Comparative Evaluation of Hybrid SARIMA and Machine Learning Techniques Based on Time Varying and Decomposition of Precipitation Time Series

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ABSTRACT

Accurate precipitation forecasts are much attractive due to their complexity. This study aimed to use the hybrid Seasonal Autoregressive Integrated Moving Average (SARIMA) model and machine learning techniques such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) to improve precipitation forecasts. Time variation analysis and time series decomposition were the two concepts applied to construct the hybrid models. The performance of the two concepts was evaluated with monthly precipitation time series of two stations in northern Iran. Time variation analysis of time series was conducted with the clustering analysis, which increased the accuracy of forecasting with 20.99% decrease in the geometric mean error ratio for the two stations. SVM model decreased the forecasted error compared to ANN in the internal process of time variation analysis. Average of Mean Relative Error (MRE) were MRE_{SVM} = 0.72, MRE_{ANN} = 0.89, and Mean Absolute Error (MAE) in the two stations were MAE_{SVM} = 18.02 and MAE_{ANN} = 23.88. Therefore, SVM outperformed the ANN model. Comparison of the two hybrid models indicated that more accurate results belonged to the concept of time series decomposition (the decrease in root mean square error from time variation to time series decomposition concepts was 13.35%). Extracting the pattern of data with SARIMA-based hybrid model with time series decomposition improved the precipitation forecasting. Configurations related to nonlinear components of time series with time steps of residual had good performance (the average of agreement index was 0.9). The results suggest that the hybrid model can be a valuable and effective tool for decision processes, and time series decomposition to linear and nonlinear components has a better performance.

Keywords: Support Vector Machines, Cluster analysis, Nonlinear component, Configuration

INTRODUCTION

The complexity of precipitation leads to the need to a comprehensive model in order to forecast time series with high accuracy (Wang et al., 2007; Wang et al., 2014). The stochastic models based on Box and Jenkins (1976) method with widespread usage for time series forecasting were considered in many studies (Liang, 2009; Narasimha Murthy et al., 2018). Among the stochastic models, seasonal autoregressive integrate moving average (SARIMA) can capture the seasonality of time series (Cryer and Chan, 2008; Box et al., 2015). Despite the successes of the SARIMA model, the improvement of model to reach the optimal forecasts always has been considered (Wang et al., 2014; Mo et al., 2018). Two groups of univariate time series forecasting methods, stochastic models such as BATS, ARIMA_f and machine learning methods such as support vector machine (SVM) were utilized to forecast geophysical process. The average of median of absolute errors (mean) for all

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stochastic models and machine learning algorithms within the simulation experiment were 0.88 and 0.82, respectively (Papacharalampou et al., 2018a). To investigate the seasonality of time series, temperature and precipitation time series were employed. Some of the used models were Autoregressive Fractionally Integrated Moving Average, and random walk. Seasonal decomposition with efficient method is most important in the modeling process such that the classical compared to automatic seasonal decomposition used by the BATS and Prophet decreased the error (Papacharalampou et al., 2018b). Eleven stochastic models such as ARMA, ARFIMA and nine machine learning methods such as SVM were used for the multi-step ahead forecasting of river discharge. Median analysis of the dimensionless metrics showed that the average MAPE for all machine-learning algorithms was 24.32 and for all stochastic models was 25.97 (Papacharalampous et al., 2019). The hybrid models with integration of the different models can be a good candidate in order to find the reliable results (Lee et al., 2018; Mo et al., 2018; Zhang et al., 2018). A review of researches indicated that the combination of SARIMA model with machine learning algorithms can be done with two concepts: time variation analysis and time series decomposition (Chen and Wang, 2007; Wang et al., 2014; Zeynoddin et al., 2018). The interannual variations of monthly data were considered in the SARIMA model process, but the influence of intermonthly variations within each year was not considered. Therefore, the comprehensive analysis with emphasis on the time variation can help to improve the time series forecasts. The improvement of SARIMA model, ISARIMA, with time variation analysis in China decreased the mean absolute error from 11.49 to 9.41 mm (ISARIMA) (Wang et al., 2014). The second concept of SARIMA-based hybrid model is related to time series decomposition to linear and nonlinear component of time series. The assumption of linear models such as SARIMA model is the linearity of time series while the hydrological process has a nonlinear structure (Tealab et al., 2017). The linear nature of the SARIMA model leads to the problems in accurate modeling of complex nonlinear time series (Khandelwal et al., 2015; Rathod and Mishra, 2018). Therefore, two components of time series should be taken into account, which leads to proposing several hybrid approaches (Chen and Wang, 2007; Yolcu et al., 2013). Monthly rainfall forecasting with time series decomposition in tropical climate showed the improvement of rainfall predictions where the mean determination coefficient of the scenario for hybrid model was reported as 0.98 (Zaynoddin et al., 2018). A combination of SARIMA and SVM (as hybrid) was used to forecast the production values. The minimum values of normalized mean square error among the hybrid, SARIMA and SVM models was related to the hybrid model (Chen and Wang, 2007). The combination of SARIMA and SVM models in the study of Ruiz-Aguilar et al. (2014) and Lee et al. (2018) rather than the single methods improved the inspection volume and atmospheric pollution forecasting, respectively. Two large datasets of short times have been used to evaluate the efficiency of random forests performance related to the variable selection in one step forecasting. Random forest can be candidate of machine learning algorithm. The first database was related to the simulated time series from a number of ARFIMA models and the second was related to time series of annual temperature. Lagged predictor variable with low number could increase the performance of random forests (Tyralis and Papacharalampous, 2017). Also, SARIMA and artificial neural network (ANN) were utilized as a hybrid model to forecast production value of the mechanical industry and the volume of passenger flows, and annual energy cost budget, respectively. The results showed the better performance of hybrid models compared to the conventional model (Jeong et al., 2014; Glis’ovic’ et al., 2016). Two machine learning algorithms,
Neural Networks (NN) and SVM, were applied to forecast temperature and precipitation time series in 50 single case studies in Greece. The comparison of the study was conducted between machine learning algorithms and four classical algorithms. The median index of agreement for precipitation forecast was increased by 5.97% from NN to SVM. Also, the minimum values of RMSE (median) between stochastic and machine learning methods were related to SVM (Papacharalampous et al., 2018c).

The main objective of the present study was to evaluate the performance of hybrid SARIMA and machine learning techniques based on the time variation analysis and time series decomposition concepts. The comparison of two concepts was conducted with the comprehensive evaluation criterion. Interannual and intermonthly variations of monthly time series were investigated with clustering analysis and then, ANN and SVM models were applied to model the internal process of ISARIMA model. Also, the combination of SARIMA and SVM models was considered to model the linear and nonlinear components of time series (with different configurations of residual).

Eventually, the hybrid model performance was evaluated for the seasonal time series.

**MATERIALS AND METHODS**

The used monthly precipitation time series for evaluating the performance of hybrid models are related to Rasht and Gorgan stations. The provinces of stations are Gilan and Golestan, where the station's location is shown in Figure 1. Two monthly time series were applied to build model during 1976-2013 and to evaluate model from 2014 to 2016. The climate of stations is very wet and Mediterranean, based on the De Martonne climate classification method.

**SARIMA Model**

Assimilation of autoregressive and moving average term with integration term led to ARIMA model construction (Ruiz-Aguilar et al., 2014). ARIMA model was extended to SARIMA due to the drawbacks of the ARIMA to model the seasonal time series (Lee et al., 2018). ARIMA modification to SARIMA is conducted to consider the seasonality pattern.

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of time series; therefore, the basis of SARIMA model is related to ARIMA model (Lee et al., 2018; Mo et al., 2018). The SARIMA model consists of several steps with the stationary check, identification and estimation, diagnostics and prediction (Jeong et al., 2014; Jadhav et al., 2017). The SARIMA model with the denotation of SARIMA \((p,d,q)(P,D,Q)\), is described as Eq. 1.

\[
\phi_p(B)\Phi_P(B^d)(1-B)^d(1-B^D)^D z_t = \theta_q(B)\Theta_Q(B^q)\epsilon_t
\]

(1)

Where, \(z_t\) is expression of time series, \(B\) is the lag operator, \(s\) is the seasonal period length, \(p\) and \(q\) are the orders of autoregressive and moving average section, respectively, \(P\) and \(Q\) are the orders of seasonal autoregressive and moving average, respectively, \(d\) is the number of differencing operation, \(D\) is the number of seasonal differencing, \(\epsilon_t\) is a white noise, \(\phi_p(B)=1-\theta_1B-...-\theta_pB^p\), is the regular autoregressive operator of order \(p\), \(\theta_q(B)=1-\theta_1B-...-\theta_qB^q\), is the regular moving average operator of order \(q\). \(\phi_p(B^d)=1-\theta_1B^d-...-\theta_pB^{pd}\), is the seasonal autoregressive operator of order \(P\), \(\theta_q(B^q)=1-\theta_1B^q-...-\theta_qB^{qD}\), is the seasonal moving average operator of order \(Q\) (BAS et al., 2017).

**SARIM Based Hybrid Model with Time Variation Analysis**

The interannual variations of monthly time series are considered with SARIMA model, but the shortcoming of the model is related to the intermonthly variations. The basis of the improvement is the clustering analysis to identify the structures within the data. The relationship between clustering process and monthly time series is defined with modeling the main statistics of each cluster with the associated time series with linear regression. Then, the main statistics of each cluster in the validation period are achieved with ARIMA model and the forecasted values are substituted in the regression model to achieve monthly time series (Wang et al., 2014). Yolcu et al. (2013) stated that modeling of time series with nonlinear models had more accurate and effective forecasts when the nonlinearity component of time series is superior to the linearity part. Wang et al. (2014) used the linear regression in the internal process of ISARIMA, therefore, in order to overcome the limitation of the proposed model, machine learning algorithms were used in this study (novel part of the study), and the methods used are explained in the following sections.

**ANN Structure**

ANN is an abstract computational model of human brain. The characteristics of a node and the nodes connectivity in the network can build ANN architecture. (Weng et al., 2016). The structure of model is a network with three layers of simple processing units connected by acyclic links (Zhang, 2003). It should be stated that the network may contain several intermediary layers between the input and output layers. Such intermediary layers are called hidden layers and the nodes embedded in these layers are called hidden nodes. The most common type of neural network consists of three layers (Weng et al., 2016). Equation 2 can be defined to explain the relationship between the input and output variables.

\[
y_t = \alpha_0 + \sum_{j=1}^{q} \beta_j y_{t-j} + \sum_{i=1}^{p} \alpha_j x_{t-i} + \epsilon_t
\]

(2)

Where, \(y_t\) is output, \(y_{t-1}, y_{t-2},..., y_{t-q}\) are inputs, \(\alpha_j (j=0,1,2,...,q)\) and \(\beta_i (i=0,1,2,...,p)\) are model parameters, \(p\) is the number of nodes and \(q\) is the number of hidden nodes (Zhang, 2003).

**SVM Structure**

In order to map the input data \(x\) into a higher-dimensional feature space \(F\) by nonlinear mapping, SVM can be applied. The regression approximation can be
Hybrid SARIMA-Machine Learning Models Evaluation

explained as the function estimation based on a given data set \( G = \{ x_i, d_i \}_{i=1}^n \), \( x_i \) represents the input vector, \( d_i \) is related to the desired value, \( n \) is the total number of data patterns. Therefore, the function of Eq. 3 can be an approximation of the regression function (Chen and Wang, 2007).

\[
 f(x) = \omega \phi(x) + b, \\
 \phi: \mathbb{R}^n \rightarrow F, \omega \in F, \\
\]

(3)

Where, \( b \) is a scalar threshold; \( \phi(x) \) is the high dimensional feature space, \( \omega \) is the coefficient.

The coefficients \( \omega \) and \( b \) can be estimated with minimizing (Chen and Wang, 2007).

\[
 R_{\text{emp}}(C) = R_{\text{emp}} + \frac{1}{2} \left[ 1 - \sum_{i=1}^{n} L_x(d_i, y_i) + \frac{1}{n} \right] \\
 L_x(d_i, y_i) = \begin{cases} 
 |d - y| - \varepsilon & |d - y| \geq \varepsilon \\
 0 & \text{otherwise} 
\end{cases} \\
\]

(4)

The term of \( L_x(d_i, y_i) \) in Eq. 4 can be representative of empirical error (risk) which its estimation is related to the insensitive loss function in Eq. (5). In order to get samples of the decision function in Eq. (3) with fewer data points, the loss function has been applied (Chen and Wang, 2007). Faced with error, the regularized constant \( C \) calculates the penalty with determination of trade-off between the empirical risk and the regularization term and that can help to improve the prediction of regression (Chen and Wang, 2007).

SARIMA Based Hybrid Model with Time Series Decomposition

SARIMA and machine learning algorithms have capabilities to model the linear and nonlinear problems. Modeling the complex nonlinear time series with SARIMA model may not be sufficient (Zhang, 2003). The procedure of hybrid model can be described by the time series, which can be comprised of the linear autocorrelation structure and a nonlinear component with the general form that is expressed as Eq. 6.

\[
 y_t = L_t + N_t, \\
\]

(6)

Where, \( L_t \) is representative of linear characteristic from SARIMA model, \( N_t \) denotes the non-linear characteristic (Lee et al., 2018).

Two factors of equation 6 can be estimated from the data. The first step of hybrid model is related to apply SARIMA to model the linear component and then the residual of the linear model has the nonlinear relationship. The residual derived from SARIMA model can be explained as Eq. 7.

\[
 \epsilon_t = y_t - \hat{L}_t, \\
\]

(7)

Where, \( \hat{L}_t \) is representative of the forecasted value of SARIMA model at time \( t \).

The residual analysis is important to find the nonlinear pattern of data (as the second step). The different configuration of residuals modeling can be expressed as equations 8-11.

\[
 \epsilon_t = f(\epsilon_{t-1}, \epsilon_{t-2}, ..., \epsilon_{t-n}) + \epsilon_t, \\
\]

(8)

\[
 \epsilon_t = f(\epsilon_{t-1}, \hat{\epsilon}_{t-12}) + \epsilon_t, \\
\]

(9)

\[
 y_t = f(y_{t-1}, \hat{y}_{t-12}, \hat{L}_t) + \epsilon_t, \\
\]

(10)

\[
 y_t = f(y_{t-1}, \hat{y}_{t-12}) + \epsilon_t. \\
\]

(11)

Where, \( f \) is the nonlinear function which can be achieved by machine learning techniques, \( \epsilon_t \) is the random error.

Equations 8 and 9 can be identified as \( \hat{N}_t \), therefore, the forecasted values can be achieved by summation of linear and nonlinear components (Lee et al., 2018; Zhang, 2003). Figure 2 shows the functional flowchart of two hybrid models.

Evaluation Criterion

In order to evaluate the efficiency of hybrid models, several statistical tests were used in the validation period (Adamowski and Karapataki, 2010; Niedbala and
Figure 2. Schematic structure of two hybrid models; time variation analysis (a) and time series decomposition (b)

Kozlowski, 2019; Taghadomi-Saberi and Razavi, 2019).

\[ RMSE = \frac{1}{N} \sqrt{\frac{\sum_{i=1}^{N} (O_i - P_i)^2}{O}} \]  

Root Mean Square Error

\[ RRMSE = \frac{RMSE}{\bar{O}} \]  

Relative Root Mean Square Error

\[ MAE = \frac{1}{N} \sum_{i=1}^{N} |P_i - O_i| \]  

Mean Absolute Error

\[ MRE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{P_i - O_i}{O_i} \right| \]  

Mean Relative Error

\[ MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{P_i - O_i}{O_i} \right| \times 100 \]  

Mean Absolute percentage Error

\[ d = 1 - \frac{\sum_{i=1}^{N} |P_i - \bar{O}| + |O_i - \bar{O}|)}{\sum_{i=1}^{N} (P_i - O_i)} \]  

Index of Agreement

\[ dm = 1 - \frac{\sum_{i=1}^{N} (P_i - O_i)}{\sum_{i=1}^{N} (P_i - \bar{O}) + |O_i - \bar{O}|)} \]  

Modified Index of Agreement

\[ UI = \frac{\left( \sum_{i=1}^{N} (P_i - O_i)^2 \right)^{0.8}}{\left( \sum_{i=1}^{N} (O_i)^2 \right)^{0.5} + \left( \sum_{i=1}^{N} (P_i)^2 \right)^{0.5}} \]  

\[ UII = \frac{\left( \sum_{i=1}^{N} (P_i - O_i)^2 \right)^{0.8}}{\left( \sum_{i=1}^{N} (O_i)^2 \right)^{0.5}} \]  

Geometric Mean Error Ratio

\[ GMER = \exp \left[ \frac{1}{N} \sum_{i=1}^{N} \ln \left( \frac{P_i}{O_i} \right) \right] \]  

Where, \( P_i \) is the predicted value, \( O_i \) is the observed value, \( \bar{O} \) is the mean of observed value, \( i \) represents the time, \( N \) is sample size of validation period.

The smaller values of RMSE, RRMSE, MAE, MRE, MAPE, UI, UII and proximity of \( d \) to one is indicative of better performance of the model. Sensitivity of RMSE to outliers rather than MAE is high (Papacharalampous et al., 2019). \( 0%<\text{MAPE}<10% \) is indicative of very accurate prediction and MAPE greater than 50% is indicative of inaccurate forecast (Lee et al., 2018). MAPE can be defined as...
scale-independent criteria, which can be an advantage for model comparison across different dataset (Papacharalampous et al., 2019). GMER greater than 1 indicates overestimation and GMER <1 shows underestimation. To evaluate the accuracy of forecasting, the used criterion is denoted as UI and the quality of forecasting is denoted as UII. UI= 0 and UII=0 are indicative of prefect forecast (Zeynoddin et al. 2018). The values of agreement index near 1 shows the better agreement of simulated and observed values. For comparison of the performance of hybrid and single models, the accuracy improvement criteria was proposed with Eq. 22 (Chen and Zhu, 2013).

$$AI = \frac{S - S_h}{S} \times 100$$ (22)

Where, S and S_h are the MAE of single and hybrid model. AI greater than 0 is indicative of the best performance of hybrid model, AI less or equal to 0 shows that hybrid model dose not outperform the single model (Chen and Zhu, 2013).

RESULTS

Two monthly time series from Rash and Gorgan stations were used to evaluate the hybrid models performance. The statistical characteristics of monthly time series in each station are presented in Table 1. The application of SARIMA and SARIMA-based hybrid model with the time variation analysis implemented to ANN and SVM models, and SARIMA-based hybrid model with time series decomposition implemented to SVM model were utilized to forecast monthly precipitation time series.

The Box and Jenkins methodology for model construction consist of some steps: Model identification, parameter estimation, and diagnostic checking (Zhang et al., 2018). The first modeling step of SARIMA was examined with the autocorrelation function and seasonal Mann-Kendal test in order to find the randomness and seasonality of time series, respectively. The best-fitted SARIMA model are SARIMA(3,0,2)×(1,1,2)_{12} and SARIMA(0,1,1)×(1,1,2)_{12} for the Rasht and Gorgan stations, respectively.

SARIMA-Based Hybrid Model with Time Variation Analysis

Hierarchical clustering algorithm was applied for cluster analysis. From the popular agglomerative methods of hierarchical algorithm, Ward’s method was used to divide the precipitation time series to different groups with similar hydrological patterns in a group. The results of clustering analysis are represented in a dendrogram, which is displayed in Figure 3. The y-axis of dendrogram shows the distance between the clusters (Liu and Ge, 2018), and the Euclidean distance was used. The x-axis can represent the objective of hierarchical clustering, which is the monthly precipitation.

The results of clustering are: Rasht station; month 1, 10 (cluster 1), month 5,6,11


<table>
<thead>
<tr>
<th>statistical characteristics</th>
<th>Gorgan</th>
<th>Rasht</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (mm)</td>
<td>Training: 45.061</td>
<td>Testing: 35.41</td>
</tr>
<tr>
<td></td>
<td>Training: 112.054</td>
<td>Testing: 101.6</td>
</tr>
<tr>
<td>Standard deviation (mm)</td>
<td>31.7</td>
<td>22.036</td>
</tr>
<tr>
<td>Minimum</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Maximum</td>
<td>166.8</td>
<td>98.6</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.748</td>
<td>0.69</td>
</tr>
<tr>
<td>Cortosis</td>
<td>0.24</td>
<td>0.488</td>
</tr>
<tr>
<td>S.E. mean</td>
<td>1.55</td>
<td>3.83</td>
</tr>
<tr>
<td>Coefficient of variation</td>
<td>0.7</td>
<td>0.62</td>
</tr>
</tbody>
</table>

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Figure 3. Dendrograms of hierarchical clustering for monthly precipitation time series in Gorgan and Rasht stations.

Figure 4. The evaluation criterion related to the comparison of ANN and SVM models performance in Rasht station with hybrid model based on time variation analysis. (cluster 2), month 7, 9, 12 (cluster 3) and month 2, 3, 4, 8 (cluster 4)-Gorgan station; month 2, 6, 8, 10 (cluster 1), month 1, 9, 12 (cluster 2) and month 3, 4, 5, 7, 11 (cluster 3). Linear regression was used in the internal process of ISARIMA to model the statistics of each cluster (maximum, minimum, truncated mean) with the associated time series of each cluster in the Wang et al. (2014) study. In order to consider the nonlinearity relationship between the statistics of each cluster and the monthly precipitation time series, ANN and SVM models were applied in this study. The sensitivity analysis of SVM was related to kernel functions and penalty parameter. The investigated kernel functions were linear, polynomial, Gaussian radial basis and sigmoid functions. The used network of this study is back propagation neural network algorithm. ANN sensitivity analysis was related to the activation functions of hidden-output layers and number of neurons. The used activation functions were logistic sigmoid, tangent sigmoid, and pure linear. Decrease in RMSE from logistic sigmoid-pure linear to tangent sigmoid-logistic sigmoid is 20.23% in Gorgan station. ANN and SVM performance comparison is shown in Figure 4.

The clustering analysis can improve the forecasted values; for example, decrease in RMSE and MRE from SARIMA model to ISARIMA is 21.29% and 70.27% in Rasht and 7.83% and 13.77% in Gorgan station, respectively. The performance of SARIMA model implemented to clustering analysis improved the evaluation criterion rather than the SARIMA model. The clustering analysis significantly improved precipitation simulation rather than the SARIMA model with the increase of forecasting accuracy to 21% (Wang et al., 2014). The evaluation criterion comparison indicated that the optimum case of
Hybrid SARIMA-Machine Learning Models Evaluation

The function of hybrid model in this section was approximated with SARIMA model and the machine learning techniques with consideration of the linearity and nonlinearity of precipitation time series. The SARIMA-based hybrid model with time series analysis implemented to SVM model had the minimum error and better performance in the previous section and that is the reason for SVM selection in hybrid model based on time series decomposition. Therefore, the hybrid model is a combination of SARIMA and SVM models. Different configurations were utilized with the composition of residuals, linear component, and predicted values. The results of comparison related to the different configurations are listed in Table 2 (C in Gorgan is 0.01 and in Rasht is 2).

The configuration composed of residuals has the minimum error with high d in Table 2. For example, RMSE and MRE decrease from configuration with time series and residual to configuration with residuals is, respectively, 44.17% and 51.19% in Gorgan station. Lee et al. (2018) used SARIMA-SVM for atmospheric pollution forecasting, and the nonlinear model was the composition of residuals. The sensitivity analysis in each model is one of the most important steps. For example, in Gorgan station for the forth configuration, the RMSE with linear kernel function decreased 10.62% with C=1 relative to the radial basis function with C=2. The sensitivity analysis has a more important role in the model performance; for example, RMSE decrease from linear kernel function (C= 0.01) to...
Table 2. Comparison of the used configurations of SARIMA-based hybrid model with time series decomposition.

<table>
<thead>
<tr>
<th>Station</th>
<th>Gorgan</th>
<th>Rasht</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evaluation criteria</td>
<td>RMSE</td>
<td>RRMSE</td>
</tr>
<tr>
<td>$\varepsilon_i = f(\varepsilon_{t-1}, \varepsilon_{t-12}) + \varepsilon_t$</td>
<td>18</td>
<td>0.5</td>
</tr>
<tr>
<td>$\varepsilon_i = f(\varepsilon_{t-1}, \varepsilon_{t-12}) + \varepsilon_t$</td>
<td>14.18</td>
<td>0.39</td>
</tr>
<tr>
<td>$y_t = f(y_{t-12}, y_{t-1}, \varepsilon_t) + \varepsilon_t$</td>
<td>25.4</td>
<td>0.7</td>
</tr>
<tr>
<td>$y_t = f(L, y_{t-12}, y_{t-1}) + \varepsilon_t$</td>
<td>23.88</td>
<td>0.665</td>
</tr>
<tr>
<td>$\varepsilon_i = f(\varepsilon_{t-1}) + \varepsilon_t$</td>
<td>18.25</td>
<td>0.5</td>
</tr>
</tbody>
</table>

The hybrid model with time series decomposition has the minimum error and better performance. The RMSE, MRE, and UI decreases of hybrid-model-based time variation to hybrid-model-based time series decomposition are 11.14%, 19.29%, and 13.29% for Rasht time series. The related values of Gorgan station are 18.73%, 5.74%, and 15.78%. UI and UII of SARIMA-based hybrid model with time series decomposition reached 0, which is indicative of forecasting accuracy and quality improvement. Time series decomposition leads to decrease in MAPE, which is indicative of accurate prediction. Also, the index of agreement and modified index of agreement for hybrid-model-based time series decomposition are increased close to 1. Time series decomposition to linear and nonlinear components led to the improvement of time series simulation in many studies such as Ruiz-Aguilar et al. (2014), Chen and Wang (2007), and Lee et al. (2018) for forecasting inspection volume, production values of machinery industry, and atmospheric pollution, respectively. GMER in all models and all stations are greater than one, which is indicative of overestimations of forecasted values. The higher and positive values of AI are related to the SARIMA-based hybrid model with time series decomposition, which indicates the outperformance of hybrid model rather than the single model. The monthly comparison indicated that minimum
RRMSE of months is related to November in Rasht (RRMSE = 0.08) and October (RRMSE = 0.11) in Gorgan. It can be stated that months with high precipitation have low error (RRMSE June-Rasht = 0.62; RRMSE June-Gorgan = 0.46). The monthly observed and simulated precipitation time series with two hybrid models are shown in Figure 7.

The $R^2$ of the fitted line comparison demonstrates its increase from SARIMA-based hybrid model with time variation analysis to SARIMA-based hybrid model with time series decomposition, which is indicative of better performance of the latter model. The observed precipitation values of Rasht is greater than Gorgan station and the performance evaluation of SARIMA-based hybrid model with time series decomposition shows that RRMSE and MRE of Rasht is lower than Gorgan station. The minimum precipitation values of Rasht station in the validation period occurred in June 2014, where the minimum value of forecasted precipitation time series using SARIMA-based hybrid with time variation analysis and SARIMA-based hybrid with time series decomposition occurs on that date. The maximum precipitation value of Gorgan station in the validation period occurs in March of 2014 and the minimum value of forecasted precipitation time series with the two hybrid models occurs on that date. Furthermore, the performance of hybrid model was investigated in the seasonal time step, and the evaluation criterion comparison and $R^2$ of the fitted line are shown in Figure 8.

Results of the seasonal time series forecasting with SARIMA-based hybrid using time series decomposition have higher accuracy, where the index of agreement in Rash and Gorgan stations are, respectively, 0.97 and 0.91, both in the optimum range of criteria. The $R^2$ of fitted line increases with time series decomposition to linear and nonlinear components. For example, the $R^2$ of fitted line in Rasht station increased from 0.845 to 0.924 and from 0.639 to 0.792 in Gorgan station. The GMER is greater than 1 for the two hybrid models, which indicates the overestimation of the forecasted time series. MAPE has lower values, which can be indicative of accurate estimation. For air quality forecasting, the hybrid model was able to process not only month or a season, but also the whole year (Diaz-Robles et al., 2008).
DISCUSSION

The results indicated that the clustering analysis could improve the SARIMA model performance because more information can be extracted from the used time series. Also, the time series with similar hydrological characteristics are grouped in a cluster that led to high performance of SARIMA based on a systematic grouping. In order to find the similarity among time series, clustering analysis is the main subject. The measurement of the distance in the space determined by observed time series can be used to find the similarity of cluster members. The ISARIMA model implement to SVM and ANN models had better results compared to ISARIMA model implement to linear regression. Linear regression can consider the relationships of a pre-specified functional form, and linear regression may not be sufficient for accurate prediction in order to model the nonlinear nature of time series (Adamowski and Karapataki, 2010). SVM model had better performance for precipitation time series simulation compared to ANN model. Comparing the performance of NN and SVM for case studies with high number was conducted and, in most cases, SVM had better results (Papacharalampous et al., 2018c). The better performance of machine learning algorithms was seen in the study of Tyrallis and Papacharalampous (2017) with two large datasets. The success of SVM model can be related to the principle of structural risk minimization instead of empirical risk minimization, as the other techniques such as ANN (Ruiz-Aguilar et al., 2014). Also, the generalization capability for relating the input to the desired output is more noticeable and some advantages of SVM models have low sensitivity to small training sets and noisy data and the avoidance of over fitting. SVM is a powerful option in nonlinear time series, especially with an unknown distribution (Hamidi et al., 2014). Adopting Kernel by SVM models led to the increase in the model efficiency in nonlinearity of time series modeling (Naguib and Darwish, 2012). Overfitting can be seen for ANN model when training takes too long time. For any pattern, this means that a model should be used to consider the noise as part of the pattern, but this problem cannot be seen for SVM model (Selvanayaki and Somasundaram, 2015). The results show that SVM sensitivity analysis is one of the most important steps, and Hamidi et al. (2014) stated that SVM model can be a robust model if appropriate Kernel function and related parameters are selected. Generally, the evaluation criterion comparison shows that the two hybrid models improved the accuracy of forecasts compared the SARIMA model. Chen and Wang (2007) indicated that the hybrid models performance are superior to the individual models in terms of both prediction error and directional change detestability. Ruiz-Aguilar et al. (2014) indicated that hybrid model based on artificial intelligent systems was an effective tool for powerful decision making. The
model basis on the linearity and nonlinearity of time series by taking advantages of two models (in term of decomposition time series in linear and nonlinear components) can improve the model efficiency. Time series with monthly variation has linear and nonlinear component and this hybrid method can be effective. Compassion of the two hybrid models indicated that applying monthly time series was more accurate than the statistics of monthly clusters. Therefore, decomposition of time series with an efficient method has more importance to forecast climatological parameters, which was proved in the study of Papacharalampous et al. (2018b) with large number of samples. The comparison of stochastic models and machine learning algorithms in the study of Papacharalampous et al. (2018a), Papacharalampous et al. (2019) and Papacharalampous and Tyralis (2018) for large scale studies in most cases showed the high performance of machine learning algorithms. However, it should be noted that the scale is more important. According to the research of Papacharalampous et al. (2018a), the different stochastic models had dissimilar error criteria. Tyralis and Papacharalampous (2018) used two approaches: past information of time series and using exogenous predictor variables alongside with the use of the endogenous ones, and the usefulness of the two approaches was proved. Rasht station, with high precipitation, had minimum RRMSE and MRE compared to Gorgan station. Also, in this study, eleven evaluation criterions were utilized for model evaluation and the trend of evaluation criterion is favorable. Each criterion investigates the performance of model from different aspects. For example, RMSE can measure the goodness of fit related to high precipitation and MAE can represent the goodness of fit belonging to moderate precipitation (Hamidi et al., 2014). The coordination of all criterions is indicative of high performance of time series decomposition for hybrid models.

CONCLUSION

Accurate precipitation forecasting is always a challenging problem, which is more attractive in many fields. SARIMA model is one of the most popular and well-known models for precipitation forecasting. Therefore, in this study, two SARIMA-based hybrid models were compared, which could improve the efficiency of SARIMA model. Time variation analysis and time series decomposition are the two concepts that were used to construct the hybrid models. ANN and SVM models were applied to complete the internal process of ISARIMA instead of linear regression, which had been used in the previous studies, and application of machine learning algorithm is prominent point of the research. The ISARIMA model with implementation to ANN and SVM increased the accuracy of forecasting. The simulation of SARIMA-based hybrid model with time series decomposition reaches the observed values, rather than the hybrid model with time variation analysis. The reason for that can be related to the nature of monthly time series with the inclusion of linearity and nonlinearity of time series, which the hybrid model could extract the governing pattern of data with accuracy. SARIMA model has shortcomings for modeling the nonlinear component of time series and, therefore, SVM model can solve this problem. The mentioned hybrid model takes advantages of SARIMA and SVM models in linear and nonlinear modeling, which is appropriate for modeling complex phenomena. To achieve the highly accurate forecasts in the field of SARIMA-based hybrid model with time series decomposition, other decomposition methods such as empirical mode decomposition (EMD) and wavelet transform methods should be investigated.

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ارزیابی مقایسه ترکیب SARIMA و یادگیری ماشین بر پایه تغییرات زمانی و تقییت

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چکیده

پیش بینی دقیق بارندگی با پیچیدگی ماهینت آن بسیار مورد توجه است. در این تحقیق از مدل ترکیبی خودهمبسته - میانگین متحرک تلفیق شده فصلی (SARIMA) و الگوریتم یادگیری مایه سری (SVM) به موفقیتی بالا دسته‌بندی ساخته شد. مدل SVM موفقیت یافته در تجزیه و تحلیل تغییرات زمانی و تقییت سری زمانی بسیار خصوصاً و خصوصاً در هنگام بروز اختلالاتی در هنگام بروز اختلالاتی در سری زمانی با کاهش خطای جذر مطلق (MRE) می‌تواند مدل SVM را بهتر بکند (MRE = 0.72, MREANN = 0.89). مشابهی بین مدل SVM و مدل SVM نیز وجود دارد (MAE = 18.02, MAEANN= 23.88). در این مدل مدل SVM در هنگام بروز اختلالاتی در سری زمانی با کاهش خطای جذر مطلق (MRE) می‌تواند مدل SVM را بهتر بکند (MRE = 0.72, MREANN = 0.89). مشابهی بین مدل SVM و مدل SVM نیز وجود دارد (MAE = 18.02, MAEANN = 23.88). در این مدل مدل SVM در هنگام بروز اختلالاتی در سری زمانی با کاهش خطای جذر مطلق (MRE) می‌تواند مدل SVM را بهتر بکند (MRE = 0.72, MREANN = 0.89). مشابهی بین مدل SVM و مدل SVM نیز وجود دارد (MAE = 18.02, MAEANN = 23.88). در این مدل مدل SVM در هنگام بروز اختلالاتی 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