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$PM_{2.5}$ Concentration Prediction Based on Winters' and Fourier Analysis with Least Squares Methods in Çerkezköy district of Tekirdağ

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Abstract: The rapid increase of the human population and industrialization rate in the globalizing world poses an important risk in terms of air pollution. Air pollution is an especially important issue for public health. Making the accurate predictions for air pollutants is an important step to take necessary measures. In this study, forecasting analysis for the future period was made by using the monthly average concentration values of Particulate Matter ($PM_{2.5}$) causing air pollution in the Çerkezköy district of Tekirdağ province between January 2017 and April 2020. "Winters' Method" and "Fourier Analysis with Least Squares Method" were used as the prediction approach. Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) model performance criteria were calculated based on the predictive values and actual values obtained. Whether the methods with structurally different algorithms differ in terms of prediction success was examined. Using the prediction methods, predictions for the next 20 months for $PM_{2.5}$ values were obtained. The predictive values obtained from both methods were intended to create a preliminary study value for decision makers and strategists working on air pollution.

Keywords: Air Pollution, Environmental Pollution, Forecasting, Fourier Analysis with Least Squares Method, Winters' Method.

INTRODUCTION

Air pollution, which directly affects human health, is one of the most serious environmental problems that need to be solved locally and globally. Activities such as industrialization, road traffic and residential warming are important emission sources [1]. According to the World Health Organization (WHO), approximately 91% of the world's population lives in unsafe air environments above the air quality limit values [2]. There are many studies showings that air pollution can be effective in the spread of the epidemic, which has become an important issue today [3-4].

The WHO examines the concept of air pollution in two ways: indoor and outdoor air pollution. Indoor-outdoor air pollution and many health-related diseases such as cancer, respiration and cardiovascular effects can be associated [5]. The adverse health effects resulting from exposure to air pollution may depend on the exposure time to pollutants and the concentration of air pollutants [6]. Due to the increase of health problems caused by air pollution, developed and developing countries attach importance to preventive studies on air quality [7].

Particulate matters (PM_s), sulfur dioxide (SO_2), carbon monoxide (CO) and nitrogen (NO) are the major air pollutants that cause outdoor air pollution, especially in crowded countries and major cities [8]. PMs are a mixture of solid particles and liquid droplets suspended in the atmosphere. These substances become visible in formations such as smoke, dust, fossil fuel residue, secondary aerosols formed by the reaction of sulfur and ammonia oxides in the air. Some particles are not visible. PMs penetrate deep into the lungs, causing many serious health problems, such as asthma. In most studies examined, PMs concentration was associated with mortality and a high correlation was obtained [9]. PMs are classified according to aerodynamic diameter sizes. PM_s with an effective aerodynamic diameter below 2.5 µm is called "$PM_{2.5}$" [10]. Worldwide the WHO has set the daily standard range of the final concentration value for $PM_{2.5}$ from 10 µg / m³ to 25 µg / m³ [11]. According to the 2017 Air Pollution Report of the Chamber of Environmental Engineers, which is the sub-institution of Union of Chambers of Turkish Engineers and Architects (UCTEA); limit values for PM_{10} in Turkey have been defined but is not defined for $PM_{2.5}$ [12]. For the Turkish Republic of Northern Cyprus (TRNC), the Environmental Protection Agency has

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set the $PM_{2.5}$ concentration target value as 25 µg / m3 per year [13]. In this study, the target value was accepted as 25 µg / m³ for $PM_{2.5}$.

Reducing the visibility of $PM_{2.5}$ plays an important role on its negative effects on human health. In this context, the fact that $PM_{2.5}$ concentration values are dynamic makes the subject of correct analysis and estimation important [3]. Prediction of $PM_{2.5}$ concentration values for future periods and monitoring of these values provides an opportunity for early prevention to people living in the region and public health professionals [9]. There are many studies in the literature that include PM_s prediction analysis. Some studies are given follows:

Diaz-Robles et al. (2008) used Autoregressive Integrated Moving Average - Artificial Neural Network (ARIMA-ANN) hybrid model in their prediction analysis for daily measurement values of PM_{10} substance causing air pollution in the city of Temuco, Chile, between 2000-2006. They compared the predictive performance of the hybrid model with the performance of ARIMA, ANN, and multiple linear regression methods [14]. Qingxin et al. (2009) revealed in their study the traditional gray prediction model based on the gray system theory for the prediction of PM_{10} data in Harbin city of China and a different version of this model. Four different methods were used to test the accuracy of the two models, and the model in the different version proved to be superior to the traditional model. Using the different version GM (1,1) model, the future 5-year PM_{10} concentration values of Harbin city were estimated [15]. Kurt and Oktay (2010) created a Geographic Classification Model for the estimation of SO_2, CO and PM_{10} levels in Beşiktaş, Istanbul, using daily pollution data, meteorological data, and spatial information [16]. Sun et al. (2013) used Hidden Markov Models (HMM) to estimate daily average $PM_{2.5}$ concentrations. In traditional HMM applications, observation distributions emanating from some hidden situations are assumed to have Gauss distributions [17]. Mahajan et al. (2017) compared the forecasting methods used in estimating hourly $PM_{2.5}$ values. In the study, a comparative analysis of the predictive performance for the additive version of the Holt-Winters Method, ARIMA model and Neural Network Autoregression (NNAR) model is presented [18]. Zhang and Ding (2017) estimated the NO_2, O_3, $PM_{2.5}$ and SO_2 densities between 2010 and 2015 using meteorological information such as temperature, wind, relative humidity in the Hong Kong region. Multiple Linear Regression (MLR), Feedback Neural Networks (FFANN) and Extreme Machine Learning (ELM) were compared as models. ELM obtained by privatization of two-layer artificial neural network has been shown to give the best results [19]. Cujia et al. (2019) analysed daily PM_{10} data in their studies to estimate the air quality of cities on the northern coast of Colombia. The aim of the study is to estimate the missing observation time series with intervention analysis. SARIMA Model (Seasonal Autoregressive Integrated Moving Average) was used to estimate PM_{10} levels [7]. Ventura et al. (2019) conducted a prediction analysis for $PM_{2.5}$ concentrations based on different time units. The Holt-Winter's Method and ANN were used as the estimation method. Success comparison of the methods was made by calculating the RMSE value [11]. Dun et al. (2020) used fractional gray linear regression and support vector machines to estimate daily PM_{10}, $PM_{2.5}$ and NO_2 values. MAPE values were calculated to compare the hybrid prediction model with the Holt Winter's Method [20].

In this study, prediction models for $PM_{2.5}$ concentration values were presented in the Çerkezköy district of Tekirdağ between January 2017 and April 2020. The "Winters' Method" and "Fourier Analysis with the Least Squares Method" approaches were used to estimate the monthly average $PM_{2.5}$ concentration values obtained from the Air Quality Monitoring Station. MAPE, RMSE and MAE were calculated from the model evaluation criteria for determining the method that gives the best estimation results. After evaluations, $PM_{2.5}$ values were estimated for the next 20 months using two methods. The success of the prediction methods has been analysed comparatively with the prediction results.

MATERIALS AND METHODS

In this study, "Winters' Method" and "Fourier Analysis with Least Squares Method" were used to predict future periods of air pollution $PM_{2.5}$ values in Çerkezköy, Tekirdağ, Turkey. RMSE, MAPE and MAE were calculated as model success evaluation criteria to evaluate prediction methods.

Winters' Method

Winters' Method is the seasonal exponential smoothing method that is among the time series methods. In Winters' Method, features such as seasonality and trend in the related time series are discussed. Since the most used time series models are divided into two as additive and multiplicative, there are two different model representations in Winters' Method [21]. In this study, additive model was used for Winters' Method.

Three different coefficients are used in Winter's Method. Among these coefficients, α is the smoothing constant, β is the seasonal smoothing constant, and γ is the trend smoothing constant. The equations for the additive model for the Winters' Method are given in Equation 1, Equation 2, Equation 3 and Equation 4, respectively.

$$A_t = \alpha * (y_t - S_{t-L}) + (1-\alpha) * (A_{t-1} + T_{t-1}) \quad \text{(Equation 1)}$$

$$T_t = \beta * (A_t - A_{t-1}) + (1-\beta) * (T_{t-1}) \quad \text{(Equation 2)}$$

$$S_t = \gamma * (y_t - A_t) + (1-\gamma) * (S_{t-L}) \quad \text{(Equation 3)}$$

$$F_{t+m} = (A_t) + (A_t * m) * (S_{t-L+m}) \quad \text{(Equation 4)}$$

Where,

t: Period,

A_t: Flattened value of the series for period t,

T_t: The trend predictive value for the t period of the series,

S_t: Seasonal forecast value for the t period of the series,

y_t: The real value of the series for the period t

m: The number of periods to be foreseen,

L: Initial value,

s: Number of seasons,

F_{t+m}: Returns the m period's predictive value.

Fourier Analysis with Least Squares Method

In time series analysis, array elements are elements of the set of random variables. Systematic elements of time series can be revealed by Fourier analysis [22]. Fourier analysis involves a function containing trigonometric terms. If the data set to be examined is considered as a one-dimensional time series, the Fourier series is determined according to the y_t values against the increasing values of the variable t (period). Therefore, fourier analysis is within the scope of "curve fitting with sinusoidal functions" [23]. When the Fourier Analysis approach is examined together with The Least Squares Method, the regression equation includes the principle of minimizing the error. The random error at period t in the equation is indicated by "e". "a_0", "a" and "b_k" are the fourier coefficients. The regression equation is given in Equation 5.

$$\hat{y_t} = a_0 + 2 * \sum_{k=1}^{K} a_k * \cos(wkt) + 2 * \sum_{k=1}^{K} b_k * \sin(wkt) + e \quad \text{(Equation 5)}$$

The "Coefficients Matrix: A" is given in Equation 6.

$$A = \begin{pmatrix} 1 & 2\cos(wt_0) & 2\sin(wt_0) & \dots & 2\cos(wKt_0) & 2\sin(wKt_0) \\ 1 & 2\cos(wt_1) & 2\sin(wt_1) & \dots & 2\cos(wKt_1) & 2\sin(wKt_1) \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 1 & 2\cos(wt_{N-1}) & 2\sin(wt_{N-1}) & \dots & 2\cos(wKt_{N-1}) & 2\sin(wKt_{N-1}) \end{pmatrix} \quad \text{(Equation 6)}$$

Matrix “G” is called "Observation Matrix". To work with matrix forms in Fourier Analysis with the Least Squares Method, "N” matrix, "n” matrix and "x” matrix are given in Equation 7, Equation 8, Equation 9, respectively. The “x” matrix is the “Unknowns Matrix” containing fourier coefficients.

$$N = A^T * A \qquad \text{(Equation 7)}$$

$$n = A^T * G \qquad \text{(Equation 8)}$$

$$x = N^{-1} * n = [\, a_0\ a_1\ b_1\ a_2\ \ b_2 \ldots\ a_k\ b_k \,]^T \qquad \text{(Equation 9)}$$

Model Success Evaluation Criteria

Performance efficiency of prediction models can be evaluated using model criteria such as, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Squared Log Error (MSLE), Correlation Coefficient (R) [24]. In equations of model evaluation criteria, $\hat{y_t}$ is the predictive value, y_t is the observed or actual value and n is the amount of observation. In this study, MAE, RMSE and MAPE were calculated as model evaluation criteria.

MAE is obtained by dividing the total error absolute value by the amount of observation. In general, a high MAE value indicates a low estimation performance. The mathematical expression of the MAE is given in Equation 10 [25].

$$\mathrm{MAE}=\frac{1}{\mathrm{T}} * \sum_{\mathrm{i}=1}^{\mathrm{t}} |\hat{y_t} - \mathrm{y_t}| \qquad \text{(Equation 10)}$$

RMSE is a measure of the deviation between the predictive values of the model and its actual values [25]. In general, a high RMSE value indicates poor performance. RMSE is given in Equation 11.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{T}} * \sum_{\mathrm{i}=1}^{\mathrm{t}} (\hat{y_t} - y_t)^2} \qquad \text{(Equation 11)}$$

MAPE is a percentage representation of the average of absolute values of errors. While prediction models with MAPE values below 10% have a "high accuracy" rating, models between 10% and 20% are classified as "accurate estimates" [26]. Models with MAPE values between 20% and 50% are "acceptable" and models above 50% are referred to as "wrong and incorrect" models [27]. Mathematical expression of MAPE is given in Equation 12.

$$\mathrm{MAPE} = \frac{1}{\mathrm{T}} * \sum_{\mathrm{i}=1}^{\mathrm{t}} \left| \frac{y_t - \hat{y_t}}{y_t} \right| * 100 \qquad \text{(Equation 12)}$$

CASE STUDY

Contrary to conventional pollution control approaches, cleaner production approach aims to reduce pollution. Pollution control approaches consider production and design stages as a constant factor [28]. Therefore, proactive control approach is important to prevent or reduce pollution types such as air pollution and water pollution especially in industrial areas. In this study, the subject of estimation is determined as an important air pollution control tool.

Çerkezköy district of Tekirdağ province receives continuous migration and continues its industrial development. Çerkezköy started to develop after the Organized Industrial Zone established in 1974, and especially after 2000, the industrial activities in the region have accelerated [29]. The rapid increase of the population and the production trend in the region also caused visible effects in air pollution. In this context, air pollution has become an important issue to be examined for the quality of human life.

In this study, using the prediction methods, the predictive values of $PM_{2.5}$ (µg / m^3) concentration values in Çerkezköy for the next 20 months (period between May 2020 and December 2021) were calculated. IBM SPSS 22.0 package program was used for the Winters' Method, and Microsoft Excel was used for the Fourier Analysis with the Least Squares Method. While comparing prediction methods, model success statuses were determined by calculating MAE, RMSE and MAPE values and alternative status of prediction methods were examined. Actual values belonging to previous periods were used as "validation set" in calculating model success criteria for prediction models. The determined 20-month period is "estimation set".

$PM_{2.5}$ (µg / m³) concentration values for Çerkezköy, Tekirdağ covering the period of January 2017 to April 2020 were obtained from the official website of the "Turkey Ministry of Environment and Urbanization". The values on this website have been obtained and used from the "Çerkezköy Air Quality Measurement Station"[30]. The monthly average $PM_{2.5}$ (µg / m³) values measured in Table 1 are given as follows.

Table 1. $PM_{2.5}$ (µg / m³) Concentration Actual Values

Month/Year	2017	2018	2019	2020
Jan	28.324	30.035	26.111	29.802
Feb	34.727	20.832	24.906	31.572
Mar	30.134	29.739	24.047	25.894
Apr	23.807	19.9	16.561	15.249
May	18.674	12.713	16.56	
June	19.242	10.361	10.67	
July	17.429	9.22	7.958	
Aug	16.096	7.717	8.447	
Sep	20.218	11	12.073	
Oct	32.993	20.877	15.008	
Nov	35.275	11.466	27.515	
Dec	37.596	27.214	28.042	

$PM_{2.5}$ (µg / m³) concentration values appear to be above the targeted limit value (25 µg / m³) in some months. The period when $PM_{2.5}$ (µg / m³) concentration values were above the target value generally includes the winter months. It can be said that $PM_{2.5}$ (µg / m³) concentration values increased due to fuel emissions of both residential and production centers. In this context, the data set has seasonal features.

The graphical view of $PM_{2.5}$ (µg / m³) concentration actual values obtained from Çerkezköy Air Quality Measurement Station was given in Figure 1.

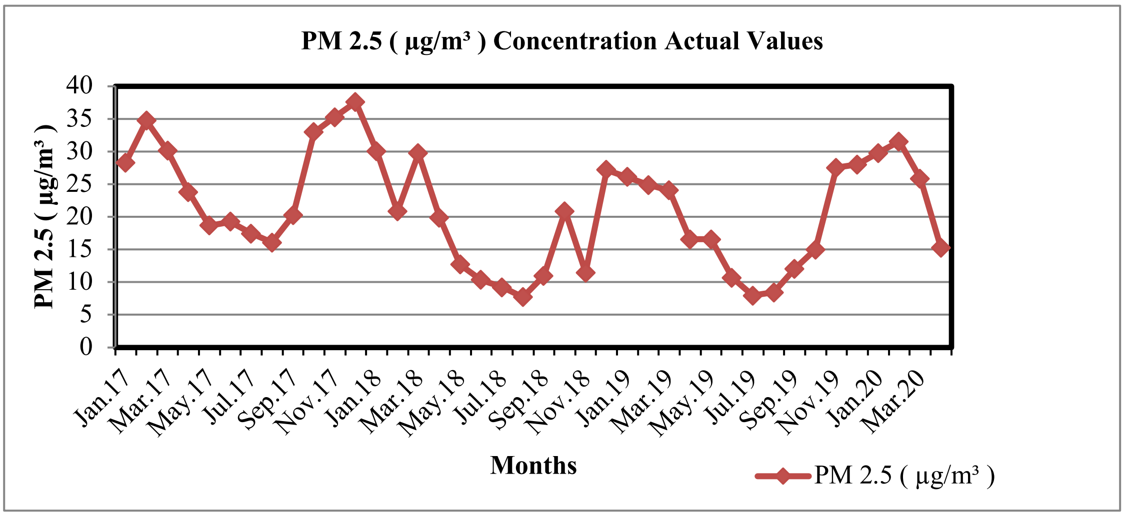

Figure 1. Graphical View of $PM_{2.5}$ (µg / m³) Concentration Actual Values

After the $PM_{2.5}$ (µg / m³) concentration value entries were made in IBM SPSS 22.0 package program and the necessary steps were followed, the Winters' Method additive model was applied. The SPSS screen output, which includes the model evaluation criteria along with some other indicators, can be seen in Table 2.

Table 2. Model Success Evaluation Criteria for Winters’ Method

Model Fit											
					Percentile						
Fit Statistic	Mean	SE	Min	Max	5	10	25	50	75	90	95
Stationary R-squared	.739	.	.739	.739	.739	.739	.739	.739	.739	.739	.739
R-squared	.790	.	.790	.790	.790	.790	.790	.790	.790	.790	.790
RMSE	**4.034**	**.**	**4.034**	**4.034**	**4.034**	**4.034**	**4.034**	**4.034**	**4.034**	**4.034**	**4.034**
MAPE	**14.329**	**.**	**14.329**	**14.329**	**14.329**	**14.329**	**14.329**	**14.329**	**14.329**	**14.329**	**14.329**
MaxAPE	93.407	.	93.407	93.407	93.407	93.407	93.407	93.407	93.407	93.407	93.407
MAE	**2.839**	**.**	**2.839**	**2.839**	**2.839**	**2.839**	**2.839**	**2.839**	**2.839**	**2.839**	**2.839**
MaxAE	11.615	.	11.615	11.615	11.615	11.615	11.615	11.615	11.615	11.615	11.615
Normalized BIC	3.066	.	3.066	3.066	3.066	3.066	3.066	3.066	3.066	3.066	3.066

The $PM_{2.5}$ (µg / m³) concentration predictive values obtained for the 20-month period between April 2020 and December 2020 with the Winters' Method additive model were shown in Figure 2.

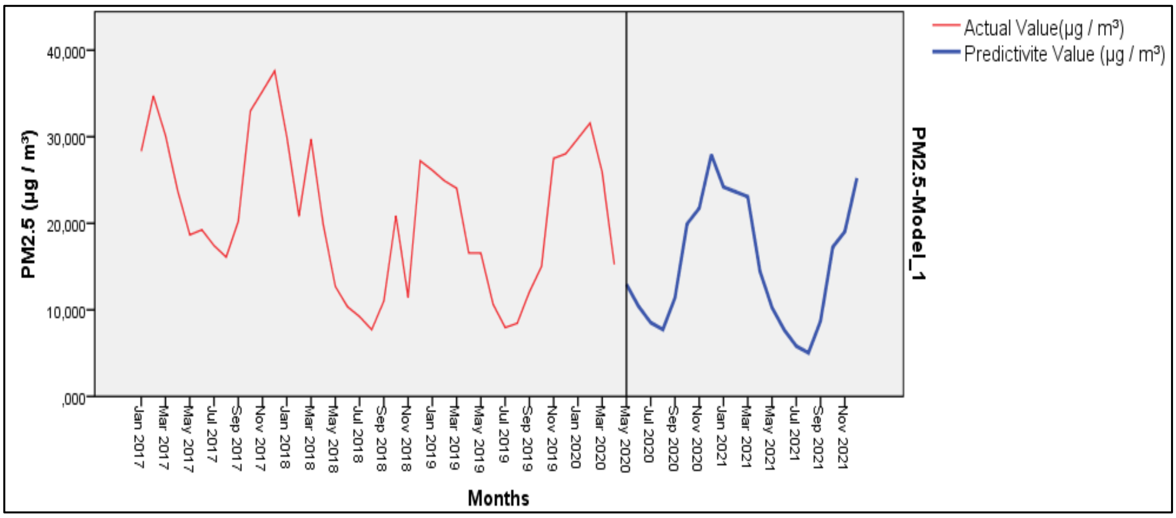

Figure 2. Winters ’Method / Graphical View of $PM_{2.5}$ (µg / m³) Concentration Predictive Values for The Period of April 2020- December 2021

Another prediction model used in the study is the Fourier Analysis with the Least Squares Method. Firstly, A = Coefficients Matrix was created. The created matrix A was given in Equation 13.

$$A=\begin{vmatrix} 1 & 2 & 0 \\ 1 & 1.732051 & 0.999999 \\ 1 & 1.000002 & 1.73205 \\ \vdots & \vdots & \vdots \\ 1 & 3.4497E^{-5} & 2 \end{vmatrix} \qquad \text{(Equation 13)}$$

After completing the matrix operations in Equation 7 and Equation 8 the "Unknowns Matrix: x" was given in Equation 14.

$$x=\begin{vmatrix} 20.588 \\ 4.802 \\ -0.049 \end{vmatrix} \qquad \text{(Equation 14)}$$

When the Fourier coefficients in the "x" matrix were replaced in Equation 9, the model prediction equation obtained was given in Equation 15.

$$\hat{y_t}=20.588 + 2*(4.802)*cos(wt) + 2*(-0.049)*sin(wt) \qquad \text{(Equation 15)}$$

Graphical representation of $PM_{2.5}$ (µg / m³) concentration predictive values obtained for 20 months by Fourier Analysis with the Least Squares Method was given in Figure 3.

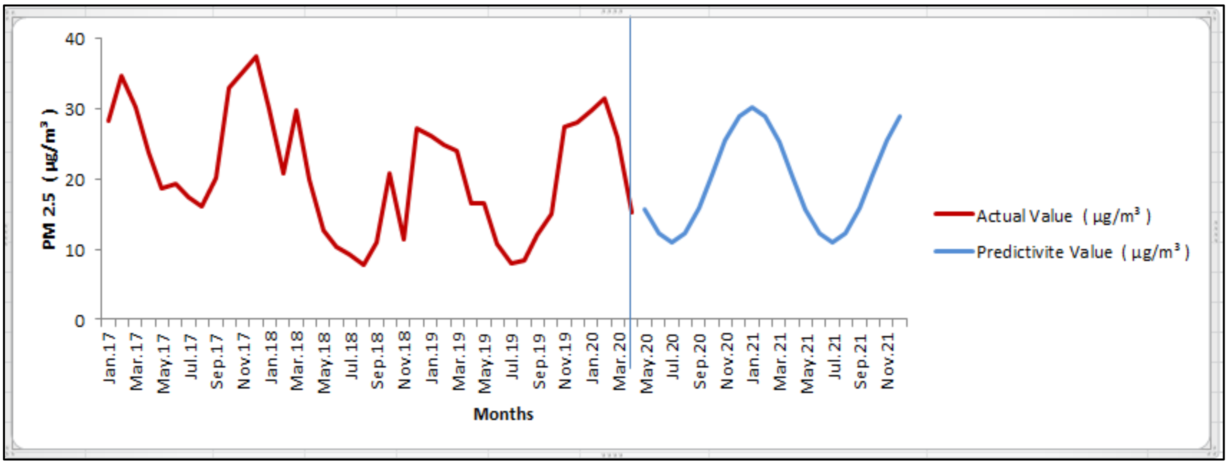

Figure 3. Fourier Analysis with Least Squares Method / Graphical View of $PM_{2.5}$ (µg / m³) Concentration Predictive Values for The Period of April 2020- December 2021

$PM_{2.5}$ (µg / m³) concentration predictive values obtained as a result of two different prediction methods were given in Table 3. According to both Winters' and Fourier Analysis with Least Squares methods, it was seen that the month of December values were high and the estimations of the two methods gave remarkably close results. The highest value was estimated in January according to Fourier Analysis with Least Squares method. In both methods, months between December and March, it was estimated that the most dangerous months for air pollution during the year. There was a serious decrease in air pollution in April.

Table 3. $PM_{2.5}$ (µg / m³) Concentration Predictive Values

Time/ Prediction Methods	Winters' Method	Fourier Analysis with Least Squares Method
May 2020	12.960	15.701
Jun 2020	10.400	12.222
Jul 2020	8.515	10.984
Aug 2020	7.733	12.320
Sep 2020	11.410	15.871
Oct 2020	19.940	20.686
Nov 2020	21.730	25.475
Dec 2020	27.930	28.954
Jan 2021	24.190	30.192
Feb 2021	23.640	28.856
Mar 2021	23.080	25.305
Apr 2021	14.510	20.490
May 2021	10.260	15.701
Jun 2021	7.699	12.222
Jul 2021	5.810	10.984
Aug 2021	5.028	12.320
Sep 2021	8.705	15.871
Oct 2021	17.230	20.686
Nov 2021	19.030	25.475
Dec 2021	25.221	28.954

The model success evaluation criteria calculated to verify the success of the prediction methods are given in Table 4. In terms of the criteria in Table 4, Winters' Method is seen to be a better prediction model than the Fourier Analysis with Least Squares Method. In Winters' Method, MAPE value was calculated as 14.329%. According to this result, Winters' Method is a "good" prediction model that gives "correct prediction results". As a result of the prediction made by Fourier Analysis with the Least Squares Method, the MAPE value was calculated as 22.934%.

Table 4. Model Success Evaluation Criteria of Prediction Models

Model Success Evaluation Criteria	Winters' Method	Fourier Analysis with Least Squares Method
MAE	2.839	4.008
RMSE	4.034	5.087
MAPE	14.329%	22.934%

According to this result, the prediction model created by Fourier Analysis with the Least Squares Method is an “acceptable” prediction model. Therefore, considering only MAPE, one of the success evaluation criteria, two prediction methods can be used as an alternative. According to the calculated values of MAE and RMSE criteria, there is no significant difference between the two methods. Considering the $PM_{2.5}$ (µg / m³) concentration predictive values obtained in Table 2, the number of predictive values exceeding the target value (25 µg / m³) in the Winters' Method is less than the Fourier Analysis with the Least Squares Method. With the Winters' Method, a forecast value above the target value was obtained for 2 months within the 20-month forecast period. When the prediction values are examined, the target value has been exceeded for a total of 7 months by Fourier Analysis with the Least Squares Method. The periods when the target value is exceeded are also the periods covering the winter months.

CONCLUSION

Çerkezköy, Tekirdağ has an important place in terms of sectors such as automotive, metal, white goods, paper, medicine, food, and sanitary ware. The region is open to investments due to its advantageous geographical position in providing the necessary conditions for the production, distribution, and marketing of industrial products. The rapid increase in industrialization and the population in Çerkezköy and its surroundings brought air pollution problems with it. In this study, the future period prediction of the air pollutant in question was made since the $PM_{2.5}$ values, which are among the particulate matter, are in a dynamic structure and the concentration measurements cannot be controlled widely at the stations. For this purpose, Winters' Method and Fourier Analysis with the Least Squares Method were used and the success of the methods were evaluated according to various criteria. In the study, the average monthly $PM_{2.5}$ concentration values obtained from the Air Monitoring Station in Çerkezköy district of Tekirdağ and containing the period between January 2017 and April 2020 were analysed. Using the prediction methods, the forecast values for the period between May 2020 and December 2021 have been determined. According to the results obtained from Winters' method additive model, the MAE value is 2.839; RMSE value was calculated as 4.034 and MAPE value as 14.329%. According to the results obtained from Fourier Analysis with the Least Squares Method, the MAE value is 4.008; RMSE value was calculated as 5.087 and MAPE value as 22.934%. Winters' Method reveals a better prediction model compared to all model evaluation criteria. When MAPE values are examined, both methods can be evaluated as alternative prediction method. When the model success criteria values between the two methods are considered, it may be more advantageous to select the Winters' Method as a prediction model; however, Fourier Analysis with the Least Squares Method also provides an acceptable prediction model, so it is an alternative prediction approach.

$PM_{2.5}$ concentration values can be modelled with different prediction techniques. In future studies, prediction models can be changed, or these methods can be hybridized by other methods. Time series models (Trend Analysis, ARIMA etc.), machine learning classifiers and various data mining techniques can also be used in forecasting (ANN, Support Vector Machine (SVM) etc.). In order to expand the scope of the study, prediction modelling with ANN can be performed by including different variables related to air pollution. The methods can be compared with each other by considering different criteria. Using the same prediction models, prediction values can be obtained for other pollutants causing air pollution. Knowing the predictive values of the substances causing air pollution and making the planning correctly will be an extremely effective strategy for decision makers to prevent air pollution.

REFERENCES

[1] Prüss-Ustün, A., Wolf J., Cordolán C., Bos, R., and Neira M., 2016, Preventing Disease Through Healthy Environments: A Global Assessment of the Burden of Disease from Environmental Risks, 1st ed., World Health Organization. Geneva, Switzerland.

[2] Ghosh, N., Roy, A., Mandal, R., and Dutta, A., 2020, Degradation of air quality (PM_{10}) with seasonal change and health risk assessment in metro city Kolkata, International Journal of Advancement in Life Sciences Research, Vol. 3(1), 24-31.

[3] Wang, Y., Wang, H., Chang, S., and Avram A., 2018, Prediction of daily PM2.5 concentration in China using partial differential equations, PLoS ONE, Vol. 13(6), 1-13.

[4] Chen D., Liu, X., Lang, J., Zhou, Y., Wei, L., Wang, X., and Guo, X., 2017, Estimating the contribution of regional transport to PM2.5 air pollution in a rural area on the North China Plain, Science of The Total Environment, Vol. 583, 280–291.

[5] Abdo, N., Khader, Y.S., Abdelrahman, M., Graboski-Bauer, A., Malkawi, M., and Al-Sharif, M., 2016, Respiratory Health Outcomes and Air Pollution in the Eastern Mediterranean Region: A Systematic Review, Rev. Environ. Healt, Vol. 31, 259–280.

[6] National Research Council (US) Committee on Indoor Pollutants, Factors That Influence Exposure to Indoor Air Pollutants, web page: https://www.ncbi.nlm.nih.gov/books/NBK234048/, retrieval date: 23 May 2020.

[7] Cujia, A., Agudelo-Castañeda, D., Pacheco-Bustos, C., and Teixeira, E.C., 2019, Forecast of PM_{10} Time-Series Data: A Study Case in Caribbean Cities, Atmospheric Pollution Research, Vol.10, 2053-2062.

[8] Rovira, J., Domingo, J.L., and Schuhmacher, M., 2020, Air quality, health impacts and burden of disease due to air pollution (PM_{10}, $PM_{2.5}$, NO_2 and O_3): Application of AirQ+ model to the Camp de Tarragona County (Catalonia, Spain), Science of the Total Environment, Vol. 703, 2-12.

[9] Bai, Y., Li, Y., Wang, X., Xie, J., and Li, C., 2016, Air Pollutants Concentrations Forecasting Using Back Propagation Neural Network Based on Wavelet Decomposition with Meteorological Conditions, Atmospheric Pollution Research, Vol. 7, 557–566.

[10] Gruszecka-Kosowska A., 2018, Assessment of the Krako´W Inhabitants' Health Risk Caused by the Exposure to Inhalation of Outdoor Air Contaminants, Stoch Environ Res Risk Assess, Vol. 32(2), 485–499.

[11] Ventura, L.M.B., De Oliveira Pinto, F., Soares, L.M., Luna, A.S., and Gioda, A., 2019, Forecast of Daily $PM_{2.5}$ Concentrations Applying Artificial Neural Networks and Holt–Winters Models, Air Quality, Atmosphere & Health, Vol. 12, 317–325.

[12] Turkey Union of Chambers of Engineers and Architects, Chamber of Environmental Engineers, Air Pollution Report, 2017, web page: http://cmo.org.tr/resimler/ekler/2145efce8f89f52_ek.pdf , retrieval date: 11 May 2020.

[13] Cyprus Environmental Protection Agency, Targets of Air Quality, web page: http://www.cevrekorumadairesi.org/air/tr-pages.php?no=76 , retrieval date: 30 May 2020.

[14] Diaz-Robles, L.A., Ortega, J.C., Fu, J.S., Reed, G.D., Chow, J.C., Watson, J.G., and Moncada-Herrera, J.A., 2008, A Hybrid ARIMA and Artificial Neural Networks Model to Forecast Particulate Matter in Urban Areas: The case of Temuco, Chile, Atmospheric Environment, Vol. 42, 8331-8340.

[15] Qingxin, F., Ying, L., and Nanqi, R., 2009, Application of grey prediction model to forecast the main air contaminant PM10 in Harbin City, IEEE.

[16] Kurt, A., and Oktay, A.B., 2010, Forecasting Air Pollutant Indicator Levels with Geographic Models 3 Days In Advance Using Neural Networks, Expert Systems with Applications, Vol. 37(12), 7986–7992.

[17] Sun, W., Zhang, H., Palazoglu, A., Singh, A., Zhang, W., and Liu, S., 2013, Prediction of 24-Hour-Average PM2.5 Concentrations Using a Hidden Markov Model with Different Emission Distributions in Northern California, Science of The Total Environment, Vol. 443, 93-103.

[18] Mahajan, S., Chen, L.J., and Tsai, T.C., 2017, An Empirical Study of PM2.5 Forecasting Using Neural Network, IEEE.

[19] Zhang, J., and Ding, W., 2017, Prediction of Air Pollutants Concentration Based on An Extreme Learning Machine: The Case of Hong Kong," International Journal of Environmental Research and Public Health, Vol. 14(2), 114. 2017.

[20] Dun, M., Xu, Z., Chen, Y., and, Wu, L., 2020, Short-term Air Quality Prediction Based on Fractional Grey Linear Regression and Support Vector Machine, Hindawi Mathematical Problems in Engineering, 1-13.

[21] Altınay, G., 2010, Aylık Elektrik Talebinin Mevsimsel Model ile Orta Dönem Öngörüsü, 2010, Enerji, Piyasa ve Düzenleme, Vol. 1(1), 1-23.

[22] Abbak, R., 2005, Deniz Düzeyi Gözlemlerinin En Küçük Kareler Yöntemiyle Spektral Analizi, Master of Science Thesis, Selçuk University, The Graduate School of Natural and Applied Sciences.

[23] Türker, E.S., and Can, E., 1989, Bilgisayar Uygulamalı Sayısal Analiz Yöntemleri, 2nd ed., Değişim Yayınları, İstanbul, Türkiye.

[24] Mohanasundaram, S., Narasimhan, B., and Kumar, G.S., 2016, Transfer Function Noise Modelling of Groundwater Level Fluctuation Using Threshold Rainfall-Based Binary-Weighted Parameter Estimation Approach, Hydrological Sciences Journal, Vol. 62(1), 36-49.
[25] Bruster-Flores, J.L., Ortiz-Gómez, R., Ferriño-Fierro, A.L., Guerra-Cobián, V.H., Burgos-Flores, D., and Lizárraga-Mendiola, L.G., 2019, Evaluation of Precipitation Estimates CMORPH-CRT on Regions of Mexico with Different Climates, Water, Vol.11, 1722.
[26] Witt, S. F., and Witt, C. A., 1992, Modeling and Forecasting Demand in Tourism, 1st ed., Academic Press, London, England.
[27] Lewis, C. D., 1982, Industrial and Business Forecasting Methods, 1st ed., Butterworths Publishing, London, England.
[28] Şimşek, A., Beytekin, İ., and Bakan, G., 2018, Cleaner Production Applications in Various Industries: Metal Industry, Environmental Research and Technology, Vol. 1(3), 51-57.
[29] G. İnce, 2010, Tarımdan Sanayiye Geçiş Sürecinde Trakya Alt Bölgesinde Göç : Çerkezköy Örneği, PhD Thesis, Namık Kemal University, The Graduate School of Natural and Applied Sciences.
[30] Turkey Ministry of Environment and Urbanization, National Air Quality Monitoring Network, web page: https://sim.csb.gov.tr/STN/STN_Report/StationDataDownloadNew , retrieval date:01 Nov 2020.