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Forecasting Air Pollution Concentrations in Iran, Using a Hybrid Model

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ABSTRACT: The present study aims at developing a forecasting model to predict the next year's air pollution concentrations in the atmosphere of Iran. In this regard, it proposes the use of ARIMA, SVR, and TSVR, as well as hybrid ARIMA-SVR and ARIMA-TSVR models, which combined the autoregressive part of the autoregressive integrated moving average (ARIMA) model with the support vector regression technique (ARIMA-SVR). The main concept of generating a hybrid model is to combine different forecasting techniques so as to reduce the time-series forecasting errors. The data used in this study are annual CO_2, CO, NO_x, SO_2, SO_3, and SPM concentrations in Iran. According to the results, the ARIMA-TSVR Model is preferable over the other models, having the lowest error value among them which account for 0.0000076, 0.0000065, and 0.0001 for CO_2; 0.0000043, 0.0000012, and 0.000022 for NO_x; 0.00032, 0.00028., and 0.0012 for SO_2; 0.000021, 0.000014, and 0.00038 for CO; 0.0000088, 0.0000005, and 0.00019 for SPM; and 0.000021, 0.000019, and 0.0044 for SO_3. Furthermore, the accuracy of all models are checked in case of all pollutants, through RMSE, MAE, and MAPE value, with the results showing that the hybrid ARIMA-TSVR model has also been the best. Generally, results confirm that ARIMA-TSVR can be used satisfactorily to forecast air pollution concentration. Hence, the ARIMA-TSVR model could be employed as a new reliable and accurate data intelligent approach for the next 35 years' forecasting.

Keywords: Accuracy, ARIMA, Predict, TSVR.

INTRODUCTION

Air pollution has now emerged in developing countries as a result of industrial activities as well as the increase in the quantity of concentration sources such as inappropriate vehicles. In Iran, also a developing country, the level of air pollutions has increased gradually since the beginning of industrialization in the 1970s, though it has reached a very harmful level in some megacities (Hosseini & Shahbazi, 2016; Lu et al, 2014; Vong et al, 2012; Balali-mood et al, 2016). The most hazardous air pollution sources in Iran come from fossil fuels. This is primarily exemplified by the byproduct of combustion fuel engines in most vehicles. Although their concentrations are regulated in most large cities, they still pose a serious hazard to human health. Impacts of these substances in the atmosphere can often be aggravated by water vapor, natural dust, and sunlight, which in turn activate chemical reactions, producing a secondary set of hazardous pollutions, such as CO_2, CO, NO, NO_x, and SO_2. Of all major air

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pollutants, particulate matter or simply the particulates (PM) are the most complicated and by far the most hazardous (Hosseini & shahbazi, 2016; Mahabwi et al, 2014; Yang et al, 2003; Naddafi et al, 2012; Liu et al, 2015; Nieto etal, 2011). Fig. 1 illustrates the trend of pollution emissions in Iran between 1978 and 2016, showing that Iran's pollution emissions are on the rise rapidly, having approximately doubled since 1990, especially in the case of CO_2 and CO.

According to Zhang & Ding (2017), any system able to predict air pollutions with sufficient anticipation can provide public authorities with the time required to manage the emergency. Based on the work of Noori et al (2015), in the past decades statistical models were able to present accurate predictions, while they could not provide a detailed explanation of air pollution (Zhang & Ding, 2017). Based on Zhu & Wei (2013) and Hussain et al. (2016), pollution forecasting is a kind of time series forecasting. It entails the use of some models, among which ARIMA has been found to be one of the most popular, thanks to its statistical properties. At the same time, SVM formulates the training process through quadratic programming, which may take much more time (Haung, 2017; Zhu & Wei, 2013). Additionally, Noori et al. (2015), Zhang et al. (2017), Sahoo et al. (2018), and Deo et al. (2018) proved that between AI and other forecasting models, SVR and related hybrid models were quite suitable for forecasting, being useful scientific tools for further exploration of time series trend such as pollutants concentrations in future. Therefore, similar to Pai & Lin (2005), He et al. (2006; Nie et al, 2012; Zhu and Wei, 2013; Abdullah et al, 2014; Chuentawat et al 2017; Haung, 2017; Pokora, 2017; Nieto et al, 2018) the present paper proposes to use the hybrid model that integrates the autoregressive of the ARIMA with the SVR which has been searched for its optimized parameters with the genetic algorithm. Table 1 summarizes the literature review on forecast, showing that several researchers highlighted the importance of hybrid models in time series forecast with many of them choosing SVR or Hybrid models.

In a nutshell, this research work aims at constructing a forecasting model for the averaged next year's pollution, applicable for the use of authorities who are responsible for regulation of air pollution in appropriate regions of the country. It collects annual data on CO_2, CO, NO_x, SO_2, SO_3, and SPM for the time period between 1978 and 2016 from the Statistical Center of Iran.

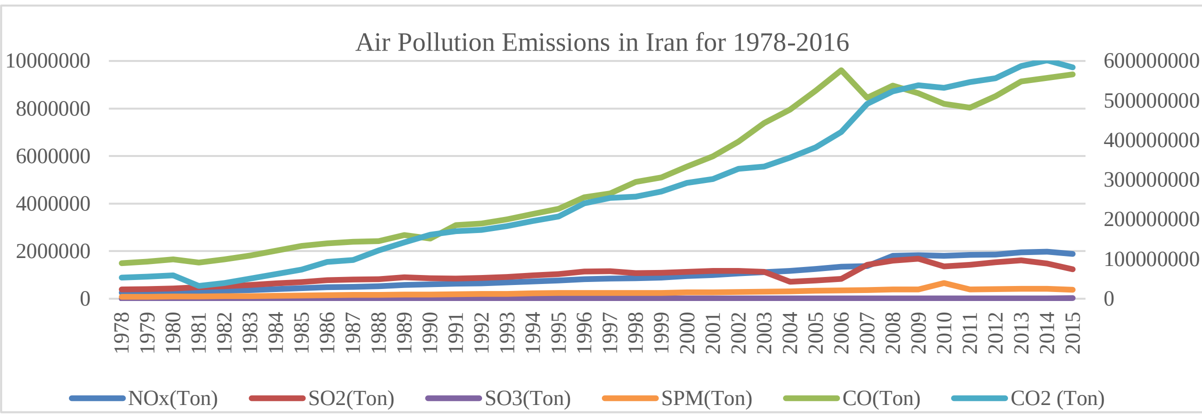

Fig. 1. Pollution trends in Iran between 1978 and 2016
Source: Statistical Center of Iran (2016).

Table 1. Summary of literature review

Author(s)	Variables	Methodology	Model Selection Criteria	Conclusion
Pai & Lin (2005)	Stock Price	ARIMA, SVM, ANN	RMSE-MAPE-MSE-MAE	ARIMA
He et al (2006)	-	ARIMA-SVM	-	ARIMA-SVM
Sanchez et al (2011)	CO, NO, NO_2, SO_2, O_3 and dust	SVR	-	SVR
Vong et al (2012)	NO_2, SO_2, O_3 and dust	SVM with different Kernels	MAE- RMSE	Linear and RBF kernels with SVM
Nie et al (2012)	-	ARIMA, SVM and ARIMA-SVM	MAPE-RMSE	ARIMA-SVM
Zaim et al (2012)	Electricity consumption	ANN and SVM	MAPE	SVM
Zhu & Wei (2013)	Carbon price	ARIMA,LSSVM and ARIMA-LSSVM	RMSE	ARIMA-LSSVM
Sujjaviriyasup & Pitiruek (2013)	Agricultural production	ARIMA, SVM and ARIMA-SVM	RMSE-MAPE-MAE	ARIMA-SVM
Manish & Thenmozhi (2014)	Stock price	ARIMA, SVM, ANN, RF, ARIMA-ANN, ARIMA-RF and ARIMA-SVM	MAE-RMSE-NMSE	ARIMA-SVM
Lu et al (2014)	Air pollution	SVM and RBF	MAE	SVM
Abdullah Ahmed & Shabri (2014)	Crude oil price	ARIMA, SVM and GARCH	RMSE-MAE	SVM
Hu & Wang (2015)	Wind speed	ARIMA, ELM, LSSVM,SVM and GPR	RMSE-MAPE-MAE	GPR
Noori et al (2015)	CO_2	ANFIS, ANN and SVR	MSE- MAE	SVR
Saleh et al (2016)	CO_2	SVM	RMSE	SVM
Hussain et al (2016)	Electricity consumption	ARIMA- Holt Winter	RMSE-MAPE	Holt-Winter
Haung (2017)	PM2.5	ARIMA, SVM and ARIMA-SVM	RMSE- MAE-MAPE	ARIMA-SVM
Pokora (2017)	Electricity price	ARIMA, SVM and ARIMA-SVM	RMSE-MAE	ARIMA-SVM
Chuentawat et al (2017)	PM10	ARIMA, SVM and ARIMA-SVM	RMSE-MAPE-MSE	ARIMA-SVM
Zhang et al (2017)	All pollutants	ARIMA, SVM, Hybrid GARCH	RMSE-MAE	Hybrid GARCH
Nieto et al (2018)	PM10	ARIMA, VARMA, MLP and SVM	RMSE	SVM
Deo et al (2018)	Electricity demand	ARIMA, MARS, SVR	RMSE-MAE	SVR, MARS

MATERIALS AND METHODS

The ARIMA model can predict the future data from two sources of information: the first one is the autoregressive (AR), data prediction at any time depending on previous data, and the second one is the moving average (MA), data prediction that depends on previous errors (Chuentawat, 2017). In ARIMA models a non-stationary time series is made stationary by applying finite differencing (d) of the data points. The mathematical formulation of the ARIMA (p,d,q) model, using lag polynomials, is given below:

$$\varphi(L)(1-L)^d y_t = \theta(L)\varepsilon_t$$
$$(1-\sum_{i=1}^{p}\varphi_i L^i)(1-L)^d y_t = (1+\sum_{j=1}^{q}\theta_j L^j)\varepsilon_t \qquad (1)$$

Here, p, d, and q are integers greater than or equal to zero, which refer to the order of the autoregressive, integrated, and moving average parts of the model, respectively. The integer d controls the level of differencing (Adhikari & Agrawal, 2013; Zhu & Wei, 2013).

Recently, a new statistical learning theory, the Support Vector Machine (SVM) has begun receiving increasing attention for classification and forecasting. SVM was first developed by Vapnik et al. at laboratories in 1995 (Adhikari & Agrawal, 2013). The SVR theory has been described in details in numerous works, e.g., Vapnik (1998), Abe (2005), and Lu & Wang (2005). Instead of categorical classification, traditionally done by SVM, the SVR is used to forecast numeric values; therefore, it focuses on finding a linear relation, mapping the input vector X in n-dimensions to the output y via linear regression (Zaim et al, 2012; Deo et al, 2018; Chuentawat et al, 2017). SVR is a supervised learning method, estimating the dependent variable y on a set of independent variables x, while applying deterministic function that can be shown as equation 2:

$$f(x)=\left\{w^{T}\phi(x)+b\right\}+noise \tag{2}$$

where w and b are the slope and offset of the regression line, respectively, and the noise term is represented by error tolerance (Noori et al, 2015).

Manish & Thenmozhi (2014) and Sujjaviriyasup & Pitiruek (2013) considered a time series, composed of a linear autocorrelation structure along with a non-linear component. Here, a hybrid model, comprising a linear and a non-linear component as represented below, was employed in the experiments:

$$Y_t = L_t + N_t \tag{3}$$

where L_t denotes the linear component and N_t, the non-linear one, both of which should get estimated from the data. These data then enter the first stage of ARIMA to account for a linear component, which means that the residuals from the linear model will contain only the non-linear relation. If e_t denotes the residual components at time t from the linear model, then:

$$e_t = Y_t - \hat{L}_t \tag{4}$$

In which $\hat{L}t$ is the forecast value for time t. Any significant non-linear pattern in the residuals will indicate the limitations of ARIMA. By modeling residuals, through the use of SVM, non-linear relations can be discovered. With n input nodes, the SVM model for the residuals will be:

$$e_{tSVM} = f_{SVM}(e_{t-1}, e_{t-2}, ..., e_{t-n}) + \mu_{tSVM} \tag{5}$$

where f_{SVM} is the non-linear function, determined by the SVM model, and μ_{tSVM}, the random error term. If the forecast from SVM is represented as $\widehat{N}_{tSVM}$, the combined forecast will be:

$$\hat{F}_{tSVM} = \hat{L}_t + \hat{N}_{tSVM} \tag{6}$$

Error criteria were adopted to establish the accuracy of the data-driven models. These include the Mean Absolute Error (MAE), MAPE and RMSE, relative error (%) based on MAE, and RMSE values, represented below (Deo et al, 2018):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|e_t\right| \tag{7}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \times 100 \tag{8}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^{\,2}} \tag{9}$$

In each of the forthcoming definitions, y_t is the actual value; f_t, the forecasted value; $e_t = y_t - f_t$, the forecast error; and n, the size of the test set (Adhikari & Agrawal, 2013).

RESULTS AND DISCUSSION

Table 2 presents the summary of the statistics of environmental pollutions data in Iran, showing the CO_2 concentration more than other chemical compounds, followed by CO in the second place.

The unit root analysis is the first step in time series analysis as the results from regression analysis give misleading conclusions, if the selected variables have a stochastic trend and the regression result is spurious. Thus to avoid this, the Augmented Dickey-Fuller (ADF) and the Kwiat-kowskie-Phillipse-Schmidte-Shin (KPSS) unit root test were adopted here for selected variables. Tests, designed on the basis of the null hypothesis that a series is I(1), are quite impotent to reject the null. Hence, KPSS is sometimes used to complement the widely-used ADF and PP tests in order to obtain robust results. Our stationary results in Table 3 indicate that, based on ADF and KPSS tests, all variables were static in first level I(1).

ARIMA models intend to describe the current behavior of variables in terms of linear relations with their past values; these models are also called Box-Jenkins ones (Box-Jenkins, 1984). An ARIMA model can be decomposed to two parts. First, it has an Integrated (I) component (d), representing the differentiation amount to be performed on the series to make it stationary that determined previous section. The second component of an ARIMA consists of an ARMA model for the series, rendered stationary through differentiation, which is further decomposed into AR and MA components. The autoregressive (AR) component captures the correlation between the current value of time series on one hand and some of its past values, on the other. For example, AR(1) in CO_2 equation means that the current observation correlates with its immediate past value at time t-1. The Moving Average (MA) component represents the duration of the influence of a random (unexplained) shock, e.g., MA(1) in SPM equation means that a shock on the value of the series at time t is correlated with the shock at t-1. Here, the study used both Autocorrelation Function (ACF) and Partial Autocorrelation Function (PCF) in order to estimate the values of p and q, via the rules reported in Table 4, with AIC and BIC criteria employed in cases where ACF and PACF diagrams failed to determine the degrees of p and q in the ARIMA model such as NO_x and CO equations. Table 4 shows the results of the best-fitted ARIMA model for all pollutants.

Table 2. Descriptive statistics of the variables (1978-2016)

Variables (Logarithm)	Mean (Thousand tons)	S.D	Min	Max
CO_2	19.14	0.88	17.27	20.21
NOx	13.59	0.62	12.45	14.49
SO_2	13.73	0.39	12.86	14.33
CO	15.25	0.64	14.21	16.07
SPM	12.31	0.52	11.27	13.39
SO_3	9.35	0.34	8.53	9.93

Source: Calculations made by the authors

Table 3. Stationary Results

Variables (Logarithm)	ADF		KPSS		Optimal Lag*
	At level	At first level	At level	At first level	
CO_2	I(0)	I(1)	I(0)	I(1)	1
NOx	I(0)	I(1)	I(0)	I(1)	5
SO_2	I(0)	I(1)	I(0)	I(1)	1
CO	I(0)	I(1)	I(0)	I(1)	2
SPM	I(0)	I(1)	I(0)	I(1)	1
SO_3	I(0)	I(1)	I(0)	I(1)	1

* *Optimal Lags are obtained from augmented Dicky* Fuller test.

Source: Calculations made by the authors

Table 4. Result of ARIMA Model selection

Equations	ARIMA Model	Model selection criteria
CO_2	ARIMA(1,1,1)	PACF and ACF
NOx	ARIMA(0,1,1)	AIC and BIC
SO_2	ARIMA(3,1,3)	PACF and ACF
CO	ARIMA(2,1,3)	AIC and BIC
SPM	ARIMA(1,1,1)	PACF and ACF
SO_3	ARIMA(3,1,3)	PACF and ACF

Source: Authors calculation.

Table 5. Comparison of the predictive performance of several prediction models

Equations (Logarithmic)	Error criteria	ARIMA	SVR	TSVR	ARIMA-SVR	ARIMA-TSVR
	RMSE	0.13	0.085	0.00038	0.003	0.0000076
CO_2	MAPE	0.062	0.024	0.00015	0.0023	0.0000065
	MAE	0.65	0.245	0.0016	0.041	0.0001
	RMSE	0.048	0.007	0.000013	0.00087	0.0000043
NO_x	MAPE	0.028	0.0094	0.000012	0.00025	0.0000012
	MAE	0.65	0.16	0.000264	0.004	0.000022
	RMSE	0.17	0.1	0.00014	0.017	0.000032
SO_2	MAPE	0.11	0.017	0.000045	0.008	0.000028
	MAE	2.04	0.26	0.00065	0.13	0.0012
	RMSE	0.02	0.019	0.00002	0.0028	0.000021
CO	MAPE	0.04	0.009	0.000018	0.0024	0.000014
	MAE	0.62	0.1	0.00033	0.053	0.00038
	RMSE	0.1	0.091	0.0000314	0.045	0.0000088
SPM	MAPE	0.05	0.025	0.000025	0.013	0.0000005
	MAE	1.25	0.2	0.00062	0.13	0.00019
	RMSE	0.1	0.083	0.000042	0.048	0.000021
SO_3	MAPE	0.05	0.03	0.000037	0.015	0.000019
	MAE	0.87	0.31	0.00097	0.96	0.0044

Source: Authors calculation.

Finally, a set of SVM, ARIMA, and hybrid models were trained and validated, their evaluation results for individual forecasting and combination forecasting, presented in Table 5. Based on the results of individual models such as ARIMA, SVR, and TSVR, ARIMA and SVR were similar, though TSVR proved to be more accurate. Besides, hybrid ARIMA-SVR and ARIMA-TSVR turned out to outperform ARIMA and SVR. Based on RMSE, MAE, and MAPE error criteria, individual TSVR model was more accurate than hybrid ARIMA-SVR. However, at least between individual and hybrid models, ARIMA-TSVR was the best, which means hybrid TSVR models, even individually, could be a more appropriate and accurate candidate for forecasting. Therefore, the proposed forecasting model was generated by integrating the autoregressive of ARIMA and SVR, whose parameters got optimized as aforementioned (to result in what is called TSVR), hence getting the model named hybrid ARIMA-TSVR. From all six data sets in Iran, the accuracy performance of hybrid ARIMA-TSVR was better that the rest. According to the results, among all the models, the ARIMA-TSVR had the lowest error value, which was 0.0000076, 0.0000065, and 0.0001 for CO_2, 0.0000043, 0.0000012, and 0.000022 for NO_x, 0.00032, 0.00028, and 0.0012 for SO_2, 0.000021, 0.000014, and 0.00038 for CO, 0.0000088, 0.0000005, and 0.00019 for SPM, and 0.000021, 0.000019, and 0.0044 for SO_3.

Once the 35 predictive values of ARIMA and hybrid TSVR were plotted against the actual values for visual comparison, the graphs for say CO_2 could be illustrated as Fig. 2. It can be seen in the graphs that the forecasting trends of hybrid ARIMA-TSVR was more similar and align to actual values, compared to the others for all data sets. Therefore, one can conclude that the hybrid ARIMA-TSVR model was more accurate than ARIMA and even ARIMA-SVR model for forecasting pollution in Iran. Generally, and based on the results obtained, it would be possible to construct a reliable pollutant forecasting model for Iran, which could be an important source of information for the authorities. Also, this kind of model is useful either in order to warn the population about adverse conditions in advance or even to implement palliative actions that could reduce the number of incidents with concentrations of pollutants particles over maximum permitted levels.

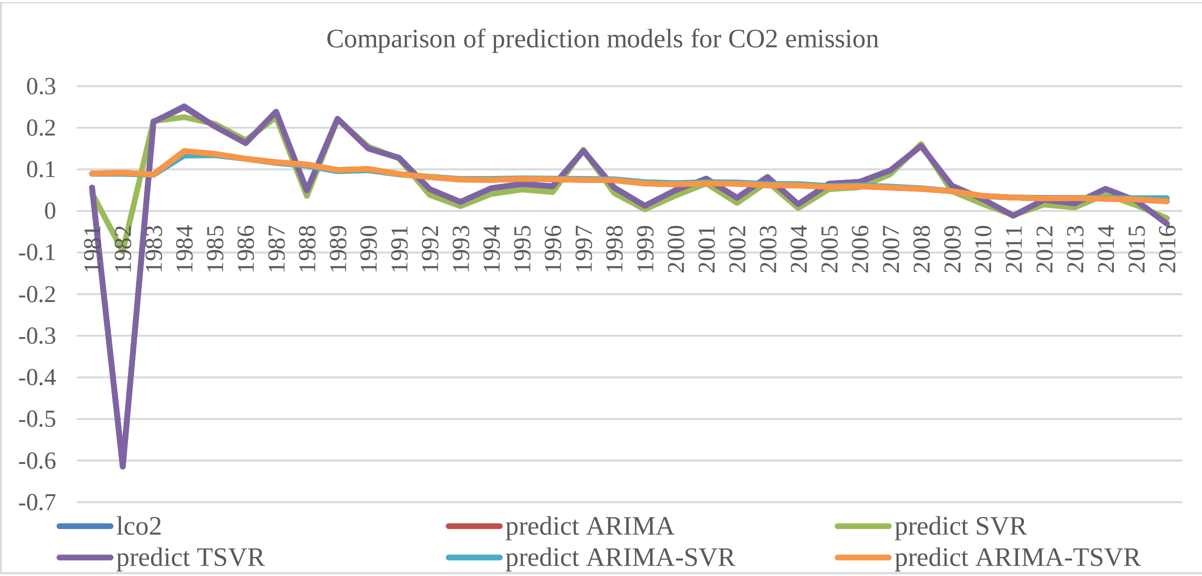

Fig.2. Comparison of Prediction Models for Logharithmic CO2.
Source: Authors calculation.

CONCLUSIONS

The present research dealt with the development of both single and hybrid forecasting models, called the ARIMA, SVR, hybrid ARIMA-SVR, and ARIMA-TSVR. These individual and hybrid models were applied to forecast the next 35 years' pollutant concentration in Iran, and their performance was tested with three RMSE, MAPE, and MAE error criteria. From the experimental results, hybrid ARIMA-TSVR model turned out to be more accurate than ARIMA, SVR, and ARIMA-SVR models for predicting yearly pollution values in Iran. The high performance of a hybrid method was consistent with the findings of other researchers (He et al, 2006; Nie et al, 2012; Sujiaviriyasup & Pitiruek, 2013; Manish & Thenmozhi, 2014; Haung, 2017; Pokora, 2017; Noori et al, 2015; Deo et al, 2018; Saho et al, 2018; and Chuentwat et al, 2017), who tried a different combination of hybrid scheme. Generally, the results of this paper as well as the mentioned researches prove that combining several models or using hybrid models can be an effective way to not only overcome the limitations of each component model but improve their forecasting performance in terms of efficiency and stability.

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