Power demand estimation during pandemic times: The case of the COVID-19 in Tehran, Iran

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The impact of the COVID-19 pandemic on power demand has been studied in some countries. In this study, we investigate the effects of the COVID-19 pandemic on power demand in Tehran, Iran. Hence, power demand variations between 2016 and 2020 are investigated in this research. Results indicate that the effects of the COVID-19 pandemic on power demand vary from month to month and day to day, depending on various factors such as government limitations and the COVID-19 mortality. It is observed that power demand annual growth is changed during both the COVID-19 pandemic and financial crisis. For instance, the average power demand growth in 2020 is 1.03%, while was 4.96% in 2019. Also, most power demand forecasting algorithms have been developed for the normal situation; therefore, we introduce two forecasting algorithms to forecast power demand. The first algorithm is developed based on the principal component regression (PCR), and the second is developed based on the twin support vector machine and quantile regression (TWSVQR). The PCR is selected due to its simplicity and high performance. The proposed PCR model considers daily, annual, and biennial power demand variation rates. The advantage of the TWSVQR method is that it is so accurate, requires a small training dataset, considers various factors for forecasting power demand, and is robust against outlier data. Finally, we investigate our proposed algorithms to forecast power demand in Tehran. Results illustrate proposed algorithms can predict power demand

keywords: *Pandemic, power demand forecasting, principal component regression, twin support vector machine, quantile regression*

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NOMENCLATURE

$\alpha_n(i,t)$	Power demand in the previous day (i-1th day) and hour t for nth observation×M1
$\gamma_n(i,t)$	Power demand in the similar day (ith day) and hour t for previous year for nth observation×M2
$\mu_n(i,t)$	Power demand in the similar day (ith day) and hour t for two years ago for nth observation×M3
$\theta_n(i,t)$	Power demand in the day and hour t-1 for nth observation
ε	Error of model
β	Coefficients of PCR
M3	Two-years power demand variation rate
M2	Annually power demand variation rate
M1	Daily power demand variation rate
P(i)	Initial demand power
P_{ava}	Is maximum achievable power
E(i,i)	Self-elasticity at i-th hour
$c_0(i)$	Actual electricity price for an hour i($/MW)
c(i)	Initial electricity price for an hour i($/MW)
Y	Vector of power demand
X	Matrix of PCR variables
σ^2	Variance of model error
$I_{n\times n}$	Identity matrix
$\hat{\beta}_k$	Estimation of Coefficients of PCR

$\psi(x)$	Mapping function
w	Weight vector
b	Threshold of SVR model
$L_\tau(v)$	Pinball loss function
ζ	l-dimensional threshold variables for SVM
ζ^*	l-dimensional threshold variables for SVM
y_i	The i-th target in SVM (in this case 1 or -1)
x_i	P-dimensional real vector
K	Kernel function
b_1 and b_2	Offsets of two hyperplanes in TWSVM
θ and δ	Slack variables in TWSVM
u_1 and u_2	Normal vectors of two hyperplanes in TWSVM
e_1 and e_2	Unit column vectors in TWSVM
c_1 and c_2	Penalty parameters in TWSVM
$L_\tau^\delta(u)$	ε-insensitive pinball loss function
τ	Regulation parameter
A	Training sample points of class '+1'
B	Training sample points of class '-1'

1. INTRODUCTION

Coronavirus disease 2019 (COVID-19) is an infectious illness identified in December 2019 in Wuhan, China. It has been the deadliest disease in the last century, infected more than 203 million people and killed more than 4.3 million individuals worldwide until August 9, 2021. Although vaccination has begun in many countries and the pandemic seems to be under control in some regions, different variants of the virus such as Alpha, Beta, and Delta have emerged or become dominant in many countries since the beginning of 2021. Therefore, the end of this pandemic is not clear and some effects may be remained for several years [1]. This had a significant impact on the human lifestyle. Many activities were shut down, while some were in a recession. Many companies chose telecommuting for all or part of their employees. Some jobs were lost, and some new jobs were created. Because almost all of these activities depend on electrical energy, it might have considerable impacts on power demand trends [2]. This encourages researchers to investigate effects of the pandemic on electricity demand in power systems. This investigation helps companies to improve the grid flexibility.

Recently, the pandemic impacts on power demand have been explored in some researches. For instance, the challenges, lessons, and emerging opportunities for energy demand during the COVID-19 pandemic were investigated in [3]. This research indicated that the overall energy demand is declining while spatial and temporal variations are complex. The power demand in China during the pandemic has been studied in [4]. Results show that the COVID-19 pandemic significantly affects the electricity demand, directly or indirectly. The demand for petroleum and electricity has experienced a reduction of 0.1% and 0.65%, respectively.

The power demand variations in Europe were inspected in [5]. Studies showed that the power demand has moderately declined during the pandemic. Compared to similar days in 2019 (before the COVID-19 pandemic), power demand has decreased in Spain, Italy, and most of European countries between 11 to 25 percent. However, in Sweden, the power demand raised about 2.1 percent. The effect of the pandemic on the power demand in Italy was investigated in [6]. That study illustrates the policies of the Italian government during the Coronavirus pandemic have greatly influenced the various sectors of industry, tourism, and services. These effects are variable for different weeks and months. For instance, power generation approximately decreased 15 percent between the last week of March 2019 and the last week of March 2020. Studies on power demand during the pandemic in Spain were provided in [7]. In Spain, the power demand decreased 13.49% from March 14 to April 30, compared to the average demand of the last five years. Effects of the COVID-19 pandemic on power demand and generation in several European countries were also investigated in [8]. During the pandemic, the power profile has changed, and peak hours have shifted in some regions. Power demand has increased for some consumers, such as hospitals and residential consumers, and decreased for other consumers, such as tourist sites and shopping centers.

Power demand variations during the pandemic in Ontario, Canada, were investigated in [9]. That research indicated the total power demand has reduced during the COVID-19 pandemic. In addition, results showed the power demand reduction was different in various regions and hours during the pandemic. Also, the effect of power demand in Japan was evaluated in [10]. Japan's power demand has reduced due to a slowdown in industrial activities during the COVID-19 pandemic. Power demand changes in Brazil due to this pandemic were considered in [11]. This research showed a decreasing trend in electricity consumption that varies from region to region: the southern of Brazil subsystem showed the most significant decline, -19% compared to the baseline. Southeast and Northeast regions were affected with a decrease of -15% and -14%, respectively. However, the northern region experienced the least variation with a 3% decline compared to the baseline.

Due to the vast effects of the COVID-19 pandemic on power demand, researchers have attempted to improve the performance of power grids during the COVID-19 pandemic. For instance, in [12], researchers improved the flexibility of power grid during the pandemic using multi-objective formulation. Also, in [13], researchers introduced a new demand forecasting algorithm during the COVID-19 pandemic in France. The model was developed based on the time series. Forecasting time series can be complex due to the inherent uncertainty nature of power grids. It seems very difficult to tell whether a series is stochastic or deterministic chaotic or some combination of these states. Therefore, novel methods for power demand forecasting should be introduced that are applicable in both COVID-19 pandemic and financial crisis. In this paper, two new methods are introduced.

Nowadays, complex relationships between demand and external factors for demand forecasting can be considered based on regression or machine learning models. Researchers in [14] reviewed energy demand forecasting methods published in 2005-2015. That paper indicated traditional power demand forecasting techniques such as econometric and time series models and soft computing methods such as neural network, support vector machine (SVM), and fuzzy logic have been used widely. Also, some papers used regression models for power demand forecasting. For support vector regression (SVR) models, different kernel functions were used to determine the SVR parameters. It was observed that different influential factors such as economic factors, industrial structure, population, import and export of energy were considered to develop forecasting models.

In [15], researchers were introduced monthly electric energy demand forecasting based on the feedforward neural network. In that paper, neural network was trained with normalized series. Two new series were used including the trend and the fluctuation around it. Neural networks were trained, separately. Also, four kinds of moving averages have been tested depending on the weights. It was observed that periodic components have already been eliminated from the trend series, meteorological and social factors can influence the trend behavior, and those factors usually repeat annually. However, neural networks have some limitations. For instance, their computation speed is very high because of distributed nature of network knowledge. Moreover, their structure, such as the number of hidden layers, learning rate, and so on, is also dependent on experience, which may effectively limit the interpretability.

In [16], a method is introduced for demand forecasting using interval time series. The paper compares vector autoregressive (VAR) and interval multi-layer perceptron (iMLP) methods. Both methods are used to forecast the demand in different periods of a day. For the VAR algorithm, two models were fitted every hour, one composed of the center and radius, and another one of the lower and upper bounds, according to the interval representation assumed by the interval time series (ITS) in the learning set. However, VAR may give a wide variety of different results, and a single measurement may provide limited information. For iMLP, the model composed of the center and radius is fitted. It was observed that ITS forecasting methods reduce forecasting risk during power system planning and operational decision making.

In [17], deep recurrent neural network (DRNN) model was used to forecast long-term power demand. DRNN has a better performance comparing to the traditional machine learning methods such as artificial neural network and linear regression models. Different DRNN variants were compared in the study for mid-term and long-term predictions of heating and electricity consumption. However, DRNN methods have high computational complexity and need an extensive dataset for training; therefore, they are not suitable for short-term power demand forecasting. Also, the long computation time and the convergence issue are other drawbacks of the model.

Although linear regression is still widely used in forecasting applications, other regression models such as quantile regression (QR) are recently used instead of linear regression in order to improve the regression model. QR method was used in [18] to forecast power demand. In QR, one or more quantiles of the dependent variable is calculated. QR usually has better performance and fewer predefined assumptions comparing to linear regression. QR is also used in cases where the aim is to obtain the conditional distribution of the dependent variable. SVQR is a kind of SVR that combines both QR and SVR. The SVQR is used to forecast power demand in [19].

However, there are some factors that are not still considered in power demand forecasting which might affect the accuracy of the forecasting model. Traditional models are usually developed for power demand forecasting over a long-term period, and it is necessary to develop a model for forecasting power demand during a day. Machine learning-based algorithms, usually need a big dataset for training. Also, the performance of these algorithms may be affected using outlier data. To address these research gaps and improve the accuracy of forecasting, a novel model is introduced in this paper.

This paper is organized in two main parts. In the first part, the power demand variation during the COVID-19 pandemic is investigated in the capital city of Tehran, Iran. This research compares power demand in Tehran during five consecutive years. In the second part, two power demand forecasting models applicable for pandemic periods are introduced. The first model is developed based on the principal component regression (PCR) analysis. In this model, power demand is estimated based on the power demand in the previous days and years considering the daily, annual and biennial power demand variation rates. The model is capable of forecasting the power demand in different normal or unpredictable conditions such as COVID-19 epidemics, economic collapse, etc. As mentioned before, machine learning models can be used to improve the performance of power demand forecasting. Therefore, the second model is introduced based on the SVR model. SVR is a kind of SVM applied to regression problems. SVR offers several advantages comparing to other approaches and provides broad application prospects in forecasting. SVR provides the flexibility to define how much error is acceptable in the model. SVM is a set of supervised learning methods used for classification, regression, and outliers' detection. The main advantage of support vector machines is their effectiveness in high dimensional spaces. Higher speed and better performance with a limited number of samples are other advantages of SVM. However, SVR models have some limitations. For instance, two hyperparameters need to be adjusted manually. Therefore, a novel method is introduced in this paper named as TWSVQR. The main contributions of this model are as follows:

- A new SVR model is developed based on QR.
- A novel twin support vector machine (TWSVM) model is used for the first time to forecast the power demand. Unlike conventional SVM models that only find one optimal hyperplane for separating the data points, TWSVM finds two non-parallel hyper-planes leading to more accurate results.
- The robust kernel function is used in the proposed model.
- Different factors for forecasting power demand are considered. These factors can be modified based on the situations or changed for different regions.
- A formula is introduced to calculate electricity prices.

The main aspects the study is summarized and depicted in Figure 1. The rest of the paper is organized as follows; in section 2, effects of the COVID-19 pandemic on the Tehran power grid are investigated. The proposed model for forecasting power demand is introduced in section 3. Numerical results and conclusion are presented in section 4 and 5, respectively.

2. POWER DEMAND VARIATIONS DURING THE PANDEMIC

COVID-19 pandemic was first reported in Iran on February 19, 2020. Until August 8, 2021, more than 95000 people have died of the infection. The government canceled public events and closed all public centers such as schools, universities, shopping centers, holy shrines and bazaars [20]. People stayed at home for the most of their time. The Iranian New Year (Nowruz) holidays,

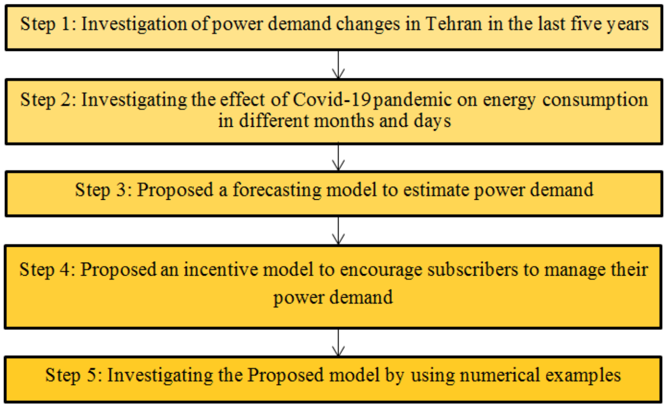

Fig. 1. aims of this research

which begin on March-19 and last until April-1 every year, were affected by the pandemic. The government limited the travel and encouraged people to stay at home. Since then, the reactions of people to the pandemic condition and the government policy have changed over time. Some activities returned to normal, and some restrictions were reduced or increased over time. The power demand has also been affected due to the new situations. Figure 2 shows the daily death due to the COVID-19 pandemic in Iran from February 19, 2020, to February 18, 2021. In this figure, label 1 on the horizontal axis corresponds to February 19, 2020, while the last label corresponds to February 18, 2021. It is observed that the number of deaths varies from day to day. The government changed limitations according to these fatalities. Some of these limitations were temporary, and some limitations are still ongoing. For example, for several months, intercity travel limitations were imposed, and then these limitations were reduced as the number of deaths from the pandemic decreased. People were also forced to stay at home after 10 p.m. All of these limitations affected people's lifestyles and activities. The tourism industry was almost shut down. It is expected that these variations will cause changes in power demand in Iran. In general, limitations were increased in Iran in three periods, temporary; between February and March 2020, in the middle of summer 2020, and the middle of autumn 2020. During these periods, the disease mortality was sharply increasing. Evalua-

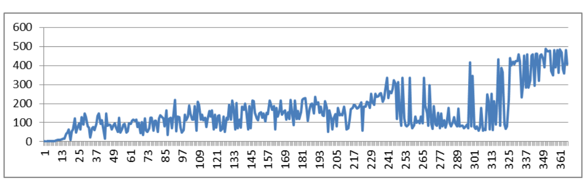

Fig. 2. daily death due to COVID-19 pandemic in Iran

tion of the power demand in Tehran is very important because Tehran is the biggest and the capital city in Iran, which has the most significant role in the country's economy. Tehran is also the largest energy consumer in the country. Moreover, the highest number of deaths due to COVID-19 was reported in Tehran. The historical electricity consumption data is gathered from [21]. Figure 3 shows the average peak power demand between 2016 and 2020 in Tehran. It is observed that the average monthly peak in 2019 is more than 2018, while the peak value in 2020 is lower than 2019. In some months of 2018, power demand has been less

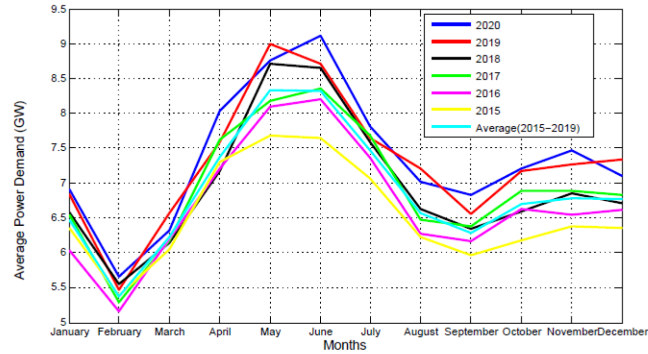

Fig. 3. average monthly peak load demand in Tehran in 5 recent years

than the corresponding months in 2017. In most months of 2018, Iran experienced a financial crisis. Thus, both the COVID-19 pandemic and the financial crisis might affect the power demand. Meanwhile, figure 3 indicates that the average monthly peak in 2020 is higher than the average monthly peak between 2015 and 2019. In addition, it seems that the COVID-19 pandemic has reduced the annual growth of the power demand. Table 1 shows the changes in power demand for all months between 2016 and 2020 compared to the previous year in percent. The power demand in February 2020 is 1.02% more than the power demand in February 2019. Also, the power demand in June 2020 is 2.59% less than power demand in June 2019. The table provides that in four months, including April, June, September, and January, power demand has decreased in 2020 compared to 2019. During these months, the government increased limitations because of the increase in deaths. This table provides that the number of months in 2018 and 2020 in which the growth of power demand has decreased compared to the similar months in the previous year is more than other years. It is worth to note that Iran has been in a financial crisis in 2018 and the COVID-19 pandemic in 2020, so this table shows that both the COVID-19 pandemic, and the financial crisis have affected the growth of power demand. Daily demand profiles for different days in

Table 1. Shape Functions for Quadratic Line Elements

	2020	2019	2018	2017	2016
February	1.02	3.86	0.6	8.48	-5.05
March	3.51	-1.4	4.91	2.42	-4.04
April	-3.69	6.99	-0.67	-0.45	2.54
May	5.94	5.71	-5.9	5.87	-1.32
June	-2.59	3.23	6.51	0.95	5.47
July	4.54	0.69	3.6	1.8	7.33
August	2.2	0.82	-1.34	4.38	4.25
September	-2.63	8.77	2.31	3.24	0.9
October	4.13	3.31	-0.61	3.59	3.23
November	0.39	8.82	-4.27	3.89	7.36
December	2.74	6.13	-0.67	5.32	2.56
January	-3.23	9.3	-1.61	3.05	4.2
Average	1.03	4.69	0.24	3.55	2.29

2018, 2019 and 2020 are presented in figure 4. In this figure, W.D

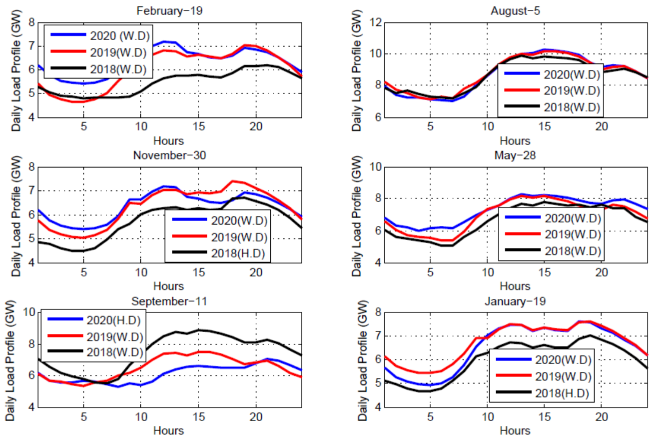

Fig. 4. daily power demand for different days since 2018

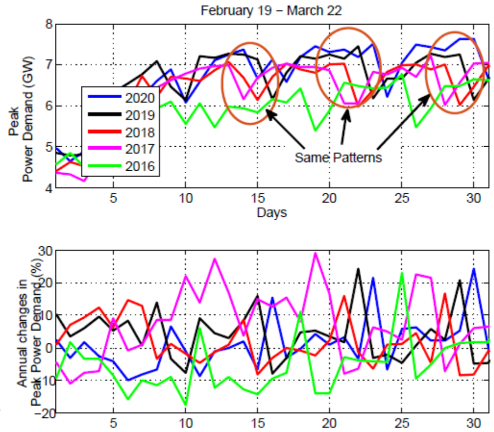

Fig. 5. peak power demand in the first period

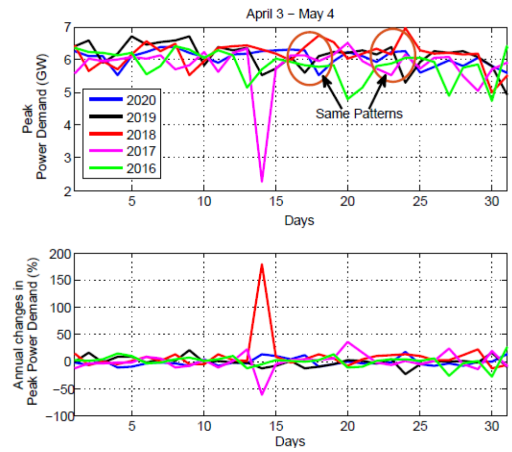

Fig. 6. peak power demand in the second period

refers to weekdays, while H.D refers to holidays. It is observed that the power demand profiles for different years are similar to each other. February 19 is investigated because the first COVID-19 disease in Iran was confirmed on February 19, 2020. It is observed that the power demand profiles in 2020 and 2019 are similar on this day, while they have grown significantly comparing to 2018. Thus, in this subfigure, the impact of the economic crisis is visible, but the effect of the pandemic is unclear. Also, it is observed that in November 30 afternoon, power demand in 2020 is lower than the same day in 2019, though it is higher than November 30, 2018. It should be noted that November 30, 2018, was a holiday, and usually, the power demand decreases on holidays. In this subfigure, effects of both the economic crisis and the pandemic are clear.

On September 11, daily power demand in 2020 is less than power demand in 2019 and 2018. It is observed that the power demand in 2020 is decreased compared to other years. On August-5, the demand did not considerably change during three years. Also, the power demand on May-28 did not noticeably differ between 2018 and 2020. This subfigure indicates that, by decreasing the COVID-19 pandemic mortality, the power demand has reached the same level as the last year. Therefore, it can be concluded that while the pandemic causes the power demand to decrease, the ending of limitations can also increase the power demand, rapidly. On January 19, the power demand in 2019 and 2020 were similar, and they were higher than a similar day in 2018. During these three days, many limitations were lifted by the government due to the reduced number of confirmed COVID-19 cases. The variations of the peak power demand at different monthly periods are also investigated in this study. The first period is the first month that the COVID-19 cases were confirmed in Iran. The last week of this period was the Iranian New Year holidays. The peak power demand and the variations compared to the same day in the previous years are shown in Figure 5. Power consumption patterns seem to be similar in 2018, 2019 and 2020. The second period is shown in figure 6. The first half of this period is the Iranian New year holiday. It can be seen that power demand decreased in 2020 compared to 2019. The third period is shown in figure 7. During this period, the number of confirmed COVID-19 cases increased sharply, and the Iranian government imposed many limitations. The peak power demand in 2020 in similar days decreased considerably compared to 2019, and in some days, it also decreased to the same level as 2018. These figures indicate that the COVID-19 disease has affected power demand in Tehran and caused a change in the monthly demand variation rate. Figure 8 shows the fourth period. In this period, many limitations were terminated, and people almost returned to a normal lifestyle. It is observed that the peak demand in 2020 increased during this period compared to the same period of previous years. As depicted in figures 5- 8, similar patterns are repeated in each year. These figures indicate same patterns are repeated on some days with a delay that are marked with brown circles in each figure. It is observed that these patterns are similar to each other for different days. Therefore, we conclude that the most significant impact of the economic crisis and the pandemic is on the variation rate of power demand. Actually, these factors do not change the power demand pattern. In other words, there is a relationship between power demands in different years. Thus, we can use historical power demand data to forecast future power demand, although the power demand prediction models must be modified considering the effect changes mentioned above. In the next section, two novel algorithms are introduced to estimate the power demand.

3. FORECASTING POWER DEMAND

Power demand variation during the pandemic in Tehran was investigated in the previous section. It is observed that the demand pattern during this pandemic is similar to the last years.

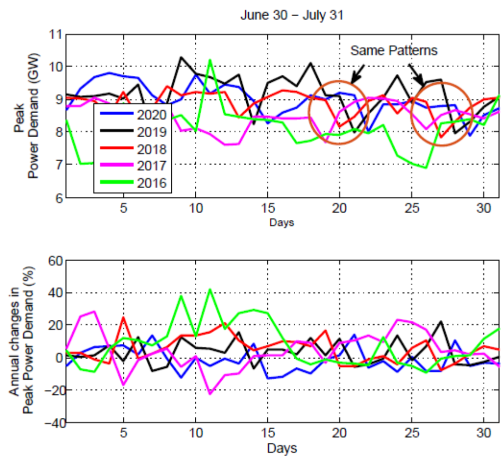

Fig. 7. peak power demand in the third period

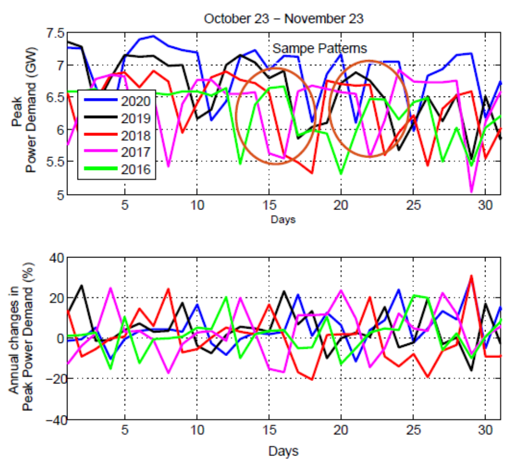

Fig. 8. peak power demand in the fourth period

In fact, the COVID-19 pandemic has affected the annual growth of energy consumption. Results in the previous section showed that it is necessary to consider the rate of power demand variation in different years. Therefore, in this section, two forecasting methods are introduced. The first method is developed based on the principal component regression (PCR), while the second is developed based on the twin support vector quantile regression (TWSVQR).

A. Power Demand forecasting based on the PCR

Regression analysis is a set of statistical processes for estimating the relationships among several variables. The most common form of regression analysis is linear regression, in which it a line that most closely fits the data according to a specific mathematical criterion is specified [22]. PCR is a regression technique based on principal component analysis. More specifically, PCR is used to estimate the unknown regression coefficients in a standard linear model. PCR is a powerful method to estimate power demand. Instead of regressing the dependent variable on the explanatory variables directly, the principal components of the explanatory variables are used as regressors in PCR. The principal components with higher variances are used as regressors. One significant application of PCR lies in overcoming the multicollinearity problem, which arises when two or more of the explanatory variables are close to being collinear. A main advantage of PCR is the availability of charts illustrating the data structure [23]. In this paper, new factors are presented for introducing a new forecasting model. Figure 9 shows the flowchart of the proposed model. The ideas behind the proposed model can be summarized as follows:

1. In two consecutive hours, many influential factors such as temperature and day type (holiday or workday) are usually similar or close to each other.
2. Usually, social limitations due to the COVID-19 pandemic or economic crisis are similar on two consecutive days (except the beginning day of the imposed limitations).
3. Investigation of the power demand variations in Tehran indicated that the power demand patterns on identical days in consecutive years are usually similar, and the difference between them can be obtained considering the annual (or biennial) growth rate.

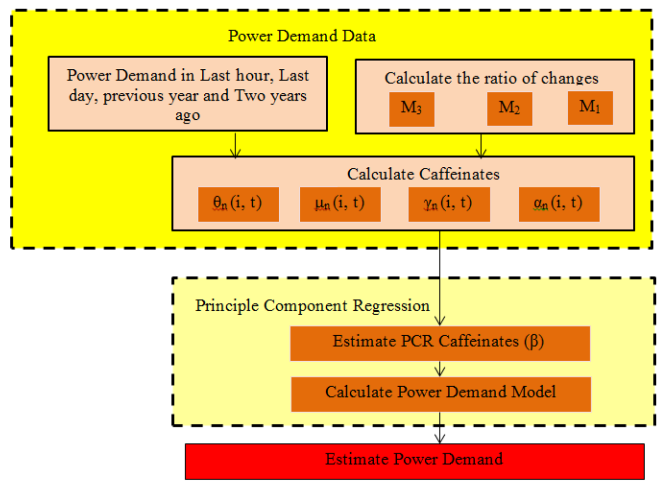

Fig. 9. Flowchart of the proposed PCR method

It is assumed that the power demand is estimated using following equation:

$$P_n(i,t) = \beta_1\alpha_n(i-1,t) + \beta_2\gamma_n(i,t) + \beta_3\mu_n(i,t) + \beta_4\theta_n(i,t-1) \quad (1)$$

where β_n is a coefficient and $\alpha_n, \gamma_n, \mu_n$ and θ_n are variables of the n^{th} observation. In addition, M1, M2 and M3 are adjustment coefficients defined as follows:

$$M_1 = \frac{\text{power demand in}(t-1)^{th}\text{hour}}{\text{power demand in } (t-1)^{th} \text{ hour previous day}} \quad (2)$$

$$M_2 = \frac{\text{power demand in}(t-1)^{th}\text{hour}}{\text{power demand in } (t-1)^{th} \text{ hour previous year}} \quad (3)$$

$$M_3 = \frac{\text{power demand in}(t-1)^{th}\text{hour}}{\text{power demand in } (t-1)^{th} \text{ hour intwo years ago}} \quad (4)$$

M1 is the daily power demand variation rate, M2 refers to the annual demand variation rate and M3 is the two-year power demand variation rate. For different observations, the Equation

(1) can be rewritten in matrix form as follows:

$$\begin{bmatrix} P_1(i,t) \\ P_1(i,t) \\ \vdots \\ P_n(i,t) \end{bmatrix} = \tag{5}$$

$$\begin{bmatrix} \alpha_1(i-1,t) & \gamma_1(i,t) & \mu_1(i,t) & \theta_1(i,t-1) \\ \alpha_2(i-1,t) & \gamma_2(i,t) & \mu_2(i,t) & \theta_2(i,t-1) \\ \vdots & \vdots & \vdots & \vdots \\ \alpha_n(i-1,t) & \gamma_n(i,t) & \mu_n(i,t) & \theta_n(i,t-1) \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{bmatrix} + \zeta$$

where n is the number of observations, ζ which is a random value with variance σ^2 , is the unavoidable error of the model. Equation (5) can be rewritten as follows:

$$Y = X\beta + \zeta \tag{6}$$

where

$$Y = \begin{bmatrix} P_1(i,t) \\ P_1(i,t) \\ \vdots \\ P_n(i,t) \end{bmatrix} = \tag{7}$$

$$X = \begin{bmatrix} \alpha_1(i-1,t) & \gamma_1(i,t) & \mu_1(i,t) & \theta_1(i,t-1) \\ \alpha_2(i-1,t) & \gamma_2(i,t) & \mu_2(i,t) & \theta_2(i,t-1) \\ \vdots & \vdots & \vdots & \vdots \\ \alpha_n(i-1,t) & \gamma_n(i,t) & \mu_n(i,t) & \theta_n(i,t-1) \end{bmatrix} \tag{8}$$

$$\beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{bmatrix} \tag{9}$$

$$var)\varepsilon) = \sigma^2 I_{n\times n} \tag{10}$$

The aim of the regression model is to find β . Solving Equation (6) using the least squares method, the optimal value for β is obtained:

$$\beta = (X^T X)^{-1} X^T Y \tag{11}$$

The application of Equation (11) might have some limitations. For instance, $(X^T X)^{-1}$ may be a non-invertible matrix. Therefore, the singular value decomposition (SVD) method is used assuming that $X = U\Delta V^T$, where the dimension of matrix U and V are $n \times 4$ and 4×4 , respectively. Here, Δ is a diagonal matrix where its elements are singular values (δ) that are listed in descending order.

$$U_{n\times 4} = [u_1, ..., u_4] \tag{12}$$

$$V_{n\times 4} = [v_1, ..., v_4] \tag{13}$$

$$\Delta = diag(\delta_1, ..., \delta_n) \tag{14}$$

Now, to calculate the coefficients based on PCR, it is assumed that:

$$W_k = X \times V_k \tag{15}$$

where k is the new dimension of the problem and must be less than 4. The value of β is estimated as follows:

$$\hat{\beta}_k = V_k \hat{\varphi}_k \tag{16}$$

where

$$\hat{\varphi}_k = (W_k^T W_k)^{-1} W_k^T Y \tag{17}$$

The optimal value for β is estimated from Equation (16)

B. power demand prediction by using TWSVQR

Generally, PCR has some limitations in selecting the optimal set of principal components for the model. Also, the applicability of PCR is based on the assumption of normality. The principal components are defined according to the maximization of classical variance, which is an optimal estimator of scale at the normal distribution. When data is impregnated with outlier information, the PCR may not be appropriate. Another problem arising in practice is that sometimes the data is inadequate. Actually, data can be missing due to different reasons. Underfitting and Overfitting are other issues in utilizing the PCR model. Overfitting happens when the details and noise in training data negatively impact the model's performance on new data. This means that the noise or random fluctuations in the training data is picked up and learned as real data by the model. Underfitting refers to a model that can neither model the training data nor generalizes to new data. Considering these imperfections, it seems necessary to use other forms of regression models. Investigation of power demand variations in Tehran showed that other some factors such as electricity price, weekday type and temperature might affect the power demand. Hence, machine learning models are appropriate and powerful tools for developing accurate demand forecasting models.

As mentioned before, new versions of SVM have been introduced recently to improve the model performance. TWSVM is a machine-learning algorithm that is developed based on SVM. It calculates a pair of non-parallel hyperplanes. The main advantage of TWSVM comparing to classic SVM is its fewer constraints, and consequently, less training time. Similar to SVM, TWSVM obtains the best classification based on an optimization tool. The objective function of quadratic programming corresponds to a particular class while its constraints are related to another class. In this section, we combine the SVQR model and TWSVM to introduce a novel algorithm named as TWSVQR. The proposed model is organized in four steps as follows:

Step 1: Introduce an SVQR formulation

Step 2: Introduce a TWSVM formulation

Step 3: Describe the proposed TWSVQR model

Step 4: Power demand forecasting using TWSVQR

Step 1:

The main objectives of SVQR are to forecast future cases calculating a regression model for the given data set $T = \{x_i, y_i\}_{i=1}^n$, where $x_i \in R^d$ and $y_i \in R$. For some scenarios, it is difficult, or even impossible, to regard linear functions between inputs and an output.

To solve this challenge, a nonlinear function, $m(x)$, is applied to perform the local polynomial regression which is defined as follows [24]:

$$f(x) = m(x) = w\psi(x) + b \tag{18}$$

where $\psi(x)$ is a mapping function defined by a kernel function, w is the weight vector, and b is the threshold. The SVQR model estimates $f(x)$ in the feature space for estimation of the τ^{th} quantile. Equation (18) can be considered as an optimization algorithm in which the optimal values for w and b for τ^{th} quantile, can be obtained using the follows optimization problem:

$$\min_{(w,b)} = \left(\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l} L_\tau(y_i - (w^T x_i + b))\right) \tag{19}$$

where $C > 0$ is a user-defined parameter, L is the pinball loss function as follows:

$$L_\tau(v) = \begin{cases} \tau v & v > 0 \\ (\tau - 1)v & O.w \end{cases} \tag{20}$$

Equation (19) is a standard form of SVM that can be converted to a Quadratic Programming Problem (QPP) by defining $\zeta = (\zeta_1, \zeta_2, ..., \zeta_l)$ and $\zeta^* = (\zeta_1^*, \zeta_2^*, ..., \zeta_l^*)$ as follows:

$$\min_{(w,b,\zeta,\zeta^*)} = \left(\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\tau\zeta_i + (\tau - 1)\zeta_1^*)\right) \tag{21}$$

Subject to:

$$y_i(w^T\psi(x) + b) \leq \zeta_i \tag{22}$$

$$((w^T\psi(x) + b) - y_i) \leq \zeta_i^* \tag{23}$$

$$\zeta_i^* \geq 0, \quad \zeta_i \geq 0 \tag{24}$$

Equations (22) (24) present the constraints of the optimization problem. These constraints are defined to prevent data points from falling out of the margin. QPP is a standard form of SVQR and can be calculated using its corresponding Wolfe dual problem.

Step 2:

The equation (21) and its constraints in (22) (24) are converted into two optimization problems. As mentioned before, the optimal problem in TWSVM is divided into two optimal subproblems: TWSVM1 and TWSVM2. These optimization subproblems are defined as follows [25]:
TWSVM1:

$$\min \frac{1}{2}\|K(A, C^T)u_1 + e_1 b_1\|^2 + c_1 e_2^T \delta \tag{25}$$

Subject to:

$$-(K(B, C^T)u_1 + e_2 b_1) + \delta \geq e_1 \quad \delta \geq 0 \tag{26}$$

TWSVM2:

$$\min \frac{1}{2}\|K(A, C^T)u_2 + e_2 b_2\|^2 + c_2 e_1^T \delta \tag{27}$$

Subject to:

$$-(K(B, C^T)u_2 + e_1 b_2) + \delta \geq e_2 \quad \delta \geq 0 \tag{28}$$

where K is the kernel function, and u_1 and u_2 are the normal vectors of two hyperplanes. Also, b_1 and b_2 are the offsets of two hyperplanes. C is the training sample points Matrix, and e_1 and e_2 are the unit column vectors. θ and δ are the slack variables. c_1 and c_2 are the penalty factors. In Equations (25) and (27), matrix A represents the training sample points of class '+1', and matrix B represents the training sample points of class '-1'. Each row in matrix A represents a sample point belonging to class '+1', while each row in matrix B represents a sample point belonging to class '-1'. In TWSVM, the testing sample point belongs to the class which hyperplane is close to it and is obtained as follows:

$$Label(x) = \arg\min_{k=1,2,...,K}\left(K(A, C^T)u_k + \frac{b_k}{\sqrt{u_k^T K(A, C^T)u_k}}\right) \tag{29}$$

Step 3:

A novel method is introduced in this step based on the descriptions in steps 1 and 2. First, it is noted that pinball loss function has an error for $v < 0$. Hence, the novel loss functions have been introduced in some recent researches. We use a new loss function introduced in [26], which is defined as follows:

$$L_\tau^\delta(u) = \max(-(1-\tau)(v + \tau\varepsilon), 0, \tau(v - (1-\tau)\varepsilon)) \tag{30}$$

In fact, Equation (30) is the new version of the pinball loss function based on the ε-insensitive factor that improves the model against outlier data. Then the optimal SVR model is defined in the form of TWSVM. The new method is named as TWSVQR, and defined as follows [26]:
TWSVQR1:

$$\min_{w^{(1}, b^{(1)}, \zeta}\left(\frac{1}{2}(Aw^{(1)} + e_1 b^{(1)})^T(Aw^{(1)} + e_1 b^{(1)}) + c_1 e_2^T \zeta\right) \tag{31}$$

subject to:

$$-(Bw^{(1)} + e_2 b^{(1)}) + \zeta + e_2\varepsilon \geq e_2 \tag{32}$$

$$-(Bw^{(1)} + e_2 b^{(1)}) + e_2 + \frac{\zeta}{\tau} + e_2\frac{\varepsilon}{\tau} \tag{33}$$

$$\zeta \geq 0 \tag{34}$$

TWSVQR2:

$$\min_{w^{(2}, b^{(2)}, \zeta}\left(\frac{1}{2}(Bw^{(2)} + e_2 b^{(2)})^T(Bw^{(2)} + e_2 b^{(2)}) + c_2 e_1^T \zeta\right) \tag{35}$$

subject to:

$$-(Aw^{(2)} + e_1 b^{(2)}) + \zeta + e_1\varepsilon \geq e_1 \tag{36}$$

$$-(Aw^{(2)} + e_1 b^{(2)}) + e_1 + \frac{\zeta}{\tau} + e_1\frac{\varepsilon}{\tau} \tag{37}$$

$$\zeta \geq 0 \tag{38}$$

Similar to standard SVR, constraints are defined to prevent data points from falling behind the margins. The optimal parameters of TWSVQR are obtained using the Lagrange method.

Step 4:

Now the TWSVRQ method is used to forecast the power demand. The main advantage of the proposed method is its flexibility. Based on the conditions, the input features can be changed. The features that are used for forecasting power demand on i-th day and t-th hour in this paper are listed as follows:

1. Power demand on i-th day and (t-1)th hour (previous hour)
2. Power demand on (i-1)th day and t-th hour (previous day)
3. power demand on i-th day and t-th hour on a similar day in last year considering average annual power demand changes

4. power demand on i-th day and t-th hour on a similar day in two years ago considering average annual power demand changes
5. Electricity price on i-th day and (t-1)th hour (previous hour)
6. Electricity price on (i-1)th day and t-th hour (previous day)
7. Temperature on i-th day and (t-1)th hour (previous hour)
8. Temperature on (i-1)th day and t-th hour (previous day)
9. Humidity on i-th day and (t-1)th hour (previous hour)
10. Humidity on (i-1)th day and t-th hour (previous day)
11. A binary factor for day's type. The number one is used for working days and the number zero is used for holidays.
12. A binary factor indicating unusual conditions. This factor is assumed one for normal days and zero for unusual days such as days during the COVID-19 pandemic or financial crisis.

Features 1 4 indicate the power demand in the previous days and hours. Electricity prices are used to consider demand response and encourage customers to manage their consumption. Environment temperature is also considered as an input because it plays an important role in energy consumption. In Iran, heating systems usually works with electrical energy; therefore, by increasing temperature, energy consumption increases (features 7 and 8). Humidity can be essential in some cities (features 9 and 10). Feature 11 is used because the energy demand can be different for different day types. As some researches point, unusual conditions may change power demand. Therefore, feature 12 is considered to improve the power demand estimation by adding uncertainty factors to the model.

It is worth noting that when the electricity price is increased, people reduce their power demand and shift some loads such as dishwashers and washing machines from peak hours to other times. Therefore, features 5 and 6 have important roles in power demand management. The energy consumption of cooling systems depends on the temperature. On hot days and hours, these devices consume more energy. Also, heaters may be used for heating on cold days. On hot days and hours, heaters consume more energy. Therefore, we need to consider features 7 and 8 in our model. Figure 10 indicates the flowchart of the proposed algorithm. When the power demand for a spatial hour is obtained, the electricity price can be calculated as follows:

$$price(i,t) = \frac{P(i,t)}{P(i-1,t)} \times price(i-1,t) \times \Lambda \qquad \textbf{(39)}$$

Equation (39) indicates that the electricity price is related to power demand and the price at the previous day. Here, Λ is a regulating factor that can be obtained as follows:

$$\Lambda = \frac{price(i,t-1)}{price(i-1,t-1)} \qquad \textbf{(40)}$$

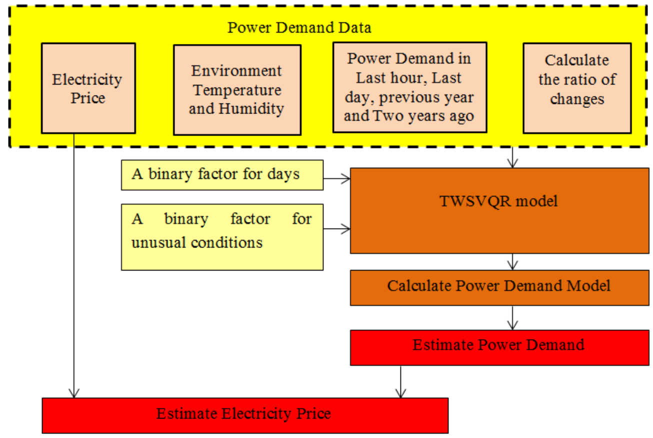

Fig. 10. the flowchart of the proposed TWSVQR algorithm

4. NUMERICAL EXAMPLES

The aim of this section is to investigate the performance of the proposed algorithms to forecast power demand in Tehran. Power demand data and electricity prices are collected from [21]. Historical temperature data are gathered from [27]. Power demand, electricity prices, and temperature data are used as input of algorithms. For both algorithms, the power demand data from 50 days is used as training data. After training the PCR algorithm, PCR coefficients are obtained and shown in table 2. It is observed that these coefficients may be changed for different days and grids.

Figure 11 indicates training data and estimated values for both PCR and TWSVQR algorithms on November 14, 2020. In this figure, blue circles showed training data in 2020, and cyan circles showed training data in 2019, and magenta circles showed training data in 2018. The annual growth rates of power demand are evident in training data. The values of these rates for November are shown in table 1. This figure clearly shows that the annual growth rate should be considered in the power demand forecasting model. The red line indicates the forecasted value of the proposed PCR model. It can be seen that this model has been able to calculate the value of power demand. However, the green line illustrates actual power demand, and it is observed that we need a more accurate model for forecasting power demand. The black line shows the TWSVQR model. This model has been able to estimate power demand more accurately. Figure 12 indicates the effect of quantile regression. This figure shows that outlier data can be visualized using quantile regression. The data points above or below the red lines are outlier data. The range of outlier data points can be changed by selecting different quantiles.

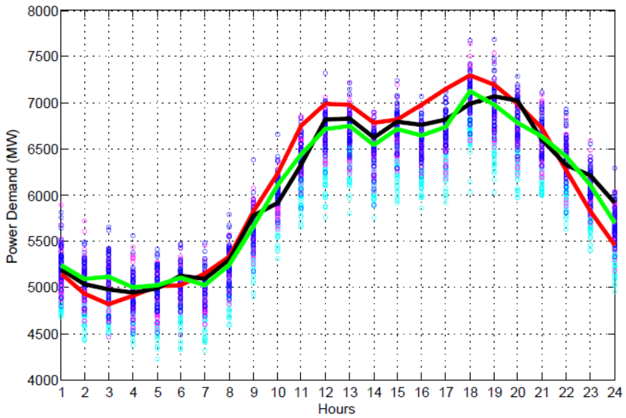

Fig. 11. training data and estimated values

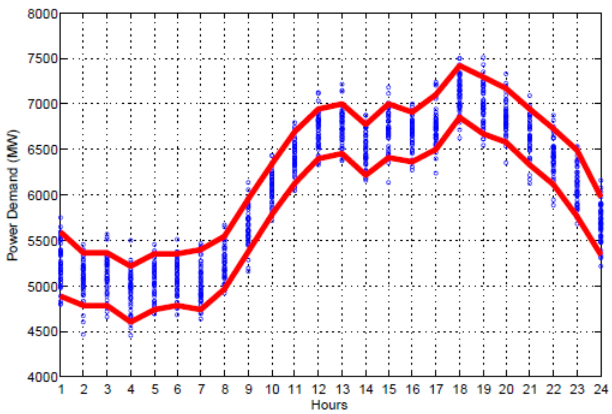

Fig. 12. Outlier detection using quantile regression

Table 2. coefficients of the PCR model

Date	β_1	β_2	β_3	β_4
February 22, 2021	1.094	0.986	0.8765	1.036
November 14, 2020	1.089	1.024	0.8641	1.029

Table 3 provides the actual power demand, estimated power demand, and absolute errors in percent for both algorithms. In this table, actual power demand data is collected from [21], and second and third columns are calculated using our algorithms. It is observed that the maximum errors for both algorithms are less than 10%. In addition, the average error for the PCR algorithm is 3.15% and for the TWSVQR algorithm is 1.61%. Therefore, the performance of the TWSVQR algorithm is better than the PCR algorithm. In addition, it is observed that the error of the algorithms is different for various days.

Table 4 provides the actual power demand, estimated power demand, and relative error in percent for different hours on February 22, 2021, for both PCR and TWSVQR algorithms. It is observed that the maximum relative errors for both algorithms are less than 10 percent. The average error for the PCR algorithm is 4.88%, while the average error for the TWSVQR algorithm is 2.05%. These results show that the performance of the TWSVQR algorithm is better than the performance of the PCR because more features are used to predict power demand in the TWSVQR algorithm. Tables 3 and 4 provide that both algorithms can forecast power demand, but the performance of the TWSVQR algorithm is better than PCR.

Table 5 provides the average errors for some different days. Details of these days are shown in this table. It is observed that some days are holidays and others are weed days. This table provides that both proposed algorithms can predict power demand during the pandemic and normal days, but the performance of the TWSVQR algorithm is better than the PCR. This table shows that the performance of the TWSVQR algorithm is better for unusual days. In addition, in figure 5, the performances of both proposed algorithms are compared with the SVQR algorithm that was introduced in [19], and the feedforward neural network (FNN) algorithm that was introduced in [15]. It is observed that the proposed TWSVQR has a better performance than SVQR. The performance of the proposed PCR algorithm and the SVQR is almost the same. However, PCR is a simple and low-computational algorithm and has better performance during the pandemic. FNN algorithm has the worst performance. In [19], researchers were used a standard pinball loss function while we use a novel loss function that is robust against outlier data.

Table 3. hourly power demand forecasting and errors for both algorithms for November 14, 2020

Hour	Actual power demand	PCR Estimated power demand	TWSVQR Estimated power demand	PCR Relative Error (%)	TWSVQR Relative Error (%)
1	5,235	5148	5198	1.66	0.71
2	5,097	4926	5036	3.35	1.20
3	5,118	4816	4979	5.9	2.72
4	5,000	4912	4939	1.76	1.22
5	5,025	5016	4987	0.18	0.76
6	5,104	5026	5126	1.53	0.43
7	5,018	5148	5097	2.59	1.57
8	5,241	5326	5292	1.62	0.97
9	5,666	5819	5776	2.7	1.94
10	6,107	6237	5913	2.13	3.18
11	6,445	6753	6329	4.78	1.80
12	6,710	6983	6816	4.07	1.58
13	6,744	6982	6823	3.53	1.17
14	6,538	6784	6621	3.76	1.27
15	6,719	6820	6798	1.51	1.18
16	6,645	6980	6761	5.04	1.75
17	6,733	7152	6819	6.22	1.28
18	7,122	7298	6987	2.47	1.90
19	6,978	7189	7069	3.02	1.30
20	6,784	6983	7028	2.93	3.60
21	6,630	6721	6598	1.37	0.48
22	6,419	6265	6325	2.4	1.46
23	6,112	5820	6216	4.78	1.70
24	5,702	5462	5917	4.21	3.77

Table 4. hourly power demand forecasting and errors for both algorithms for February 22, 2021

Hour	Actual power demand	PCR Estimated power demand	TWSVQR Estimated power demand	PCR Relative Error (%)	TWSVQR Relative Error (%)
1	5659	5216	5432	7.83	4.01
2	5501	5129	5329	6.76	3.13
3	5416	5046	5284	6.83	2.44
4	5406	5098	5324	5.70	1.52
5	5499	5098	5309	7.29	3.46
6	5447	5129	5329	5.84	2.17
7	5736	5369	5468	6.40	4.67
8	6249	5760	6106	7.83	2.29
9	6733	6584	6687	2.21	0.68
10	6843	6625	6718	3.018	1.82
11	7066	6726	6918	4.81	2.09
12	7288	7073	7152	2.95	1.87
13	7282	7103	7199	2.46	1.14
14	7003	7160	6921	2.24	1.17
15	7114	6729	6983	5.41	1.84
16	7028	7124	6986	1.37	0.60
17	6985	6520	6857	6.66	1.83
18	7043	6533	6979	7.24	0.91
19	7320	7038	7216	3.85	1.42
20	7195	7639	7462	6.17	3.71
21	7021	6831	6919	2.71	1.45
22	6798	6909	6629	1.63	2.49
23	6487	6219	6354	4.13	2.05
24	6080	6355	6102	4.52	0.36

Table 5. Compare the performance of both proposed algorithms for different days

Date	Day	Average Error PCR (%)	Average Error TWSVQR (%)	Average Error SVQR (%)	Average Error FNN (%)
February 19, 2020	Tuesday	5.32	2.36	5.37	5.79
February 19, 2019	Wednesday	3.75	1.29	3.63	4.92
April 3, 2020	Friday	4.19	1.97	4.43	4.29
April 3, 2019	Wednesday	3.72	1.42	3.79	4.42
June 30, 2020	Tuesday	7.63	4.31	7.83	8.53
June 30, 2019	Sunday	4.34	2.85	3.92	4.78
October 23, 2020	Friday	4.74	2.84	5.18	5.62
October 23, 2019	Wednesday	3.28	1.96	3.09	4.37
November 12, 2020	Friday	5.24	3.75	5.87	5.98
November 12, 2019	Wednesday	4.52	2.84	4.29	4.86
December 4, 2020	Saturday	5.17	3.49	5.31	5.74
December 4, 2019	Thursday	3.34	1.91	2.88	3.45

5. CONCLUSION

This paper has two purposes. The first purpose is to investigate the effect of the COVID-19 pandemic on power demand in Tehran. The second one is to introduce novel methods for forecasting power demand. Power demand variations between 2016 and 2020 are investigated. This paper indicates that both the COVID-19 pandemic and economic crises affect power demand. During the pandemic, the power demand is affected by governmental limitations. Results indicate annual power demand growth is reduced during the pandemic and economic crisis. In 2018, Iran was in a financial crisis, and in 2020, the COVID-19 pandemic affected Iran. The average power demand growth in 2018 is 0.24% and is less than in 2019 and 2017. Also, results indicate the average power demand growth in 2020 is 1.03% and less than in 2019. Although power demand is affected by the pandemic and financial crisis, the power demand pattern is almost similar on the same days. Our study illustrates that to estimate the power demand, the rate of power demand changes in the different years must also be considered. In this paper, two models are introduced to forecast power demand. The first model is developed based on PCR. This model considers power demand in the previous days and hours by considering daily, annual, and biannual power demand variation rates. The second model is developed based on TWSVQR. In this model, a new loss function is used to robust the model against outlier data. This model considers different factors such as electricity price and air temperature and humidity to estimate power demand. Also, this model can be modified for considering unusual conditions such as the COVID-19 pandemic. In the simulation results, we investigate the performance of our algorithms to predict power demand in Tehran. It is observed that the average errors for TWSVQR, PCR, SVQR, and FNN are 2.58%, 4.60%, 4.63%, and 5.23%, respectively. Our proposed TWSVQR has the best performance because it uses a novel loss function that is robust against outlier data. In addition, TWSVQR needs less data to train. Therefore, we can conclude, the main advantage of this model is its flexibility and robustness.

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