Sustainable Cities and Society 95 (2023) 104623

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Energy demand forecasting in seven sectors by an optimization model based on machine learning algorithms

Majid Emami Javanmard [a,b,c], S.F. Ghaderi [a,b,*]

[a] School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran
[b] Research Institute for Energy Management and Planning, University of Tehran, Tehran, Iran
[c] Faculty of Engineering and Applied Science, University of Regina, Regina, Saskatchewan, S4S 0A2, Canada

ARTICLE INFO

Keywords:
Energy consumption
Energy demand management
Forecasting
Machine learning
Mathematical Programming
Optimization Model

ABSTRACT

With the growth of population, many countries face the challenge of supplying energy resources. One approach to managing and planning these resources is to predict energy demand. This study presented an integrated approach by applying six Machine Learning (ML) algorithms (ANN, AR, ARIMA, SARIMA, SARIMAX, and LSTM) and mathematical programming to predict energy demand in Iran up to 2040. The data relating to electricity generation and fuel consumption in power plants, electricity imports and exports, and seven major energy-consuming sectors in Iran (residential, commercial, industrial, transportation, public, agriculture, and others) are collected. The data employed to forecast energy demand in each sector with ML algorithms and prediction accuracy indices evaluated the algorithms' prediction accuracy in every sector. Then, the optimization model for prediction accuracy improvement is introduced. The ML algorithms results are employed as inputs to the integrated model and executed by two PSO and Grey-Wolf Optimizer algorithms for different sectors. The energy demand in these seven sectors until 2040 is predicted, and five prediction accuracy metrics are used to validate the integrated optimization results. The outcomes of the proposed method in all sectors reflect its more accurateness than ML algorithms, such that the MAPE index equals 0.002–0.012 and 0.004–0.013 for the proposed model executed by the PSO and Grey-Wolf Optimizer algorithms. In general, the PSO algorithm indicates a 75.65% growth in the total energy demand of all sectors, and the Grey-Wolf Optimizer algorithm forecasts a 82.94% growth.

1. Introduction

Several countries face challenges related to energy resource supply. The increase in population and economic growth of countries has led to a rise in energy consumption, which has created several challenges and problems for governments and nations. Energy consumption has increased significantly due to various factors in different parts of the world. According to the Global Energy Statistical website, energy consumption worldwide has increased by approximately 70% from 1990 to 2020, and Iran is the ninth-largest energy consumer in the world (Available on Global Energy Statistical, Website). According to the Statistics Organization of Iran, energy consumption has increased by 100% from 1990 to 2000, then by 104% from 2000 to 2010, and 40% from 2010 to 2018 (Statistical Center of Iran, 2017). As energy consumption continues to increase, it might significantly affect countries' economic growth and political conditions, further highlighting the need to develop an accurate model for energy consumption prediction (Lee & Tong, 2012). Therefore, energy consumption prediction in different sectors can help better management and decision-making of governments and energy-producer companies (Peng, Wang, Xia & Gao, 2022). In most countries, the three main sectors are energy consumers, housing, industry, and transportation (Somu, MR & Ramamritham, 2021). In recent years, several investigations have been performed to predict energy consumption in different sectors, and different data, different time-series, machine learning, and hybrid algorithms with different prediction accuracies have been employed to forecast energy consumption.

Typically, the first component impacting the performance of prediction algorithms is tied to the applied data, which can positively or negatively influence prediction accuracy. (Wang, Li & Li, 2018) employed the historical data of energy consumption in India and China to predict energy demand with time series algorithms. To predict energy

* Corresponding author.
E-mail address: ghaderi@ut.ac.ir (S.F. Ghaderi).

https://doi.org/10.1016/j.scs.2023.104623
Received 27 October 2022; Received in revised form 9 April 2023; Accepted 29 April 2023
Available online 2 May 2023

consumption in the residential sector, (Wen, Zhou & Yang, 2020) utilized the energy consumption variables of different types of buildings. (Jnr, Ziggah & Relvas, 2021) used the historical data series on energy consumption to implement a hybrid approach and predict electricity demand in Ghana. Climate change and energy consumption variables were used in Liu et al. (2021) study for predicting energy demand in the commercial and residential sectors. (Ağbulut, 2022) considered the population, GDP, CO2 emission, and energy consumption variables as inputs to the ANN and SVM algorithms to predict energy consumption and CO2 emission in the transportation sector. According to another study presented in 2009, energy consumption in Turkey was predicted until 2020 using ANN with GDP and energy consumption variables in four sectors (Hamzaçebi, 2007). In another study, a combination of ARIMA and SVR algorithms has been applied to predict electricity consumption in Turkey for a long time with population, GDP, energy import and export, and energy consumption (Kaytez, 2020). Considering the present literature, the data used for predicting energy demand fall into two categories: historical data collected for the implementation of time series algorithms and GDP, population, and energy consumption data applied for implementing some algorithms like ANN, LSTM, and SVM. However, population-related data are collected every five or ten years in some developing countries, such as Iran (Available, at). Hence, there is a gap in the literature that can be bridged by finding alternative variable(s) for the population in predicting energy demand with machine learning algorithms.

In one of the first investigations in the occupation of energy consumption prediction, a case study on electricity consumption in Iran's agricultural sector in the years between 1981 and 2005 has been presented, which has used genetic and ANN algorithms to predict energy consumption (Azadeh, Ghaderi, Tarverdian & Saberi, 2007). In Azadeh, Ghaderi and Sohrabkhani (2008), in order to predict the consumption of electricity in Iran monthly, the ANN algorithm has been used based on a multilayer network for 131 months. Due to the high energy consumption in the transportation sector, in Zhang, Mu, Li and Ning (2009), a model was developed using energy consumption data between 1990 and 2006 and the partial least square regression (PLSR) method to predict energy consumption in 2010, 2016, and 2020 in China Transportation sector. In another study, three-time series algorithms have been used to predict energy consumption to predict crude oil and gas consumption for electricity generation in India (Kumar & Jain, 2010). According to Zhang and Wang (2012), electricity consumption data for 1983–2003 were collected to provide a long-term and annual projection of urban electricity consumption. Fuzzy Wavelet algorithms were used to predict electricity consumption in high-consumption cities. In Chen and Yu (2014), four algorithms, including ANN, SVR, AR, and AR-Kalman, are used to predict the energy production of wind turbines in a short time by analysing wind speed data. In Wang, Du and Wang (2020), the LSTM algorithm has been employed to predict energy consumption for a long time. LSTM has been shown to provide higher prediction accuracy than other algorithms based on comparing results with different algorithms. Energy consumption prediction is also essential for managing smart power grids. In Dubey, Kumar, García-Díaz, Sharma and Kanhaiya (2021), ARIMA, SARIMA, and LSTM algorithms have been applied to predict electricity consumption daily to reduce power outages and increase awareness of electricity consumption. In another study, the SARIMAX algorithm was utilized to indicate energy consumption in Japan. This study shows that the SARIMAX algorithm can be used for any load prediction problem (Elamin & Fukushige, 2018). In Peng et al. (2022), the LSTM algorithm has been employed to forecast energy consumption and increase prediction accuracy compared to previous studies. This study's results revealed the proposed algorithm's high forecast accuracy. In another research, Elman Neural Network and Genetic algorithm have been operated to forecast power consumption in public buildings (Ruiz, Rueda, Cuéllar & Pegalajar, 2018). In Research (Albuquerque, Cajueiro & Rossi, 2022), ML algorithms have been used to forecast power consumption in Brazil.All in all, different studies have employed time series algorithms and machine learning to predict energy demand in a certain sector and examined the performance of algorithms just for a single sector. However, since the type, trend, and volume of the data on energy consumption differ in various sectors, it is possible to evaluate the performance of algorithms in predicting energy demand in different sectors. Besides, sector-separated predictions can provide policy-makers with advantages to make minute decisions for advancing toward sustainable societies.

In addition to different algorithms applied to predict energy consumption in various studies, the methods of combining algorithms and models for optimizing prediction accuracy are used in multiple studies to improve prediction accuracy. In Ardakani and Ardehali (2014), annual data for energy consumption prediction in Iran and the United States from 1967 to 2009 have been collected, and electricity consumption from 2010 to 2030 has been predicted using the ANN algorithm and optimization by improved particle swarm optimization (IPSO). In another study, machine learning algorithms have been applied to predict energy consumption in the residential sector. Then, a new approach has been proposed by combining machine learning algorithms, which has provided more optimal and accurate results compared to the implementation of algorithms individually (Chou & Tran, 2018). In general, different methods are employed to solve optimization problems. In Ye, Dang, Ding and Yang (2019), the discrete grey model (DGM) has been applied to optimize the results of energy consumption prediction. In Jayabarathi, Raghunathan, Adarsh and Suganthan (2016), it was indicated that the grey wolf optimizer (GWO) method could be applied to solve an economic problem. Study (Javanmard & Ghaderi, 2022) presents a hybrid model with nine machine-learning algorithms and an optimization model for greenhouse gas emissions. Study (Javanmard, Tang, Wang & Tontiwachwuthikul, 2023) presents a hybrid model to predict energy demand and CO2 emissions in the transportation sector. Regarding the literature on hybrid algorithms to forecast energy demand, there exists a capacity to improve the prediction accuracy of algorithms. Also, it's possible to analyse the performance of the hybrid algorithms with different data to provide adequate results for energy demand management. Some of the studies in energy consumption prediction are presented in Table 1 as the following.

The originalities of this research are centralized on three aspects concerning the present gaps in the literature on energy demand prediction. In the first step, this research endeavors to identify and apply a suitable alternative to fill the present gap in the data, like population, in predicting energy demand in some developing countries, such as Iran. In the second step, it seeks to predict energy demand in significant energy-consuming sectors in an integrative way using different machine learning algorithms. The purpose is to obtain high-accurate results and evaluate the performance of algorithms with respect to the distinct data type, volume, and linearity/nonlinearity in different energy-consuming sectors. As the third originality of this research, machine learning algorithms are combined with an energy-predicting optimization model, whose prediction accuracy can be improved, and the performance of the hybrid approach is evaluated according to the various data in seven sectors. The originalities of this research include the following:

- By addressing the difficulties caused by the lack of specific data types in developing countries like Iran, this research addresses a significant gap in the literature on energy demand prediction. In particular, the present research differs from other studies in that it excludes population and GDP statistics from the energy consumption forecasting. Instead, a comprehensive dataset is gathered and used as the input for machine learning algorithms. This dataset includes energy generation rates in power plants, energy import and export rates, GHG emissions, and energy consumption data in seven sectors: residential, commercial, industrial, public, transportation, agricultural, and other sectors.

Table 1
Energy Consumption Forecasting Models Review.

Literatures	Energy Consumption							Country	Data-Set Collection	Scope	Methods		
	Residential	Industrial	Commercial	Public	Transportation	Agriculture	Other				Machine Learning Algorithms	Mathematical Programming	Hybrid Model
(Hamzaçebi, 2007)	*	*	–	–	*	*	–	**Turkey**	**1990–2004**	**Annual**	**ANN**	–	–
(Zhang et al., 2009)	–	–	–	–	*	–	–	**China**	**1990–2006**	**Annual**	**Partial Least Square Regression**	–	–
(Kumar & Jain, 2010)	–	–	–	–	–	–	**Total**	**India**	**1970–2006**	**Annual**	–	–	**Grey-Markov Model**
(Zhang & Wang, 2012)	–	–	–	–	–	–	**Total**	**China**	**1983–2003**	**Annual**	**ANN**	–	**Fuzzy Wavelet Neural Network (FWNN)**
(Wang et al., 2020)	–	–	–	–	–	–	*	–	**March 2018 to July 2018**	**Monthly**	**LSTM, ARMA, ARFIMA, BPNN**	–	–
(Ardakani & Ardehali, 2014)	–	–	–	–	–	–	**Total**	**Iran, USA**	**1967–2009**	**Annual**	**ANN**	–	**ANN-PSO, ANN-IPSO, ANN-GD**
(Chou & Tran, 2018)	*	–	–	–	–	–	–	**Taiwan**	–	**Hourly**	**ANN, ARIMA, LR, SVM**	–	–
(Ye et al., 2019)	–	–	–	–	–	–	**Total**	**China**	**1993–2015**	**Annual**	–	–	**Optimized Discrete Grey Model**
(Kaboli, Selvaraj & Rahim, 2016)	–	–	–	–	–	–	**Total**	**Iran**	**1992–2013**	**Annual**	**Artificial Cooperative Search (ACS)**	–	–
(Yuan et al., 2016)	–	–	–	–	–	–	**Total**	**China**	**1965–2014**	**Annual**	**ARIMA**	–	**Grey Model-ARIMA**
(Dong, Li, Rahman & Vega, 2016)	*	–	–	–	–	–	–	**USA**	–	**Hourly**	**ANN, (SVR), (LSSVM)**	–	*
(Barak & Sadegh, 2016)	–	–	–	–	–	–	**Total**	**Iran**	**1990–2008**	**Annual**	**ARIMA**	–	**ARIMA–ANFIS**
(Wang, Luo, Zhao & Sun, 2018)	–	–	–	–	–	–	**Total**	**China**	**1980–2016**	**Annual**	**SVM**	–	**AMVO-SVM**
(Katsatos & Moustris, 2019)	*	–	–	–	–	–	–	**Greece**	–	**Hourly**	**ANN**	–	–
(Zhang & Guo, 2020)	*	–	–	–	–	–	–	**China**	–	**Hourly**	–	–	**(CGANs), (MPGA), (IDA)**
(Gao, Ruan, Fang & Yin, 2020)	*	–	–	–	–	–	–	**China**	–	**Hourly**	**LSTM, CNN**	–	–
(Fan, Wei, Li & Hong, 2020)	–	–	–	–	–	–	**Total**	**Australia**	–	**Daily**	**AR**	–	**EMD-SVR-PSO-AR-GARCH model**
(Bolandnazar, Rohani & Taki, 2020)	–	–	–	–	–	*	–	**Iran**	–	–	**SVR, RBF, MLR**	–	–
(Dong et al., 2021)	–	–	*	–	–	–	–	**China**	–	**Hourly**	**ANN, SVR, MLR**	–	–
(Azadeh et al., 2008)	–	*	–	–	–	–	–	**Iran**	**1979–2003**	**Annual**	**ANN**	–	–
This Research	*	*	*	*	*	*	*	**Iran**	**1990–2018**	**Annual**	**ANN, AR, ARIMA, LSTM. SARIMA, SARIMAX**	*	**Machine Learning Algorithms + Mathematical Programming**

- This study makes individual predictions for the energy consumption in seven sectors in the second step. This strategy offers a useful instrument for managers and politicians in energy demand management to make informed decisions. Also, six machine learning methods are used in this study to forecast the energy demand in these sectors. As the type, amount, and linearity/nonlinearity of each sector's energy consumption statistics vary, several data sets are used to assess the algorithms' performance to achieve high-accuracy predictions.
- The next stage in this research uses a unique strategy by combining mathematical modelling and machine learning techniques to improve the accuracy of energy demand prediction. This method represents one of the first studies to use a hybrid technique to predict energy consumption. The optimization model is developed to prevent future variations in the prediction outcomes. The suggested model, built from the existing literature, is implemented using the PSO and GWO algorithms to ensure that the prediction results stay consistent going forward. The performance of the hybrid model is then assessed under various circumstances, taking data fluctuations across seven energy-consuming sectors into account.
- In the end, after predicting energy demand in seven sectors by 2040 using a hybrid model and machine learning algorithms, the suggested technique is assessed for its validity and robustness using five prediction accuracy metrics. The findings of this study can help decision- and policy-makers in the field of sustainable energy management and planning to make well-informed choices and implement sensible measures. This work adds to the body of knowledge by presenting an original and trustworthy method for forecasting energy demand, which can aid in achieving a sustainable development agenda.

The rest of this article is organized as follows. The methods used in this study are described in detail in Section 2. Section 3 presents the energy demand projections for seven sectors through 2040 and the accompanying prediction accuracy findings. Section 4 provides recommendations for managing energy demand in each sector after examining forecast performance and analysing the energy demand projection findings for 2040. The work is concluded in Section 5, which also suggests possible future research areas.

2. Material and methods

This study proposed a mathematical model based on the ML algorithm to accurately forecast the energy consumption of different sectors in Iran until 2040. At first, the data associated with the energy generation power plants and seven energy-consuming sectors in Iran between 1990 and 2018 were collected. The energy consumption rate in the residential, industrial, commercial, public, transportation, and agricultural sectors, besides the energy consumption of other sectors regarded as an inclusive domain called others, were considered. In the first step, the energy consumption of every sector was predicted by six machine learning algorithms (AR, ARIMA, SARIMA, SARIMAX, and ANN). Since machine learning algorithms present distinct performance and prediction accuracy with different data, several algorithms were employed concerning the data's type, volume, linearity, and non-linearity. Next, five prediction accuracy indices were used to examine every ML algorithm's prediction accuracy in each energy-consuming sector. Afterward, the mathematical model with a prediction error minimization objective was presented, and the ML algorithms' outputs were employed as input data to the mathematical model. Considering the performance of metaheuristic algorithms in solving optimization models, the present study employed two PSO and Grey-Wolf Optimizer, the two most applied and desirable algorithms, to implement its model. These two algorithms implemented the optimization model to forecast energy demand in seven sectors. Afterward, the results were evaluated by five prediction accuracy indices and compared with the results of the ML algorithms in terms of their accuracy. Lastly, the energy consumption in every sector until 2040 was predicted. Fig. 1 illustrates the general process of this study.

2.1. Data pre-processing

In the present study, various energy data between 1988 and 2018, related to the practical annual energy production capacity of ten types of power plants (heater, gas, combined cycle, diesel, hydro, nuclear, wind, solar, heat recovery, biogas burner), the annual export and import of energy, and the amount of electricity consumed in seven sectors of residential, commercial, industrial, public, transportation, agriculture, have been extracted from the databases of the Ministry of Energy of Iran (Iran Ministry of, Energy). Previous studies extensively used the GPD and Population data for predicting energy consumption. However, this research uses the energy production data set. The correlation between energy production in power plants and GDP is high, and it can negatively affect prediction accuracy, so the GDP data is disregarded due to its correlation with the energy production data in power plants. Moreover, based on the announcement of the Statistical Centre of Iran (Available, at), the population data are collected every five years in Iran; for this reason, the population data is ignored too. Besides, the data volume was smaller than the examined literature. The extracted data for each sector were presented by year in Appendix A. The amount of energy consumption, energy production, greenhouse gas emissions, and fossile feul consumption in power plants for 29 years in the seven studied sectors in Iran is indicated in Fig. 2.

According to the collected data for 29 years, the highest energy consumption has been in the residential and industrial sectors. The agricultural, public and commercial sectors are also in the next energy consumption ranks, and the "Other" and transportation sectors also had the lowest energy consumption. In general, energy consumption has increased 5.75 times over 29 years. Then, after implementing the prediction algorithms, the results of the ML algorithms were collected and used as input data for the optimization model to forecast energy demand in each sector. The data of this sector are presented in Appendix B.

2.2. Machine leaning algorithms

Various algorithms are employed in energy research to predict various industries. In the present investigation, six commonly used algorithms from earlier research were utilized to predict power consumption in seven areas. Energy demand has been predicted using the ANN, LSTM, AR, ARIMA, SARIMA, and SARIMAX algorithms for 22 years from 2018 to 2040. Then, for each algorithm's implementation, 15% of the data is considered for testing data, and 85% is called train data. Since the data's linearity, nonlinearity, types, and volumes impacted the algorithms' performance and prediction accuracy; this research applied six algorithms with different structures. On the other hand, concerning the structure of the proposed technique in this study, the machine learning algorithms' outputs were considered inputs to the mathematical model. Notably, the availability of the prediction results of several algorithms could improve the performance of the mathematical model in raising prediction accuracy.

2.2.1. Autoregressive (AR) algorithm

The Autoregressive approach has been extensively utilized in numerous studies to make predictions. The Autoregressive method is one of the time series methods that can predict future outcomes linearly using prior data (Chen & Yu, 2014). The AR algorithm is one of the most effective prediction algorithms for predicting processes with seasonal components. The general instance of employing the AR method in the study by Bollerslev (1986) is provided. The AR algorithm was utilized for energy management and electrical demand prediction in research done by Ahmad and Chen (2019). Based on using the AR algorithm in energy consumption prediction, the suggested study has employed this

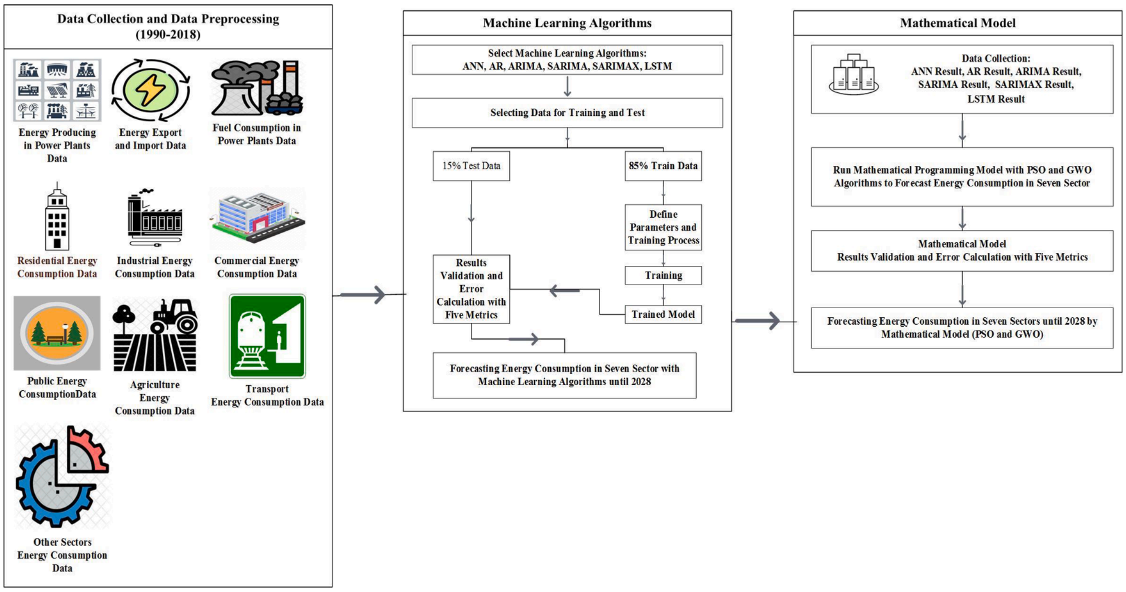

Fig. 1. Research Flowchart.

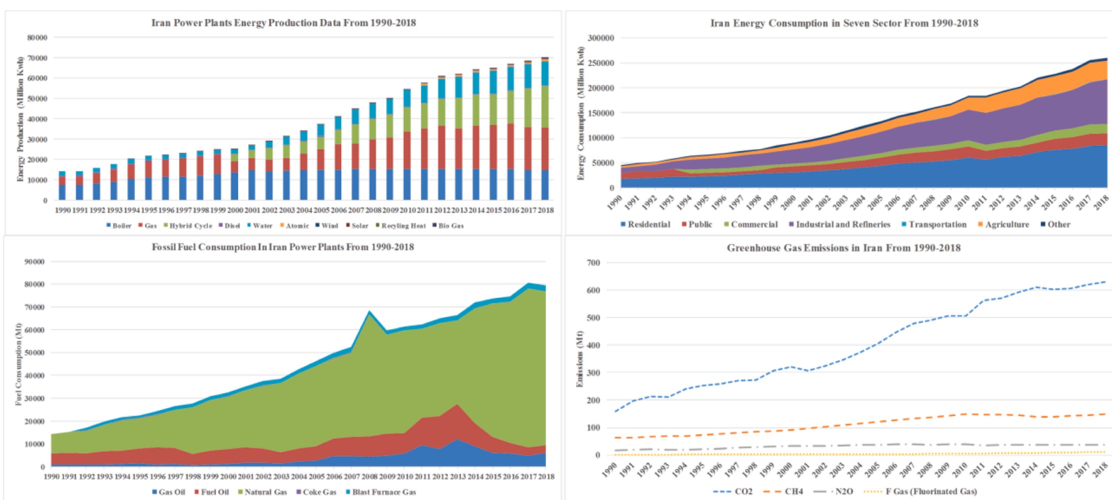

Fig. 2. Data for Energy Demand Forecasting.

method to predict 22 years of energy demand in seven distinct parts, given that the annual energy consumption data for each sector make up the input data for the AR algorithm.

2.2.2. Artificial neural networks (ANN) algorithm

One of the most prevalent machine learning approaches for predicting energy consumption is the artificial neural network (ANN) (Dong, Liu, Liu, Li & Li, 2021). The ANN is the ML technique inspired by the human brain's capacity to solve complicated issues (Elbeltagi & Wefki, 2021). The ANN is one of the algorithms employed in energy consumption prediction research. This method, which does not involve programming, can evaluate nonlinear systems in order to predict energy consumption (Ahmad et al., 2014). The input layer is the first portion of the ANN algorithm's structure; the hidden layer is the second part, and the output layer is the third part. The prediction accuracy of the ANN algorithm is assessed for diverse data by comparing the ANN algorithm output and the predicted outputs using prediction accuracy indices (Javanmard, Ghaderi & Hoseinzadeh, 2021), (Shapi, Ramli & Awalin, 2021). One of the first studies to utilize the ANN algorithm to predict yearly energy consumption in industrial sectors was that of (Azadeh, Ghaderi & Sohrabkhani, 2008). The ANN algorithm was used to predict a building's hourly energy consumption in research performed by Jeong, Koo and Hong (2014). The data of seven energy-consuming portions were investigated using the ANN algorithm in this study, and the energy consumption data was used as input to the ANN algorithm. Five prediction accuracy metrics were used to assess the algorithm's prediction accuracy for predicting 22 years of energy consumption in each industry. There were 17 input data for every sector, and the Train and Test data constituted 85% and 15% of the data, respectively (data for the years 2015–2018). Besides, the Levenberg-Marquardt learning method in the ANN algorithm was utilized in this study. To forecast energy demand in every sector, we changed the number of neurons and selected the best prediction accuracy of ANN for every sector. Fig. 3 depicts the overall structure of this study's use of the ANN algorithm to predict energy demand in each component. Energy data on production from power plants, fossil fuel consumption for energy production in power plants, and greenhouse gas emissions are all considered inputs for the ANN algorithm, while energy consumption data from seven sectors is the objective data for prediction.

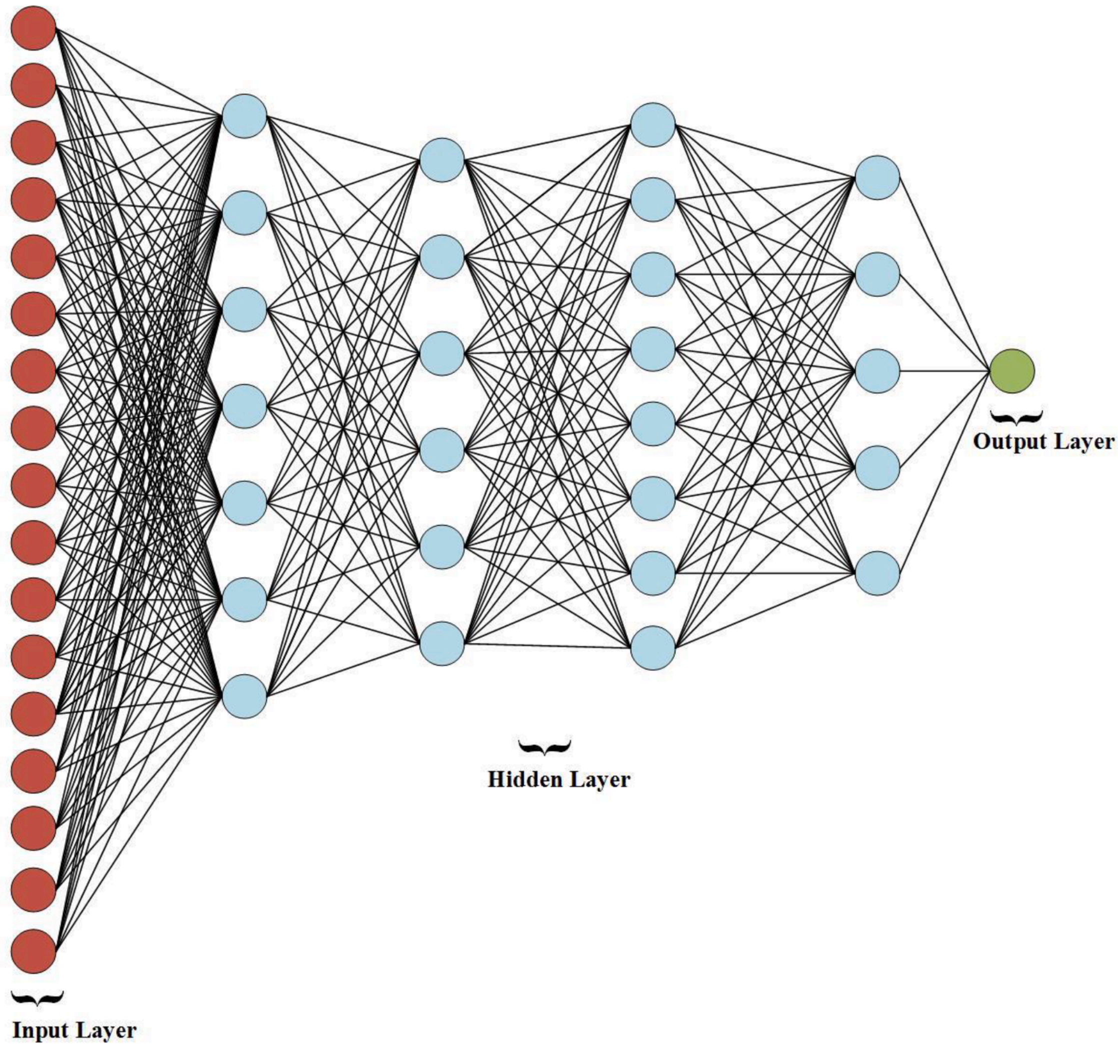

Fig. 3. the Structure of the ANN for energy demand prediction in each sector.

2.2.3. ARIMA algorithm

The Autoregressive Moving Average (ARIMA) method is one of the most fundamental time series techniques. This technique uses time series principles to predict future outcomes as a linear equation based on input data and taking prediction error into account (Deb, Zhang, Yang, Lee & Shah, 2017). Because of its great accuracy and simplicity, the ARIMA algorithm has been widely employed in energy research (Prado, Minutolo & Kristjanpoller, 2020). One of the benefits of the ARIMA algorithm is that it can follow linear trends and predict outcomes (Ghasemi, Shayeghi, Moradzadeh & Nooshyar, 2016). The ARIMA algorithm is an extension of the AR algorithm, and its general form may be found in Eq. (1) (Zhou et al., 2020).

$$F_t(p,\ d,\ q) = \ (1-\gamma_1)F_{t-1} + (\gamma_2-\gamma_1)F_{t-1} + \ldots + \left(\gamma_p-\gamma_{p-1}\right)F_{t-p} - \gamma_p F_{t-p-1} + \delta_1 e_{t-1} - \delta_2 e_{t-2} - \ldots - \delta_q e_{t-q} \tag{1}$$

where t is the number of periods, p is the number of time series hysteresis data utilized in the prediction model, q is the data's hysteresis prediction error, and d is the differential order in which the time series data is required to stabilize the data The ARIMA algorithm parameters are described in Tsay (2005) in their broad form and detailed description. Various studies in the realm of energy have employed the ARIMA algorithm. The ARIMA technique, for example, was employed in Kaytez (2020) to predict long-term energy consumption. The ARIMA method was also used to predict fuel consumption in Turkey (Ediger & Akar, 2007). The ARIMA method was employed to predict energy consumption in seven distinct parts in this study because of its widespread usage in the area of energy. The algorithm's 22-year projection for each sector is then provided until 2040. Also, the parameters were manually selected in the ARIMA algorithm, and different parameters provided to find the best prediction accuracy were used per iteration to predict energy demand in every sector. The input data for the ARIMA algorithm, like the input data for the AR algorithm, has been considered for predicting energy demand in seven sectors.

2.2.4. SARIMA algorithm

Another extensively used technique for energy prediction is the SARIMA algorithm. The SARIMA method is an extension of the ARIMA algorithm that may improve prediction accuracy by eliminating seasonal aspects (Jeong et al., 2014). There are six stages to the SARIMA algorithm: Autoregressive, Merge, Moving Average, Seasonal Autoregressive, Seasonal Merger, and Seasonal Moving Average. This method, in general, provides the correct order based on seasonal changes and avoids data instability (Xu, Chan & Zhang, 2019). SARIMA is an ARIMA algorithm with a seasonal pattern, expressed as Eq. (2) (Dubey et al., 2021).

$$\mathrm{ARIMA}\ (\mathrm{p},\mathrm{d},\mathrm{q}) * (\mathrm{P},\mathrm{D},\mathrm{Q})\mathrm{s} \tag{2}$$

The first function (p, d, q) represents the non-seasonal element of the model, whiles (P, D, Q) represent the seasonal part, and s denotes the numeral of seasons in the SARIMA method. In Study (Box, Jenkins, Reinsel & Ljung, 2015) shows the SARIMA algorithm's general equation. In energy research, the SARIMA algorithm is commonly utilized. The SARIMA algorithm was used in research by Fang and Lahdelma (2016) to predict heat demand in urban heating systems. The SARIMA algorithm was used to predict solar consumption in another investigation (Wang, Wang & Li, 2020). The SARIMA method was utilized in the study by Jeong et al. (2014) to predict power consumption in educational establishments. The SARIMA algorithm was employed in the current research to predict energy consumption in seven distinct sectors. The result of the SARIMA method has been used as one of the optimization model's inputs. Moreover, the SARIMA algorithm parameters were manually selected, and parameters with the best prediction accuracy were used in this study. In addition, the effect of eliminating seasonal effects was analysed by SARIMA concerning the different data in seven sectors. Also, historical energy consumption data in different sectors is considered input for the SARIMA algorithm to predict energy demand.

2.2.5. SARIMAX algorithm

Another frequently employed time series method for energy demand prediction is Seasonal Autoregressive Integrated Moving Average with Exogenous factors (SARIMAX). SARIMAX is an enhanced version of the SARIMA algorithm that can predict seasonally and non-seasonally, regardless of other factors (Whitt & Zhang, 2019). In general, the SARIMAX takes into account the interactions of exogenous factors on the data while making predictions, which may increase the model's prediction accuracy and performance (Elamin & Fukushige, 2018). Research (Tarsitano & Amerise, 2017) gives the general equation for implementing the SARIMAX method. The SARIMAX method has been used in several energy studies. The SARIMAX algorithm was used in Sheng and Jia (2020) to predict energy consumption in the near term and regulate energy consumption. Based on the capabilities of the SARIMAX algorithm and the acquired data, the SARIMAX method was utilized to forecast energy demand in seven parts during 22 years in the current research. To obtain the best prediction accuracy, the present study manually set the parameters of the SARIMAX algorithm and considered the best SARIMAX prediction accuracy with the employed data. The input data for the SARIMAX algorithm has also been considered, similar to the AR, ARIMA, and SARIMA algorithms, with the difference that in this study, time factor has been considered as an exogenous variable.

2.2.6. Long short-term memory (LSTM) algorithm

The LSTM method is a deep-learning approach and an enhanced variant of the recurrent neural network (RNN) method that has a reasonable learning ability to predict sequential data and has been employed to forecast energy consumption in many studies (Somu et al., 2021). The LSTM algorithm, on the other hand, is an advanced tool for accurately predicting time series problems (Ding, Chen, Hu & Xu, 2021). In order to tackle the gradient problem, the LSTM method uses unique components known as "memory blocks," which operate in recurrent layers. Memory cells are linked by three gates (input gate, output gate, and forget gate) in the memory blocks of the LSTM algorithm (Wang et al., 2020). The research (Hochreiter & Schmidhuber, 1997) presented the general equation for the LSTM algorithm. The LSTM algorithm has been used to forecast gas and energy consumption in various research, including ((Laib, Khadir & Mihaylova, 2019; Zhou et al., 2020)). Based on the given data, the LSTM algorithm was used in this study to predict energy demand in various sectors. The input data to the LSTM algorithm has been considered similar to the ANN algorithm.

2.3. Optimization model

The authors are now attempting to optimize the prediction results depending on the findings of the algorithms' prediction. The MAPE index is one of the most reliable indices for determining an algorithm's prediction accuracy. The goal function of reducing the MAPE value is considered in this study. The outputs of six algorithms that are utilized to forecast energy demand in each area are sent into the optimization model as input data. The new prediction value of the proposed model is determined by weighting each algorithm and weighting the algorithms' predictions, in addition to the value of the intercept minus the actual quantity of projected data, and then the model offers the optimal state of the MAPE index. The 22-year prediction values will be achieved in the second step by getting the optimal weight coefficients of each method. The following is the MAPE optimization model. The model was implemented using PSO and Grey-Wolf Optimizer methods. The following equations represent the optimization model. On the whole, the proposed model has been adapted from Javanmard and Ghaderi (2022). However, this study adds a constraint to the proposed model to preclude the possibility of a high additive weight of optimal coefficients. Since optimal factors are also used to predict future results, this constraint can prevent the likely deviation in the results.

$$Min\ MAPE = \frac{1}{N}\left(\sum_{n=1}^{N}\frac{|Y_N - Y_{Real}|}{Y_{RealUnzero}}\right) \tag{3}$$

St:

$$Y_N = \sum_{i=1}^{n}(a_1x_1 + a_2x_2 + \ldots + a_nx_n\ ) + a_{n+1} \tag{4}$$

$$0 \le a_i \le 1 \tag{5}$$

$$\sum_{i=1}^{n} a_i \le 1.2 \tag{6}$$

$$-100 \le a_{n+1} \le 100 \tag{7}$$

$$Y_{RealUnZero} = \begin{cases} If\ Y_{Real} = 0,\ Y_{RealUnZero} = 0.00000001 \\ If\ Y_{Real} > 0,\ Y_{RealUnZero} = Y_{Real} \\ If\ Y_{Real} < 0,\ Y_{RealUnZero} = Y_{Real} \end{cases} \tag{8}$$

The objective function presented in Eq. (3) which is the minimization of the MAPE metric. The computation of the value ofY_N, which is calculated with the predicted values of the algorithms for the test data, was regarded in Eq. (4). In Eq. (5), the interval of the coefficients of the algorithms was determined. In Eq. (6), the additive weight of optimal coefficients constraint with a value of <1.2 is presented for the prevention of a large additive weight of optimal coefficients. Yet, the model is free in selecting coefficients. In Eq. (7), the width range from the origin was considered. Moreover, in Eq. (8), the interval of the actual amount of the test data, if it is equal to zero, was considered. In the optimization model, the number of data test is N, which in the present study is equal to 4, Y_N is the predicted value of the test data N, Y_{Real} is the actual predicted data amount, a_i implies the optimal weighting coefficients of the algorithms, x_i is referred to as the predicted value of the algorithms, a_{n+1} is the value of the intercept considered between 100 and −100, i = 1,2,..., n is the number of prediction algorithms, and $Y_{RealUnZero}$ denotes the actual predicted amount of the data if it is zero.

In the next step, after implementing the model and determining the optimal coefficients of each algorithm, Eq. (9) is used to obtain 22-year predictions, which are the optimal coefficients multiplied by the j^{th}-year predictions of each method. Then, the total weight of the prediction algorithms is optimized each year in addition to the intercept equal to the j^{th}-year prediction of the model.

$$Y_j = \sum_{i=1,\ j=1}^{i=n,\ j=m}\left(a_1y_{j1} + \ a_2y_{j2} + \ldots + a_ny_{ji}\right) + a_{n+1} \tag{9}$$

Where Y_j is the prediction in the year j, a_i denotes the algorithm's optimal weight coefficients, y_{ji} implies the prediction of the i^{th} algorithm in the year j, which in this study, a 22-year prediction, is equal to $m = 10$, and six different algorithms are used to predict; it is clear that $n = 6$. In addition, the optimization model based on optimum coefficients and the predictions of machine learning algorithms are used to forecast energy consumption every year for 22 years.

2.4. GWO algorithm

The Grey-Wolf Optimizer method is a metaheuristic algorithm inspired by the life of grey wolves that mimics the hierarchy of leadership and how grey wolves hunt in the wild. The leadership hierarchy is divided into four groups of wolves; alpha provides the most suitable solution, beta provides the second most suitable solution, delta provides the third most appropriate solution, and finally, omega provides the rest of the available solutions (Mirjalili, Mirjalili & Lewis, 2014). The Grey-Wolf Optimizer algorithm generally has three stages of searching, encircling, and attacking, which are considered model-solving steps (Ghalambaz, Yengejeh & Davami, 2021). The general equation of the Grey-Wolf Optimizer algorithm has been presented in Mirjalili et al. (2014) and (Jayabarathi et al., 2016).

Since the Grey-Wolf Optimizer method is utilized to solve optimization models, the optimization model of energy consumption prediction accuracy is solved first using the Grey-Wolf Optimizer algorithm in the current study. The Grey-Wolf Optimizer technique is then used to get the prediction algorithms' optimal weight coefficients and the predicted test data quantity. The prediction accuracy metrics of the Grey-Wolf Optimizer algorithm are then computed and compared to the six prediction algorithms utilized, as well as the PSO algorithm in the following stage. If the GWO algorithm's prediction accuracy is high, the GWO algorithm will be used to provide a 22-year prediction of energy consumption in seven sectors. The present study iterated the model 950 times to discover the optimal solution with the Grey-Wolf Optimizer algorithm for each sector.

2.5. PSO algorithm

The Particle Swarm Optimization (PSO) method is a meta-heuristic approach for addressing optimization issues that are based on bird and insect batch and swarm behaviour. Several studies ((Kennedy & Eberhart, 1995; Kıran, Özceylan, Gündüz & Paksoy, 2012)) have utilized this strategy to solve different optimization issues. The PSO method discovers the most optimum solutions to a problem by presenting a collection of existing answers as a batch of particles in the issue space (Marini & Walczak, 2015). The PSO method's general formula has been published in Xu et al. (2018) and (Poli, Kennedy & Blackwell, 2007). The post-implementation optimization model with the GWO algorithm has been implemented with the PSO algorithm in the proposed study, and the results of predicting the accuracy of this algorithm have been compared with six energy consumption prediction methods in seven sectors. The prediction accuracy of PSO and Grey-Wolf Optimizer algorithms is then compared, and the 22-year prediction of the PSO algorithm for energy consumption prediction is presented in seven different sectors. Also, this study considered the population and number of iterations at 1000 and 950, to implement the mathematical model with the PSO algorithm.

2.6. Validation metrics for ML algorithms and optimization model

Various indices are used to assess the prediction accuracy of machine learning algorithms, time series, and deep learning. In this study five indices have been employed to assess the accuracy of ML algorithms and optimization model with PSO and Grey-Wolf Optimizer. RMSE, NMRSE, MAPE, MAE, and RAE indices have been used to assess the accuracy of the prediction. The formula of root-mean-square error (RMSE) has been presented in Eq. (10), which is defined as the standard deviation of the difference between the actual value and the predicted value of the data (Somu et al., 2021).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{x}_i - x_i)^2}{n}} \tag{10}$$

Where $\hat{x}_i$ is the predicted amount of test data, x_i denotes the actual amount of test data, and n is the number of test data. The following metric examined in this study is the Normalized Root Mean Square Error (NRMSE), which is given in Eq. (11) (Qu, Qian & Pei, 2021).

$$NRMSE = \left(\frac{RMSE}{x_{max} - x_{min}} \right) \tag{11}$$

Where x_{max} and x_{min} are the maximum and minimum amounts of test data for predicting the consumption in each sector, respectively, and then, the mean absolute percentage error (MAPE) index is calculated according to Eq. (12) (Somu et al., 2021), (Xiao, Li, Xie, Liu & Huang, 2018).

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\hat{x}_i - x_i}{x_i} \right| \tag{12}$$

The MAPE index shows the deviation of the predicted value for the test data from the actual data. Another index examined in this study for prediction algorithms is the Mean Absolute Error (MAE), which shows the absolute difference between the predicted test data and the actual test data for energy consumption and is given by Eq. (13) (Chou & Ngo, 2016).

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |\hat{x}_i - x_i| \tag{13}$$

Finally, the Relative Absolute Error (RAE) index has been used to evaluate the prediction accuracy of algorithms for predicting energy consumption in seven different sectors, which is presented in Eq. (14) (Jamei, Ahmadianfar, Olumegbon, Karbasi & Asadi, 2021).

$$RAE = \frac{\sum_{i=1}^{n} |x_i - \hat{x}_i|}{\sum_{i=1}^{n} |x_i - \bar{x}_i|} \tag{14}$$

In Eq. (14), $\bar{x}_i$ is the average amount of the actual test data. In general, the closer the amount of the indices is to zero, the higher the accuracy of the evaluated method, and the predictions of the examined algorithm will be more acceptable than other algorithms.

3. Results

On average, Iran's energy consumption has annually increased by 6.48% from 1990 to 2018 and brought about energy supply problems. Now, considering the significance of energy prediction in managing and planning to respond to the energy demand, this study has predicted energy consumption in Iran in seven domains until 2040 using a mathematical model based on ML algorithms. The results of replicating the implementation of the proposed approach for seven domains reflect the approach's effectiveness and high prediction accuracy with different data. The MATLAB R2020b software was used for implementing all algorithms and the mathematical model. In the following, the results obtained for every domain are presented:

3.1. Residential sector energy demand forecasting result

The residential domain is one of the energy-intensive sectors in Iran, such that 38.4% of the country's consumed energy belonged to this domain in 1990. On average, the residential domain has annually witnessed an energy consumption upsurge of about 5.9%, and energy consumption in this domain constituted 32.76% of the total consumed energy in Iran in 2018. The historical data in the residential sector experienced a linear, annually-increasing trend and were available from 1990 to 2018. The results of the ML algorithms and the optimization model in this sector generally depended on the data type and performance of the algorithms and model. Fig. 4 depicts the accuracy of predicting energy consumption in the Iranian residential sector using ML algorithms for the Test data employed in this study, and Table 2 represents the prediction accuracy indices of the machine learning algorithms in the residential domain.

As Fig. 4 and Table 2 display, the results of predicting with machine learning algorithms differ concerning the data applied in this study. The best prediction accuracy in the residential domain belongs to the SARIMA algorithm, and the ARIMA, ANN, AR, and SARIMAX algorithms are placed in the next ranks, respectively. However, LSTM did not yield desirable prediction accuracy in the applied data. Considering the attributes and trend of the data in the Residential sector, the ARIMA and SARIMA algorithms rendered higher prediction accuracy than other methods, while SARIMA enhanced prediction accuracy by eliminating seasonal effects. However, considering the exogenous variables' interactive effects, the SARIMAX algorithm displayed lower prediction accuracy than SARIMA in the residential sector. In addition, the LSTM algorithm underfitting the results with the residential sector data, which were useless in the optimization model. Then, the outputs of the machine learning algorithms in the residential sector were considered as the inputs to the mathematical model to raise prediction accuracy, and two PSO and Grey-Wolf Optimizer algorithms executed the mathematical model. Table 3 displays the optimal coefficients for the ML algorithms.

Fig. 5 shows the prediction accuracy results for the residential sector after implementing the model with PSO and Grey-Wolf Optimizer methods, and Table 4 presents the prediction accuracy indices for the optimization model.

According to Table 4 and Fig. 5, the prediction accuracy of the optimization model concerning energy demand forecasting in the residential sector was higher than the accuracy of the ML algorithms. Furthermore, the model's accuracy was higher when executed by the PSO algorithm. The prediction accuracy of energy demand in the residential sector was 4.11 and 3.38 times more than the accuracy of the SARIMA algorithm when the PSO and Grey-Wolf Optimizer methods were implemented for the model. Appendix B (Residential Sheet) and Fig. 6 display the prediction results of SARIMA and the optimization model concerning energy demand in the residential sector until 2040.

The SARIMA algorithm predicts that energy demand will increase annually by 3.58% in the residential sector on average, and the energy demand forecasting in this sector will witness a 116% increase in 2040 compared to 2018. On the other hand, the optimization model executed by the PSO and Grey-Wolf Optimizer algorithms predicts average annual rises of 2.21% and 2.69% in the energy demand of the residential sector until 2040, respectively. The PSO and Grey-Wolf Optimizer methods forecast that energy demand in this sector will increase by 61.76% and 79.19% in 2040 compared to 2018.

Table 2
Residential Sector ML Algorithms Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
ANN	**6109.185**	**0.679153**	**0.067954**	**5571.156**	**1.077683**
AR	**4296.41**	**0.47762**	**0.05061**	**4122.585**	**1.7391**
ARIMA	**3444.22**	**0.382891**	**0.034096**	**2713.656**	**0.740667**
SARIMA	**3651.574**	**0.405942**	**0.033114**	**2606.394**	**0.480733**
SARIMAX	**10,025.49**	**1.1145**	**0.1226**	**9937.176**	**4.53918**
LSTM	**47,223.28**	**5.2497**	**0.58223**	**47,082.34**	**65,535**

3.2. *Commercial sector energy demand forecasting result*

The energy consumption in the commercial sector in Iran allocated 13.22% of the whole energy consumption to itself in 1994, and this rate has annually increased by 4.33% on average. However, 7.29% of the whole energy consumed in this country belonged to this sector in 2018. With a relatively linear and fluctuating trend, the data were not fully accessible and existed from 1994 to 2018 in the Commercial sector. The accuracy of prediction with the ML algorithms and the optimization model depended on the volume, type, linearity, and nonlinearity of the data in this sector. Fig. 7 depicts the forecasting outcomes of the ML algorithms concerning energy demand in the commercial sector, and Table 5 represents the prediction accuracy indices of the methods.

With respect to the data applied for predicting energy demand in the commercial sector and according to Fig. 7 and the prediction accuracy indices, ARIMA reveals the best prediction accuracy than other algorithms. SARIMA, AR, ANN, and SARIMAX also provide desirable prediction accuracies, respectively. Alternately, LSTM does not render accurate predictions regarding the type, uptrend, and downtrend of the 29-year data on energy consumption in the commercial sector. By eliminating the seasonal effects, SRAIMA presented higher prediction accuracy than the AR method. However, concerning the interactive effects of the exogenous variables in SRAIMAX, the prediction accuracy was lower than SARIMA. LSTM also overestimated the results, conceivably due to the smallness of the data. The PSO and GWO executed the optimization model with the outcomes of the ML algorithms in the commercial sector as its inputs. Table 6 shows the optimization coefficients of every machine learning algorithm in the mathematical model.

Fig. 8 and Table 7 represent the prediction accuracy results and prediction accuracy indices of the optimization model, respectively.

According to Fig. 8 and Table 7, the optimization model has increased prediction accuracy concerning energy demand forecasting in the commercial sector. This model has also improved the prediction

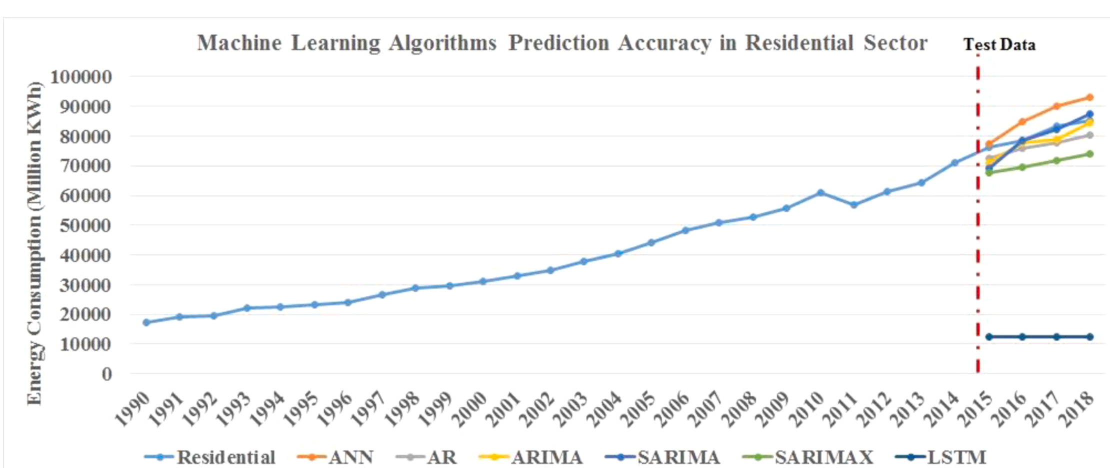

Fig. 4. Machine Learning Algorithms Forecasting Accuracy Diagram for Residential Sector Energy Consumption.

Table 3
Optimal Coefficients of ML Algorithms for Residential Sector Energy Demand Predict.

Optimal Coefficient	AR	ANN	ARIMA	SARIMA	SARIMAX	LSTM	Bias
PSO	**0.141797**	**0.895309**	**3.13E-06**	**0.000797**	**0**	**0**	**9.962648**
GWO	**0.005202**	**0.912363**	**0.000539**	**0.131753**	**0**	**0**	**−100**

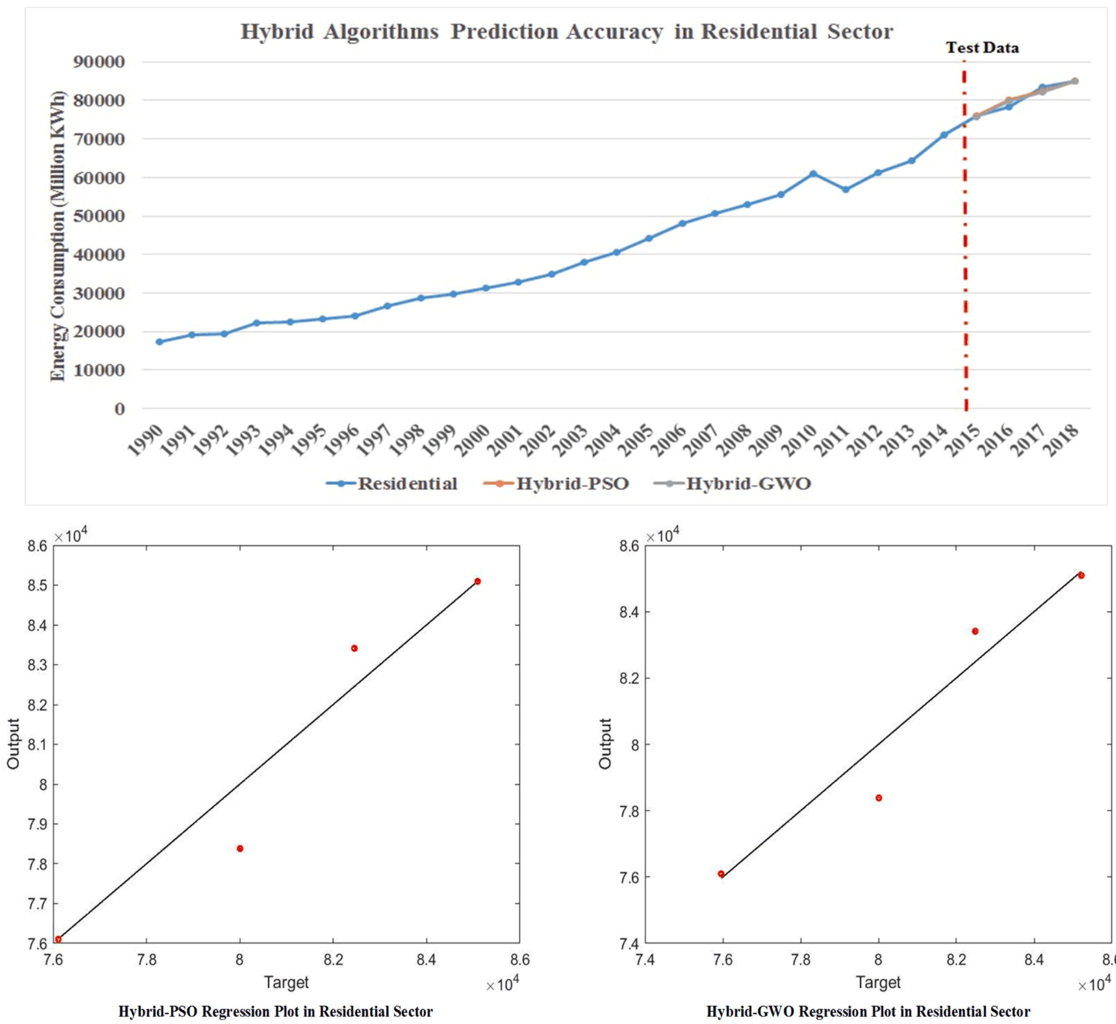

Fig. 5. Optimization Model Forecasting Accuracy Diagram for Residential Energy Consumption.

Table 4
Residential Sector Optimization Model Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
PSO	**943.4156**	**0.104879**	**0.008052**	**645.4519**	**0.225708**
GWO	**999.7327**	**0.111139**	**0.009794**	**783.9639**	**0.269781**

accuracy of the ML algorithms. When executed by the PSO and Grey-Wolf Optimizer, the model provides prediction accuracies that are 21.96 and 10.89 times ARIMA's accuracy. The reason for this small difference in the prediction accuracy in this sector is related to the implementation structure of both algorithms. Appendix B (Commercial Sheet) and Fig. 9 display the prediction results of energy demand in the commercial sector until 2040.

For the commercial sector energy demand forecasting, ARIMA predicts an annual 2.90% increase on average, a 2% decline in 2019 compared to 2018, and a 87.13% rise in 2040 compared to 2018. The PSO and Grey-Wolf Optimizer algorithms also predict average annual increases of 2.60% and 2.67% in the energy demand in this sector. PSO predicts an increase of 9.22% in energy demand in 2019 and a rise of 75.43% in 2040 compared to 2018. These values equal 8.09% in 2019 and 78.16% in 2040 for the Grey-Wolf Optimizer algorithm.

3.3. Industrial sector energy demand forecasting

In Iran, the industrial sector is another energy-intensive sector, allocating 22.65% of the country's consumed energy in 1990 to itself. This rate has increased by 8.2% annually, constituting about 34.065 of the total energy consumed in 2018. The data on energy consumption in the Industrial sector was available from 1990 to 2018 and showed a linearly increasing trend. The ML algorithm's prediction accuracy and the optimization model depended on the sector's applied data. Fig. 10 displays the forecasting results of the ML algorithms concerning energy consumption in the industrial sector, and Table 8 presents the prediction accuracy indices of these algorithms.

According to Fig. 10 and Table 10, the best prediction accuracy concerning energy consumption in the industrial sector pertains to the

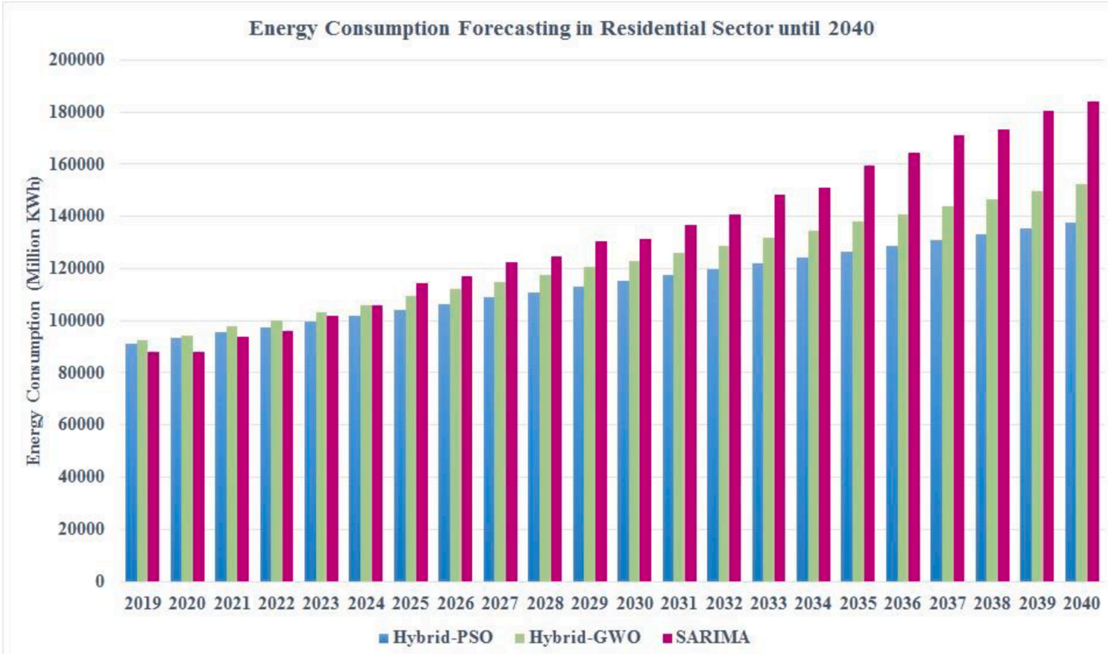

Fig. 6. Residential Sector Energy Demand Forecasting.

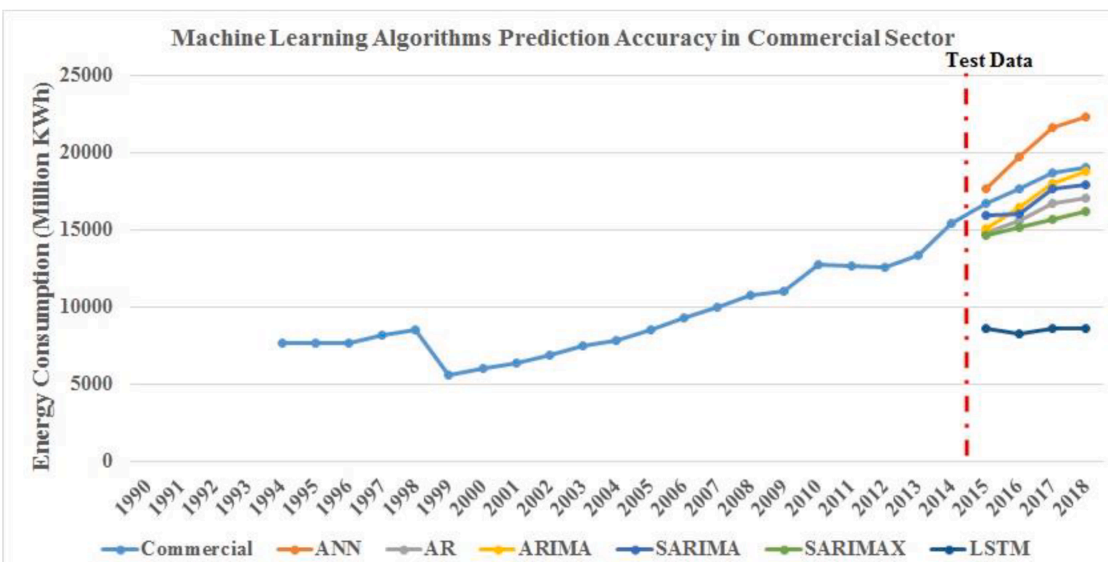

Fig. 7. Machine Learning Algorithms Forecasting Accuracy Diagram for Commercial Sector Energy Consumption.

Table 5
Commercial Sector ML Algorithm Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
ANN	**2497.60415**	**1.083418275**	**0.127190639**	**2328.584651**	**1.414030486**
AR	**1953.979**	**0.847603**	**0.108755**	**1953.241**	**2.384351**
ARIMA	**1068.554451**	**0.463520778**	**0.053722128**	**938.6109255**	**0.720792904**
SARIMA	**1180.923**	**0.512264**	**0.063354**	**1140.114**	**1.266848**
SARIMAX	**2577.357**	**1.118014**	**0.141293**	**2552.568**	**4.876073**
LSTM	**9542.774**	**4.139493**	**0.527021**	**9501.419**	**79.17172**

ARIMA algorithm. The AR, SARIMA, ANN, and SARIMAX algorithms allocate the next ranks to themselves, and the LSTM prediction accuracy is inappropriate. Concerning the data trends, the ARIMA algorithm increased prediction accuracy in this sector relative to the AR algorithm. However, by adding the seasonal effect removal component in the SARIMA algorithm, it is clear a decline in the prediction accuracy compared to the AR and ARIMA algorithms. The SARIMAX algorithm was also less accurate than AR, ARIMA, and SARIMA with regard to the

Table 6
Optimal Coefficients of ML Algorithms for Commercial Sector Energy Demand Predict.

Optimal Coefficient	ANN	AR	ARIMA	SARIMA	SARIMAX	LSTM	Bias
PSO	**0.077636808**	**0.72480188**	**0.00015554**	**6.5235E-06**	**0.312222356**	**0**	**−6.5423**
GWO	**0.040899115**	**0.505873933**	**0.015903226**	**0.106280762**	**0.463656071**	**0**	**−100**

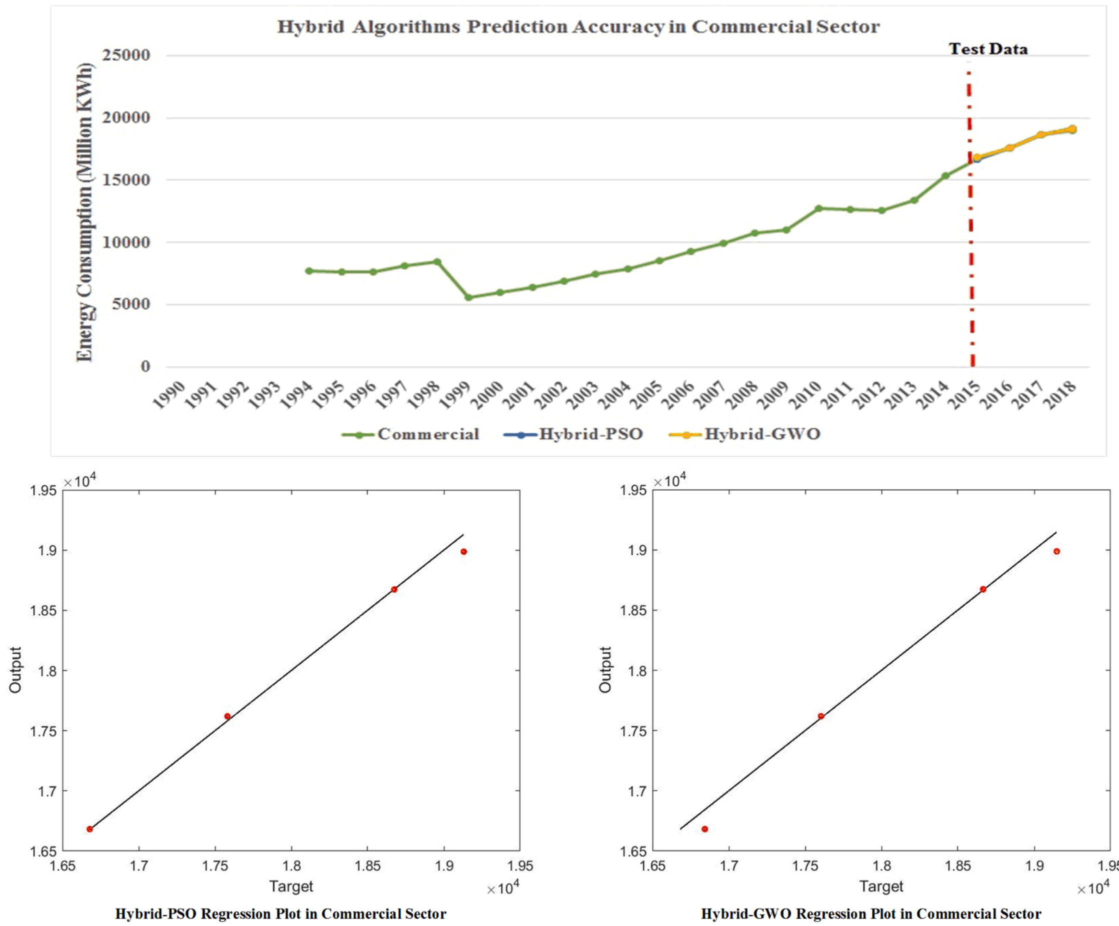

Fig. 8. Optimization Model Forecasting Accuracy Diagram for Commercial Sector Energy Consumption.

Table 7
Commercial Sector Optimization Model Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
PSO	**83.17942**	**0.036082**	**0.002987**	**53.69358**	**0.060111**
GWO	**84.18996**	**0.03652**	**0.003032**	**54.48609**	**0.06098**

effects of exogenous variables and the absence of the seasonal effects. In this sector, the LSTM algorithm also underestimated the results, which could not improve despite alterations in the numbers of neurons and iterations. The PSO and Grey-Wolf Optimizer executed the optimization model with the outcomes of the ML algorithms as its inputs. Table 9 presents the optimal coefficients of the mathematical model.

Fig. 11 and Table 10 display the prediction accuracy of the mathematical model and the prediction accuracy indices, respectively.

According to Fig. 11 and Table 10, the prediction accuracy of the optimization model is higher than those of the ML algorithms concerning energy demand forecasting in the industrial sector. The model's prediction accuracy was 1.53 and 1.25 times ARIMA's accuracy when executed by the PSO and Grey-Wolf Optimizer algorithms, respectively. Appendix B (Industrial Sheet)and Fig. 12 illustrate the energy demand prediction of the industrial sector until 2040.

Concerning energy demand forecasting in the industrial sector, ARIMA predicts an annual 2.27% increase until 2040 on average, a 3.86% increase in 2019 compared to 2018, and a 82.40% rise in 2040 compared to 2018. On the other hand, the optimization model executed by the PSO and Grey-Wolf Optimizer algorithms predicts annual increases of 2.78% and 269% in energy demand until 2040, and reveals a 0.09% increase in 2019 and a 2.7% compared to 2018. Furthermore, the mathematical model executed by the PSO and Grey-Wolf Optimizer algorithms predicts that energy demand will increase by 110.7% and 106.94% until 2040, respectively, compared to 2018.

3.4. Public sector energy demand forecasting

The energy demand in the public sector constituted 26.44% of the country's whole energy consumption in 1990. This value has increased annually by 4.26% on average until 2018, comprising 9.26% of the country's consumed energy in 2018. The public sector data were accessible from 1990 to 2018 and had a nonlinear trend with extreme fluctuations. The type and trend of the data in the public sector directly impacted the ML algorithm's prediction accuracy and the optimization model. Fig. 13 shows the prediction results of the ML algorithms concerning energy consumption in the public sector, and Table 11

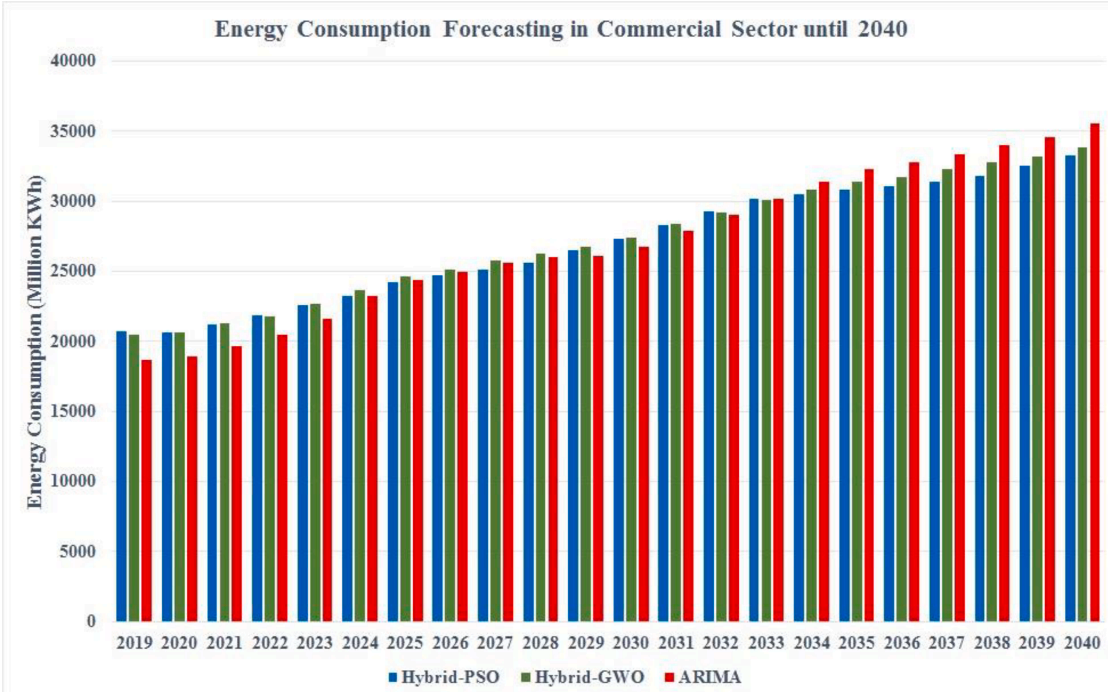

Fig. 9. Commercial Sector Energy Demand Forecasting.

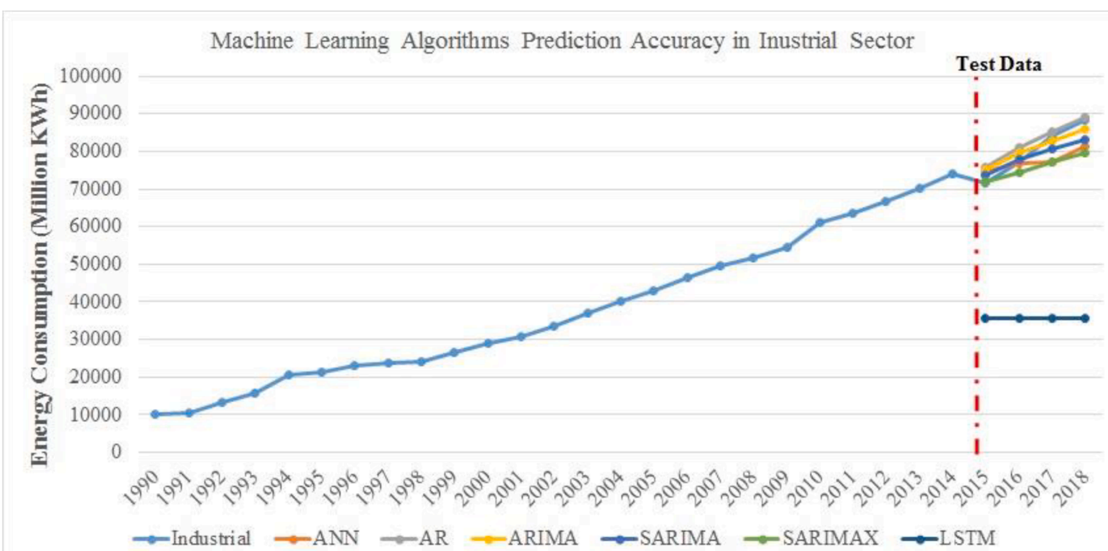

Fig. 10. Machine Learning Algorithms Forecasting Accuracy Diagram for Industrial Sector Energy Consumption.

Table 8
Industrial Sector ML Algorithm Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
ANN	5178.390	0.30775	0.05252	4365.874	2.24087
AR	2795.567	0.16614	0.03087	2348.353	0.52747
ARIMA	2543.181	0.151141	0.030755	2434.545	0.690728
SARIMA	3316.103	0.19707	0.03445	2854.2075	0.9192
SARIMAX	5815.934	0.345641	0.055321	4695.156	1.785385
LSTM	45,080.89	2.67916	0.55221	44,616.84	65,535

represents the indices of the ML algorithms.

As Fig. 13 and Table 11 show, AR reveals higher prediction accuracy than other algorithms, and ARIMA, SARIMA, ANN, and SARIMAX also provide high-accurate predictions. However, LSTM is not an accurate predictor of energy demand in the public sector. Regarding the type and trend of the applied data in the public sector, and considering the inter-data trend, removal of seasonal effects, and impact of exogenous variables, the prediction accuracy decreased in the ARIMA, SARIMA, and SARIMAX algorithms compared to AR. Later, the optimization model was executed by the PSO and Grey-Wolf Optimizer algorithms with the outputs of the ML algorithms as its inputs. Table 12 presents the optimal coefficients obtained for the public sector.

Fig. 14 and Table 13 present the prediction accuracy of the model and prediction accuracy indices in this sector.

Similarly, the optimization model has higher prediction accuracy than the ML algorithms; however, it manifests very close predictions with PSO and Grey-Wolf Optimizer. Moreover, the prediction accuracy

Table 9
Optimal Coefficients of ML Algorithms for Industrial Sector Energy Demand Predict.

Optimal Coefficient	ANN	AR	ARIMA	SARIMA	SARIMAX	LSTM	Bias
PSO	**1.41E-15**	**0.95526**	**6.261E-16**	**3.43E-15**	**4.78E-16**	**0**	**−100**
GWO	**0.04064**	**0.80048**	**0.01439**	**0.04665**	**0.0923**	**0**	**100**

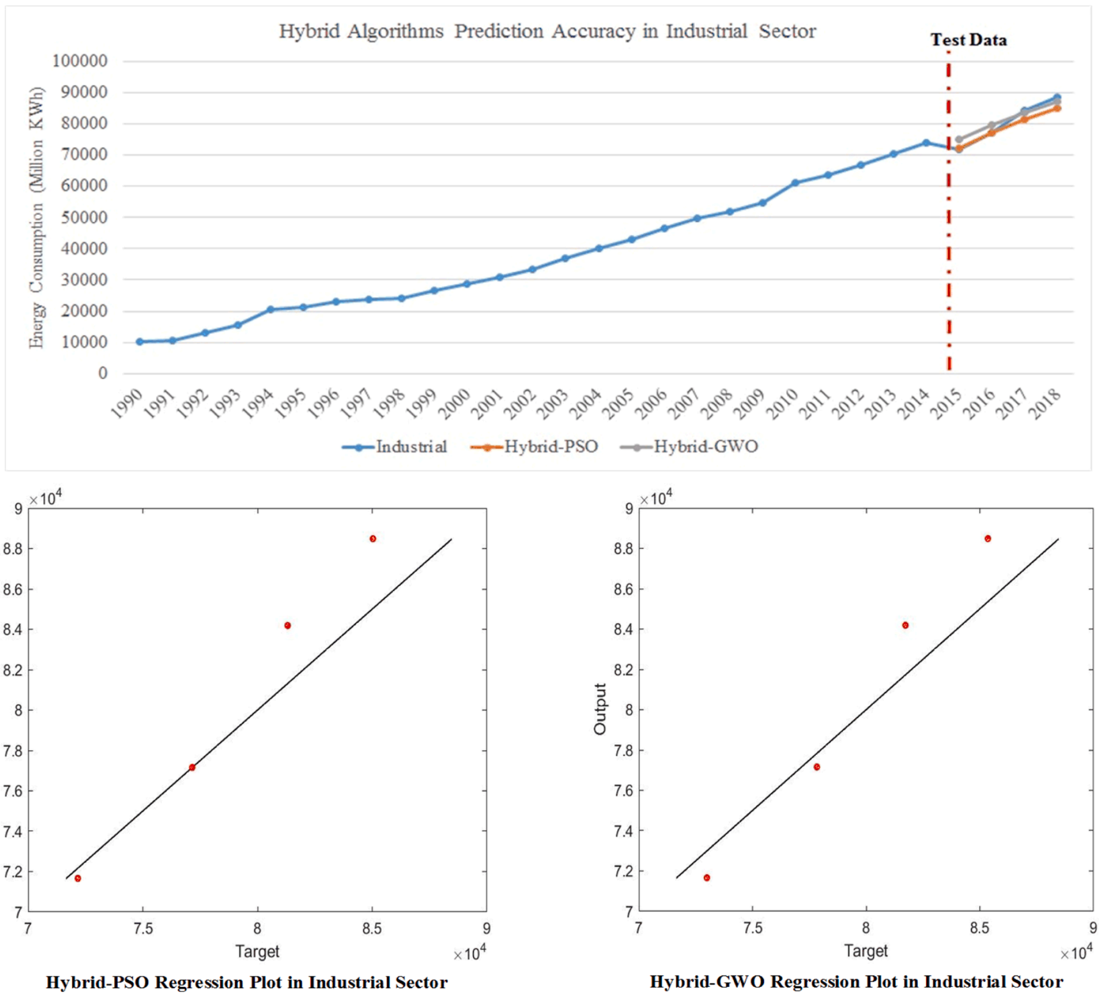

Fig. 11. Optimization Model Forecasting Accuracy Diagram for Industrial Sector Energy Consumption.

Table 10
Industrial Sector Optimization Model Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
PSO	**2256.919**	**0.134128**	**0.02003**	**1706.219**	**0.40118**
GWO	**2129.782**	**0.126573**	**0.02450**	**1882.837**	**0.46189**

of the model is 4.78 and 4.57-times AR's accuracy when implemented by PSO and Grey-Wolf Optimizer, respectively. Appendix B (Public Sheet) and Fig. 15 display the prediction results of energy demand in the public sector by the optimization model and AR algorithm until 2040.

AR predicts a relatively linear trend for the rise of energy demand in the public sector until 2040, such that energy demand will annually increase by 1.71% on average. Meanwhile, this algorithm predicts a 3.1% decrease in energy demand in this sector in 2019 and a 44.48% increase in 2040 compared to 2018. However, the optimization model implemented by the PSO and Grey-Wolf Optimizer predicts a sinusoidal trend in the public sector until 2040. The energy demand increases in some years while decreasing in others. Nonetheless, when implemented by PSO and Grey-Wolf Optimizer, this model predicts that energy demand in the public sector will increase annually by 1.96% and 1.97% on average. However, a 5.16% and 5.1% increase are predicted in the energy demand for 2019. Furthermore, increases of 53.27% and 53.56% are predicted in 2040 compared to the year 2018.

3.5. Transportation sector energy demand forecasting

Transportation is another energy-consuming sector in countries. The data on the energy consumed in this sector were available from the year 1999 and were employed in this study. This sector allocated 0.1% of the total consumed energy in 1999 to itself, and this value reached 0.2% in 2018. This sector has annually experienced various fluctuations in the consumption rate, annually increasing by 40.5% on average. The data volume in the Transport sector was a totally 27.5% smaller than the data in other sectors. They were available from 1998 to 2018 and experienced a fluctuating trend. For this reason, the prediction results of the machine learning algorithms and mathematical model were different from the outcomes of the other sectors. Fig. 16 displays the prediction accuracy of machine learning algorithms concerning energy

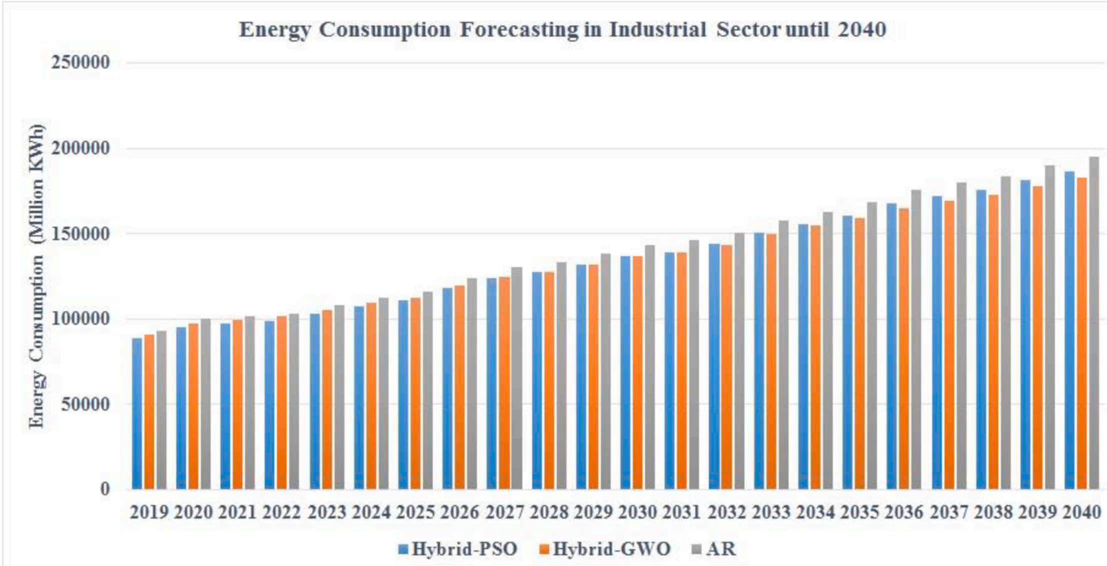

Fig. 12. Industrial Sector Energy Demand Forecasting.

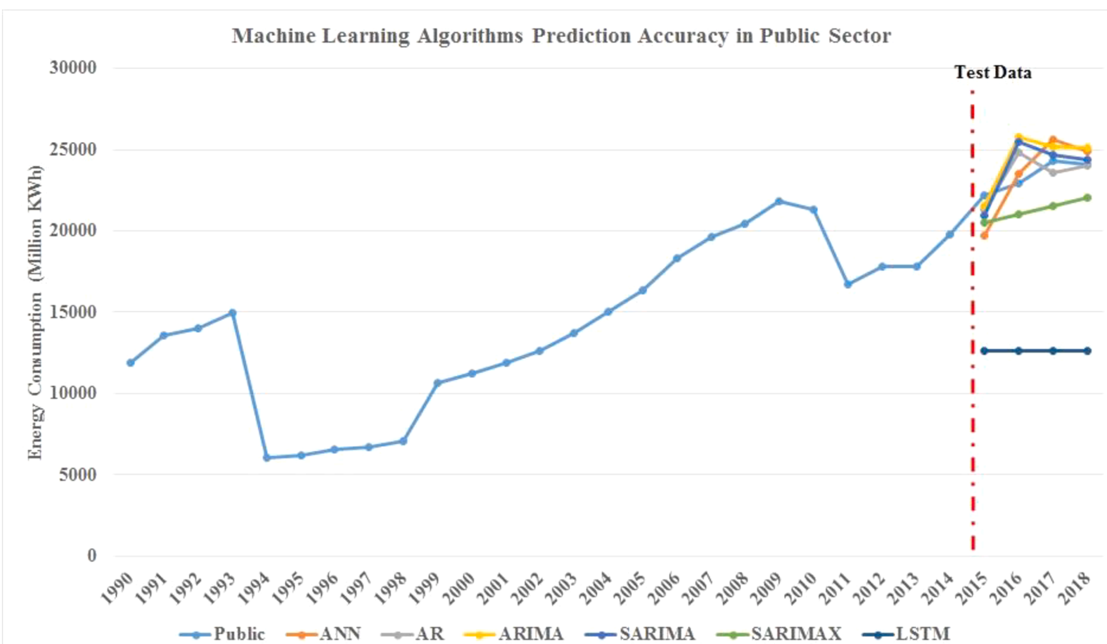

Fig. 13. Machine Learning Algorithms Forecasting Accuracy Diagram for Public Sector Energy Consumption.

Table 11
Public Sector ML Algorithm Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
ANN	1482.383649	0.695204075	0.055966798	1291.098608	0.69613121
AR	1104.246	0.51786	0.038499	886.551	0.84329
ARIMA	1611.3001	0.7556	0.05835	1356.594	0.94224
SARIMA	1437.906805	0.674345451	0.048446795	1108.714021	0.762828882
SARIMAX	2119.491	0.99399	0.08838	2076.50	4.1243
LSTM	10,817.91504	5.073355198	0.460513473	10,783.21387	65,535

consumption in the transportation sector, and Table 14 presents the prediction accuracy indices in this sector.

As Fig. 16 and Table 14 show, the machine learning algorithms do not provide desirable prediction accuracies due to the lack of data and the extensive alterations and fluctuations in energy consumption in this sector. Nevertheless, AR reveals higher prediction accuracy than other algorithms. The next ranks belong to SARIMA, ARIMA, ANN, SARIMAX, and LSTM, respectively. Concerning the data applied in the transport

Table 12
Optimal Coefficients of ML Algorithms for Public Sector Energy Demand Predict.

Optimal Coefficient	ANN	AR	ARIMA	SARIMA	SARIMAX	LSTM	Bias
PSO	**0.07691**	**2.563E-15**	**7.525E-17**	**1.346E-16**	**0.999**	**0**	**100**
GWO	**0.07857**	**0.00168**	**0.001935**	**0.00283**	**0.998**	**0**	**−100**

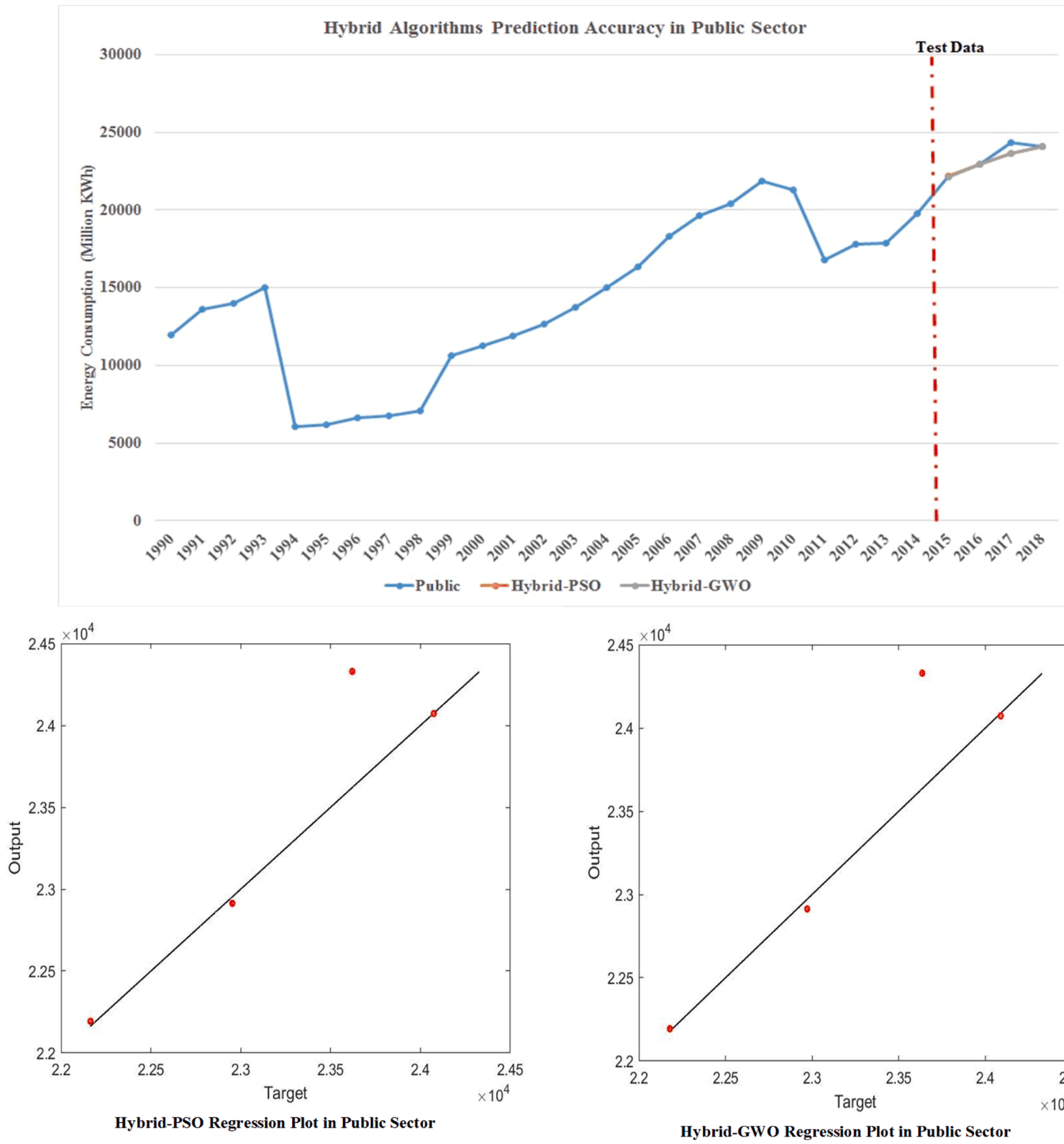

Fig. 14. Optimization Model Forecasting Accuracy Diagram for Public Energy Consumption.

Table 13
Public Sector Optimization Model Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
PSO	**354.024**	**0.16602**	**0.00805**	**194.4744**	**0.302033**
GWO	**354.6985**	**0.16634**	**0.00841**	**202.6671**	**0.311392**

sector and the inter-data trend, the ARIMA algorithm reduced prediction accuracy compared to the AR algorithm. In contrast, the SARIMA algorithm yielded higher accuracy than ARIMA by eliminating the seasonal effects. However, the SARIMAX algorithm still had lower prediction accuracy than AR. ANN, SARIMA. Also, LSTM and SARIMAX provided unsuitable accuracy and underestimated the results with various parameters. The outcomes of ANN, SARIMAX, and LSTM in this sector display the best prediction accuracy of these algorithms with regard to the data applied in the Transport sector and do not improve even by setting different parameters. PSO and Grey-Wolf Optimizer implemented the optimization model with the outcomes of the ML algorithms as its inputs. Table 15 presents the optimal coefficients of the mathematical model in the transportation sector.

The model was examined in terms of its prediction accuracy. Fig. 17 and Table 16 show the prediction accuracy of the optimization model and the prediction accuracy indices in the transportation sector, respectively.

As Fig. 17 and Table 16 reveal, the model implementation makes the

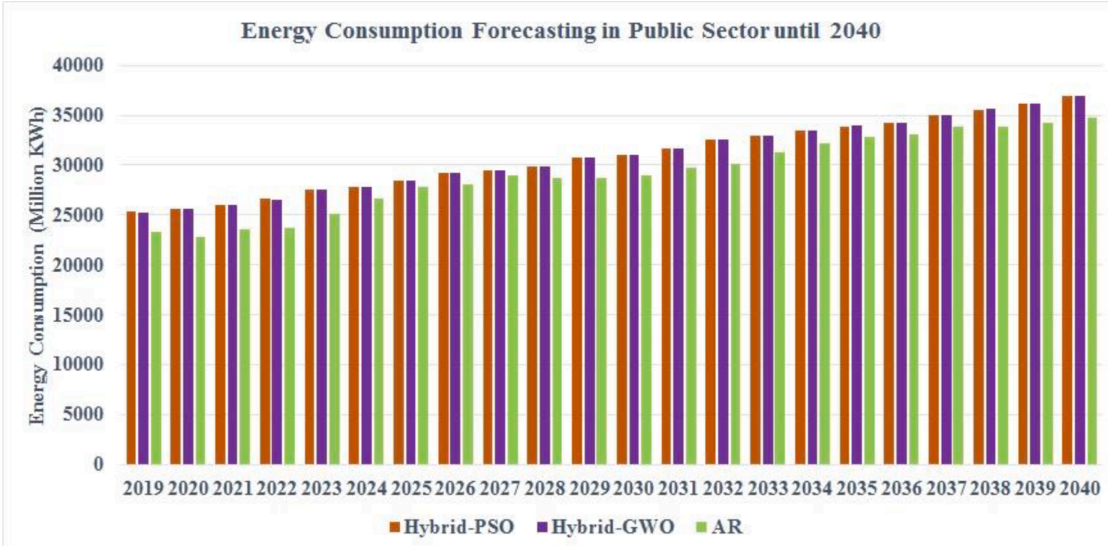

Fig. 15. Public Sector Energy Demand Forecasting.

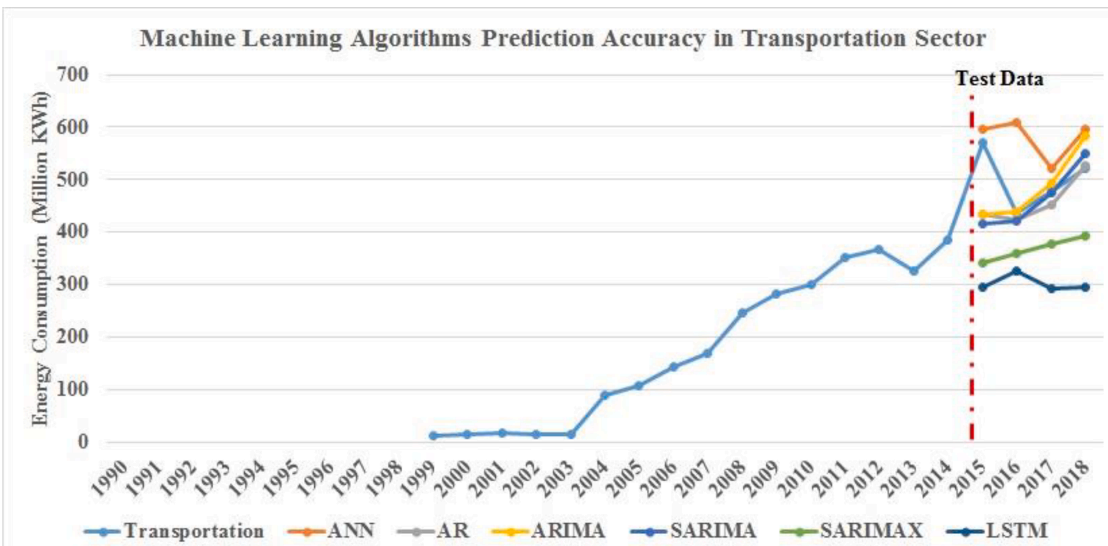

Fig. 16. Machine Learning Algorithms Forecasting Accuracy Diagram for Transport Sector Energy Consumption.

Table 14
Transport Sector ML Algorithm Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
ANN	**97.7078**	**0.72861**	**0.17025**	**79.7504**	**2.71301**
AR	**69.6755**	**0.51957**	**0.08182**	**44.4745**	**1.30902**
ARIMA	**74.6834**	**0.55692**	**0.09841**	**53.6818**	**1.06309**
SARIMA	**78.6262**	**0.58632**	**0.09035**	**49.6442**	**1.046315**
SARIMAX	**145.415**	**1.08437**	**0.25845**	**133.419**	**7.62451**
LSTM	**293.7401**	**2.19045**	**0.56573**	**286.521**	**10.9528**

prediction accuracy linked to energy demand in the transport sector considerably increase. In this respect, the prediction accuracy of the optimization model implemented by the PSO and Grey-Wolf Optimizer algorithms is 1.27 and 1.26-times AR's accuracy. Appendix B (Transportation Sheet) and Fig. 18 present the optimization model and AR algorithm predictions concerning energy demand in this sector until 2040.

AR predicts an average annual raise of 3.03% in energy demand in the transportation sector, a 3.8% reduction in 2019, and a 75.24% increase in 2040. Likewise, the optimization model implemented by PSO and Grey-Wolf Optimizer predicts an average annual energy demand of 2.43% and 2.81% in this sector, respectively. According to its

Table 15
Optimal Coefficients of ML Algorithms for Transport Sector Energy Demand Predict.

Optimal Coefficient	ANN	AR	ARIMA	SARIMA	SARIMAX	LSTM	Bias
PSO	**8.4183E-07**	**0.796946562**	**1.42362E-05**	**0.000653947**	**0**	**0**	**99.9999205**
GWO	**0.000336979**	**0.726281109**	**0.029118491**	**0.042067013**	**0**	**0**	**100**

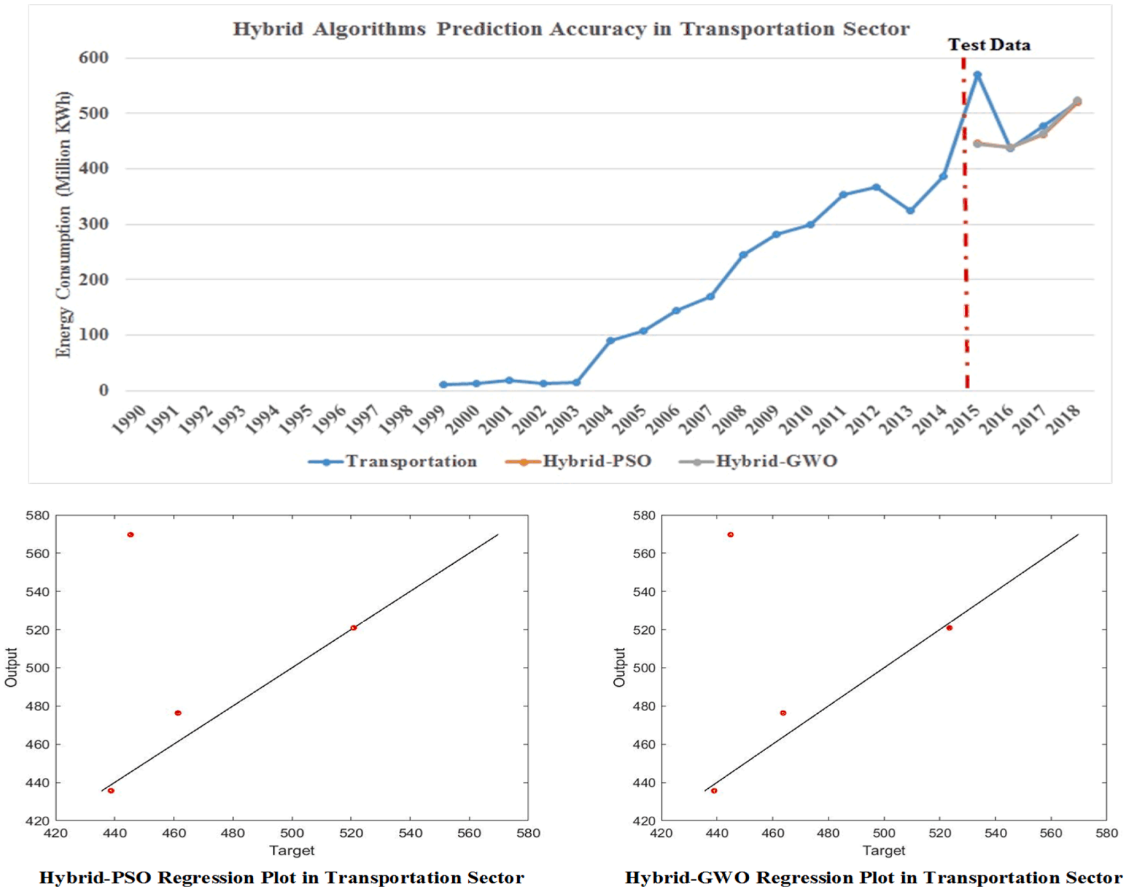

Fig. 17. Optimization Model Forecasting Accuracy Diagram for Transportation Setor Energy Consumption.

Table 16
Transportation Sector Optimization Model Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
PSO	62.68061162	0.46741694	0.064172935	35.60193238	1.313484496
GWO	62.83430866	0.468563077	0.064758841	35.95028588	1.290667773

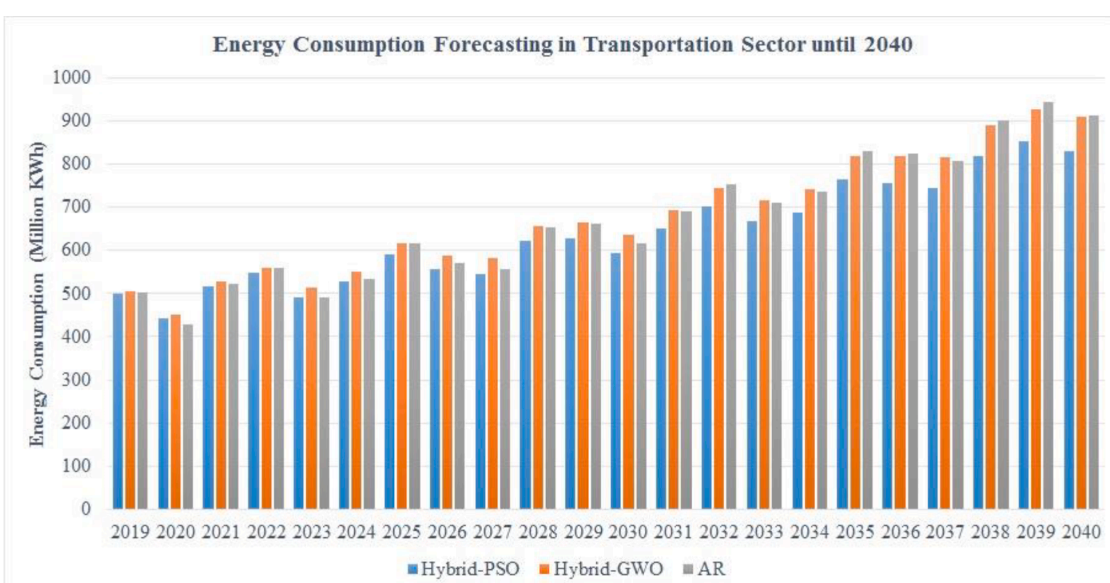

Fig. 18. Transport Sector Energy Demand Forecasting.

predictions, energy demand will decrease by 4.1% and 3.3% in 2019 and by 59.14% and 74.74% in 2040. Generally, the optimization model predicts a sinusoidal trend for energy demand in this sector from 2019 to 2040.

3.6. Agriculture sector energy demand forecasting

In Iran, agriculture is another important energy-consuming sector allocating about 8.23% of the total energy consumed in the country to itself in 1990. The energy consumption in this sector has annually increased by 8.9% on average and constituted 14.46% of the whole consumed energy in 2018. The Agricultural sector data were available from 1990 to 2018 and possessed a linearly increasing trend. The results of the ML algorithms and optimization model were obtained with respect to these data. Fig. 19 and Table 17 show the prediction accuracy of the ML algorithms and the prediction accuracy indices in the agriculture sector, respectively.

According to Fig. 19 and Table 17 and considering the data on the agricultural sector, the best prediction accuracy pertains to AR, and the SARIMA, ARIMA, ANN, and SARIMAX algorithms also manifest accurate predictions, respectively. However, LSTM fail in providing proper prediction accuracy. Considering the inter-data trend, witnessed a slight reduction in the prediction accuracy of ARIMA algorithm compared to AR algorithm. This also happened to the SARIMA algorithm with lower accuracy than AR algorithm. However, by eliminating the seasonal effects, prediction accuracy of SARIMA outperformed ARIMA in this sector, while SARIMAX algorithm provided lower prediction accuracy than SARIMA by adding the effect of the exogenous variables. Furthermore, with alterations in the parameters, the best prediction accuracy of the ANN and LSTM algorithms was presented for the data in this sector. In this step, the outcomes of the machine learning algorithms were used as the inputs to the optimization model. The results of optimal coefficients are presented in Table 18.

The results of the optimization model implemented by the PSO and GWO algorithms were examined in terms of prediction accuracy in the agricultural sector. Fig. 20 and Table 19 display the prediction accuracy of the model and prediction accuracy indices in this sector, respectively.

Typically, the optimization model provides higher prediction accuracy than the ML algorithms. The prediction accuracy of the model with PSO and Grey-Wolf Optimizer algorithms is 1.72 and 1.45-times AR's accuracy. In the following, Appendix B (Agriculture Sheet) and Fig. 21 illustrates energy demand in the agricultural sector until 2040.

AR predicts that energy demand in the agricultural sector annually increases by 2.76% on average, 2.63% in 2019, and 82.04% in 2040 compared to 2018. Likewise, the optimization model implemented by PSO and Grey-Wolf Optimizer predicts an average annual increase of 1.77% and 2.22% in energy demand in this sector, respectively. According to its predictions, energy demand will increase by 9.23% and 5.68% in 2019 and by 43.4% and 60.84% in 2028 compared to 2018.

3.7. Other sectors energy demand forecasting

This study considered the total energy consumption in other Iranian sectors from 1990 to 2018 as the energy consumed in the other sector. This value equalled 4.2% of the whole consumed energy in 1990 and reached 1.88% in 2018. The energy consumption in this sector has witnessed an annual rise of 8.05% from 1990 to 2018. The data of the Other sector were available from 1990 to 2018 and possessed a nonlinear trend with extreme fluctuations in different years. For this reason, the prediction results of the ML algorithms and the mathematical model were different in this sector. The ML algorithms were implemented to predict energy consumption in the other sector. Fig. 22 depicts the prediction results of these algorithms, and Table 20 represents the prediction accuracy indices.

According to Fig. 22 and Table 20, SARIMAX reveals higher prediction accuracy than other algorithms, and ARIMA, AR, SARIMA, and ANN allocate the following ranks. However, the prediction of the LSTM is inappropriate concerning the data on energy consumption in the other sector and the algorithm results are underfitting. By considering the effect of the exogenous variables and removing seasonal impacts, SARIMAX presented the highest prediction accuracy in the Other sector. Similarly, the ARIMA displayed higher accuracy than SARIMA and AR using the data in this sector. Next, the optimization model was executed by the outcomes of the ML algorithms for predicting energy consumption in this sector. Table 21 displays the optimal coefficients of the model for this sector.

The results of the optimization model implemented by the PSO and Grey-Wolf Optimizer algorithms for the prediction of energy consumption in the other sector are presented in Fig. 23, and the prediction accuracy indices are provided in Table 22.

As Fig. 23 and Table 22 illuminate, the implementation of the optimization model increased prediction accuracy concerning energy demand in the other sector, such that the prediction accuracy of the optimization model implemented by the PSO and Grey-Wolf Optimizer

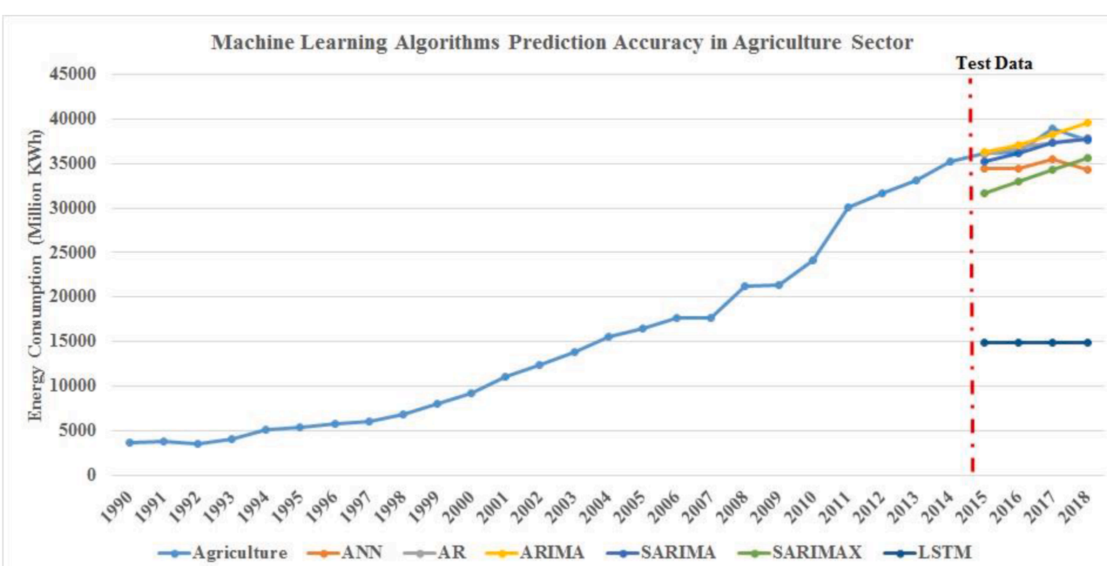

Fig. 19. Machine Learning Algorithms Forecasting Accuracy Diagram for Agriculture Sector Energy Consumption.

Table 17
Agriculture Sector ML Algorithm Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
ANN	**2441.802**	**0.85288**	**0.06068**	**2228.944**	**1.8972**
AR	**880.729**	**0.3076**	**0.01686**	**642.536**	**1.0667**
ARIMA	**1308.653**	**0.45709**	**0.02667**	**988.305**	**0.82520**
SARIMA	**924.5629295**	**0.322935009**	**0.017940522**	**678.3981051**	**0.736011841**
SARIMAX	**3735.411**	**1.304719**	**0.09614**	**3577.623**	**2.71301**
LSTM	**21,881.89**	**7.6429**	**0.58685**	**21,851.01**	**65,535**

Table 18
Optimal Coefficients of ML Algorithms for Agriculture Sector Energy Demand Predict.

Optimal Coefficient	ANN	AR	ARIMA	SARIMA	SARIMAX	LSTM	Bias
PSO	**0.586148**	**6.85E-06**	**0.054999**	**0.181016**	**0.238848**	**0**	**−28.4250**
GWO	**0.353379**	**0.008023**	**0.111470**	**0.536140**	**0.018365**	**0**	**93.29472**

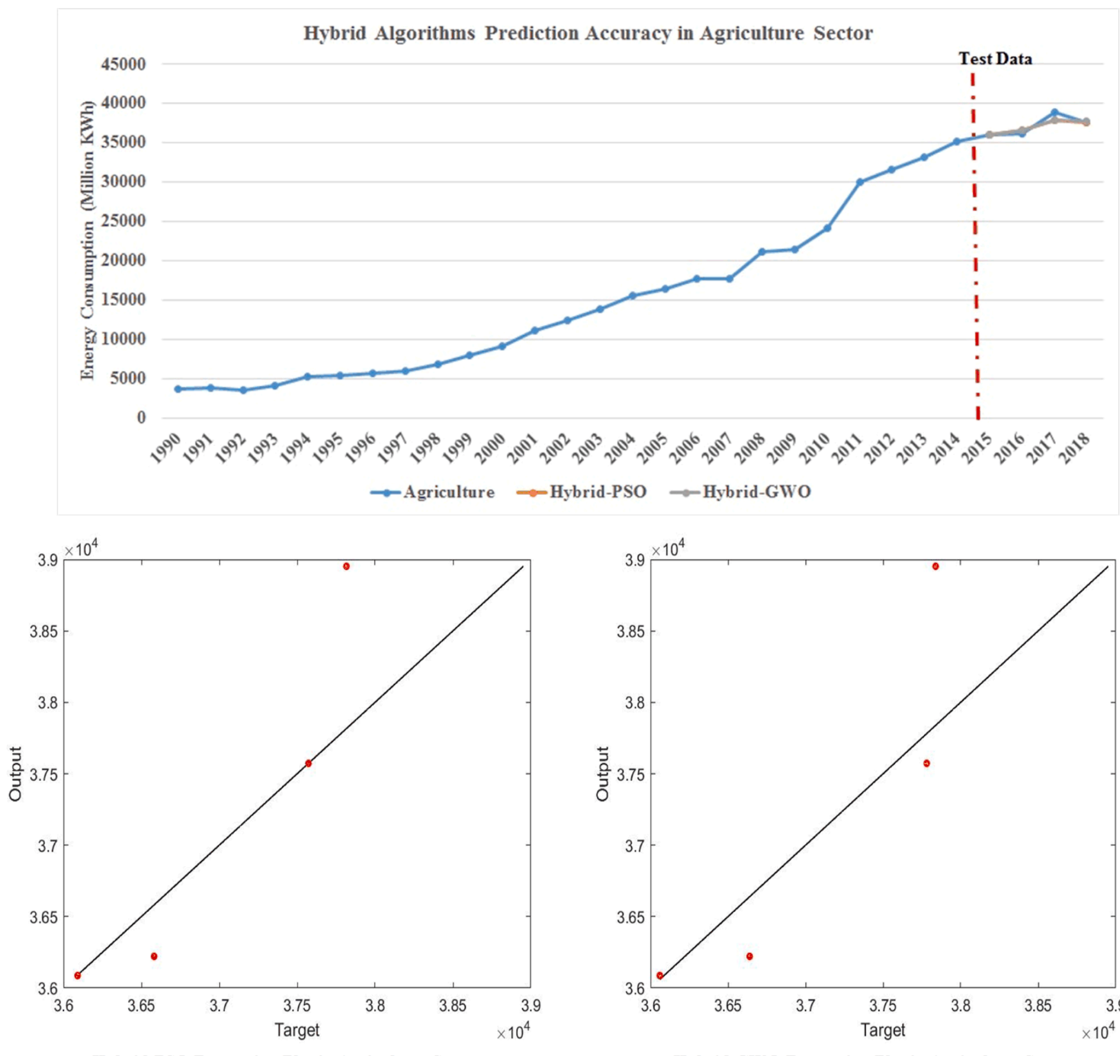

Fig. 20. Optimization Model Forecasting Accuracy Diagram for Agriculture Sector Energy Consumption.

Table 19
Agriculture Sector Optimization Model Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
PSO	**594.4304817**	**0.207625037**	**0.009755834**	**373.2259449**	**0.548157096**
GWO	**604.7771022**	**0.211238946**	**0.011615061**	**442.0877471**	**0.606593236**

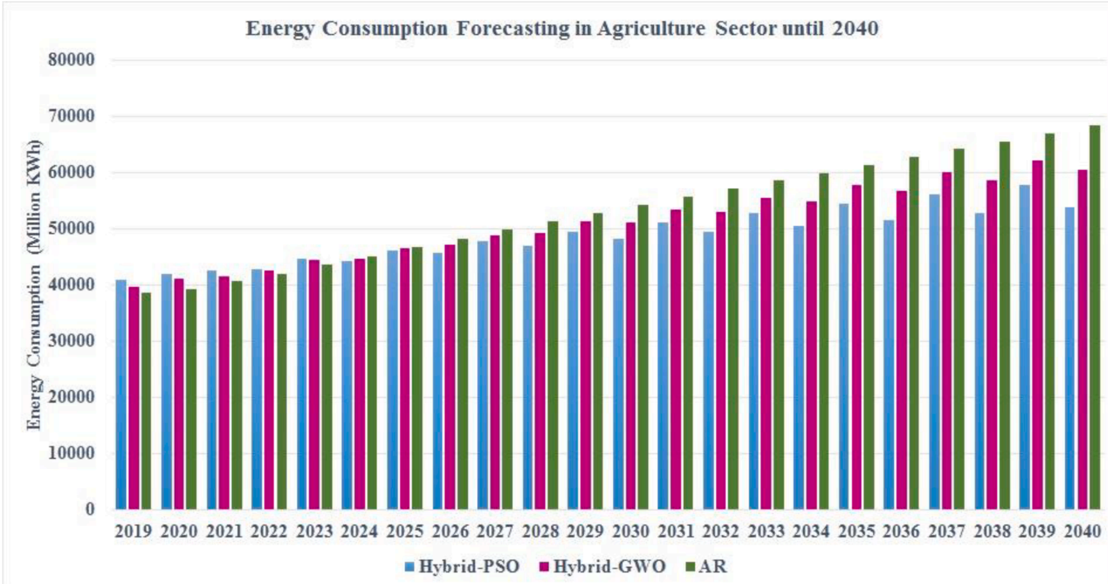

Fig. 21. Agriculture Sector Energy Demand Forecasting.

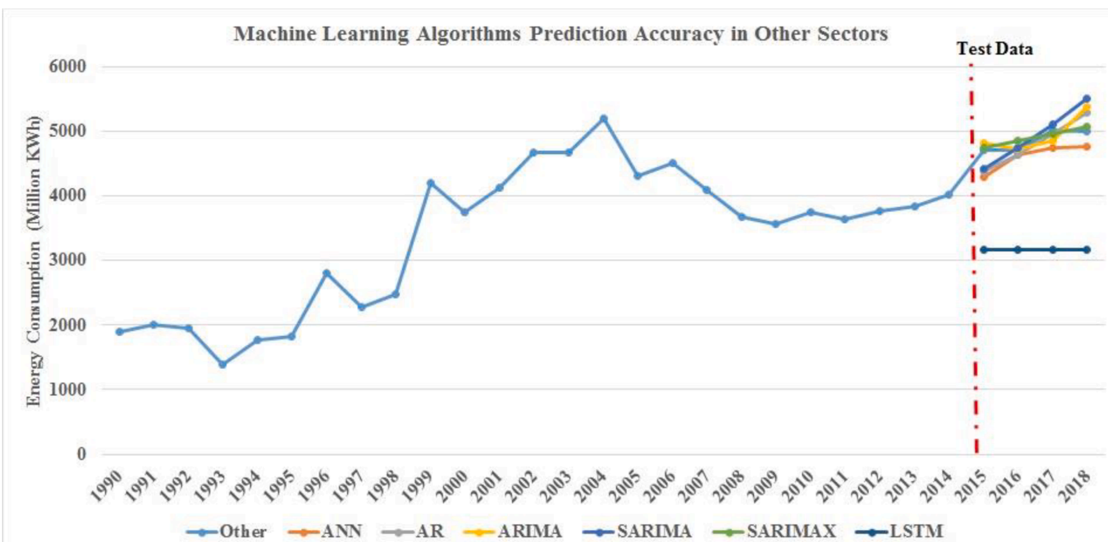

Fig. 22. Machine Learning Algorithms Forecasting Accuracy Diagram for Other Sector Energy Consumption.

Table 20
Other Sector ML Algorithm Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
ANN	**274.319**	**0.863725**	**0.05019**	**243.5799**	**1.53159**
AR	**221.8824**	**0.698622**	**0.037631**	**181.8838**	**0.592145**
ARIMA	**216.6348**	**0.682099**	**0.035292**	**173.9063**	**0.817985**
SARIMA	**301.5018**	**0.949313**	**0.047833**	**233.6096**	**0.645591**
SARIMAX	**93.8694**	**0.29555**	**0.017475**	**84.16319**	**0.79243**
LSTM	**1344.722**	**4.23401**	**0.274725**	**1336.125**	**65,535**

algorithms was 1.45% and 1.25% times SARIMAX's accuracy. Fig. 24 and Appendix B (Other Sheet) illustrate energy demand in the other sector from 2018 to 2040.

SARIMAX predicts an average annual increase of 1.77% in energy consumption in this sector, a rise of 3.13% in 2019, and an upsurge of 47.29% in 2040 compared to 2018. Likewise, the optimization model implemented by PSO and GWO predicts an average annual increase of 1.67% and 1.81% in energy consumption in this sector until 2040. According to its predictions, energy consumption increased by 1.52% and 1% in 2019 and reduced by 44.12% and 48.52% in 2040 compared to 2018.

Table 21
Optimal Coefficients of ML Algorithms for Other Sector Energy Demand Predict.

Optimal Coefficient	ANN	AR	ARIMA	SARIMA	SARIMAX	LSTM	Bias
PSO	**2.97E-16**	**7.030E-16**	**3.615E-15**	**6.191E-16**	**0.96489**	**0**	**100**
GWO	**0.01417**	**0.075937**	**0.011475**	**0.022745**	**0.688516**	**0**	**100**

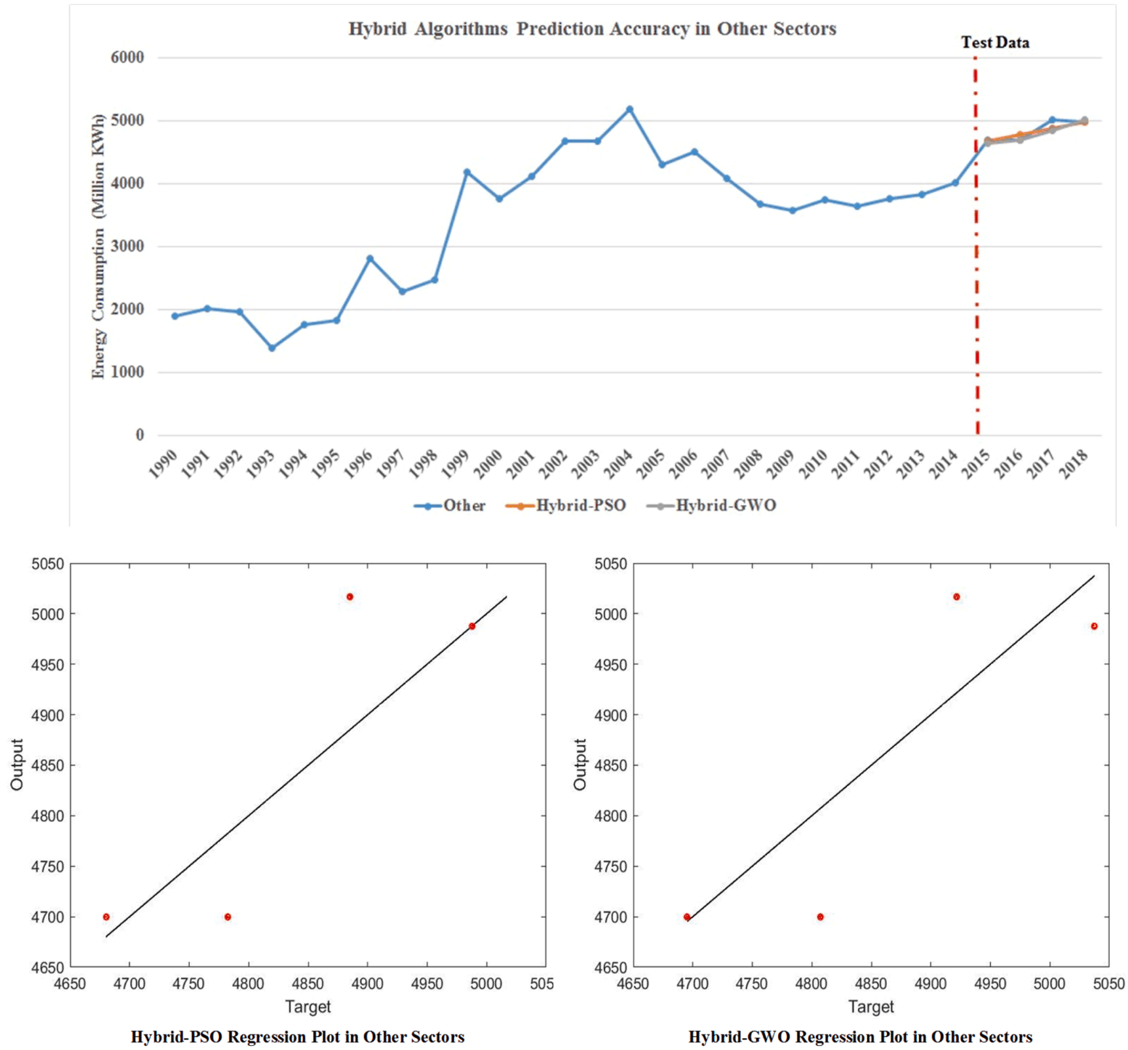

Fig. 23. Optimization Model Forecasting Accuracy Diagram for Other Sector Energy Consumption.

Table 22
Other Sector Optimization Model Indices.

Test Data	RMSE	NRMSE	MAPE	MAE	RAE
PSO	78.5674	0.24737	0.0120231	58.5898	0.57172
GWO	76.15716	0.239789	0.0132013	64.27183	0.562954

4. Discussion

Predicting energy demand is a significant tool for managing and planning the supply of energy resources needed by the country and can help macro policies to respond to energy demands. In this respect, an important challenge ahead of different prediction studies pertains to the prediction accuracy of various prediction algorithms and models, whose prediction accuracies extensively depend on the collected data in every study. Moreover, another important challenge is the limitation of available data. Many of these models and algorithms do not provide acceptable results with small data. However, the present research presented a mathematical model based on ML algorithms that could be implemented by small data and render high prediction accuracy. Concerning the problem in the supply of energy and data limitation in Iran, the energy demand prediction was examined in different sectors in Iran until 2040. Implementing the model with the data with varying features helped to probe the stability of the proposed model. Fig. 25 shows the results of implementing the proposed model by the PSO algorithm with the highest prediction accuracy concerning energy consumption in residential, industrial, commercial, transportation, public, agriculture, and other sectors until 2040.

Implemented by the PSO algorithm, the proposed model predicts that energy demand in Iran annually will increase by 2.59% from 2018 to 2040, and this surge is about 75.65% in 2040 compared to 2018. Meanwhile, the predicted energy demand in all sectors equals 456,211.4 Million Kilowatt/hour in 2040. According to the prediction of the proposed model, energy demand in the industrial, residential, agriculture, public, commercial, other, and transportation sectors constitutes 40.86%, 30.17%, 11.81%, 8.08%, 7.30%, 1.57%, and 0.181% of the total energy demand in 2040, respectively. Table 23 presents the prediction accuracy of the proposed approach separated by different sectors according to the MAPE index.

As Table 30 clearly shows, the prediction accuracy improved by the utilization of the proposed approach. Besides, although the data in every sector were different in terms of the type, linearity, non-linearity, and performance volume of the ML algorithms, the proposed approach presented higher prediction accuracy than ML algorithms in addition to improving prediction accuracy. This reflects the performance robustness of the proposed model in predicting energy demand with different small data. On the whole, the present study employed more updated data than Study (Ardakani & Ardehali, 2014), which examined energy consumption in Iran, and small data to implement the model. On the hand, the predictions in Study (Ardakani & Ardehali, 2014) were general, while

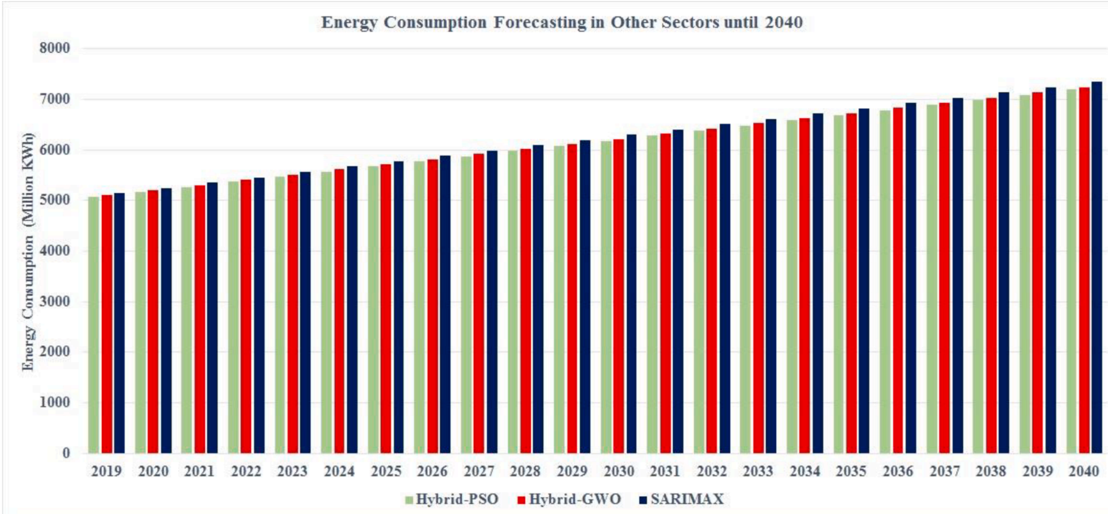

Fig. 24. Other Energy Demand Forecasting.

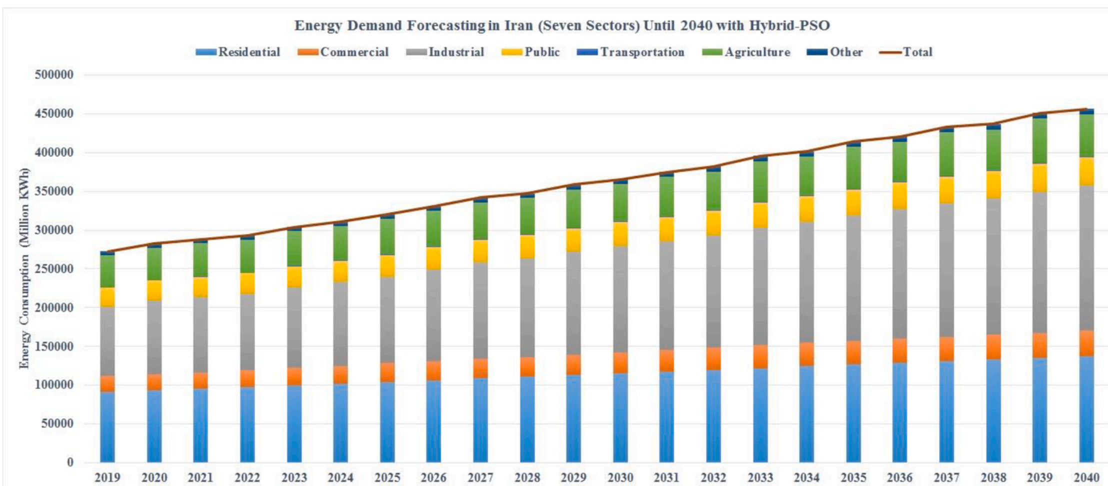

Fig. 25. Energy Demand Forecasting in Iran Until 2040.

Table 23
Prediction Accuracy Comparison.

MAPE	Machine Learning Algorithm						Optimization Model	
	ANN	AR	ARIMA	SARIMA	SARIMAX	LSTM	PSO	GWO
Residential	0.06795	0.0506	0.0340	0.0331	0.12262	0.5822	0.008052	0.00979
Commercial	0.12719	0.1087	0.05372	0.0633	0.1412	0.5270	0.002446	0.004933
Industrial	0.05252	0.03087	0.03075	0.034450	0.05532	0.54725	0.020034	0.020659
Transportation	0.17025	0.08182	0.09841	0.090355	0.25845	0.56573	0.06417	0.06475
Public	0.05596	0.03849	0.05835	0.04844	0.08838	0.4605	0.008050	0.008418
Agriculture	0.06068	0.01686	0.02667	0.017940	0.09614	0.58685	0.00975	0.011615
Other	0.05019	0.03529	0.04783	0.1075	0.01747	0.2748	0.012023	0.013201

the present research implemented the model for seven different sectors and investigated the robustness of the proposed model, whose results would help management and planning in these sectors. The results of this research show that the prediction accuracy of the proposed integrated model has increased and can compete with other integrated approaches introduced in other studies such as (Peng et al., 2022), (Ye et al., 2019), and (Yuan, Liu & Fang, 2016). However, it is necessary to implement the models with similar data and compare the prediction accuracy results for a more meticulous examination. Furthermore, by adding the deviation-preventing constraint to (Javanmard & Ghaderi, 2022) optimization model, this study shows that this addition does not distort the model's performance, and at the same time, the prediction deviation risk of future results declines as well.

It is generally predicted that energy demand will increase by 61–116% in the Residential sector, 82–110% in the Industrial sector, 75–87% in the Commercial sector, 44–53% in the Public sector, 59–75% in the Transport sector, 43–82% in the Agricultural sector, and 44–48% in the Other sector. Decisions- and policy-makers in the energy supply domain can manage or reduce energy demand regarding the significance of every sector and the surge of energy demand in different sectors. For example, many of these sectors enjoy the capacity to utilize renewable energy generation systems and intelligent appliances that decrease energy consumption. While these facilities can help energy supply resources and reduce consumption, they can decrease the emission of greenhouse gases. It is suggested that decision- and policy-makers in the energy supply domain pave the way for reducing energy consumption with incentive policies that encourage using these systems. On the other hand, in different sectors, it is possible to establish local, concentrated, and integrated energy generation systems that enable energy consumption management and reduction.

5. Conclusion

Energy demand forecasting with high accuracy is a critical mechanism for governments and decision-makers in developed and developing countries for energy management and response to demand. Energy demand prediction approach in seven critical sectors of energy consumption (residential, industrial, commercial, transportation, public, agricultural, and other sectors) is presented in this study for a more detailed study of energy consumption in each sector using six prediction algorithms, and an optimization model was presented for prediction accuracy to achieve high prediction accuracy. Concerning, the applied data, SARIMA in the Residential and Agriculture sectors, AR in the Transport, Public, and Industrial sectors, ARIMA in the Commercial sector, and SARIMAX in the Other sector provided higher prediction accuracy than other machine learning algorithms used in this research. After the implementation of the prediction accuracy optimization model with PSO and Grey-Wolf Optimizer algorithms, the prediction accuracy was improved in all sectors, and MAPE was 0.002446 and 0.012023 for the PSO algorithm in all sectors, and for the Grey-Wolf Optimizer algorithm, the MAPE was between 0.00493 and 0.013201, indicating the high prediction accuracy of optimization model by implementing PSO and Grey-Wolf Optimizer algorithms. By evaluating the prediction of total energy consumption in seven sectors, the PSO algorithm predicts a 75.65% increase for 2040 compared to 2018, and the Grey-Wolf Optimizer algorithm predicts a 82.94% increase for the total energy consumption in seven sectors in 2040. The research results have indicated that integrated machine learning algorithms based on mathematical programming with the small data used in this study have the capacity to predict with high prediction accuracy, and the proposed approach can be employed for different problems in future research. Also, the integrated model can be evaluated in future studies with different and more prediction algorithms.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We have presented the data in the manuscript.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2023.104623.

References

Ağbulut, Ü. (2022). Forecasting of transportation-related energy demand and CO2 emissions in Turkey with different machine learning algorithms. *Sustainable Production and Consumption, 29*, 141–157.
Ahmad, A. S., Hassan, M. Y., Abdullah, M. P., Rahman, H. A., Hussin, F., Abdullah, H., et al. (2014). A review on applications of ANN and SVM for building electrical energy consumption forecasting. *Renewable and Sustainable Energy Reviews, 33*, 102–109.
Ahmad, T., & Chen, H. (2019). Nonlinear autoregressive and random forest approaches to forecasting electricity load for utility energy management systems. *Sustainable Cities and Society, 45*, 460–473.
Albuquerque, P. C., Cajueiro, D. O., & Rossi, M. D. (2022). Machine learning models for forecasting power electricity consumption using a high dimensional dataset. *Expert Systems with Applications, 187*, Article 115917.
Ardakani, F. J., & Ardehali, M. M. (2014). Long-term electrical energy consumption forecasting for developing and developed economies based on different optimized models and historical data types. *Energy, 65*, 452–461.
Available at: https://www.amar.org.ir/english.
Available on Global Energy Statistical Website: https://yearbook.enerdata.net/total-energy/world-consumption-statistics.html.
Azadeh, A. Ghaderi, Ghaderi, S. F., & Sohrabkhani, S. (2008a). Annual electricity consumption forecasting by neural network in high energy consuming industrial sectors. *Energy Conversion and management, 49*(8), 2272–2278.
Azadeh, A., Ghaderi, S. F., & Sohrabkhani, S. (2008b). A simulated-based neural network algorithm for forecasting electrical energy consumption in Iran. *Energy policy, 36*(7), 2637–2644.
Azadeh, A., Ghaderi, S. F., Tarverdian, S., & Saberi, M. (2007). Integration of artificial neural networks and genetic algorithm to predict electrical energy consumption. *Applied Mathematics and Computation, 186*(2), 1731–1741.
Barak, S., & Sadegh, S. S. (2016). Forecasting energy consumption using ensemble ARIMA–ANFIS hybrid algorithm. *International Journal of Electrical Power & Energy Systems, 82*, 92–104.
Bolandnazar, E., Rohani, A., & Taki, M. (2020). Energy consumption forecasting in agriculture by artificial intelligence and mathematical models. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 42*(13), 1618–1632.
Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics, 31*(3), 307–327.
Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: Forecasting and control*. John Wiley & Sons.
Chen, K., & Yu, J. (2014). Short-term wind speed prediction using an unscented Kalman filter based state-space support vector regression approach. *Applied Energy, 113*, 690–705.
Chou, J. S., & Ngo, N. T. (2016). Time series analytics using sliding window metaheuristic optimization-based machine learning system for identifying building energy consumption patterns. *Applied energy, 177*, 751–770.
Chou, J. S., & Tran, D. S. (2018). Forecasting energy consumption time series using machine learning techniques based on usage patterns of residential householders. *Energy, 165*, 709–726.
Deb, C., Zhang, F., Yang, J., Lee, S. E., & Shah, K. W. (2017). A review on time series forecasting techniques for building energy consumption. *Renewable and Sustainable Energy Reviews, 74*, 902–924.
Ding, Z., Chen, W., Hu, T., & Xu, X. (2021). Evolutionary double attention-based long short-term memory model for building energy prediction: Case study of a green building. *Applied Energy, 288*, Article 116660.
Dong, B., Li, Z., Rahman, S. M., & Vega, R. (2016). A hybrid model approach for forecasting future residential electricity consumption. *Energy and Buildings, 117*, 341–351.
Dong, Z., Liu, J., Liu, B., Li, K., & Li, X. (2021). Hourly energy consumption prediction of an office building based on ensemble learning and energy consumption pattern classification. *Energy and Buildings, 241*, Article 110929.
Dubey, A. K., Kumar, A., García-Díaz, V., Sharma, A. K., & Kanhaiya, K. (2021). Study and analysis of SARIMA and LSTM in forecasting time series data. *Sustainable Energy Technologies and Assessments, 47*, Article 101474.
Ediger, V.Ş., & Akar, S. (2007). ARIMA forecasting of primary energy demand by fuel in Turkey. *Energy policy, 35*(3), 1701–1708.
Elamin, N., & Fukushige, M. (2018). Modeling and forecasting hourly electricity demand by SARIMAX with interactions. *Energy, 165*, 257–268.
Elbeltagi, E., & Wefki, H. (2021). Predicting energy consumption for residential buildings using ANN through parametric modeling. *Energy Reports, 7*, 2534–2545.
Fan, G. F., Wei, X., Li, Y. T., & Hong, W. C. (2020). Forecasting electricity consumption using a novel hybrid model. *Sustainable Cities and Society, 61*, Article 102320.
Fang, T., & Lahdelma, R. (2016). Evaluation of a multiple linear regression model and SARIMA model in forecasting heat demand for district heating system. *Applied energy, 179*, 544–552.
Gao, Y., Ruan, Y., Fang, C., & Yin, S. (2020). Deep learning and transfer learning models of energy consumption forecasting for a building with poor information data. *Energy and Buildings, 223*, Article 110156.
Ghalambaz, M., Yengejeh, R. J., & Davami, A. H. (2021). Building energy optimization using Grey Wolf Optimizer (GWO). *Case Studies in Thermal Engineering, 27*, Article 101250.
Ghasemi, A., Shayeghi, H., Moradzadeh, M., & Nooshyar, M. (2016). A novel hybrid algorithm for electricity price and load forecasting in smart grids with demand-side management. *Applied energy, 177*, 40–59.
Hamzaçebi, C. (2007). Forecasting of Turkey's net electricity energy consumption on sectoral bases. *Energy policy, 35*(3), 2009–2016.
Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation, 9*(8), 1735–1780.
Iran Ministry of Energy, Statistics; Available online at http://www.moe.gov.ir.
Jamei, M., Ahmadianfar, I., Olumegbon, I. A., Karbasi, M., & Asadi, A. (2021). On the assessment of specific heat capacity of nanofluids for solar energy applications: Application of Gaussian process regression (GPR) approach. *Journal of Energy Storage, 33*, Article 102067.

Javanmard, M. E., & Ghaderi, S. F. (2022). A Hybrid Model with Applying Machine Learning Algorithms and Optimization Model to Forecast Greenhouse Gas Emissions with Energy Market Data. *Sustainable Cities and Society, 82*, Article 103886.
Javanmard, M. E., Ghaderi, S. F., & Hoseinzadeh, M. (2021). Data mining with 12 machine learning algorithms for predict costs and carbon dioxide emission in integrated energy-water optimization model in buildings. *Energy Conversion and Management, 238*, Article 114153.
Javanmard, M. E., Tang, Y., Wang, Z., & Tontiwachwuthikul, P. (2023). Forecast energy demand, CO2 emissions and energy resource impacts for the transportation sector. *Applied Energy, 338*, Article 120830.
Jayabarathi, T., Raghunathan, T., Adarsh, B. R., & Suganthan, P. N.. (2016). Economic dispatch using hybrid grey wolf optimizer. *Energy, 111*, 630–641.
Jeong, K., Koo, C., & Hong, T. (2014). An estimation model for determining the annual energy cost budget in educational facilities using SARIMA (seasonal autoregressive integrated moving average) and ANN (artificial neural network). *Energy, 71*, 71–79.
Jnr, E. O. N., Ziggah, Y. Y., & Relvas, S. (2021). Hybrid ensemble intelligent model based on wavelet transform, swarm intelligence and artificial neural network for electricity demand forecasting. *Sustainable Cities and Society, 66*, Article 102679.
Kaboli, S. H. A., Selvaraj, J., & Rahim, N. A.. (2016). Long-term electric energy consumption forecasting via artificial cooperative search algorithm. *Energy, 115*, 857–871.
Katsatos, A. L., & Moustris, K. P.. (2019). Application of Artificial Neuron Networks as energy consumption forecasting tool in the building of Regulatory Authority of Energy, Athens, Greece. *Energy Procedia, 157*, 851–861.
Kaytez, F. (2020). A hybrid approach based on autoregressive integrated moving average and least-square support vector machine for long-term forecasting of net electricity consumption. *Energy, 197*, Article 117200.
Kennedy, J., & Eberhart, R. (1995). In *Particle swarm optimization, 4* pp. 1942–1948). IEEE.
Kıran, M. S., Özceylan, E., Gündüz, M., & Paksoy, T. (2012). A novel hybrid approach based on particle swarm optimization and ant colony algorithm to forecast energy demand of Turkey. *Energy conversion and management, 53*(1), 75–83.
Kumar, U., & Jain, V. K.. (2010). Time series models (Grey-Markov, Grey Model with rolling mechanism and singular spectrum analysis) to forecast energy consumption in India. *Energy, 35*(4), 1709–1716.
Laib, O., Khadir, M. T., & Mihaylova, L. (2019). Toward efficient energy systems based on natural gas consumption prediction with LSTM Recurrent Neural Networks. *Energy, 177*, 530–542.
Lee, Y. S., & Tong, L. I.. (2012). Forecasting nonlinear time series of energy consumption using a hybrid dynamic model. *Applied Energy, 94*, 251–256.
Liu, S., Zeng, A., Lau, K., Ren, C., Chan, P. W., & Ng, E. (2021). Predicting long-term monthly electricity demand under future climatic and socioeconomic changes using data-driven methods: A case study of Hong Kong. *Sustainable Cities and Society, 70*, Article 102936.
Marini, F., & Walczak, B. (2015). Particle swarm optimization (PSO). A tutorial. *Chemometrics and Intelligent Laboratory Systems, 149*, 153–165.
Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. *Advances in engineering software, 69*, 46–61.
Peng, L., Wang, L., Xia, D., & Gao, Q. (2022). Effective energy consumption forecasting using empirical wavelet transform and long short-term memory. *Energy, 238*, Article 121756.
Poli, R., Kennedy, J., & Blackwell, T. (2007). Particle swarm optimization. *Swarm intelligence, 1*(1), 33–57.
Prado, F., Minutolo, M. C., & Kristjanpoller, W. (2020). Forecasting based on an ensemble autoregressive moving average-adaptive neuro-fuzzy inference system–neural network-genetic algorithm framework. *Energy, 197*, Article 117159.
Qu, J., Qian, Z., & Pei, Y. (2021). Day-ahead hourly photovoltaic power forecasting using attention-based CNN-LSTM neural network embedded with multiple relevant and target variables prediction pattern. *Energy, 232*, Article 120996.
Ruiz, L. G. B., Rueda, R., Cuéllar, M. P., & Pegalajar, M. C.. (2018). Energy consumption forecasting based on Elman neural networks with evolutive optimization. *Expert Systems with Applications, 92*, 380–389.
Shapi, M. K. M., Ramli, N. A., & Awalin, L. J.. (2021). Energy consumption prediction by using machine learning for smart building: Case study in Malaysia. *Developments in the Built Environment, 5*, Article 100037.
Sheng, F., & Jia, L. (2020). Short-Term Load Forecasting Based on SARIMAX-LSTM. In *2020 5th International Conference on Power and Renewable Energy (ICPRE)* (pp. 90–94). IEEE.
Somu, N., MR, G. R., & Ramamritham, K. (2021). A deep learning framework for building energy consumption forecast. *Renewable and Sustainable Energy Reviews, 137*, Article 110591.
Statistical Center of Iran, (2017)., Statistical Center of Iran; 2017[Available from: Https://www.amar.org.ir/.
Tarsitano, A., & Amerise, I. L.. (2017). Short-term load forecasting using a two-stage sarimax model. *Energy, 133*, 108–114.
Tsay, R. S.. (2005). *Analysis of financial time series, 543.* John wiley & sons.
Wang, J. Q., Du, Y., & Wang, J. (2020). LSTM based long-term energy consumption prediction with periodicity. *Energy, 197*, Article 117197.
Wang, Q., Li, S., & Li, R. (2018). Forecasting energy demand in China and India: Using single-linear, hybrid-linear, and non-linear time series forecast techniques. *Energy, 161*, 821–831.
Wang, X., Luo, D., Zhao, X., & Sun, Z. (2018). Estimates of energy consumption in China using a self-adaptive multi-verse optimizer-based support vector machine with rolling cross-validation. *Energy, 152*, 539–548.
Wang, Z. X., Wang, Z. W., & Li, Q. (2020). Forecasting the industrial solar energy consumption using a novel seasonal GM (1, 1) model with dynamic seasonal adjustment factors. *Energy, 200*, Article 117460.
Wen, L., Zhou, K., & Yang, S. (2020). Load demand forecasting of residential buildings using a deep learning model. *Electric Power Systems Research, 179*, Article 106073.
Whitt, W., & Zhang, X. (2019). Forecasting arrivals and occupancy levels in an emergency department. *Operations Research for Health Care, 21*, 1–18.
Xiao, J., Li, Y., Xie, L., Liu, D., & Huang, J. (2018). A hybrid model based on selective ensemble for energy consumption forecasting in China. *Energy, 159*, 534–546.
Xu, S., Chan, H. K., & Zhang, T. (2019). Forecasting the demand of the aviation industry using hybrid time series SARIMA-SVR approach. *Transportation Research Part E: Logistics and Transportation Review, 122*, 169–180.
Xu, Y., Zhang, M., Ye, L., Zhu, Q., Geng, Z., & He, Y. L.. (2018). A novel prediction intervals method integrating an error & self-feedback extreme learning machine with particle swarm optimization for energy consumption robust prediction. *Energy, 164*, 137–146.
Ye, J., Dang, Y., Ding, S., & Yang, Y. (2019). A novel energy consumption forecasting model combining an optimized DGM (1, 1) model with interval grey numbers. *Journal of Cleaner Production, 229*, 256–267.
Yuan, C., Liu, S., & Fang, Z. (2016). Comparison of China's primary energy consumption forecasting by using ARIMA (the autoregressive integrated moving average) model and GM (1, 1) model. *Energy, 100*, 384–390.
Zhang, G., & Guo, J. (2020). A novel ensemble method for hourly residential electricity consumption forecasting by imaging time series. *Energy, 203*, Article 117858.
Zhang, M., Mu, H., Li, G., & Ning, Y. (2009). Forecasting the transport energy demand based on PLSR method in China. *Energy, 34*(9), 1396–1400.
Zhang, P., & Wang, H. (2012). Fuzzy wavelet neural networks for city electric energy consumption forecasting. *Energy Procedia, 17*, 1332–1338.
Zhou, C., Fang, Z., Xu, X., Zhang, X., Ding, Y., & Jiang, X. (2020). Using long short-term memory networks to predict energy consumption of air-conditioning systems. *Sustainable Cities and Society, 55*, Article 102000.