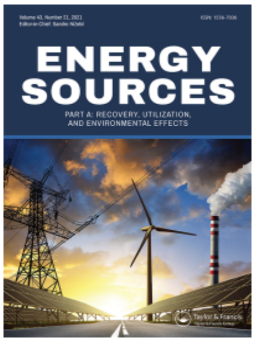

Energy Sources, Part A: Recovery, Utilization, and Environmental Effects

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ueso20

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ENERGY SOURCES, PART A: RECOVERY, UTILIZATION, AND ENVIRONMENTAL EFFECTS
2022, VOL. 44, NO. 3, 6660–6677
https://doi.org/10.1080/15567036.2021.1955048

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Optimal site selection for wind energy: a case study

Onur Derse [a] and Ebru Yılmaz [b]

[a]Department of Management and Organization, Logistics, Tarsus University, Tarsus, Mersin, Turkey; [b]Department of Industrial Engineering, Faculty of Engineering, Çukurova University, Adana, Turkey

ABSTRACT

Renewable energy sources (RES) have gained attraction in recent years. The optimal site selection problem is one of the most important problems in the area of RES. In this study, the optimum site selection problem for wind energy, which is one of the RES types, is discussed. Eighty-one provinces in Turkey are evaluated using the Pareto diagram and the provinces with high potential wind energy are obtained. Long-term electricity consumption estimates are performed for the 13 provinces using ARIMA and Time Series Analysis methods. Also, in the article, an integrated optimum site selection problem in GAMS 23.5 software is modeled by the predicted future energy demand. As a result of the study, the total 41 installation decisions are made for the strategic optimal site selection decision between 2021 and 2025 years. Minimizing the total cost proposed as an objective function of the developed mathematical programming model, the total cost is found as 52526500 currency unit. It is seen that the decision to install the power plant is mostly made for Balıkesir, Çanakkale and İzmir, and the number of plants for the provinces are 6, 6 and 5, respectively. The computational results show that the developed model produces effective solutions and minimizes the total cost by focusing on strategic optimal site decisions. According to the sensitivity analysis results, increasing the percentage of use in wind energy approximately 4–5% from 3.5% in total percentage will reduce the total cost by approximately 3.62%.

ARTICLE HISTORY
Received 29 December 2020
Revised 6 July 2021
Accepted 7 July 2021

KEYWORDS
Renewable energy sources; wind energy; mathematical programming model; prediction methods; optimal site selection

Introduction

Energy, social, economic, and environmental situation is vital for the sustainable development. In recent years, energy consumption has increased exponentially in different areas such as industrial production, agricultural production, health, population, education, etc. (Suganthi and Samuel 2012). Energy types can be divided into two classes as renewable energy and nonrenewable energy. The use of nonrenewable energies can bring about some problems. Environmental problems, import dependence (Bhowmik et al. 2017), and depletion of the energy sources are some of these problems. RES has addressed to prevent or minimize those problems. Also, the usage of renewable energy sources is increasing daily (Ioannou, Angus, and Brennan 2017) and these sources can provide the world's energy demand (Luna-Rubio et al. 2012).

Iqbal et al. (2014) have handled the various algorithms for renewable energy sources. Site selection is one of these problems for the efficient and optimal use of renewable energy sources. For an optimal site selection, future energy estimates must be conducted optimally. In recent years, fundamental changes in industry and economy caused the increase of the world's energy consumption and hence

CONTACT Onur Derse onurderse@tarsus.edu.tr Department of Management and Organization, Logistics, Tarsus University, 33400, Tarsus, Mersin, Turkey

It is based on the ongoing Ph.D. thesis in the Department of Industrial Engineering, Institute of Natural and Applied Sciences at Çukurova University.

accurate demand forecasts became essential for decision-makers to develop an optimal strategy that contains risk reduction and the improvement of the economy (De Oliveira and Oliveira 2018).

The motivation for this study is to model an integrated optimum site selection problem by predicting future energy demand. The main purpose of the study is to provide the optimum design for meeting the energy need. In this study, site selection for wind energy, which is one of the most important renewable energy sources, is addressed, and all the provinces in Turkey are evaluated to decide the most optimal areas for wind power. It is possible to collect research questions under three main headings. The first research question is, which provinces have the highest wind energy potentials? The second research question is, what will be the energy demands for these provinces in the next five years? The third research question is what should be the optimum site selection? By addressing these research questions, provinces with high potential are determined with a Pareto diagram by considering all provinces in Turkey, and estimation models are applied to determine the energy demands for those provinces. An integrated mathematical programming model is developed based on the prediction results. The optimal location of wind energy strategy for the next five years is addressed utilizing the developed mathematical model for Turkey. It is important to predict future energy demand for planning a strategically correct layout, and the integration of demand forecasts and mathematical programming model is a novelty in this study. Demand, potential, installed power, and related costs are taken into account in this study, in which prediction models and mathematical programming model are integrated. Besides, this study will guide the use of renewable energy resources accurately in future studies.

This article first presents the current state of renewable energy and the motivation of the study. Then, Literature Review section presents a literature review on site selection and demand forecasting. The Pareto diagram for determination of provinces with high potential, the ARIMA method and time series analysis for electricity demand prediction, and the developed mathematical programming model are presented in Materials and Methods section. Results for ARIMA, time series analysis, developed mathematical programming model, sensitivity analysis, and discussions are given in Results and Discussions section. Finally, the conclusion and recommendations for future studies are given.

Literature review

There are many studies about renewable energy sources (RES) and the problem of site selection for RES is one of the most studied research areas. Erdogan, Cakici, and Colpan (2017) discuss an optimization study of a hybrid solar-geothermal power plant based on the Taguchi method as a case study. Sindhu, Nehra, and Luthra (2017) use AHP-TOPSIS analysis to select the most suitable location for solar energy, taking into account factors such as social, economic, and technical. In their study, Mahdy and Bahaj (2018) make an application using AHP and GIS in the problem of offshore wind energy location selection. Zhang et al. (2018) use fuzzy modeling for wind power plant site selection. Ghosh (2018) discusses the site selection problem for wave energy using an artificial neural network and a multi criteria decision making (MCDM) technique. Rouyendegh et al. (2018) examine the provinces of Çanakkale, İzmir, Samsun, and Mersin for wind energy. They share the installation results with two different MCDM methods for wind energy. Deveci et al. (2020a) propose the fuzzy-based MCDM approach and discuss the selection of the most suitable offshore wind site in their study. Deveci et al. (2020b) investigate the importance of the criteria that affects the optimum site selection of offshore wind farms. However, mathematical programming models are addressed in the site selection problem for renewable energy sources generally. For biomass energy, Xie and Ouyang (2013) discuss a multi-term future capacity expansion problem by addressing biomass energy and a multitype facility site selection problem together and present a mixed-integer programming model for this problem. Ebadian et al. (2013) develop a deterministic mathematical programming model for biomass storage systems. Marufuzzaman et al. (2014) offer a mathematical model for a reliable multimodal transportation network of a biofuel supply chain system. Paulo et al. (2015) aim to provide total cost minimization in the supply chain design problem for bioenergy utilizing the mixed-integer linear programming

(MILP) model. Also, Marvin, Schmidt, and Daoutidis (2013), Fattahi and Govindan (2018); Derse (2018) develop a mathematical programming model for biomass energy. For solar energy, Schwarz, Bertsch, and Fichtner (2018) deal with the problem of solar energy site selection using a mathematical programming model. Merzifonluoglu and Uzgoren (2018) develop stochastic programming models and heuristic algorithms to determine the best strategy of photovoltaic installations for the area addressed, taking into account the uncertainties in load, power generation, and system performance. For wind energy, Abbey and Joos (2009) develop a stochastic mixed-integer programming model for the wind energy system through the GAMS program for optimal dimensioning of the storage system. Kongnam et al. (2009) provide the mixed-integer nonlinear programming (MINLP) model and discuss the optimum capacity calculation for wind energy. Chen, Wang, and Stelson (2018) develop a mathematical programming model to minimize the energy costs of turbines based on wind energy. Ari and Gencer (2020) examine six regions of 81 provinces in Turkey (Bursa, Hatay, Manisa, İzmir, and two different regions from Balıkesir) in their study. In their study, they examine the installation decision and total cost minimization for wind energy. De La Torre and Conejo (2005) develop an MINLP model for maximizing profit by addressing tidal energy. Trapanese (2008) discusses a stochastic mathematical programming model based on wave energy to maximize energy efficiency. De Ladurantaye, Gendreau, and Potvin (2009) discuss the profit maximization problem for hydro-electric energy through deterministic and stochastic mathematical programming models. Kuznia et al. (2013) address the power system design problem for renewable energy with a stochastic mixed-integer programming model, taking into account the renewable energy generation, storage device, and transmission network. Xie, Nian, and Cheng (2018) develop a stochastic mathematical programming model for geothermal energy. Derse et al. (2020) provide a mathematical programming model that includes production, storage, transportation, safety, location, and personnel assignment decisions and minimizes the total cost for the facility layout optimization.

A few examples of site selection problems for wind energy are given in Table 1. In Table 1, the studies on wind energy location selection are examined in terms of scope and method. Among the values taken into consideration in the studies discussed, the cost item generally stands out. The existence of wind energy is free of charge, but the costs of setting up, maintaining, or operating the turbines must be taken into account to use wind energy. Therefore, situations consisting of these items should be addressed.

To make the optimum site selection, future periods must be predicted correctly. Therefore, there are also estimation studies conducted. Many different methods such as time series analysis, ARIMA, fuzzy logic, genetic algorithm, regression, and neural networks are used to estimate energy

Table 1. Some study for wind energy site selection.

Authors (year)	Scope of the Study	Method of Study
Grady, Hussaini, and Abdullah (2005)	Optimum site selection of wind turbines for maximum production capacity is aimed, while the number of installed turbines and the area occupied by each wind farm are limited.	Genetic algorithm
Jones and Wall (2016)	An application in the field of site selection dealing with offshore wind farm is offered.	Goal Programing
De La Cruz and Martín (2016)	The study examines offshore and onshore wind turbines, evaluates their efficiency and selects the turbine type and appropriate area.	Mixed-Integer Nonlinear Programing (MINLP)
Chen, Wang, and Stelson (2018)	It is aimed to minimize the energy costs of turbines based on wind energy. The study includes turbine cost, turbine power and turbine wind speed.	Mathematical Programing Model
Lotfi et al. (2018)	First, it is aimed to evaluate and rank candidate cities in the region considered. Later, a budget-constrained mathematical model is developed.	Mathematical Programming Model, MCDM (Fuzzy TOPSIS)
Solangi et al. (2018)	The problem of site selection for wind energy is realized by considering techno-economic and socio-strategic factors.	MCDM (Factor Analysis, Analytical Hierarchy Process (AHP), Fuzzy TOPSIS)
Ari and Gencer (2020)	For wind energy, it is aimed to ensure the optimum site selection by providing power maximization.	Mixed Integer Linear Programing (MILP)

consumption (Suganthi and Samuel 2012). Predictions are mainly carried out with time series analysis, which is one of the most widely used methods for estimating electrical energy. In the study of Nogales et al. (2002), energy estimation is conducted by using time series analysis. Zucatelli et al. (2019), in their study, perform wind speed estimation using a time series-based method for a region in Uruguay. Zheng et al. (2020) provide short-term forecasting using time series analysis for solar energy. De Felice, Alessandri, and Catalano (2015) and Najafi et al. (2016) present medium-term energy estimates in their studies. In the study of Rahman et al. (2016), the long-term energy demand of Bangladesh is estimated by time series analysis. ARIMA techniques can be used because of their accuracy and mathematical robustness (Contreras et al. 2003). Contreras et al. (2003) and Zhou et al. (2006) provide a method for estimating electricity prices based on the ARIMA methodology. Erdogdu (2007) utilizes ARIMA modeling conducting an electricity demand forecast for Turkey. Ediger and Akar (2007) use the ARIMA method for predicting the future primary energy demand in Turkey between 2005–2020 years. In Erdogdu's (2010) study, short- and long-term price and income elasticity of demand for the natural gas sector in Turkey is estimated using ARIMA modeling. Rehman et al. (2017) estimate energy demand of Pakistan for electricity, natural gas, oil, coal, and LPG in their study. In the study, the demand for the industrial sector until 2035 is estimated. Al-Musaylh et al. (2018) and De Oliveira and Oliveira (2018) use the ARIMA method to estimate the energy demand in their studies.

Materials and methods

In this study, the site selection problem for wind energy is discussed. The main purpose of the study is to ensure the optimum design for providing the energy need. In the study, all provinces in Turkey are assessed. The aim is to find the most optimal site selection. The flow chart of the developed system is illustrated in Figure 1. The study takes place in four steps. As a first step, potential wind energy data are compiled. As a second step, the application of the Pareto diagram provides the determination of high potential provinces. This step determines the provinces that account for approximately 80% of Turkey's total wind energy potential. After that, with the forecasting methods, electricity consumption estimates of high potential provinces in the future are performed. In this step, the ARIMA method and time series analysis method are used. As the last step, an integrated mathematical programming model

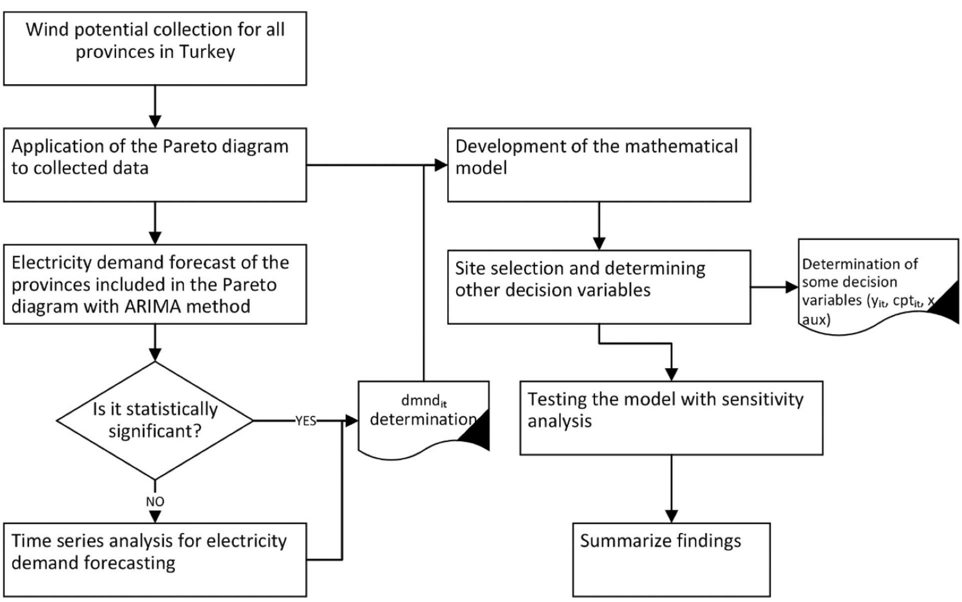

Figure 1. Flow chart of the proposed system.

with estimation outputs is developed. As a result of the algorithm, it is determined in which province the installation decision will be made, how many installations will be in total, and what the appropriate capacities of the provinces are.

In the first step, the data is collected. The wind energy potential data of provinces is obtained from the official institution "Republic of Turkey Ministry of Energy and Natural Resources." The data gives information about the potential that can be used in the provinces without specifying a time period and the data is actual.

After collecting the data, the Pareto Diagram is used to determine the provinces with high potential. The Pareto diagram is also known as the 80/20 principle. The Pareto diagram is useful in providing a summary of critical information (Grosfeld-Nir, Ronen, and Kozlovsky 2007). This method can be defined as determining values that provide 80% of the total criteria as value. The provinces forming the wind energy potential of 80% in Turkey are obtained. The provinces that provide 80% of the cumulative total are obtained as 13 provinces. Pareto diagram result for wind energy is obtained as Balıkesir, Bursa, Çanakkale, Edirne, Hatay, İstanbul, İzmir, Kırklareli, Manisa, Mersin, Muğla, Samsun, and Tekirdağ.

Prediction methods

Electricity consumption values for all provinces called "Regional Statistics, Electricity consumptions by users: Total consumptions (MWh)" are collected from "Turkish Statistical Institute ((TURKSTAT), https://biruni.tuik.gov.tr/bolgeselistatistik/degiskenlerUzerindenSorgula.do?d-4326216-e=2&6578706f7274=1)." The electricity consumption values of 13 provinces according to the wind energy potential Pareto diagram are selected. These consumption values include the values between 1995 and 2018 years and the data is actual.

ARIMA method and time series forecasting are used as the estimation method in this study. First, the ARIMA method is used. For the provinces that are not found to be statistically significant in the ARIMA method, the time series analysis method is applied.

ARIMA method

ARIMA is also known as the Box–Jenkins methodology. For a long time, ARIMA models are used in the many estimate problems. In an ARIMA (p, d, q) model, the future values of variable and past observations are assumed to be a linear function of the random error (Khashei and Bijari 2011). The ARIMA (p, d, q) methodology consists of four steps. Initially, the stationarity test is performed and for this test, autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs are looked at (Box and Jenkins 1976). If it is understood that the data is not stable as a result of a visual examination of ACF and PACF graphics; until the non-stationary data disappears, the process of stabilization is applied by differentiating it. Then, the appropriate parameter (p, d, q) values of the model are determined based on the stationary data after differentiation and its correlogram (Erdogdu 2010). In the second step, the model is created and predicted based on the results obtained from the first step, and then the diagnostic check is performed in the third step. To check if the model fits the data reasonably, it is looked at the values of the prediction in the previous step and checked whether any of the ACF and PACF of the residues individually are statistically significant. If they are not statistically significant, this means that the ARIMA (p, d, q) values are completely random and there is no need to look at another ARIMA (p, d, q) model. In the last stage, estimation is made according to the applied, controlled, and statistically significant ARIMA (p, d, q) model (Erdogdu 2010). In this study, the steps mentioned above are applied for the ARIMA model, and the SPSS program is used in the ARIMA model stage.

Time series analysis

Time series analysis is an analysis method that is used to predict the next period or periods by taking into account the data of the past. In this study, time series analysis is carried out using the SPSS program. MAPE (mean absolute percentage error) and R-squared values are examined for the selection of the most appropriate estimator among the estimation methods applied in the SPSS program. MAPE (mean absolute percent error) is calculated to measure relative error by considering negative and positive errors (Goodwin and Lawton 1999). The fact that the MAPE value is close to the minimum shows that the accuracy is high, and results below 10% mean that there is a very good accuracy value. R-square type is used for goodness of fit of summary statistics (Cameron and Windmeijer 1997).

Mathematical programming model

In this study, a developed mixed-integer nonlinear programming (MINLP) model is solved using GAMS optimization software. By considering wind energy, the site selection problem between 2021 and 2025 years for 13 provinces is discussed. A MINLP model is developed for this problem. The nomenclature for the model is demonstrated in Table 2.

Table 2. Nomenclature of the proposed model.

Nomenclature	Description
I,T	set of provinces, periods
$stup_{it}$	site setup cost
$mntc_{it}$	maintenance cost
$oprt_{it}$	operating cost
$dmnd_{it}$	electricity consumption demand
k_i	installed power
p_i	provincial potential of wind energy
v	the amount of resources a power plant can provide
lmt	the upper limit of the cost that can be spent
prcnt	percentage of wind energy resources in general use
WW	a large number
y_{it}	integer number decision variable indicating how many plants will be installed
cpt_{it}	positive decision variable indicating the capacity to be used
x	total number of power plants opened
aux	the auxiliary binary decision variable

Minimize

$$\sum_i \sum_t stup_{it} * y_{it} + \sum_i \sum_t mntc_{it} * y_{it} + \sum_i \sum_t oprt_{it} * y_{it} \tag{1}$$

$$p_i - k_i = cpt_{it}, t = 1;\ \ i \tag{2}$$

$$cpt_{it} - (dmnd_{it} * prcnt) \leq aux * WW,\ \ i,\ \ t \tag{3}$$

$$(dmnd_{it} * prcnt) - cpt_{it} \leq (1 - aux) * WW,\ \ i,\ \ t \tag{4}$$

$$(aux * (dmnd_{it} * prcnt)) + ((1 - aux) * cpt_{it}) \leq y_{it} * v,\ \ i,\ \ t \tag{5}$$

$$cpt_{it} - y_{it} * v = cpt_{i(t+1)}, t = 1, \ldots, T - 1;\ \ i \tag{6}$$

$$\sum_i \sum_t y_{it} = x \tag{7}$$

$$\sum_{i} y_{it} * stup_{it} \leq lmt, \quad t \tag{8}$$

$$y_{it},\ x \geq 0\, and\, integer, \quad i, \quad t \tag{9}$$

$$aux \in (0, 1) \quad i, \quad t \tag{10}$$

$$cpt_{it} \quad i, \quad t \tag{11}$$

As a multi-objective mathematical programming model, the minimization of total of installation cost, maintenance cost, and operating cost is taken into account and in Equation (1) these costs are expressed in the objective function, respectively. Equation (2) is a limitation that shows the capacity that can be used in that province. Equation (3), Equation (4), and Equation (5) provide demand constraints. Equation (6) for each period refers to the potential that can be established. Equation (7) shows the total number of plants installed. Equation (8) is the equation that shows the maximum budget per period for the installation of the facility. Equation (9) expresses the positive and integer constraint for the y_{it} and x decision variables. Equation (10) states that the aux decision variable is the binary decision variable. Equation (11) shows that the cpt_{it} decision variable is the real number. The potential value and maximum budget value are the limitations of the model.

Input data for mathematical programming model

The index i, used in this study, indicates the provinces discussed. The index i consists of 13 provinces and these provinces are Balıkesir, Bursa, Çanakkale, Edirne, Hatay, İstanbul, İzmir, Kırklareli, Manisa, Mersin, Muğla, Samsun, and Tekirdağ. The reason for choosing these provinces is that they have the highest potential for wind energy according to the Pareto diagram. The index t shows the next period and covers the years between 2021 and 2025 years.

The electricity demand forecasts between 2021 and 2025 years obtained from the forecast models are expressed as $dmnd_{it}$. The parameter value v represents the potential amount that a power plant can provide and it is assumed to be 2200 MW. The prcnt value is assumed as 3.5%. The lmt value is assumed as 75000000 currency unit. WW is a large number. p_i values that are obtained from the official institution “Republic of Turkey Ministry of Energy and Natural Resources” define the values of wind energy potential in the provinces of the year in MW. In Table 3, k_i parameters are assumed as the values of installed powers in the provinces in MW.

Table 3. K_i parameters based on provinces.

Parameters	Balıkesir	Bursa	Çanakkale	Edirne	Hatay	İstanbul	İzmir
k_i (MW)	950	50	310	135	360	185	875
Parameters	Kırklareli	Manisa	Mersin	Muğla	Samsun	Tekirdağ	
k_i (MW)	48	545	123	49	0	130	

Table 4 shows the assumed values of $stup_{it}$ facility installation cost, $mntc_{it}$ maintenance cost, $oprt_{it}$ operating cost.

Table 4. Some parameters based on periods.

Parameters	Years	Balıkesir	Bursa	Çanakkale	Edirne	Hatay	İstanbul	İzmir	Kırklareli	Manisa	Mersin	Muğla	Samsun	Tekirdağ
$stup_{it}$ (*10^4)	2021	110	118	110	110	100	125	120	105	115	115	100	102	105
	2022	121	123	121	121	119	136	134	120	122	122	119	119	120
	2023	134	135	134	134	130	147	145	131	134	134	130	130	131
	2024	145	146	145	145	140	158	150	142	145	145	140	141	142
	2025	155	157	155	155	155	170	165	152	156	156	155	151	152
$mntc_{it}$(*10^2)	2021	260	240	260	260	250	240	240	275	250	250	300	300	275
	2022	285	265	285	285	270	265	265	290	270	270	330	330	290
	2023	300	280	300	300	290	280	280	305	290	290	355	355	305
	2024	320	295	320	320	305	295	295	330	305	305	370	370	330
	2025	350	310	350	350	325	310	310	360	325	325	385	385	360
$oprt_{it}$(*10^2)	2021	130	120	130	130	125	120	120	137	125	125	150	150	137
	2022	145	135	145	145	140	135	135	150	140	140	165	165	150
	2023	150	140	150	150	145	140	140	160	145	145	170	170	160
	2024	160	150	160	160	155	150	150	170	155	155	185	185	170
	2025	175	160	175	175	170	160	160	180	170	170	195	195	180

Results and discussions

Results for ARIMA

At this stage, electricity consumption is estimated in the future years by using 24-year electricity consumption values between 1995 and 2018 years. Thirteen provinces selected according to the wind energy potential Pareto diagram are evaluated according to the relevant methods in the SPSS program. While applying the ARIMA model, initially the time series charts, autocorrelation function (ACF), and partial autocorrelation function (PACF) charts are examined and the stationarity test is performed on every province basis. Then, ARIMA (p, d, q) is formed by determining the appropriate p, d, and q values for each province. By controlling the statistically significant ARIMA (p, d, q) values, the estimation is made for the statistically significant values.

The ARIMA model steps mentioned above are applied to all provinces considered. As a result of the implementation steps of the ARIMA model, statistically significant results are obtained for some provinces, while statistically significant results are not found for some provinces. Table 5 shows the provinces and values that are statistically significant results for AR (p), ARMA (p, q), or ARIMA (p, d, q) models.

Table 5. Statistically significant provinces.

Province	AR(p), ARMA(p,q), ARIMA(p,d,q)			Estimate	SE	Sig.
Balıkesir	ARIMA(1,1,1)	AR	Lag 1	0.988	0.073	0.000
		Difference		1		
		MA	Lag 1	0.841	0.284	0.007
Bursa	ARIMA(1,1,1)	AR	Lag 1	1.000	0.006	0.000
		Difference		1		
		MA	Lag 1	0.983	0.177	0.000
Çanakkale	ARIMA(1,1,1)	AR	Lag 1	0.911	0.167	0.000
		Difference		1		
		MA	Lag 1	0.714	0.290	0.022
Edirne	ARIMA(0,1,0)	Constant		28993.435	8940.420	0.004
		Difference		1		
İstanbul	ARIMA(1,1,1)	AR	Lag 1	1.000	0.007	0.000
		Difference		1		
		MA	Lag 1	0.976	0.334	0.008
İzmir	ARIMA(0,1,0)	Constant		572788.913	181611.460	0.005
		Difference		1		
Kırklareli	ARMA(1,1)	Constant		1508644.643	661852.348	0.033
		AR	Lag 1	0.940	0.084	0.000
		MA	Lag 1	−0.458	0.208	0.039
Manisa	ARIMA(1,1,1)	AR	Lag 1	0.989	0.065	0.000
		Difference		1		
		MA	Lag 1	0.832	0.265	0.005
Mersin	ARIMA(1,1,1)	AR	Lag 1	0.990	0.048	0.000
		Difference		1		
		MA	Lag 1	0.832	0.232	0.002
Muğla	ARIMA(1,1,1)	AR	Lag 1	0.982	0.062	0.000
		Difference		1		
		MA	Lag 1	0.684	0.235	0.008
Samsun	ARIMA(1,1,1)	AR	Lag 1	0.995	0.044	0.000
		Difference		1		
		MA	Lag 1	0.901	0.285	0.005
		MA	Lag 1	0.987	0.134	0.000

Figure 2 shows the five-year electricity forecast values for some provinces handled by the ARIMA method in terms of MWhaccording to years.

For a better understanding of Figure 2, Figure 2 is shown in two parts as Figures 3 and 4.

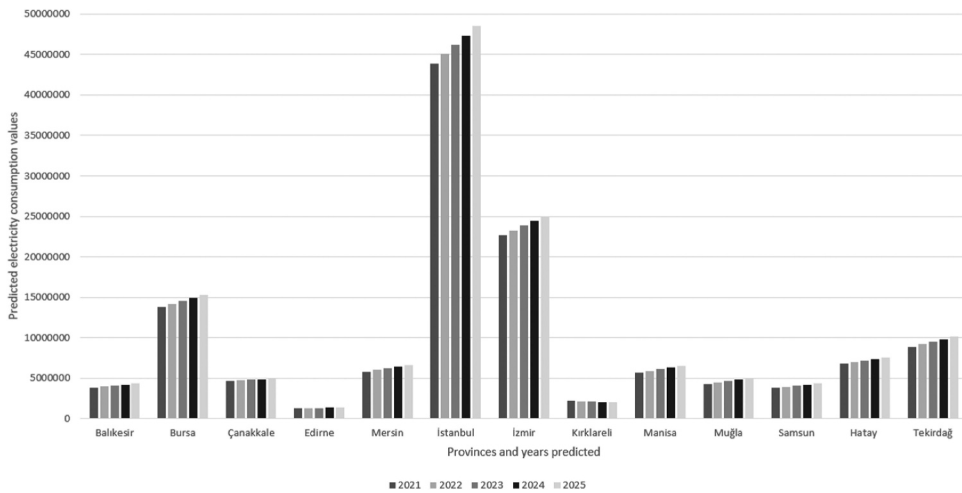

Figure 2. Predicted provinces, years and electricity consumption values.

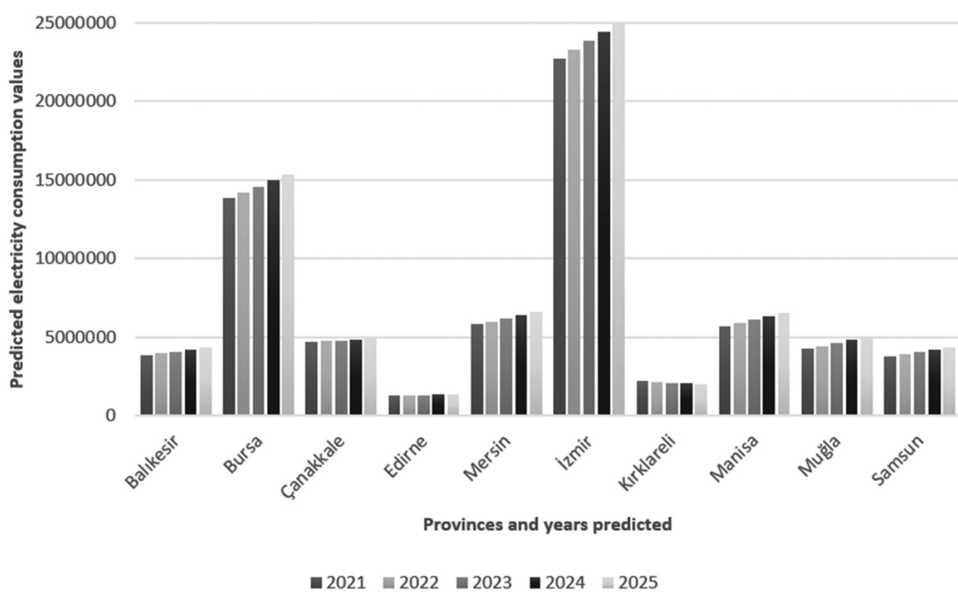

Figure 3. Predicted electricity consumption values for some provinces with the ARIMA method.

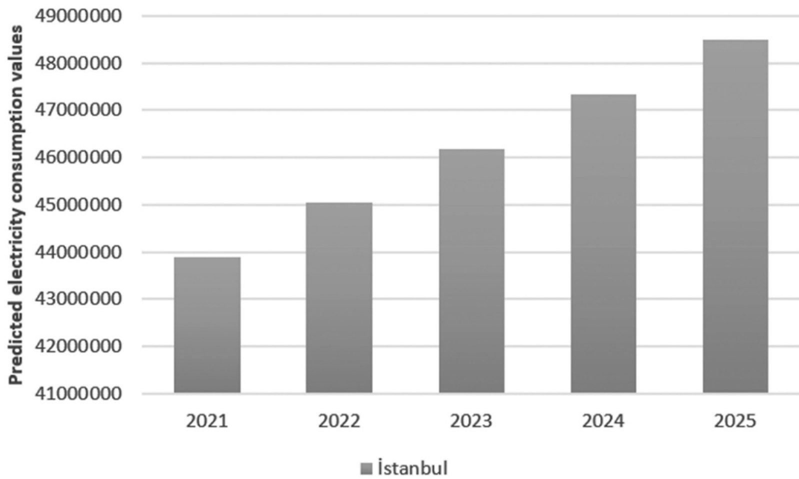

Figure 4. Predicted electricity consumption values for İstanbul with the ARIMA method.

Results for time series analysis

First, the ARIMA method is applied to 13 provinces considered as a result of the Pareto diagram. Since the results of provinces of Hatay and Tekirdağ are not statistically significant, time series analysis is applied for these two provinces. It is seen that there is an increasing trend when data between 1995 and 2018 years are entered into the system for the two provinces considered. The trend for both provinces shows that this data can be tested with exponential correction methods for the estimation. Among the tried exponential correction methods, it can be seen that the most appropriate method for these two provinces is Holt exponential smoothing method. The correction coefficient is taken as α = 0.05 in the analyses performed and the MAPE values and R-square values obtained from the Holt exponential correction technique obtained as a result of the analyses are shown in Table 6.

Table 6. Model results for the provinces considered.

	Model Statistics	
Model	R-square	MAPE (%)
Hatay-Model	0.965	5.703
Tekirdağ-Model	0.966	6.904

As a result of the data entered between 1995 and 2018 years, the estimates are made between 2021 and 2025 years and it is seen that these estimation results have an increasing trend. Figure 5 shows the predicted values of five-year electricity consumption for provinces considered by time series analysis in terms of MWh according to years.

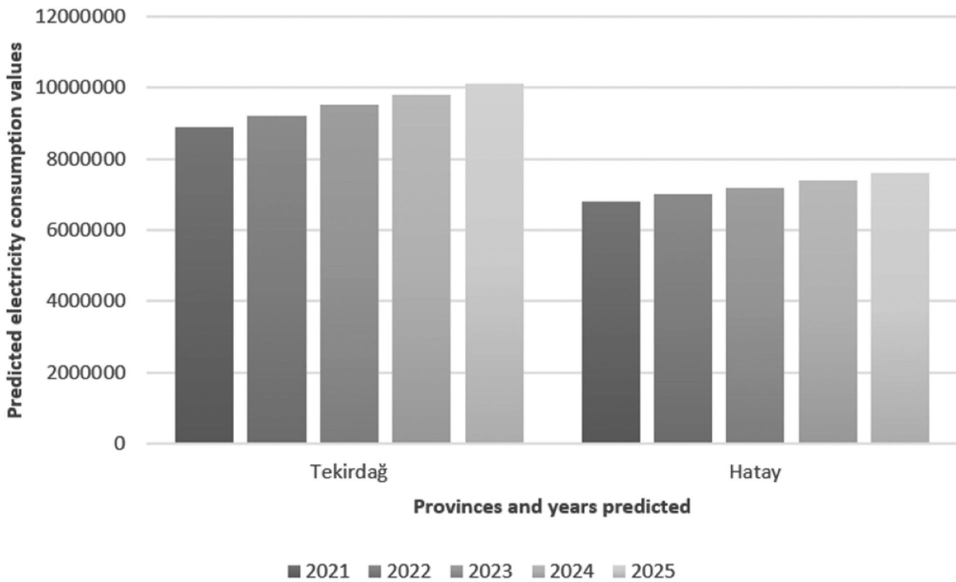

Figure 5. Predicted electricity consumption values for Hatay and Tekirdağ with the Time Series Analysis method.

Some results for mathematical programming modeling

In the developed mathematical programming model, as a result of the minimization of the total cost proposed as an objective function it is found as 52526500 currency unit. Table 7 shows the values of the decision variable y_{it}. This variable shows how many facilities should be established for each period in each province. The total number of power plants installed (x) is 41.

Table 7. Number of power plants that can be established in provinces.

Provinces (i)/Period (t)	2021	2022	2023	2024	2025
Balıkesir	6				
Bursa		1		1	
Çanakkale	5	1			
Edirne		1		1	
Hatay				1	1
İstanbul	1	1			
İzmir	5				
Kırklareli		2			
Manisa	2	1			
Mersin	1	1			
Muğla				1	2
Samsun	2			1	
Tekirdağ				1	2

Sensitivity analysis

It is examined how the total cost results change by changing the lmt parameter in Table 8. This parameter shows the maximum budget per period.

Table 8. Change of lmt value and total cost.

lmt parameter value (*10^5)	600	700	750	850	900
Total Cost	49650000	52526500	52526500	50623000	50623000

prcnt value indicates the percentage of wind energy in overall energy consumption in Turkey. In Table 9, the changing of the total cost with the different values of this parameter is examined. It can be seen that the increase in the value of wind energy in total percentage decreases the total cost value.

Table 9. Change of prcnt value and total cost.

prcnt parameter value (*10^5)	3.5%	4%	5%
Total Cost	52526500	50623000	50623000

Parameter $dmnd_{it}$ shows the electricity consumption forecast between 2021 and 2025 years. By examining the change of this parameter, its effect on the total cost and installation decision is examined. The estimation is made using the time series analysis method for all provinces instead of the ARIMA method. When the data between 1995 and 2018 years are entered into the system for all provinces, it is seen that there is an increasing trend and this trend shows that the data can be tested with exponential correction methods for the estimation. Among the exponential correction methods tried, it is seen that the most appropriate method for all provinces is the Holt exponential correction method. The correction coefficient is a taken as α = 0.05. $dmnd_{it}$ demand parameter value results are as in Table 10 and Table 11. Table 10 shows the R-square and MAPE values of the provinces examined. Table 11 shows the values of the estimates made for all provinces by years in MWh.

Table 10. R-square and MAPE values for provinces examined.

	Model Statistics			Model Statistics			Model Statistics	
Model	R-square	MAPE (%)	Model	R-square	MAPE (%)	Model	R-square	MAPE (%)
Balıkesir	0.980	4.336	İstanbul	0.987	3.026	Mersin	0.982	4.490
Bursa	0.968	5.058	İzmir	0.965	5.541	Muğla	0.986	3.728
Çanakkale	0.971	11.419	Kırklareli	0.927	7.065	Samsun	0.980	5.124
Edirne	0.967	4.191	Manisa	0.984	4.826	Tekirdağ	0.966	6.904
Hatay	0.965	5.703						

Table 11. Prediction values by years for the provinces determined.

	Prediction Values (MWh)						
Prediction Years	Balıkesir	Bursa	Çanakkale	Edirne	Hatay	İstanbul	İzmir
2021	3761946	13583630	4994223.62	1277596	6798992	44031788	22172458
2022	3864236	13929821	5188397.16	1309122	6997562	45233837	22770176
2023	3966527	14276013	5382570.71	1340648	7196133	46435885	23367893
2024	4068817	14622205	5576744.26	1372174	7394704	47637934	23965611
2025	4171107	14968397	5770917.81	1403700	7593275	48839982	24563329
Prediction Years			Prediction Values (MWh)				
	Kırklareli	Manisa	Mersin	Muğla	Samsun	Tekirdağ	
2021	2717258	5543619	5623653	4287956	3779315	8895487	
2022	2794989	5718588	5779054	4505467	3897463	9201335	
2023	2872720	5893558	5934455	4722979	4015611	9507184	
2024	2950451	6068528	6089856	4940490	4133759	9813033	
2025	3028182	6243498	6245257	5158001	4251907	10118881	

According to the results, there is no difference in y_{it} decision variable value. The total number of facilities opened (x) and total cost values do not change depending on this situation.

Discussions

This study covers the 13 different provinces in Turkey for siting wind energy according to Pareto diagram, and in this study, the total cost minimization is made examining installation decisions. Similarly, when the literature is reviewed, there are studies examining installation decisions and total cost minimization such as Ari and Gencer (2020). However, our study is an integrated model in which demand forecasts are developed and strategically periodic decisions are made.

In this study, it is seen that increasing the budget allocated for wind energy between 13.3% and 20% provides a total cost advantage in the long term according to Table 8. Similarly, when the literature is examined, De La Cruz and Martín (2016) show that choosing the optimum turbine location saves up to 30% in investment costs.

In this study, the most installation decisions are made for Balıkesir, Çanakkale, and İzmir. Total installation decisions are as shown in Figure 6. When the literature is reviewed, Rouyendegh et al. (2018) discussed two different MCDM methods for wind energy in their study. According to Rouyendegh et al. (2018), it is obtained that by using the Intuitionistic Fuzzy TOPSIS method, the most important alternative is Izmir, and by using the Fuzzy TOPSIS method, Çanakkale is the most important alternative.

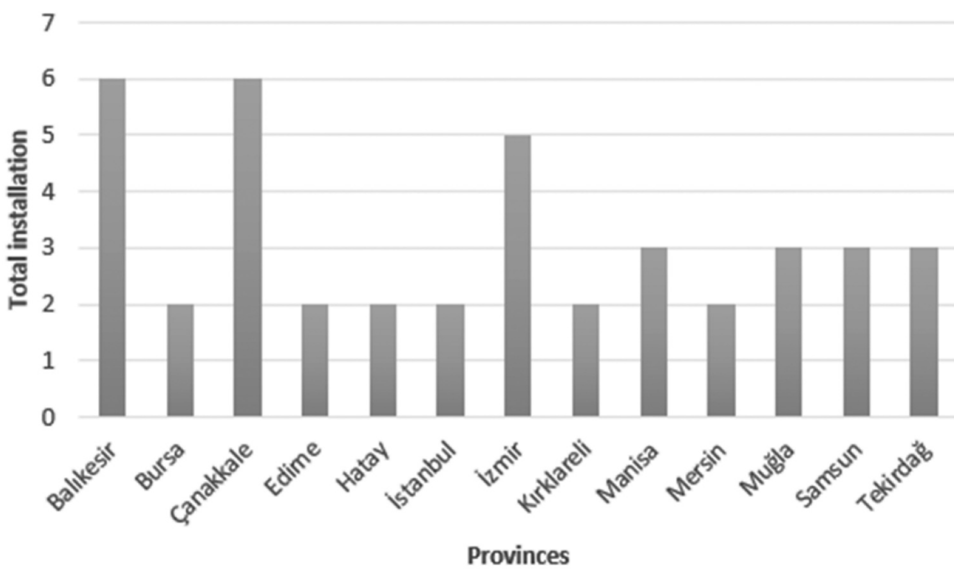

Figure 6. Total installation decisions.

Conclusion

Depletion of energy resources and increasing negative effects of nonrenewable energy sources on the environment increase the use of renewable energy sources (RES). RES is significant for a sustainable and clean environment. Wind energy source that is the one of the RES is also frequently used today for their environmental benefits. Energy obtained from wind energy sources is used in many different areas such as transportation, lighting, cooling, and heating. For the optimal use of wind energy, optimal layout decisions, and accurate predictions must be made. This study, it is aimed to select the optimum site for wind energy. The all provinces in Turkey are evaluated using the Pareto diagram and the high potential provinces with wind energy are obtained. The long-term electricity consumption estimates are performed for the 13 provinces obtained by Pareto diagram using ARIMA and Time Series Analysis methods. Then, an integrated mathematical programming model with estimation methods is proposed. In this model, it is aimed to provide the demand in the provinces more with wind energy and to minimize the total cost. The calculation results show the decision to establish 41 power plants in 13 different provinces. This decision covers the period between 2021 and 2025 years. In the developed mathematical programming model, as a result of the minimization of the total cost proposed as an objective function, it is found as 52526500 currency unit. It is seen that the decision to install the power plant is the mostly made for Balıkesir, Çanakkale and İzmir. While a decision is made to install 22 power plants in 2021, 8 power plants in 2022, 6 power plants in 2024, and 5 power plants in 2025, there is no decision to install a power plant in 2023. The sensitivity analysis shows that the percentage of wind energy use and the budget allocated for the period have an effect on the total cost. The percentage of use in wind energy is assumed as 3.5%. According to the sensitivity analysis results, increasing the percentage of use in wind energy approximately 4–5% from 3.5% in total percentage reduces the total cost by approximately 3.62%. According to this result, the importance of using wind energy is revealed. It is seen that increasing the budget allocated for wind energy between 13.3% and 20% provides a total cost advantage in the long term. In addition, it is seen that the values estimated according to the sensitivity analysis do not change in the long term due to small deviations. This indicates a consistent calculation result. In this study, the advantage of an optimum layout design is revealed by making an integrated decision with demand forecasts. As a result of this approach, it is seen that increasing wind energy use and investment in wind energy provides a total cost advantage in the long term.

The increase in the total production share of renewable energy sources such as wind energy can provide advantages such as a sustainable environment, and a decrease in carbon emissions for the province where the installation is made.

In future studies, the other energy sources such as solar energy, geothermal energy, biomass energy can be considered. In addition, the model can be expanded by considering different factors such as wind power plant sizes, set up time of wind power plant and carbon emission reduction in future studies.

Acknowledgments

Thanks Republic of Turkey Ministry of Energy and Natural Resources and Mustafa ÇALIŞKAN from Republic of Turkey Ministry of Energy and Natural Resources for giving the potential data of provinces.

Notes on contributors

Onur Derse is working as a Lecturer in the Department of Management and Organization of Tarsus University, Mersin, Turkey. His main research areas include operations research, risk analysis, mathematical programming models, optimization, and renewable energy.

Ebru Yılmaz is working as an Assistant Professor in the Department of Industrial Engineering, Faculty of Engineering, Çukurova University, Adana, Turkey. Her main research areas include operations research, mathematical programming models, optimization, and modeling of manufacturing and service systems.

ORCID

Onur Derse http://orcid.org/0000-0002-4528-1999
Ebru Yılmaz http://orcid.org/0000-0002-7382-4081

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