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Forecasting dengue epidemics using a hybrid methodology

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HIGHLIGHTS

- We propose a hybrid ARIMA-NNAR model for dengue forecasting.
- Predictions of dengue cases in three dengue endemic regions were examined.
- Dengue cases can be accurately forecasted using the proposed hybrid methodology.

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ABSTRACT

Dengue case management is an alarmingly important global health issue. The effective allocation of resources is often difficult due to external and internal factors imposing nonlinear fluctuations in the prevalence of dengue fever. We aimed to construct an early-warning system that could accurately forecast subsequent dengue cases in three dengue endemic regions, namely San Juan, Iquitos, and the Philippines. The problem is solely regarded as a time series forecasting problem ignoring the known epidemiology of dengue fever as well as the other meteorological variables. Autoregressive integrated moving average (ARIMA) model is a popular classical time series model for linear data structures whereas with the advent of neural networks, nonlinear structures in the data set can be handled. In this paper, we propose a novel hybrid model combining ARIMA and neural network autoregressive (NNAR) model to capture both linearity and nonlinearity in the data sets. The ARIMA model filters out linear tendencies in the data and passes on the residual values to the NNAR model. The proposed hybrid approach is applied to three dengue time-series data sets and is found to give better forecasting accuracy in comparison to the state-of-the-art. The results of this study indicate that dengue cases can be accurately forecasted over a sufficient time period using the proposed hybrid methodology.

1. Introduction

Dengue incidence has increased drastically in recent decades, putting almost half of the humans at risk [1]. Dengue fever (DF) is caused by four closely related serotypes (DEN-1, DEN-2, DEN-3, and DEN-4) of dengue virus. The virus is transmitted to humans by the bites of infected female Aedes aegypti and Aedes albopictus mosquitoes [2]. Although the case fatality rate of DF is meager, it can progress to severe complications such as dengue hemorrhagic fever (DHF) and dengue shock syndrome (DSS). The dengue endemic countries of Asia and Latin America have reported that DHF and DSS are among the leading causes of hospitalization and death therein. The prevalence of DF is geographically dispersed over the countries situated in the tropical and subtropical regions [2,3], with local variations in risk and circulation of

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multiple dengue serotypes. However, no medicine is still available to cure DF; treatment only includes medications for clinical symptoms. Although some candidate vaccines (including live attenuated mono, tetravalent formulation inactivated whole virus vaccines, and recombinant subunit vaccines) are undergoing various phases of clinical trials but none of the vaccines are yet employed [4,5].

Consequently, health care officials have to rely on early warning systems in order to optimally disseminate available resources in the dengue-prone areas. Impact of severe complications of DF can be reduced by effective case management in endemic regions [6]. Policy-makers can employ preventive measures and allocate sufficient resources in the areas with the highest epidemic risk, whenever one can notify the local health care officials on time. Thus, forecasting the future dengue incidence is of utmost interest. Time series forecasting tools are suited when very little knowledge is available regarding the data generating process. Previously, various attempts were made to predict dengue epidemics with several degrees of success (see [6–12]). Using dengue incidence data from Guadeloupe, French West Indies, time series analysis was carried out in [7]. Authors used Seasonal Autoregressive Integrated Moving Average (SARIMA) model and incorporated climatic data as independent variables to predict dengue outbreaks. They concluded that incorporation of temperature data improved dengue prediction. Racloz et al. [8], reported a systematic literature review of dengue forecasting models and analyzed different modeling methods and their outputs in terms of acting as an early warning system. Yamana et al. [9] proposed three forecasting frameworks to predict outbreak characteristics in San Juan. Further, they used Bayesian model averaging to create superensemble forecasts combining the individual model predictions. They concluded that the superensemble forecasts outperformed each component system. In a recent study, various machine learning models were tested to forecast dengue incidence in Guangdong province, China [10]. The study concluded that support vector regression model achieved better prediction performance in comparison with other candidate models compared therein. Using three different component models namely: (1) two-dimensional Method of Analogue models incorporating both dengue and climate data; (2) additive seasonal Holt–Winters models with and without wavelet smoothing; and (3) simple historical models, Bukzak et al. [11] investigated the predictive capabilities of ensemble models. They used data from San Juan and Iquitos and predicted three outbreak characteristics (peak week, peak height and total cases in a season) for each location. It was found that there were separate ensembles for predicting each of the three targets at each of the two locations. Johnson et al. [12] used nonparametric nonlinear Gaussian process regression to predict targets of outbreak characteristics in San Juan and Iquitos. They found that their approach had better predictive capability than the classical generalized linear (autoregressive) model. Lauer et al. [6] developed statistical models that use biologically plausible covariates to forecast DHF incidence in Thailand. They found that functions of past incidence contribute most strongly to model performance, whereas the importance of environmental covariates varies regionally. These attempts to anticipate the future dengue cases have increased our understanding and have given some insights into further challenges in forecasting epidemics.

Among various traditional models, ARIMA is popularly used for forecasting linear time series. Machine learning models such as artificial neural Networks (ANN), support vector machines (SVM), Long Short Term Memory (LSTM) are proved to perform well for nonlinear data structures in time series data. Dengue data sets are neither purely linear nor nonlinear. They usually contain both linear and nonlinear patterns. If this is the case, then the individual ARIMA or ANN is inadequate to model such situations. Therefore, the combination of linear and nonlinear models can be well suited for accurately modeling such complex autocorrelation structures. Several hybrid methodologies were discussed in previous literature to solve a variety of time series problems arose in econometrics, financial stocks, electricity and other applied areas [13–22]. Zhang's hybrid ARIMA-ANN model [23] has gained popularity due to its capacity to forecast complex time series accurately. The pitfall of hybrid ARIMA-ANN model lies in the selection of the number of hidden layers in the ANN architecture that involves subjective judgment. To ignore this drawback, we took recourse to the NNAR model which is more of a "white-box-like" approach. NNAR fits a feed-forward neural network model with only one hidden layer to a time series with lagged values of the series as inputs (also flexible to handle some other exogenous data). The advantage of NNAR over ANN, SVM, LSTM is that NNAR is a nonlinear autoregressive model, and it provides less complexity, easy interpretability and better prediction as compared to others in many situations. Due to this, NNAR is getting more attention in recent literature of non-stationary time series forecasting [24].

The primary motivation of this paper is to handle the time series data with several decisions regarding how we describe the recent dynamics of the observed values of the series. Taking a final decision in policy making based on a component model may be dangerous in such a severe problem like dengue forecasting where one frequently observes changes in the dynamic properties of the variable being measured. Hybridization of two or more models are the most common solution to this problem where one can take advantages of diversity among models to reduce both the bias and variances of the prediction error obtained using single models [25]. Even from the practitioners' point of view, hybrid models are more effective when the complete data characteristics are not known [26]. Motivated from these discussions, this paper proposes a novel hybrid ARIMA-NNAR model that captures complex data structures and linear plus nonlinear behavior of dengue data sets. In the first phase of our proposed model, ARIMA catches the linear patterns of the data set. Then the NNAR model is employed to capture the nonlinear patterns in the data using residual values obtained from the base ARIMA model. The proposed model has easy interpretability, robust predictability and can adapt seasonality indices as well. Through experimental evaluation, we have shown the excellent performance of the proposed hybrid model for the dengue epidemics forecasting for three different regional data sets.

2. Methodology

The deficiencies of the single time series models can be overcome with the hybrid methodology. Achieving stationarity in both the mean and variance is considered essential in classical time series forecasting methods but the literature of machine learning methods are capable of effectively modeling any type of data patterns and can therefore be applied to the original data [27]. In the process of capturing typical patterns in the data, a combination of linear and non-linear time series model is often applied to showcase the salient features of the data sets. Few popular hybrid models in this literature are hybrid ARIMA-ANN [17,28], hybrid ARIMA-SVM model [18] and hybrid ARIMA-LSTM [29] where the main motivation was to understand both linear and nonlinear patterns of the time series data. These models have shown better performance in terms of prediction accuracy for different forecasting problems of economics, sales, finance, carbon price, stock, electricity, etc. In this work, we propose a novel hybridization of ARIMA and NNAR model to solve the dengue forecasting problem. Below we give a brief description of the component models used in the hybridization.

2.1. ARIMA model

The ARIMA model, introduced by Box and Jenkin [30], is a linear regression model indulged to track linear tendencies in stationary time series data. The model is expressed as ARIMA(p,d,q) where p, d, and q are integer parameter values that decide the structure of the model. More precisely, p and q are the order of the AR model and the MA model respectively, and parameter d is the level of differencing applied to the data. The mathematical expression of the ARIMA model is as follows

$$\begin{aligned} y_t &= \theta_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} \\ &\quad + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}, \end{aligned}$$

where y_t is the actual value, ε_t is the random error at time t, ϕ_i and θ_j are the coefficients of the model. It is assumed that ε_{t-l} ($\varepsilon_{t-l} = y_{t-l} - \hat{y}_{t-l}$) has zero mean with constant variance, and satisfies the i.i.d condition. The methodology consists of three iterative steps: (1) model identification and model selection; (2) parameter estimation of the model parameters, (3) model diagnostics checking (namely, residual analysis) are performed to find the 'best' fitted model.

In the model identification and model selection step, differencing is applied once or twice to achieve stationarity for non-stationary data. As stationarity condition is satisfied, the autocorrelation function (ACF) plot and the partial autocorrelation function (PACF) plot are examined to select the AR and MA model types. The parameter estimation step involves an optimization process utilizing metrics such as the Akaike Information Criterion (AIC) and/or the Bayesian Information Criterion (BIC). Finally, in the model checking step, the residual analysis is carried out to finalize the 'best' fitted ARIMA model. ARIMA model is a data-dependent approach that can adapt to the structure of the data set. But it has the major disadvantage that any significant nonlinear data set can restrict the ARIMA model. Therefore, the proposed hybrid model uses NNAR model to deal with the nonlinear data patterns for forecasting complex time series structure.

2.2. NNAR model

Neural nets are based on simple mathematical models of the brain, used for complex nonlinear forecasting. A neural network can be thought of as a network of "neurons" that are arranged in layers (viz. input, hidden and output layers). The forecasts are obtained by a linear combination of the inputs. The weights are selected in the network model using a "learning algorithm" that minimizes the mean squared error.

NNAR model is a nonlinear time series model which uses lagged values of the time series as inputs to the neural network [24]. NNAR(p,k) is a feed-forward neural networks having one hidden layer with p lagged inputs and k nodes in the hidden layer. For example, an NNAR(9,5) model is a neural network that uses the last nine observations ($y_{t-1}, y_{t-2}, \ldots, y_{t-9}$) as inputs for forecasting the output with five neurons in the hidden layer. This model can be applied to the original nonlinear data without putting any restrictions on the parameters to ensure stationarity. An NNAR(p,k) model uses p as the optimal number of lags (calculated based on the AIC value) for an AR(p) model and k is set to $k = [\frac{(p+1)}{2}]$ for non-seasonal data sets. To forecast the time series, the NNAR model is applied iteratively with the logistic activation function within the network. For one step ahead forecast, we can utilize the available historical inputs whereas for two steps ahead forecast, we need to use the one step ahead forecast as an input, along with the historical data. This process proceeds until all the required forecasts are computed.

2.3. Formulation of the hybrid model

ARIMA model is one of the traditional statistical models for linear time series prediction. On the other hand, the NNAR model can capture nonlinear trends in the data set. So, the two models are consecutively combined to encompass both linear and nonlinear tendencies in the model [31]. A hybrid strategy that has both linear and nonlinear modeling abilities is a good alternative for forecasting dengue cases. Both the ARIMA and the NNAR models have different capabilities to capture data characteristics in linear or nonlinear domains. Thus, the hybrid approach can model linear and nonlinear patterns with improved overall forecasting performance. There exist numerous time series models in the literature, and

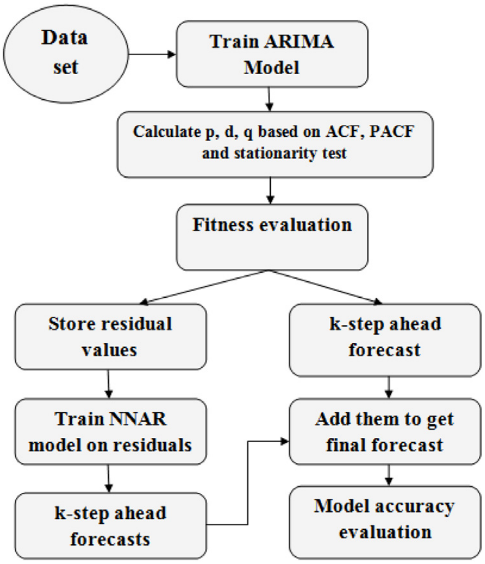

Data set
Train ARIMA Model
Calculate p, d, q based on ACF, PACF and stationarity test
Fitness evaluation
Store residual values
k-step ahead forecast
Train NNAR model on residuals
Add them to get final forecast
k-step ahead forecasts
Model accuracy evaluation

Fig. 1. Flow diagram of the proposed model.

several research shows forecast accuracy improves in hybrid models. The aim of developing a novel hybridization is to harness the advantages of single models and reduce the risk of failures of single models. The underlying assumption of the hybrid approach based on linear and nonlinear model assumption is that the relationship between linear and nonlinear components are additive. The strength of single models for hybridization is very important, and this selection is essential to show the consistent improvement over single models. This paper presents a novel hybridization of ARIMA and NNAR to overcome the limitation of single models and utilize their strengths. With the combination of linear and nonlinear models, the proposed methodology can guarantee better performance as compared to the component models.

The hybrid model (Z_t) can be represented as follows

$$Z_t = Y_t + N_t,$$

where Y_t is the linear part and N_t is the nonlinear part of the hybrid model. Both Y_t and N_t are estimated from the data set. Let, $\hat{Y}_t$ be the forecast value of the ARIMA model at time t and ε_t represent the residual at time t as obtained from the ARIMA model; then

$$\varepsilon_t = Z_t - \hat{Y}_t.$$

The residuals are modeled by the NNAR model and can be represented as follows

$$\varepsilon_t = f(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-n}) + \varsigma_t,$$

where f is a nonlinear function modeled by the NNAR approach and ς_t is the random error. Therefore, the combined forecast is

$$\hat{Z}_t = \hat{Y}_t + \hat{N}_t,$$

where, $\hat{N}_t$ is the forecast value of the NNAR model. The rationale behind the use of residuals in the diagnosis of the sufficiency of the proposed hybrid model is that there is still autocorrelation left in the residuals which ARIMA could not model. This work is performed by the NNAR model which can capture the nonlinear autocorrelation relationship.

In summary, the proposed hybrid ARIMA-NNAR model works in two phases. In the first phase, an ARIMA model is applied to analyze the linear part of the model. In the next stage, an NNAR model is employed to model the residuals of the ARIMA model. The hybrid model also reduces the model uncertainty which occurs in inferential statistics and forecasting time series. A flowchart of the hybrid ARIMA-NNAR model is presented in Fig. 1.

3. Experimental evaluations

In this section, three popular open-access dengue data sets, namely San Juan, Iquitos and the Philippines data are used to determine the effectiveness of the proposed model. The properties of these data sets are different and have been used in previous studies [9,12]. Different linear and nonlinear models have been studied on these data sets that shows highly nonlinear patterns in these regions. Mean absolute error (MAE); root mean square error (RMSE) and symmetric Mean Absolute Percent Error (SMAPE) are used to evaluate the performances of the proposed model and other single models for dengue data sets.

3.1. Data sets

Among the three data sets, two are weekly dengue incidence data, and one is monthly data. For the endemic regions San Juan and Iquitos, weekly laboratory-confirmed cases for the time periods from May 1990 through October 2011 and from July 2000 through December 2011, respectively are considered in this study. Weekly dengue incidence data for the San Juan region and Iquitos region are made available in this link.[1] The Philippines data set contains the monthly recorded cases of dengue per 100,000 population in the Philippines. Monthly incidence of dengue in the Philippines is collected from kaggle (see the link: https://www.kaggle.com/grosvenpaul/dengue-cases-in-the-philippines/) for the time period January 2008 through December 2016. The Philippines monthly data set contains a total of 108 monthly observations and we use the total cases reported from all regions in the Philippines in this study. San Juan weekly data set contains a total of 1144 observations whereas Iquitos data set contains only 520 observations.

3.2. Performance measures

The metrics used in this study to evaluate the performance of different forecasting models (including the proposed model) are RMSE, MAE and SMAPE [32].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{(|\hat{y}_i| + |y_i|)/2}$$

where y_i is the target output, $\hat{y}_i$ is the prediction and n denotes the number of data points. By convention, the lower the value of these metrics, the better the forecast model is.

3.3. Analysis of results

We have divided three dengue data sets into training and testing data. For weekly data sets we have kept last six months data for testing model accuracy. We have kept one year data as test data for the Philippines datas et. The behavior of the data set can be regarded as nonlinear and non-gaussian. The time series plot of the data set show a cyclical pattern with a mean cycle of about 1 year (see Table 1). We have studied ARIMA, ANN, SVM, LSTM, NNAR model for this data. The data set is divided into two samples of training and testing to assess the forecasting performance of the proposed model. For example, the training set of Philippines contains 96 observations (January 2008–December 2015), is exclusively used for model building. Further, the last 12 month's data (January 2016–December 2016) are used for model evaluation. We have applied our proposed hybrid ARIMA-NNAR model along with other single and hybrid models to all the three data sets as follows.

Linear modeling is done with ARIMA(p,d,q) using "forecast" package in R statistical software. Nonlinear modeling with NNAR approach is done with "caret" package using "nnetar" function and ANN with "nnfor" package using "mlp" function in R statistical software. Another single model SVM with gaussian kernel function for time series forecasting was implemented in Matlab using the toolbox by [33]. LSTM is a deep neural network model for time series forecasting, more useful for large data sets, was implemented using Matlab "Deep Learning Toolbox".

Before fitting an ARIMA model, the order of the model must be specified. The ACF plot and the PACF plot aid the decision process. We choose the 'best' fitted ARIMA model using AIC value, for each train data set. The method we use to compute the log-likelihood function for the AIC metric is the maximum likelihood estimator. After fitting the ARIMA model, we generate predictions for every 3 months, six months and one year time steps to compute the residual value. Further, ARIMA residuals are modeled with NNAR(p,k) model having a pre-defined Box–Cox transformation set to $\lambda = 0$ to ensure the forecast values to stay positive. The value of p and k obtained by training the network and this is indeed a data dependent approach. Further, we add both the linear and nonlinear forecasts to obtain the final forecast results. ARIMA(4,1,0) was fitted to the Philippines data having AIC $=$ 1156.4 and log-likelihood value as -573.2. Further, the model residuals were trained using NNAR(18,10) model with an average of 20 networks, each of which is a 18-10-1 network with 201 weights. Then the forecast results of ARIMA along with NNAR residual forecasts are added together to obtain the final forecast values. And finally we compute RMSE, MAE, SMAPE and reported them in Table 2. For the San Juan data set we fit an ARIMA(1,0,2) model achieving AIC $=$ 8830.49 and log-likelihood $= -4410.24$ for the model. Further, an NNAR with p $=$ 14 and k $=$ 8 is trained. In a similar way as explained above, the final forecast values are computed

[1] http://dengueforecasting.noaa.gov/.

Table 1
Training data sets and corresponding ACF, PACF plots.

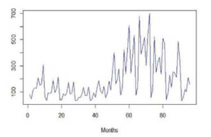
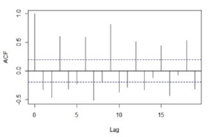
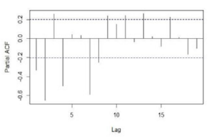
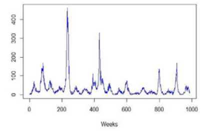
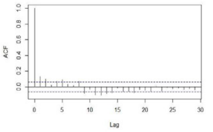
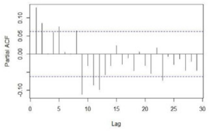
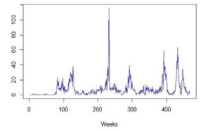
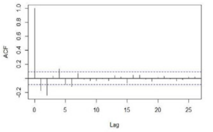
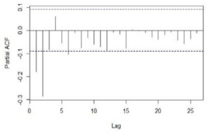
Region	Training data	ACF plot	PACF plot
Philippines			
San Juan			
Iquitos			

Table 2
Quantitative measures of performance for different forecasting models on the Philippines data set.

Model	6-months ahead forecast			1-year ahead forecast		
	RMSE	MAE	SMAPE	RMSE	MAE	SMAPE
ARIMA	102.42	81.47	0.898	136.4	127.2	0.961
SVM	96.59	72.08	0.803	120.6	108.8	0.801
ANN	88.75	68.38	0.670	107.4	98.19	0.688
LSTM	112.91	96.19	0.887	137.4	127.3	0.788
NNAR	**57.28**	**47.24**	**0.441**	97.57	75.55	0.689
Hybrid ARIMA-SVM	83.17	70.80	0.897	93.12	74.09	0.735
Hybrid ARIMA-ANN	81.38	69.43	0.874	92.98	77.33	**0.686**
Hybrid ARIMA-LSTM	84.38	71.04	0.878	90.06	72.38	0.721
Hybrid ARIMA-NNAR	65.39	60.44	0.553	**89.87**	**68.39**	**0.686**

and model performance metrics are reported in Table 3. Iquitos data set fits an ARIMA(0,1,3) and its residuals are trained with NNAR(5,3) model. In a similar way, we applied hybrid ARIMA-ANN, hybrid ARIMA-SVM, and hybrid ARIMA-LSTM models over three dengue data sets. All the experimental results are reported in Tables 2–4. The estimated values of the proposed model for three data sets along with actual test values are depicted in Fig. 2.

The study and analysis reveal a few exciting time series characteristics in dengue data sets. The Philippines training data set (see Table 1) exhibits a conceptual shift in the data. Due to the presence of data shift in this data, linear model and many hybrid models perform poorly. The performance measures, as reported in Table 2, also reflect an inconsistency in forecast results. NNAR model shows the best result for short term forecast and our proposed hybrid ARIMA-NNAR model outperforms all other models for long term forecasts. In the analysis of San Juan data set, the proposed model shows superiority and outperforms all the competitive model in a significant margin. In the case of Iquitos data set, the hybrid models perform well and exhibit the importance of combined methodology based on linear and nonlinear models over single models. Among hybrid models, the performance of the proposed model and the hybrid ARIMA-ANN model are impressive whereas hybrid ARIMA-SVM and hybrid ARIMA-LSTM models seem not to perform well since they were mostly used for stock market forecasting and large data sets. This gives a guide to time series practitioners to understand the use of hybrid models. Overall, we can conclude from Tables 2–4 that the proposed hybrid ARIMA-NNAR model either outperforms single and hybrid models or remains competitive for three dengue data sets.

4. Discussion

A time series can be classified into discrete or continuous, deterministic or stochastic, stationary or nonstationary, and linear or nonlinear time series. Time series analysis starts with trend, seasonality, stationarity, outlier, residual analysis, followed by building a forecasting model based on the characteristics of the data set [32]. In practice, it is often challenging to determine whether a time series under study is generated from a linear or nonlinear underlying process. Since all the available real-world time series data sets are complex in nature and often contain both linear and nonlinear patterns, a single model may be insufficient to meet the whole data characteristic adequately. Thus, a hybrid model combining

Table 3
Quantitative measures of performance for different forecasting models on San Juan data set.

Model	3-months ahead forecast			6-months ahead forecast		
	RMSE	MAE	SMAPE	RMSE	MAE	SMAPE
ARIMA	7.801	7.230	0.636	21.68	17.59	0.668
SVM	9.988	7.120	0.612	28.90	22.27	0.798
ANN	9.511	6.991	0.577	26.33	20.79	0.765
LSTM	10.500	7.095	0.630	28.50	23.05	0.800
NNAR	7.635	6.708	0.581	24.49	19.25	0.696
Hybrid ARIMA-SVM	8.150	7.695	0.640	23.01	18.95	0.703
Hybrid ARIMA-ANN	7.781	7.238	0.635	21.48	17.45	0.663
Hybrid ARIMA-LSTM	7.981	7.592	0.643	22.92	19.03	0.690
Hybrid ARIMA-NNAR	**7.438**	**6.569**	**0.570**	**20.73**	**16.56**	**0.612**

Table 4
Quantitative measures of performance for different forecasting models on Iquitos data set.

Model	3-months ahead forecast			6-months ahead forecast		
	RMSE	MAE	SMAPE	RMSE	MAE	SMAPE
ARIMA	1.296	1.027	0.694	1.349	1.122	0.711
SVM	2.150	2.005	0.905	2.612	1.978	0.885
ANN	2.090	1.901	0.901	2.148	1.899	0.869
LSTM	3.188	2.953	0.968	3.528	2.108	0.984
NNAR	2.199	2.018	0.959	2.324	1.999	0.949
Hybrid ARIMA-SVM	1.308	1.010	0.717	1.328	1.220	0.710
Hybrid ARIMA-ANN	**1.188**	**0.819**	**0.610**	1.190	0.944	0.643
Hybrid ARIMA-LSTM	1.554	1.249	0.720	1.992	1.234	0.798
Hybrid ARIMA-NNAR	1.285	0.955	0.684	**1.172**	**0.938**	**0.636**

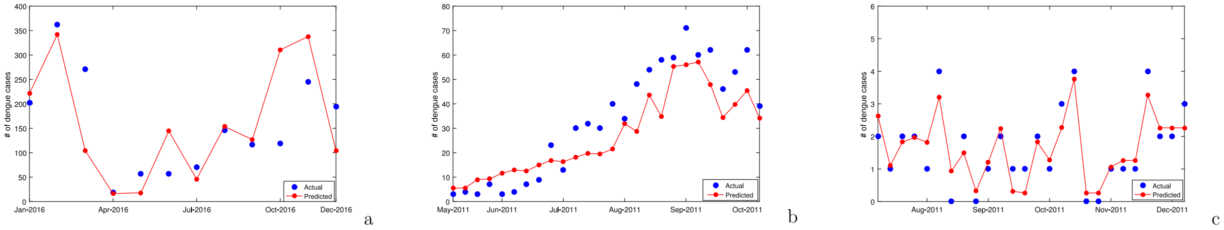


Fig. 2. Actual vs predicted forecasts (using ARIMA-NNAR model) of the Philippines (a), San Jaun (b) and Iquitos (c) data sets.

both the linear and nonlinear components is indeed useful. The basic assumption in the hybrid methodology is additive relationship between the linear and nonlinear components of the time series [34]. Hybrid schemes are best suited for both stationary or nonstationary time series and situations when the data exhibits both linear and nonlinear patterns. In the development of the hybrid methodology, we need the component model to be sub-optimal, and it will be useful to combine individual forecasts based on different information sets to produce superior forecasts. Based on our experience on dengue forecasting, our model is best suited in the situations where the data sets will have enough nonlinearity and non-stationarity. Experimental finding also suggests that the presence of the concept shift in time series leads to inconsistency in the performance among different time series models.

5. Conclusions

In this paper, we have built a hybrid model that performs superior for forecasting dengue epidemics. Our proposed hybrid ARIMA-NNAR model filters out linearity using the ARIMA model and predicts nonlinear tendencies with the NNAR approach. Hybrid ARIMA-NNAR model not only explains the linear and nonlinear autocorrelation structures present in the data better than the traditional component and other hybrid models but also yield better forecast accuracy than them. However, the limitation of the proposed methodology lies in the assumption of an additive relationship between linear and nonlinear components. It is often true that no model can be universally employed in all circumstances, and this is in relevance with "*no free lunch theorem*" [35]. Finally, we can conclude that our proposed model can help policy-makers to predict the subsequent dengue outbreaks accurately and respond to epidemics more effectively. Thus, this will reduce the impact of future outbreaks and will govern the employment of resources. Behavior of the proposed model for seasonal and multivariate time series data gsets can be considered as a future research work of this paper.

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