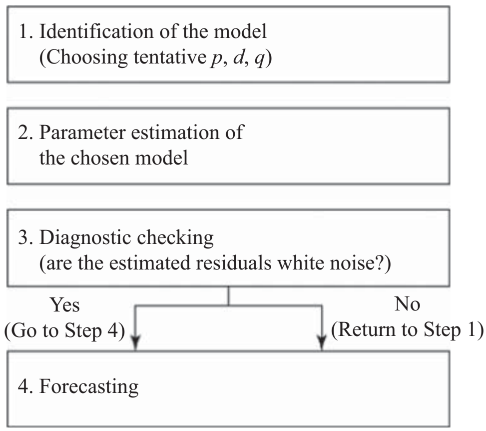
ANN model

ANN is a computational model mimicking biological neural systems as an information-processing system (Zhang *et al.*, 1998). The main elements of ANN are neurons, connections and a learning algorithm (Yildiz and Yezegel, 2010). The neuron is the information-processing unit. It consists of a set of synapses with each synapse having a weight representing the strength of the signal. In a neuron k, input data x_j at synapse j are multiplied by the synaptic weight w_{kj}. This product for each synapses is summed across all synapses to give a single value called a linear combiner v_k that includes a bias b_k. The bias increases or decreases the input of the activation function $\varphi(.)$ (Haykin, 1999, see Figure 3). The output of neuron y_k can be used by other neurons (Butler, 2006).

A neuron k may thus be expressed mathematically as:

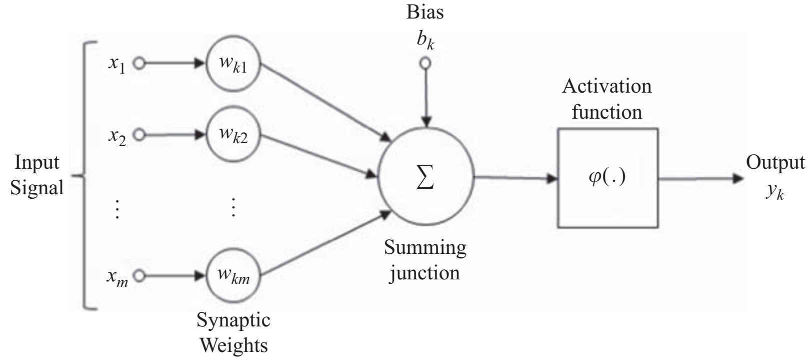
$$y_k = \varphi(v_k), \tag{2}$$

where $v_k = \sum_{j=1}^{m} w_{kj}x_j + b_k$.



Source: Gujarati and Porter (2009)

Figure 2.
The box-jenkins methodology



Source: Haykin (1999)

Figure 3.
Non-linear model of neuron

We use a non-linear autoregressive neural network (NARNN) estimation procedure (Ruiz *et al.*, 2016). The mathematical form of the NARNN is as follows:

$$y_t = \varphi\left(y_{t-1}, y_{t-2}, \ldots, y_{t-p}\right) + \varepsilon_t, \tag{3}$$

with variables, coefficients and constants as before.

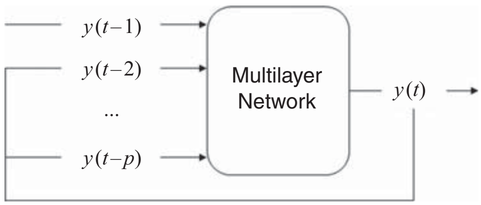
The architecture of an NARNN is shown in Figure 4. The number of hidden layers and the number of neurons per layer are optimised through an iterative, trial-and-error procedure. Notwithstanding the flexibility on choosing the number of hidden layers and the number of neurons per layer, a higher number of neurons leads to more complexity in the network. A lower number of neurons limits the network's generality and computing power (Ruiz *et al.*, 2016). The Levenberg–Marquardt back propagation procedure is the most common learning rule used for the NARNN due to its speed (Ayala and Coelho, 2016; Dudek, 2016; Ebtehaj and Bonakdari, 2016; Wang *et al.*, 2015).

Hybrid model

We apply Zhang's (2003) hybrid model. This is based on the assumption that the ARIMA model is used to analyse the linear part of the data, such that its residual contains non-linear information. The ANN model then examines non-linearity in the residual. The first step in building a hybrid model is to consider a time series as an autocorrelation structure with linear, L_t, and non-linear components, N_t (Zhang, 2003).

Let r_t denote the residual of the ARIMA model, then:

$$r_t = y_t - \hat{L}_t, \tag{4}$$



Source: Ruiz *et al.* (2016)

Figure 4.
Architecture of NARNN

where $\hat{L}_t$ is the ARIMA forecast. The residuals are modelled using an ANN as:

$$\hat{r}_t = f(r_{t-1}, r_{t-2}, \ldots, r_{t-q}) + \varepsilon_t, \tag{5}$$

where f is a neural network function, q is the number of input delays and ε_t is the random error. Hence, the hybrid forecast is:

$$\hat{y}_t = \hat{L}_t + \hat{r}_t + \varepsilon_t. \tag{6}$$

Forecast evaluation methods

Following common practice (Khandelwal *et al.*, 2015), the performance of each forecasting model is evaluated using the mean square error (MSE) and the mean absolute percentage error (MAPE) criterion, defined as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2, \tag{7}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(\hat{y}_i - y_i)}{y_i}\right| \times 100, \tag{8}$$

where y_t and $\hat{y}_i$ are actual and forecasted value of time series, respectively.

Results and discussion

Four forecasting models predicting the cash required by the government are tested using the methods described in the third section. Each model represents one of the different types of intermittent expenditure and their aggregated total: model 1 for goods and services expenditures; model 2 for capital expenditures; model 3 for social aid; and model 4 for total intermittent expenditures. Each model is analysed using ARIMA, ANN and the Hybrid models separately. The best model is determined through forecast evaluation criteria described in the previous section.

Identification data

We first establish the level of integration and maximum lag lengths to determine the AR and MA terms in the ARIMA model and the delay in the NARNN model. We use the Augmented Dicky–Fuller unit root test to check for stationarity of the different series. The results shown in Table III indicate that the variables are stationary.

Correlograms of the ACF and PACF of the series are presented in Figures 5–8. These suggest that the maximum lags in G, C, S and T are 1, 1, 3 and 1, respectively.

ARIMA model

All possible ARIMA models, based on the maximum lag for each variable, are estimated. The selected ARIMA specification for each model is chosen based on the Schwarz

Variable	Test critical values at 1%	*t*-statistic	Conclusion
G	−3.45	−14.30	Stationary/I(O)
C	−3.45	−12.18	Stationary/I(O)
S	−3.45	−8.69	Stationary/I(O)
T	−3.45	−13.85	Stationary/I(O)

Table III. Unit root test

Bayesian Criteria. The values of p, d and q are ARIMA(1, 0, 0), ARIMA(1, 0, 0), ARIMA(1, 0, 2) and ARIMA(1, 0, 0) for models 1, 2, 3 and 4, respectively. The estimation results are summarised in Table IV. All coefficients are significance at the 1 per cent level.

The verification of the different ARIMA models is determined by examining the correlograms of residuals to check they appear to be white noise.

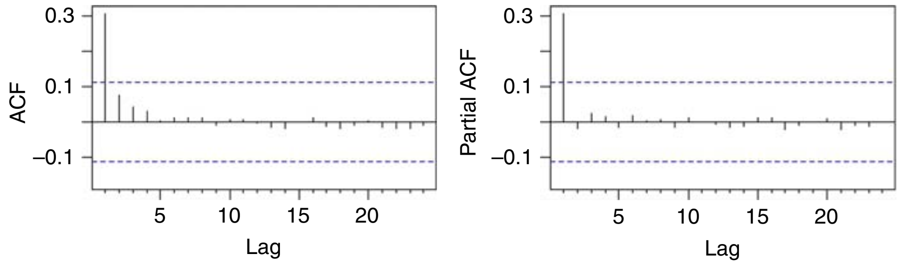


Figure 5.
Correlogram of the ACF and PACF for *G*

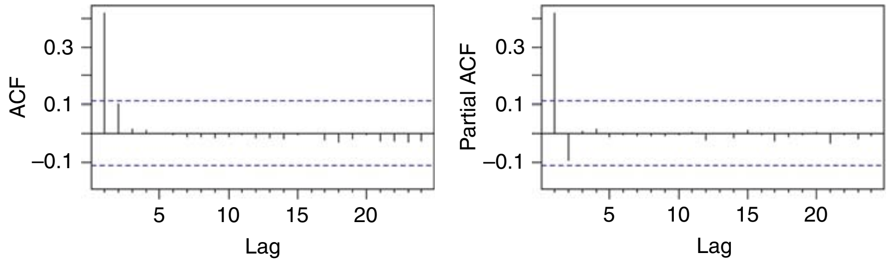


Figure 6.
Correlogram of the ACF and PACF for *C*

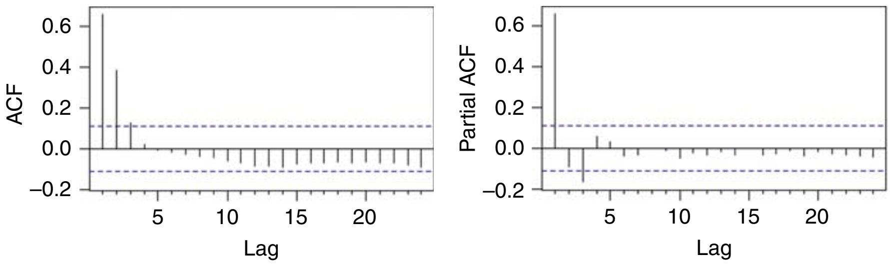


Figure 7.
Correlogram of the ACF and PACF for *S*

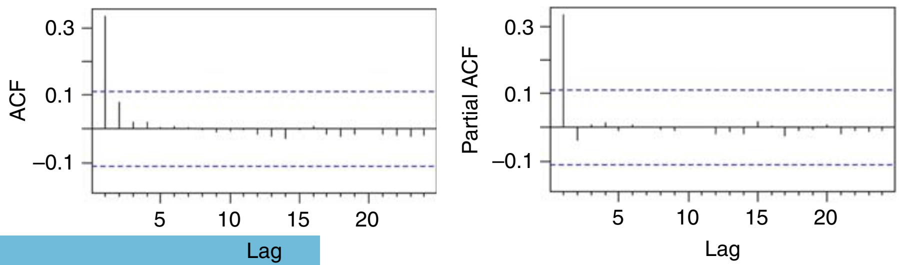


Figure 8.
Correlogram of the ACF and PACF for *T*

ANN model

The NARNN models are developed utilising the MATLAB Toolbox with some modification to accommodate the data. The model selected optimises the performance of training and testing data, using the MSE criteria. The feedback delay for each model is determined based on the maximum lag for each variable. A hidden layer with ten neurons is selected through a trial-and-error process, whereby increasing or decreasing the number of neurons eventually fails to enhance the performance of the network. The transfer function in the hidden layer and output layer, and the training-algorithm, are set as defaults. The data division is divided into contiguous blocks such that there are 263 from 420 for training, 52 from 420 for validation and 105 from 420 for testing. This division is to ensure the testing sets are consistent with the ARIMA model. Architectures of the NARNN for the different models are summarised in Table V.

Hybrid model

The hybrid models represent both linear and non-linear component of the dynamic processes. The ARIMA model estimates the linear component of the time series. The residual generated from the ARIMA model is then modelled using the ANN model, employing the NARNN architecture described in the above section.

Forecasting evaluation

The forecast performance of each model is shown in Table VI. Overall, the best model performance, based on the MSE criteria, is achieved by the ANN. By the MAPE criteria, however, ARIMA is superior for models 1 and 4, while the Hybrid is superior in the case of model 2 and ANN remains superior in the case of model 3.

Parameter term	Model 1 (G)	Model 2 (C)	Model 3 (S)	Model 4 (T)
Intercept, θ	27.48	27.06	25.93	28.39
AR(1), α_1	0.37	0.48	0.40	0.40
MA(1), β_1			0.34	
MA(2), β_2			0.35	

Table IV. Parameter estimation

Model	Number of neurons (input-hidden-output)	Input variable	Output
Model 1 (G)	1-10-1	y_{t-1}	y_t
Model 2 (C)	1-10-1	y_{t-1}	y_t
Model 3 (S)	3-10-1	$y_{t-1}, y_{t-2}, y_{t-3}$	y_t
Model 4 (T)	1-10-1	y_{t-1}	y_t

Table V. Architecture of proposed ANN models

		MSE			MAPE	
Model (variable)	ARIMA	ANN	Hybrid	ARIMA	ANN	Hybrid
Model 1 (G)	17.22	11.94	15.50	5.64	8.21	6.80
Model 2 (C)	19.67	17.50	18.79	6.76	7.16	6.32
Model 3 (S)	34.74	31.17	34.89	18.85	14.18	17.87
Model 4 (T)	18.66	14.14	17.34	5.67	6.33	6.25

Table VI. Performance comparison of forecasting models

The results therefore vary according to the criteria used to judge model performance. By the MSE criteria, ANN consistently provides the best method of forecasting each type of government expenditure. The MAPE criteria however show no single method to be superior in every model. Under this criterion, the ARIMA is best for goods expenditure (model 1) and total intermittent expenditure (model 4); the Hybrid method is best for capital expenditure (model 2), and the ANN method is best for social aid expenditure (model 3). Based on the MSE criteria, the structure of all variables is non-linear. The performance of the forecast under the MAPE criteria suggests that goods expenditure and total intermittent expenditure behave linearly, social aid expenditure is non-linear and capital expenditure is a combination the two. Actual and fitted values for each variable are plotted in Figures 9–12.

Conclusions

Having good quality GCM is important to governments, nations and their regions. The Greek crisis of 2010 provides an illustration of a government mismanaging its cash resources. A number of studies have argued in favour of strengthening cash forecasts to achieve more effective GCM, particularly in developing countries. Literature that focusses specifically on government cash forecasting is rare, however. This paper contributes to closing that gap by investigating which modelling methods produce the best government cash forecasting models based on standard forecasting criteria and using weekly Indonesian Government intermittent expenditure from 2008 to 2015.

The results show that building a government cash forecasting model with an accuracy that meets an acceptable level of materiality for the cash manager is possible and that success depends on adopting a flexible method suitable to the type of data used. Combining ARIMA and ANN methods into a Hybrid model does not always provide the best performance. Moreover, aggregating government expenditure does not always lead to improved forecasting accuracy. This conclusion is consistent with the findings of Taskaya-Temizel and Casey (2005).

The generality of the findings reported in this paper are limited by its case study nature. The case study concerns particular features of the Indonesian Government's cash

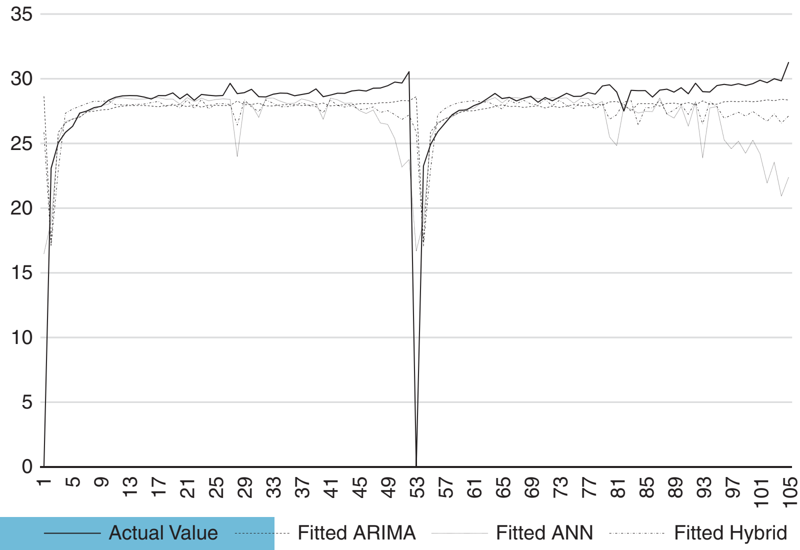


Figure 9.
Actual and fitted values for G

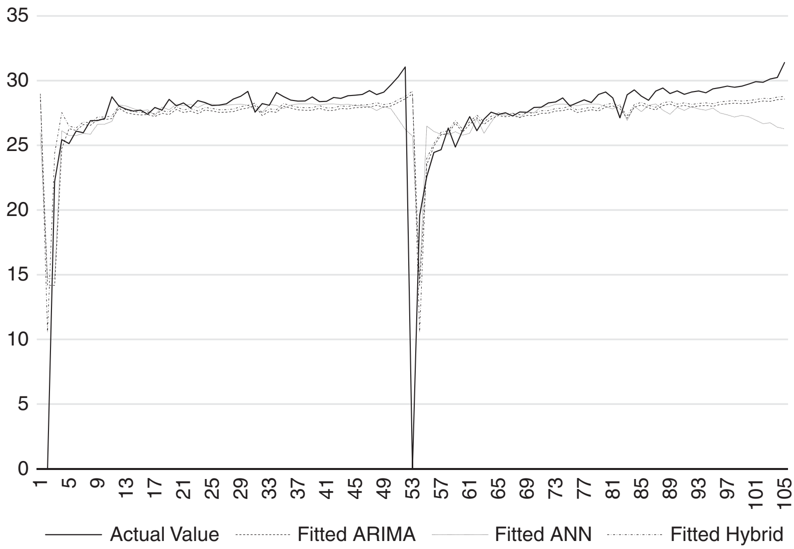


Figure 10.
Actual and fitted values for C

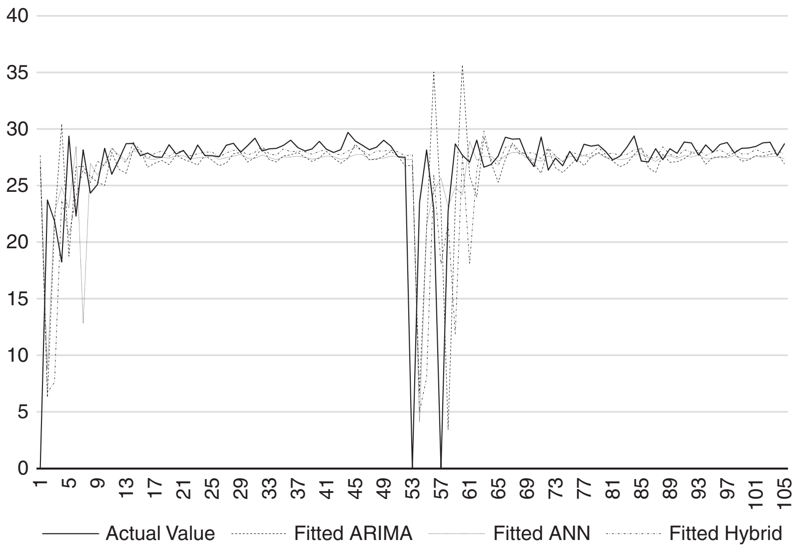


Figure 11.
Actual and fitted values for S

management processes. These, without doubt, reflect various idiosyncratic features that may not be in evidence, at least to the same extent, in other governmental cash management processes. Cultural differences within the institutions involved and the specific nature of the Indonesian economy limit the extent to which the results of the study can inform cash management practices in other government systems.

Nevertheless, the study provides evidence of the impact of forecasting criteria and different forecasting methods on forecast performance in different government expenditure categories.

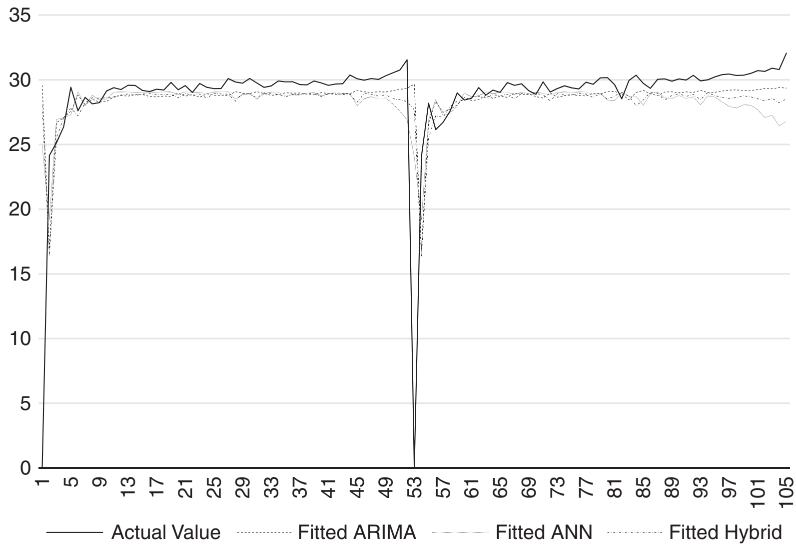


Figure 12.
Actual and fitted values for *T*

It also provides a framework for future research into cash forecasting methods for modelling cash management in government and other public sectors. We use an autoregressive model without incorporating other variables that might influence government cash disbursement. Other predictive methods relying on both statistical and machine learning techniques that include significant factors determining government cash disbursements are promising areas of future research. Additional areas of potential research value are the choice of the most appropriate criteria for assessing the accuracy of government cash forecasts and the performance of forecasting models using different periodicities of government expenditures.

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