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Analyzing and Predicting the Monthly Temperature of Tehran Using ARIMA Model, Artificial Neural Network, and Its Improved Variant

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Abstract

The temperature has been a highly discussed issue in climate change. Predicting it plays an essential role in human affairs and lives. It is a challenging task to provide an accurate prediction of air temperature because of its complex and chaotic nature. This issue has drawn attention to utilizing the advances in modelling capabilities. ARIMA is a popular model for describing the underlying stochastic structure of available data. Artificial Neural Networks (ANNs) can also be appropriate alternatives. In the literature, forecasting the temperature of Tehran using both techniques has not been presented so far. Therefore, this article focuses on modelling air temperatures in the Tehran metropolis and then forecasting for twelve months by comparing ANN with ARIMA. Particle Swarm Optimization (PSO) can help deal with complex problems. However, its potential for improving the performance of forecasting methods has been neglected in the literature. Thus, improving the accuracy of ANN using PSO is investigated as well. After evaluations, applying the seasonal ARIMA model is recommended. Moreover, the improved ANN by PSO outperforms the pure ANN in predicting air temperature.

Keywords: Temperature, Forecasting, ARIMA, ANN, PSO, Tehran.

1 | Introduction

Scientists and experts have expressed deep concerns about global climate change in recent decades. Because of its adverse impacts on natural resources, human health, and economies, this issue has attracted many

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researchers together with government representatives, businesses, and citizens. Accurate forecasting of climate factors is essential to prevent lives and properties from losses. Climate forecasting is considered a challenging problem for its chaotic and complex nature. In the literature on weather forecasting, various techniques have been developed to model its underlying stochastic nature. The general approaches to modelling and forecasting time series include statistical methods, artificial intelligence, and hybrid models [1]. The current study employs statistical and artificial intelligence methods for this reason. In addition, it aims to improve artificial intelligence in hybrid models.

The Box-Jenkins (BJ) method is a statistical modelling approach that handles linear datasets to discover the relationship between various phenomena. As a popular model, the autoregressive integrated moving average (ARIMA) is built by the BJ iterative procedure [2]. The advantages of the BJ method are robustness, more straightforward application, fewer factors, and comprehensive utilization from engineering to economics and natural sciences. Based on historical climate data, a model is defined to forecast a particular area at a given period. In meteorology, the time evolution of various climate indicators, including rainfall [3], [4], humidity [5], [6], wind speed [7], [8], and temperature, have been studied. In recent years, the rise in average global temperature has been a highly discussed subject in climate change. Temporal changes can directly or indirectly affect energy consumption, water sources, the environment, and the health of creatures (for example, see [9]–[11]. Appropriately predicting the temperature trends seems crucial to planning for human affairs, establishing sound energy policies, and developing businesses [12]. Given the importance of predicting the fluctuations in forthcoming temperatures, several case studies have been conducted in some countries using various ARIMA models. Among those, the reader can refer to the United States [13], China [14], Spain, Germany, Poland, Finland [15], Iraq [16], India [17], and Pakistan [18].

Artificial Intelligence (AI) methods, classified into machine learning and deep learning predictors, are powerful tools for dealing with nonlinear and linear datasets [1]. Artificial Neural Networks (ANNs), as well as Support Vector Machines (SVMs), are the most appropriate approaches for weather prediction [19]. Similar to the human brain, these techniques obtain facts via learning. Then, the acquired information is stored within the interneuron connection, called synaptic weight conditions. Some advantages of ANN are:

I. Reaching a high-precision model at a satisfactory time without comprehensive information about the occurrence of a phenomenon and without making assumptions as in statistical models.

II. Solving many nonlinear problems which are challenging to solve using traditional methods.

III. Obtaining the prediction results by ANNs for unfamiliar users with complicated mathematical computations [20].

Different ANNs have been successfully implemented in numerous climate problems instead of traditional methods (for predicting rainfall, humidity, wind speed, and air temperature, refer to [21]–[24]). Johnstone and Sulungu [25] reviewed the applicability of ANNs in temperature forecasting. Most real-world cases are such complex problems. Those are without any determined mathematical formulation and, or with non-polynomial solving time. Metaheuristic algorithms can help deal with such problems [26]. Tran et al. [12] reviewed the applications of ANNs for temperature prediction. For more accurate predictions, they suggested the combination of ANNs with Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). As one of the best metaheuristics, PSO has successfully been applied in optimizing models, computational intelligence, and scheduling problems [27]. In this study, we investigate the utilization of PSO to improve the accuracy of ANN.

Our focus is on Iran, a country that often experiences drought because of its dry and semi-dry climate. The severe impacts of temperature fluctuations in different regions of Iran have led to studying its changes by some researchers and experts. For example, Namazian et al. [28] compared ANN and ARIMA models for predicting temperature variations in Gorgan City from 1970 to 2010. Shiravand and Dostkamiyan [29] analyzed temperature fluctuations in southwest Iran using a general circulation model and neural network. At Karkheh Basin, the ARIMA model was applied to forecasting the monthly drought [30]. Aghelpour et al. [31]

provided monthly temperature predictions in five cities from different geographical regions of Iran. They compared the accuracy of the seasonal ARIMA (SARIMA) model with the support vector regression and its variant as a novel model. Fahimi Nezhad et al. [32] predicted the maximum seasonal temperature in Tehran city using ANN. Kazemi et al. [33] utilized a hybrid model of a GA and neural network to forecast the monthly air temperature of Tabriz and Kermanshah stations. Tehran, the capital of Iran, with a population of around 9 million in the wider metropolitan area, seems particularly important in implementing temperature forecasting.

The current study aims to model the average monthly air temperatures in the Tehran metropolis by considering a given period and forecasting for twelve months. Accordingly, the following objectives are pursued:

I. Modelling the temperature data in the Tehran metropolis using ARIMA and ANN.

II. Utilizing the PSO algorithm to improve the accuracy of ANN.

III. Implementing short-term forecasting for one-year-ahead temperatures.

IV. Comparing the models using some performance criteria to suggest the best.

The rest of the paper is arranged as follows. Modelling approaches of BJ and ANN are introduced in the second section, and then some measures are defined to evaluate the methods. Employing those approaches for modelling monthly temperatures in the Tehran metropolis is illustrated in the third section. Moreover, comparisons are made between different models. The fourth section concludes the article and recommends some future directions.

2 | Methods

In some applications, stochastic behaviours are detected from chronologically collected data. This section introduces the BJ and the ANN methods to analyze the time series data. Since the eventual aim is predicting, some measures are also presented to select an appropriate method.

2.1 | BJ Approach

By tradition, applying the univariate BJ approach is appropriate to form linear models for predicting. In this subsection, models for non-seasonal and seasonal data are first introduced. Then, the steps of the BJ method are stated to forecast the time series by considering those models (refer to [2] for more information).

2.1.1 | Typical time series models

ARIMA models

Initially, this mixed model needs to express AR and MA terms as follows:

$$\varphi_p(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p, \quad \varphi_p \neq 0. \tag{1}$$

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q, \quad \theta_q \neq 0, \tag{2}$$

where ϕ_i and θ_i are the AR and the MA of i^{th} order, respectively. B indicates the backshift term. By merging p autoregressive, d integrated, and q moving average terms, an ARIMA(p, d, q) model is expressed as follows:

$$\varphi_p(B)(1-B)^d X_t = C + \theta_q(B) a_t, \tag{3}$$

where X_t is homogeneous non-stationary when $W_t=(1-B)^d X_t$ is stationary, C represents the constant term, μ specifies the process mean, and $a_t \sim N(0, \sigma_a^2)$ indicates a random error. Under stationarity conditions, the ARMA model is defined as follows (Z_t is stationary time series):

$$\varphi_p(B) Z_t = C + \theta_q(B) a_t. \tag{4}$$

SARIMA models

The generalized formulation of ARIMA processes to model the seasonal structure is called SARIMA. The following equation states the multiplicative SARIMA model and its seasonal AR and MA terms, respectively (note that $Z_t \sim ARIMA(p, d, q)(P, D, Q)_S$ and s denotes the number of periods for each season).

$$\varphi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D Z_t = \theta_q(B)\Theta_Q(B^s)a_t. \quad \textbf{(5)}$$

$$\Phi_P(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \ldots - \Phi_P B^{Ps}. \quad \textbf{(6)}$$

$$\Theta_Q(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - \ldots - \Theta_Q B^{Qs}. \quad \textbf{(7)}$$

2.1.2 | Practical rules of BJ modelling

Three main steps of the BJ approach for constructing appropriate models are expressed as follows (*Fig. 1* summarizes the procedure):

I. Identification: this phase probes to discover a tentative model. Initially, original data over time are visually assessed to realize the underlying structures. It is necessary to determine whether stationary requirements are fulfilled or not. If the variance of the original data is not stable, Box-Cox transformation is suggested for implementation. After variance stabilization, we may encounter level changes. The stationarity circumstance of the mean can be achieved by differencing. The degree of difference may be regular (d) or seasonal (D). After removing the integrated terms by differencing, simpler ARMA and SARMA models are obtained. Eventually, the Autocorrelation Function (ACF) and Partial ACF (PACF) are depicted to disclose the correlative pattern. Accordingly, a tentative model is distinguished.

II. Estimation: this phase estimates the parameters of the tentative model. Some essential issues in this phase are stated below:

- *The stationarity and invertibility circumstances of the estimated coefficients should be established.*
- *Models with non-significant coefficients tend to yield non-parsimonious models and less accurate forecasts. An estimated coefficient is significant if |t-value|≥2.0.*
- *Highly correlated coefficients may be considered of poor quality. The specific dataset greatly influences the estimations. A faintly different dataset can generate relatively different estimations. Thus, a suitable alternative model with less correlation between estimations is preferred.*
- *A model with better performance measures is preferred. It fits well with observations and generates predictions with minor errors.*
- *When both the AR and MA terms are incorporated into a model with nearly equal values, the problem of coefficient near-redundancy occurs. Those values are suggested to be eliminated to reach a parsimonious model with stable coefficients.*

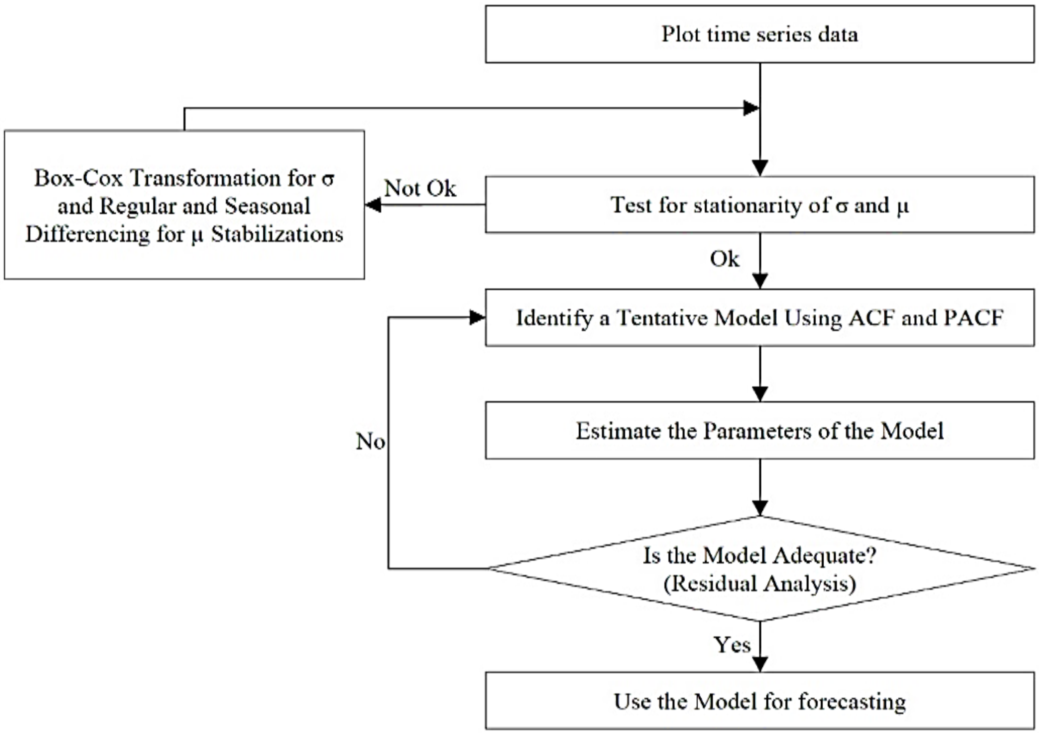


Fig. 1. BJ Modelling procedure.

Diagnostic checking: this phase calculates residuals ($\hat{a}_t$) and examines their properties and ACF and PACF graphs to validate the model. The estimated autocorrelations of residuals $r_k(a)$, $k=1,2,\ldots,K$ are checked via a chi-squared statistic.

$$\tilde{Q} = n(n+2)\sum_{k=1}^{K}(n-k)^{-1} r_k^2(\hat{a}), \quad \sim \quad \chi^2(K-p-q). \tag{8}$$

When the outcome is statistically significant, residuals are not independent. Hence, the model is distinguished as inadequate, and returning to the first phase is required to identify another model. Reviewing the graphs of normality, histogram, and so on can also be helpful in the third phase. After validation, the residuals would follow the white noise condition. The ultimate aim of the BJ approach is forecasting. Sampling errors slightly impact the resulting predictions of a correctly estimated model. Prediction accuracy can be assessed by obtaining Confidence Intervals (CIs). Some important points about a good model are summarized in *Table 1*.

2.2 | ANN Approach

This study uses Multi-Layer Perceptron (MLP) as a type of ANN. It includes input, output, and hidden layers. Each layer contains a group of nerve cells (neurons). Those neurons have connections to all neurons of other layers. One can restrict such connections. However, in each layer, there is no connection between neurons. The Back Propagation Algorithm (BPA) is used as the training algorithm in MLP.

Fig. 2 shows links inside a neural network. Inputs in the neural network contain information about different variables. In applying neural networks as a forecasting tool, inputs are independent variables that influence the response variable. However, the relationship between the independent variables and the dependent variable is unknown. Thus, the neural network seeks such a relationship. On the other hand, outputs include input-dependent variables. When the neural network is applied for prediction, the output is considered a response variable to find the corresponding values for the future.

Generally, input and output data are divided into three groups, including training, testing, and validation, to make predictions supported by the neural network. First, a certain percentage of input and output data are presented as training data. At this level, the BPA attempts to consider random weights for each data and, then, to achieve a relation between inputs and outputs. The rest of the data are divided into two groups, including test and validation data. As the essential part of the neural network, the education section tries to find the relation between them on a group of incoming and outgoing data. Then, the relationship is evaluated on test data, and approval or disapproval of communications created is reviewed on data validation.

Unfortunately, using the trial and error method and making random relations between inputs and outputs can not lead to a good result in the prediction by the neural network. For this reason, metaheuristic algorithms have been studied recently. In this study, using the PSO algorithm in the training step of the neural network is considered and discussed.

Table 1. Features of an appropriate model.

1- Being parsimonious (clarifying the structure of observations by the fewest coefficients).
2- Being stationary (by satisfying some inequalities for AR coefficients).
3- Being invertible (by satisfying some inequalities for MA coefficients).
4- Having estimated coefficients of high quality (significant and not highly correlated coefficients).
5- Having uncorrelated (white noise) residuals.
6- Fit well enough to the available data. and
7- Forecasting the future satisfactorily.

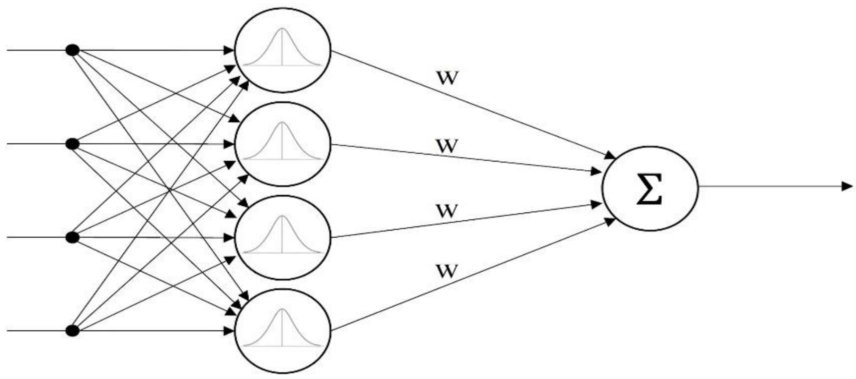


Fig. 2. Structure of applied MLP neural network.

A new optimization method was developed in the early 1990s by simulating the group behaviour of natural organisms [26]. In this algorithm, s indicates the position of each factor, and v denotes its speed. Each factor recognizes its best value so far (pbest) and identifies the best value obtained in the group (gbest). The position of each factor is obtained based on the speed of each particle. The speed is calculated using the equation below:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \times \left(pbest_i - s_i^k\right) + c_2 rand_2 \times \left(gbest - s_i^k\right). \tag{9}$$

Where v_i^k and s_i^k are the speed and the current position of the i^{th} factor in k^{th} repeat, respectively. w is the weight function, and c_j is the weighting coefficient. A random number is defined as rand~Uniform (0,1). Moreover, $pbest_i$ indicates the best personal experience of the i^{th} particle [34]. When the second and third terms are eliminated in *Eq. (9)*, the factor flies in the previous orientation until it accesses the border. Factor attempts to seek new regions. Thus, the first term corresponds to the variations in the search process. Factors are attempting to converge to pbests or gbest gradually. The current position of search points in the solution space could be modified by $s_i^{k+1}=s_i^k+v_i^{k+1}$. Each factor modifies its current position by combining vectors (*Fig. 3*). The steps of the PSO algorithm are described as follows [34]:

I. Creating initial conditions for each factor. Initial searching points (s_i^0) and speeds (v_i^0) of each factor are randomly generated in a permitted space.

II. Evaluating the search point. The value of the objective function is computed for each factor.

III. Modifying any search point.

Stopping condition: if the current iteration reaches the preset number of repeats, stop. Otherwise, go to Step 2.

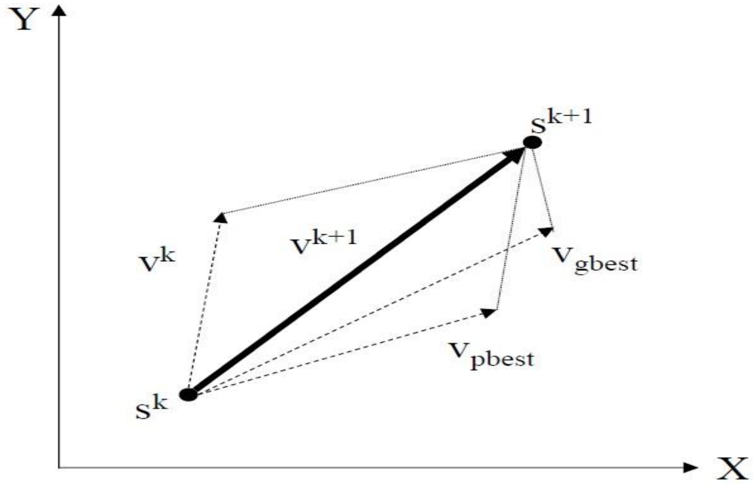


Fig. 3. The concept of modifying search points by PSO.

2.3 | Measures for Comparing the Performance of Models

Since a random-shock element exists, we cannot define a model that perfectly fits the available dataset. Therefore, the models are assessed via various measures according to statistical errors. Some models may become comparable in most aspects. Thus, we presented five measures as follows:

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\hat{a}_t^2}. \quad \textbf{(10)}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|\hat{a}_t\right|. \quad \textbf{(11)}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\hat{a}_t}{Z_t}\right|.100. \quad \textbf{(12)}$$

$$\mathrm{MDAPE} = \mathrm{Median}\left(\left|\frac{\hat{a}_t}{Z_t}\right|.100\right). \quad \textbf{(13)}$$

$$R^2 = 1 - \frac{\mathrm{SSE}}{\mathrm{SST}}, \quad \textbf{(14)}$$

where MSE and RMSE indicate the mean square error and its square root, respectively. MAE is the mean absolute error. Moreover, MAPE and MDAPE are the mean and the median absolute percentage error terms, respectively. R^2 refers to the correlation coefficient. Among alternatives, we prefer a model with the smaller criteria mentioned above, except for R^2, where its larger rate is desired.

3 | Case Study: Analysis, Results, and Discussion

This study analyzes a recorded dataset at Iran Meteorological Organization (IRIMO). Among the essential weather parameters, the temperature is measurable with a higher degree of accuracy. The study area is shown in *Fig. 4*. In this station, the longitude is 52°44', and the latitude is 35°45' with 1975.5 m height of sea level and possessing a semi-dry climate. The historical average monthly air temperatures in the Tehran metropolis were accessible only from Jan. 1951 to Dec. 2009. In the following subsections, an ARIMA model is estimated using the data from 1951 to 2008. Then, it is applied to forecast twelve months in 2009. Similarly, modelling and forecasting are implemented using ANN approaches. After comparing the results, the appropriate approach is recommended.

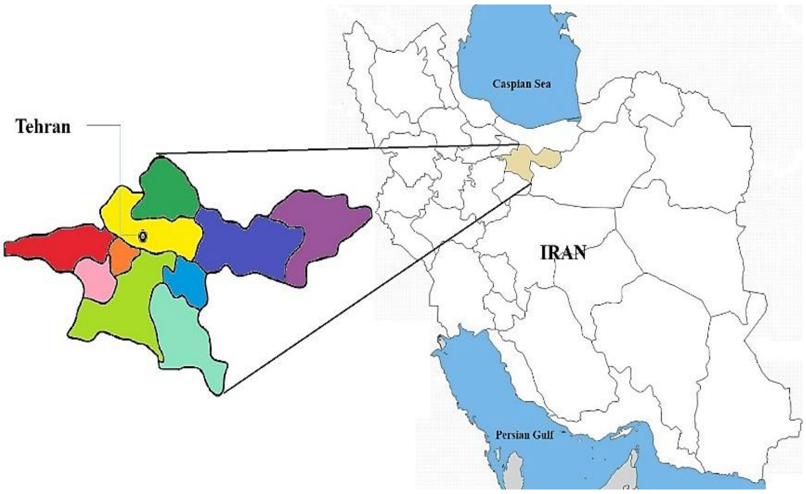


Fig. 4. The study region in Iran.

3.1 | BJ Approach

Initial data analysis

Fig. 5 plots the dataset during the periods. We used Minitab statistical software to analyze. The data seem to be stationary by preliminary inspection. Moreover, the symmetric variation of up and down is an impression of seasonality. Nevertheless, autocorrelation analysis and estimation results must be considered. *Fig. 6* presents a boxplot for investigating the average monthly air temperatures during the years. The boxes in Jan., Feb., and Sep. only indicate outliers. The trend of temperatures seems to increase between Feb. and Jul. and decline between Aug. and Jan. The hottest temperatures are confirmed in Jul. In contrast, the lowest average temperature is verified for Jan when severe cold weather is experienced.

Identification

Since the non-stationarity of the mean was doubted in *Fig. 5*, ACF and PACF graphs were investigated in *Fig. 7* (note that the variance was stable and Box-Cox transformation was unnecessary). ACF showed a slow tailing off. Moreover, the spikes at the 1^{st}, 12^{th}, and 24^{th} lags were significant. After a difference of size of 12 months, the seasonal pattern was eliminated, as shown in *Fig. 8*. The second seasonal differences of the series were taken as well. Comparing the first and second differences revealed the preference for the first difference to create an appropriate model. *Fig. 9* depicts the ACF and PACF graphs of the first differenced observations. The stationarity is proved by the fast dropping off to zero in the ACF graph. Non-seasonal AR term p=1 and seasonal MA term Q=1 are determined for the significant spikes at lag one in PACF and at lag 12 in ACF, respectively (see *Table 1*). Thus, ARIMA $(1,0,0)(0,1,1)_{12}$ is suggested as an initial tentative model for more investigation. Note that some neighbouring tentative models, including ARIMA $(1,0,0)(1,1,1)_{12}$, ARIMA$(0,0,1)(0,1,1)_{12}$ and ARIMA$(0,0,1)(1,1,1)_{12}$, could be considered as for comparisons.

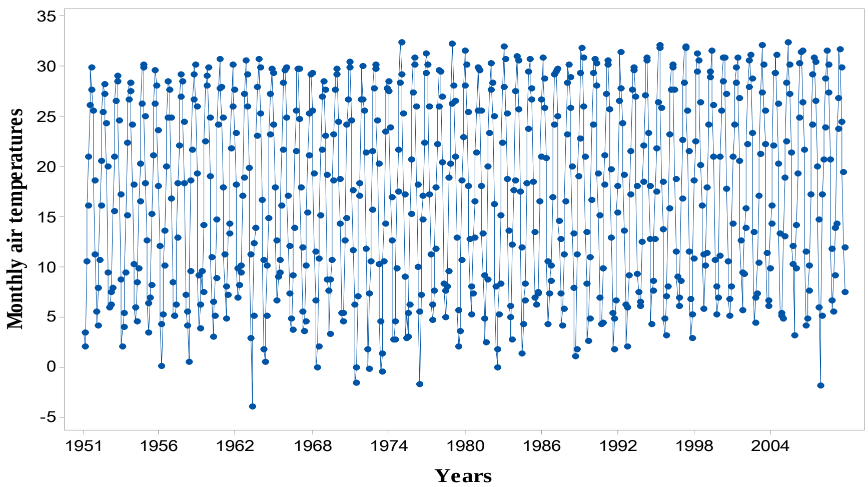


Fig. 5. The average monthly air temperatures (Jan. 1951 - Dec. 2008).

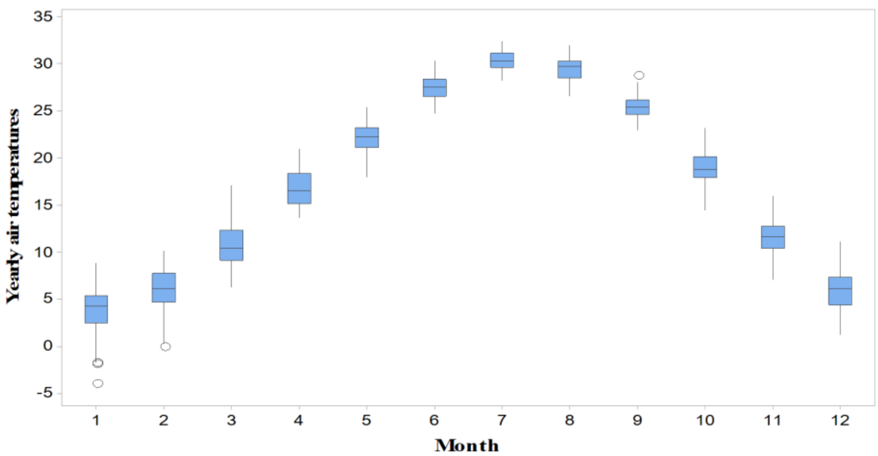
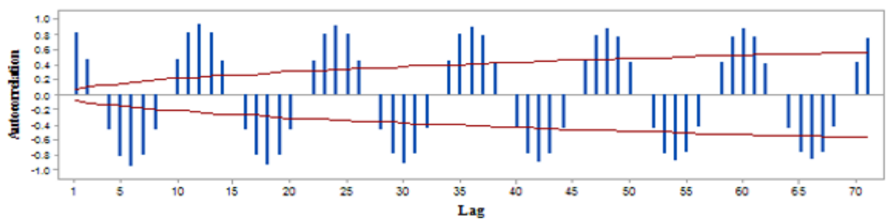


Fig. 6. Boxplot of the monthly average air temperature (Jan. 1951 - Dec. 2008).



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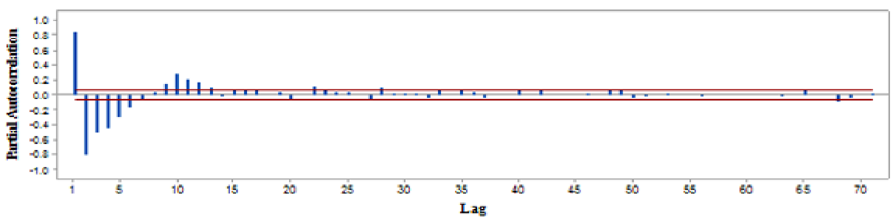


b.

Fig. 7. a. ACF and b. PACF graphs of the average monthly air temperatures (Jan. 1951 - Dec. 2008).

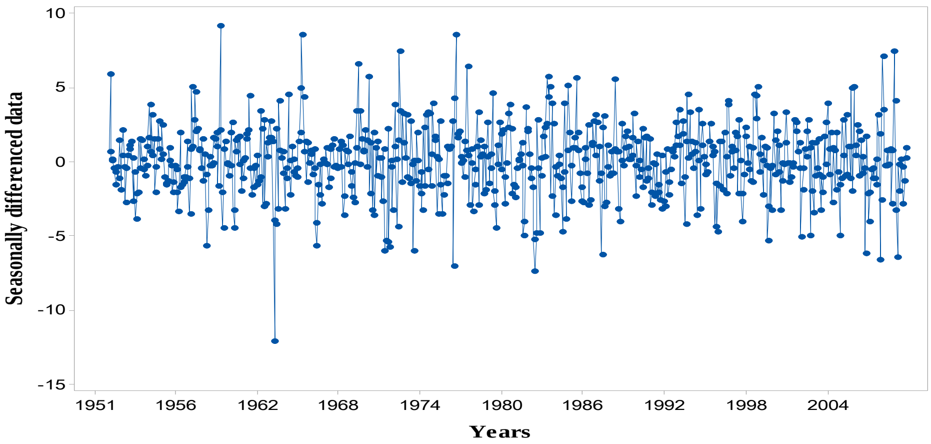


Fig. 8. The seasonally differenced average monthly air temperatures (Jan. 1951 - Dec. 2008).

Estimation

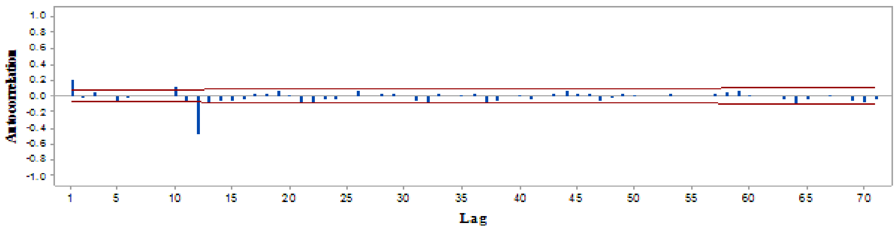
The least squares method is applied for parameter estimation. *Table 2* shows the results. For the non-seasonal part, the stationarity is confirmed since the estimated ϕ_1=0.2427 is less than one. The MA part only includes seasonality. Thus, the invertibility condition is satisfied since the estimated θ_1=0.9581 is less than one. One can reach the same decisions by looking at |t-value|>2. The quality of coefficients is investigated as follows:

I. Statistical significance (at a 5% level). A t-value statistic is computed to test whether the actual coefficient equals zero. According to *Table 2*, each coefficient significantly equals a non-zero value.

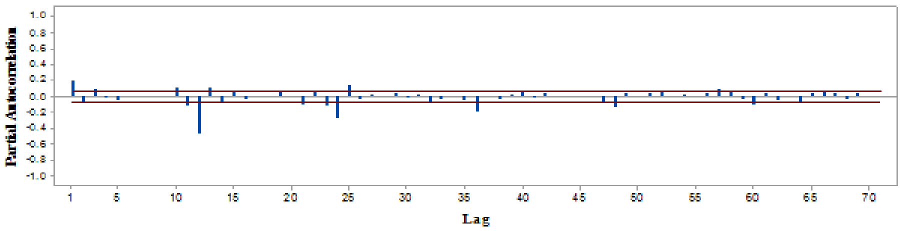
II. Correlation matrix. The absolute correlation values among the coefficients are significantly smaller than 0.9 (see *Table 2*). Thus, this model seems suitable.

III. The written model as $(1-0.2427B)(1-B^{12})Z_t=(1-0.9581B^{12})a_t$ does not indicate near-redundancy coefficients.

Using the defined equations in Section 2.3, we obtained RMSE=1.6876 and MAPE=0.1106 to assess the closeness of fit. These criteria are of type the-smaller the-better. Smaller criteria lead to a well-fitted model and provide reliable predictions.



a.



b.

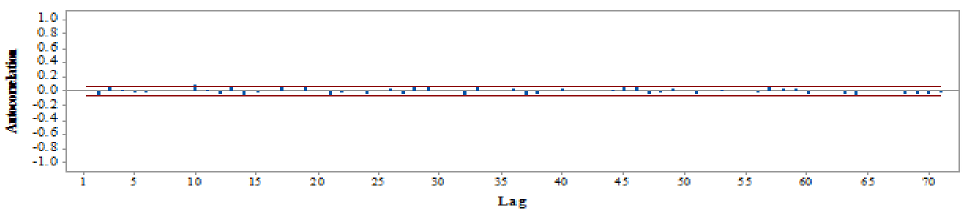
Fig. 9. a. ACF and b. PACF graphs of first seasonally differenced average monthly air temperatures (Jan. 1951 - Dec. 2008).

Table 2. Estimating the ARIMA (1,0,0)(0,1,1) 12 model.

Parameter Estimation				
Type	**Coef.**	**S.E. Coef.**	**T**	**P-value**
AR (1)	0.2427	0.0368	6.59	0.000
Seasonal MA $(1)_{12}$	0.9581	0.0152	62.98	0.000
Constant	0.0307	0.0038	7.98	0.000
Correlation Matrix				
	AR (1)	Seasonal MA$(1)_{12}$		
Seasonal MA $(1)_{12}$	-0.011	-		
Constant	-0.001	-0.092		
Chi-Square Statistic				
Lag	12	24	36	48
Chi-square	13.9	26.8	37.9	47.6
DF	9	21	33	45
P-value	0.126	0.178	0.257	0.368

Diagnostic checking

Fig. 10 shows that almost all the bars are inside the 95% confidence limit. Hence, the model does not need any modification. The residuals' independence was assessed by the chi-square statistic of the Ljung-Box test in *Table 2*. The set of residuals was not dependent because of significant p-values. Supplementary investigations can be pursued by four graphs (*Fig. 11*). The normality assumption is acceptable since the residuals mainly sit in a straight line. The Anderson-Darling test with p-value=0.34 also confirms the normality. The bell-shaped and symmetrical characteristics of the histogram infer a normal distribution (approximated as $N(0, 0.72^2)$). A random pattern and a scattered trend are deduced from *Fig. 11.b* and *Fig. 11.c,* respectively (note that observations 181 and 685 seem suspicious). Accordingly, the validity of ARIMA $(1,0,0)(0,1,1)_{12}$ is confirmed. We also estimated and checked another neighbouring model as ARIMA $(0,0,1)(0,1,1)_{12}$. The last model outperforms the initial one according to the evaluations by the measures in *Table 3*. Therefore, the last model is chosen for forecasting and more comparisons.



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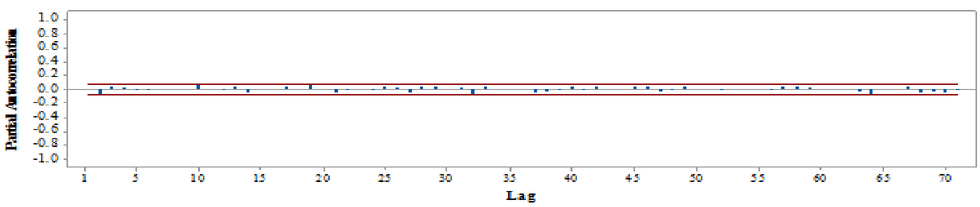

b.

Fig. 10. The latest model for further prediction and comparison; a. ACF and b. PACF graphs of residuals of the first seasonally difference average monthly air temperatures (Jan. 1951 - Dec. 2008).

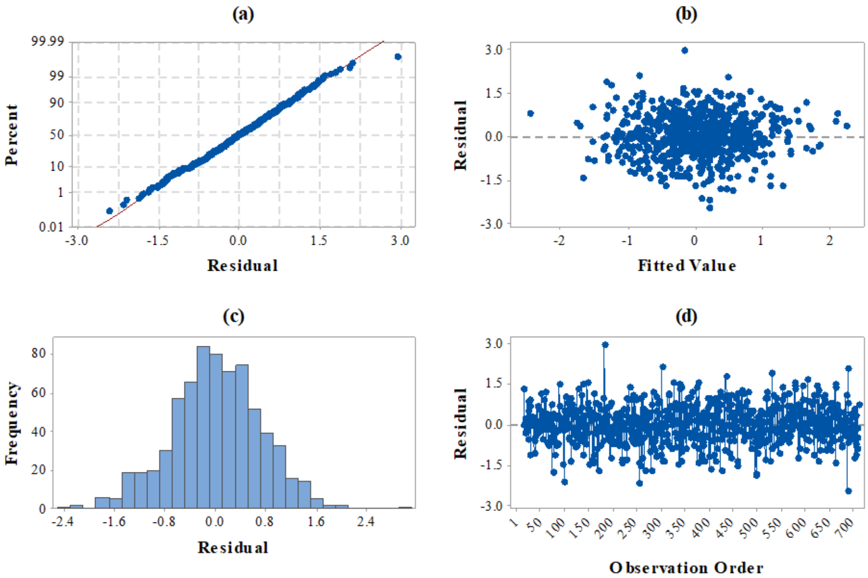

Fig. 11. Residual examination; a. normal plot, b. residual vs. fitted values, c. histogram and d. time series plot.

Forecasting

The dataset of air temperatures in the Tehran metropolis from Jan. 1951 to Dec. 2008 was considered for modelling. Here, the predicting capability is tested for the existing data in 2009. This can be checked by a 95% CI as forecast$\pm 1.96\sigma_a$. According to *Fig. 12*, the actual data lie inside the CI in nearly all periods. This implies that the model appropriately captures the structure among data and provides reliable predictions.

Table 3. Performance comparisons of the best models.

Model	MSE	RMSE	MAE	MAPE	MDAPE	R^2
ARIMA(1,0,0)(0,1,1)$_{12}$	2.8481	1.6876	1.2818	0.1106	0.0571	0.9690
ARIMA (0,0,1)(0,1,1)$_{12}$	2.8320	1.6829	1.2791	0.1080	0.0567	0.9692

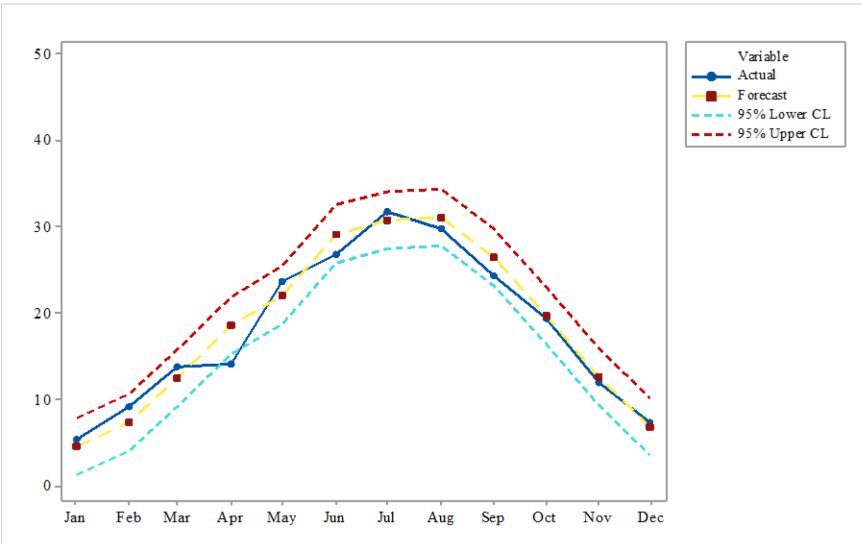

Fig. 12. Forecasting by ARIMA (0,0,1)(0,1,1)12 model (Jan. 2009 - Dec. 2009).

3.2 | ANN Modeling

The modelling procedures of average monthly air temperatures in the Tehran metropolis were investigated using the ANN and the ANN-PSO. Note that all calculations have been facilitated under coded programs in the MATLAB (version R2016b) environment. First, the parameters of ANN and ANN-PSO are tuned using the Taguchi Design of Experiment (DOE) method. In this regard, three levels are considered for each parameter. Then, ANN and ANN-PSO are run nine times, and R2 is calculated for each experiment. Finally, based on signal-to-noise criteria [35], [36], the best value of each parameter is recognized. The levels for each parameter and the best values are provided in *Table 4*. The associated performances of both approaches are shown in *Table 5*. As mentioned, we prefer a model with smaller criteria except for R^2, where its larger value is desired. The ANN-PSO shows significantly better performance than the ANN modelling. *Fig. 13* and *Fig. 14* depict the forecasts for the 12 months in 2009 and their associated 95% prediction limits. For both plots, the actual lines fall within the CIs in most cases. This implies reliable predictions within the reported uncertainty. However, it can be realized that forecasted values in *Fig. 14* track the actual data with fewer fluctuations than those in *Fig. 13*. Furthermore, the 95% CI of the ANN-PSO is tighter than that of pure ANN. Following these conclusions, the ANN-PSO is adequate for the air temperatures time series.

Table 4. Parameter tuning for ANN and ANN-PSO.

Model	Parameter	Level 1	Level 2	Level 3	Best Value
ANN	(Train%, Test%)	(70%,30%)	(80%,20%)	(90%,10%)	(80%,20%)
	Regression weight	0.1	0.2	0.3	0.1
ANN- PSO	(Train%, Test%)	(70%,30%)	(80%,20%)	(90%,10%)	(80%,20%)
	Population size	100	150	200	200
	Maximum iteration	300	400	500	500
	Velocity coefficient (C1)	1.1	1.2	1.3	1.1
	Velocity coefficient (C2)	1.1	1.2	1.3	1.3

Table 5. Performance comparisons of ANNs.

Model	MSE	RMSE	MAE	MAPE	MDAPE	R^2
ANN	31.8953	5.6476	4.3030	0.2502	0.2443	0.6456
ANN-PSO	11.4580	3.3850	2.6139	0.1541	0.1539	0.8727

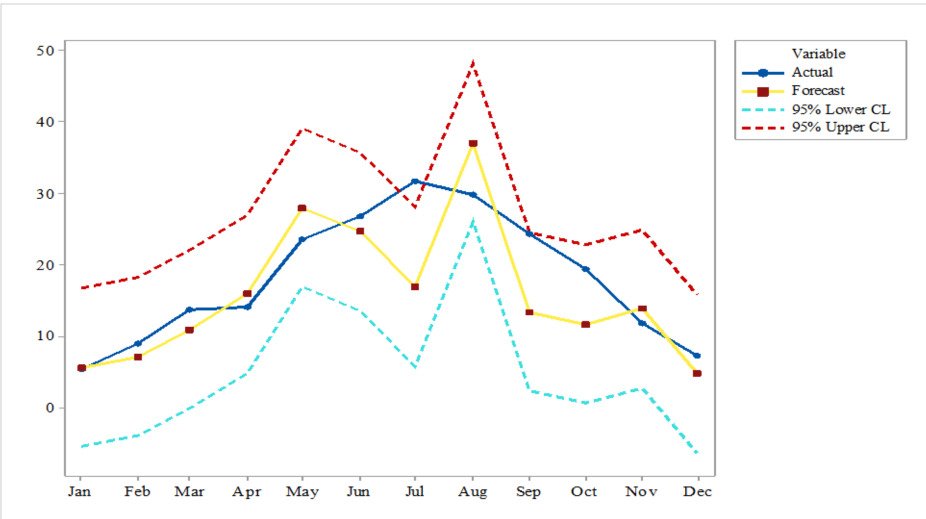

Fig. 13. Forecasting by ANN (Jan. 2009 - Dec. 2009).

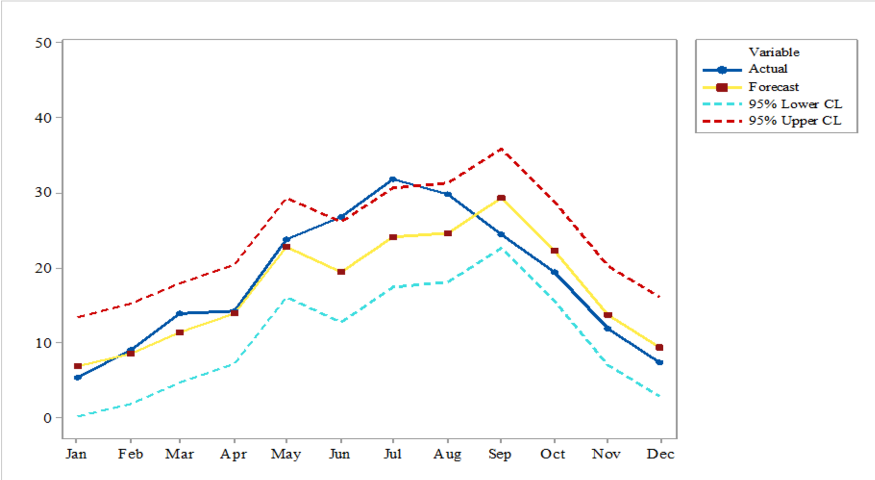

Fig. 14. Forecasting by ANN-PSO (Jan. 2009 - Dec. 2009).

3.3 | Performance Comparison of BJ and ANN Approaches

In this subsection, comparisons are made between two different modelling approaches. ARIMA $(0,0,1)(0,1,1)_{12}$ and the ANN-PSO were previously selected among the other alternatives. Their performance measures are gathered in *Table 6*. Accordingly, and by looking at the improved rates, ARIMA $(0,0,1)(0,1,1)_{12}$ is recommended with decent predictability for average monthly air temperatures in the Tehran metropolis.

Table 6. Performance comparisons: ARIMA vs. ANN-PSO.

Model	MSE	RMSE	MAE	MAPE	MDAPE	R^2
ARIMA$(0,0,1)(0,1,1)_{12}$	2.8320	1.6829	1.2791	0.1080	0.0567	0.9692
ANN-PSO	11.4580	3.3850	2.6139	0.1541	0.1539	0.8727
Improved Percentage (%) using ARIMA	75.28	50.28	51.07	29.92	63.16	11.06

4 | Conclusions

This study aimed to model and forecast the average monthly air temperatures in the Tehran metropolis. The historical data were accessible only from 1951 to 2009. Thus, the period from Jan. 1951 to Dec. 2008 was considered for modelling. Then, a prediction for the 12 months of 2009 was implemented. In this regard, two methods were introduced. Firstly, ARIMA, one of the most popular models, was presented in an iterative procedure of BJ for describing the underlying stochastic structure. After testing different models for the air temperature data, SARIMA $(1, 0, 0)(0, 1, 1)_{12}$ was distinguished as appropriate to predict by employing various performance evaluation criteria. Secondly, ANN was introduced as an appropriate alternative to traditional linear methods for modelling and forecasting. Moreover, the potential of the PSO algorithm was investigated to improve the performance of ANN. According to the results, the improved ANN by PSO outperformed the pure ANN in predicting Tehran's air temperatures. A comparison was made between seasonal ARIMA $(0, 0, 1)(0, 1, 1)_{12}$ and the ANN-PSO modeling. Finally, SARIMA $(0, 0, 1)(0, 1, 1)_{12}$ was selected to capture the autocorrelative structure in the temperature data and provided the most reliable forecasts within the reported uncertainty.

Global climate change has attracted many scholars to prevent losses due to its adverse effects. Accurate climate forecasting is a challenging problem because of its chaotic and complex nature. Given the temperature dataset, the BJ modelling approach can bring significant benefits for forecasting. Applying the BJ procedure, introduced in Section 2.1, can assist practitioners and decision-makers in creating models under similar conditions and establishing better strategies for the upcoming years. We recommend using Minitab in this regard since it needs no programming. If users are unfamiliar with statistical modelling concepts, we recommend applying the improved ANN by PSO instead of pure ANN. However, applying this technique requires programming software like MATLAB.

Future work may be extended toward applying the proposed approaches for modelling and forecasting some other kinds of data. For example, the BJ method has recently been used for forecasting wind power generation [37], yearly inflation rate [38], and trends in the quality and productivity field of research [39]. Hybrid modelling approaches can also be investigated once higher predicting accuracy is preferred. In the mentioned station of the current study, interested scholars can pursue similar investigations and decide on the predictability of models on the condition that they have access to recent datasets. Forecasting the temperature of an electric arc furnace using a recurrent neural network [40], COVID-19 time series using a hybrid intelligent approach [41], air passenger demand using a regression approach [42], and industrial business cycles using a five-step procedure to develop composite leading indicators [43] are among the other real-world applications.

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Conflicts of Interest

All co-authors have seen and agree with the manuscript's contents, and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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