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Demand forecasting and PV/EV-integrated energy system modeling for achieving a sustainable island

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A R T I C L E I N F O

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A B S T R A C T

Due to the increasing demand in the electric energy and transportation sector, future planning for these sectors is essential. This paper deals with forecasting electricity and gasoline demand for the Qeshm island located in the south of Iran and modeling its energy system. In this regard, using a time series analysis model, ARIMA, the electricity and gasoline demand of the island in 2030 is forecasted. Then, by compiling different scenarios for the island's power and transportation network, supply and demand modeling for the island's energy system is conducted. Finally, using a multi-criteria decision-making method, the energy scenarios are ranked and the best one is selected. The results of the research showed that increasing the share of solar energy as well as electric vehicles in the island's energy and transportation network, from the worst to the best case, has a direct relationship with reducing energy consumption (up to 17.3 %), reducing emissions (up to 23.8 %) and, as a result, increasing the sustainability of the island. Also, investing only in the development of thermal power plants, regardless of renewable sources and electric transportation, will reduce the economic and environmental efficiency of the island's energy system in the long term.

1. Introduction

Annual global primary energy consumption per capita nearly doubled from 1965 to 2019, and the CO_2 emission in 2019 jumped over three times that of 1965. Among all sectors, the transportation sector approximately accounted for 23 % of CO_2 emissions worldwide [1]. Thereby, Electric Vehicles (EVs) can play an important role in eliminating CO2 emissions. Though there are many obstacles through decarbonizing the transportation sector, this issue should be prioritized by governments and legislators. Another way to tackle climate change and its drawbacks is the decarbonization of the energy sector by taking advantage of new technologies and effective policies [2,3].

The best way to reduce CO2 emissions is renewable energy resources, where their presence is missing in the Iranian energy mix. From the other perspective, renewable energy resources can diversify the energy mix of countries and secure the energy supply [4]. However, unfortunately, the share of renewable energy consumption from 1.5 % in 1980 has decreased to 0.58 % in 2018, which shows the lack of effective policies and investments. Another culprit for this problem is the abundance of fossil fuel resources which reduces the interest of governments and investors in this area. By the end of 2018, 92.4 % of Iran's electricity was generated by fossil-fueled thermal power plants and 5.1 % by hydropower. The share of other renewable energy resources is just 0.5 % as 2 % of the electricity comes from nuclear resources [5].

Modeling the energy systems in the last decades helped researchers to analyze the energy systems in various aspects [6–11]. Predicting future demand and economic planning as well as studying the environmental or social effects of an energy system are just some aspects of a

Abbreviations: ARIMA, Auto-Regressive Integrated Moving Average; TAC, Total Annual Cost; BWM, Best Worst Method; AIC, Akaike Information Criterion; EV, Electric Vehicles; OEMOF, Open Energy Modelling Framework; NSGA-II, Non-dominated Sorting Genetic Algorithm II; ANN, Artificial Neural Network; MCDM, Multi-Criteria Decision-Making; ANP, Analytic Network Process; VIKOR, Vlse Kriterijumsk Optimizacija Kompromisno Resenje; ELECTRE, ÉLimination Et Choix Traduisant la REalité; PROMETHEE-II, Preference Ranking Organization METHod for Enrichment of Evaluations; PACF, Partial Autocorrelation Function; TPES, Total Primary Energy Supply; RES, Renewable Energy Share; WASPAS, Weighted Aggregated Sum Product Assessment; BIC, , Bayesian Information Criterion; XGBoost, extreme gradient boosting; MILP, Mixed-integer Linear Programming; SAM, System Advisor Model; SVM, Support Vector Machine; AHP, Analytic Hierarchy Process; WSM, Weighted Sum Method; TOPSIS, Technique for Order Preference by Similarity to Ideal Solution; SMART, Simple Multi-Attribute Rating Technique; ACF, Autocorrelation Function; WPM, Weighted Product Method.

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broader concept of energy systems modeling. This paper aims to model the energy system and predict the energy demand of Qeshm island as a case study to discuss the probable future scenarios and their impacts on energy mix and carbon emissions.

According to the thematic structure of this research, the review of related articles can be placed in three categories: papers that deal with the modeling of energy systems; research that has dealt with forecasting energy supply and demand; And finally, articles that have benefited from multi-criteria analysis in energy systems.

Several papers have addressed the modeling and analysis of energy systems from different aspects. In this area, Yousefi et al. [6] examined the future energy demands of the southern regions of Iran, using the Holt-Winters method and energy planning frameworks. Ziqi Liu et al. [7] used the extreme gradient boosting (XGBoost) algorithm in the short-term power consumption forecasting for two load types. As a case study, they presented an illustrative rural energy scheduling and demonstrated how the cost of the scheduling scheme can be affected by energy storage capacity.

Hilpert et al. [8] introduced the Open Energy Modelling Framework (OEMOF) as an innovative approach to energy system, providing a toolbox to construct comprehensive energy system models. Yousefi et al. [9] optimized a hybrid energy system by HOMER software in an off-grid mode considering different prices of diesel to illustrate the feasibility of integrating renewable energy resources and energy storage systems into the grid in case of natural disasters.

In another research, Gupta et al. [10] presented a MILP model to optimize a hybrid energy generation system cost consisting of a photovoltaic array, biomass (fuelwood), biogas, small/micro-hydro, a battery bank, and a fossil fuel generator. The optimization minimized the cost function considering the demand and potential constraints. Yousefi et al. [11] compared the emissions and net present costs of different alternatives while completely meeting the building needs in terms of heating or cooling loads by MATLAB modeling and taking advantage of Non-dominated Sorting Genetic Algorithm (NSGA-II).

Fazlollahi et al. [12] examined firstly a multi-period energy system optimization model with a single-objective function. Then, a multi-objective optimization perspective to systematically generate a good set of solutions. Yousefi et al. [13] used System Advisor Model (SAM) energy modeling software to model the distributed PV system, illustrating the priority of tiered pricing compared to flat pricing in terms of techno-economic feasibility.

Continuing the review of related research, some papers have predicted energy consumption trends using different methods. Tabasi et al. [14] analyzed the energy supply and demand to describe energy consumption in each sector. They used a regression model to analyze the correlation between many variables contributing to energy consumption. Then they predicted future energy consumption and evaluated their model's significant decrease in energy consumption prediction as a consequence of the uprising trend of renewable energy adoption in each sector. Soto et al. [15] evaluated the transferability and accuracy of twelve energy models for predicting energy demand in the residential sector. They figured out that a high disaggregation level does not necessarily bring about more accurate results.

Debnath et al. [16] conducted statistical research on energy forecasting methods reviewing 483 energy planning models. They found that the top three widely used methods in descending order are Artificial neural network (ANN), support vector machine (SVM), and autoregressive integrated moving average (ARIMA). Zhang et al. [17] reviewed forecasting methods in three intervals, i.e., short, medium, and long-term. They considered machine learning models the best for short and long-term energy demand forecasting. Qiang Ji et al. [18] first divided the world into seven areas and analyzed the status of renewable energies from various aspects and unique viewpoints. Then, they implemented an integrated prediction model including the ARIMA, NNM (neural network model), and SVM models to forecast the development overview of renewable resources by one-way regression in different regions.

Multi-criteria decision-making (MCDM) aims to optimize complex scenarios with different indicators, conflicting objectives, and criteria. It has been popularly used in energy planning as it provides the decision makers with the flexibility to make decisions amongst various alternatives considering all the criteria and objectives simultaneously [19]. For researchers interested in the energy decision-making field, different aspects such as year of publication, MCDM method, document type, statistical analyses, country, and published journal can be interesting. In this regard, Kaya et al. [20] examined published papers that use traditional MCDM methods to handle energy problems systematically.

Zavadskas et al. [21] examined the main advantages and disadvantages of MCDM methods to provide an overview and in-depth analysis of using them to evaluate renewable energy technologies implemented in households. An improved framework through a hybrid MCDM method has been introduced by Alizadeh et al. [22]. They used Iran as a case study for the analysis aiming to help countries in renewable energy planning and decision-making. Ghosh et al. [23] used the ANP method to predict an index of the suitability of locations for wave energy generation.

Lee et al. [24] ranked renewable energy sources for power generation in Taiwan using four MCDM methods, i.e., WSM (Weighted Sum Method), VIKOR (Vlse Kriterijumsk Optimizacija Kompromisno Resenje), TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), and ELECTRE (ÉLimination Et Choix Traduisant la REalité). Yousefi et al. [25] used the Analytic Hierarchy Process (AHP), to optimize three objective functions to reduce costs and energy consumption as well as reducing CO2 emissions.

Mirjat et al. [26] used the AHP to assess the sustainability of energy modeling outputs for long-term planning. They ranked their different alternatives and determined the most favorable electricity generation scenario. Ghodusinejad et al. [27] evaluated a PV system in five different cities of Iran with diverse climatic conditions to verify the effect of weather and climatic conditions. They defined various performance indicators and used the SMART (Simple Multi-Attribute Rating Technique) method to rank the studied cities.

In another case study located in Isfahan province, Iran, to assess the feasibility of using hybrid energy systems, various components of the hybrid energy system were taken into consideration and evaluated by Hosseini Dehshiri [28]. Chiu et al. [29] ranked the clean power generation technologies existing in by innovative hybrid MCDM model. They used an aggregated weighting and ranking method to prioritize the power generation technologies based on a case study of Bangladesh. Finding the best location for implementing an offshore wind power station directly affects the success of offshore wind energy projects. A new hybrid MCDM method of the optimal offshore wind power station was proposed by Abdel-Basset et al. [30] by combining the AHP and PROMETHEE-II (Preference Ranking Organization METHod for Enrichment of Evaluations) methods.

In this paper, using a hybrid approach, the energy system of Qeshm island in Iran has been investigated and modeled, with the aim of achieving a sustainable island. In a general view, this research includes three general stages: forecasting energy demand in the field of electricity and transportation; energy system modeling in the base year and forecast year; and finally, multi-criteria analysis of the proposed scenarios.

As seen in the papers reviewed above, the approach of the papers was mainly based on one or two axes. So that the papers that deal with time series analysis, mostly lack a comparative approach based on multi-criteria decision-making, or energy planning has not been considered in them. On the contrary, some papers that have dealt with energy modeling and planning, have not had a forward-looking approach. A comparative representation of the previous papers and current work is provided in Table 1. In this context, this paper, in particular, has used the three axes of "time series analysis", "energy modeling" and " multi-criteria decision-making and analysis " simultaneously to provide a complete research package around the subject. The main reason for

Table 1
Comparative analysis of the previous papers and current work.

Research	Energy systems modeling	Forecasting energy supply and demand	MCDM application
[7]	✓	×	×
[8]	✓	×	×
[9]	✓	×	×
[10]	✓	×	×
[11]	✓	×	✓
[14]	✓	✓	×
[15]	×	✓	×
[16]	×	✓	×
[17]	×	✓	×
[20]	×	×	✓
[21]	×	×	✓
[26]	×	×	✓
[27]	✓	×	✓
This study	✓	✓	✓

using this holistic approach can be summarized in the following cases:

a) By considering the time series analysis, modeling of the studied energy system is conducted both in the present time and for the future. This will help the decision-makers to observe and analyze the results of different scenarios in the transition from the current situation to the future state.
b) Simultaneous utilization of a multi-criteria decision-making approach with energy modeling for the present and future horizons helps decision-makers rank choices and analyze them. In fact, this turns the sometimes-scattered concepts into coherent subjects and makes the analysis of scenarios conform to the logic of principled decision-making instead of a qualitative review.

Therefore, the contribution of this paper to the literature includes the following:

1. Presenting a comprehensive hybrid model based on time series analysis, energy modeling and multi-criteria decision-making, in order to investigate the performance of the energy system of a certain geographical area.
2. Long-term forecast of electricity and gasoline demand in Qeshm island;
3. Simultaneous modeling of the electricity and transportation system of Qeshm island (as the largest island of Iran and also the Persian Gulf) by considering different scenarios for the future.

In this context, the research framework is presented in Section 2. The demand forecasting process and results are provided in Section 3. The multi-criteria energy planning is presented in Section 4. In Section 5, the research results are presented and discussed. Finally, the conclusion of the paper is provided in Section 6.

2. Research framework

2.1. Study area

Qeshm island is located in the south of Iran and Hormozgan province (Fig. 1). This island, with an area of 155 square kilometers, has a population of about 150 thousand people according to the last census of 2016. Qeshm island is located at 55° longitude and 26° latitude in the east of the Persian Gulf. By the end of 2020, the average temperature of this island has been reported as 26.5 °C with an average of 11 rainy days per year. Also, the average rainfall on this island has been reported to be 119.9 mm per year until the end of 2020, which is the average of all available statistics from the beginning of this measurement until the end of this year [31].

Fig. 2 is the monthly average solar radiation of the island for a whole year. In late spring and first summer days (June), the sun's radiation reaches its highest annual point of >7 kWh/m^2/day on average. After its turning point in this month, the trend of solar radiation reverses and drops to its lowest annual value in December to about half of that of June.

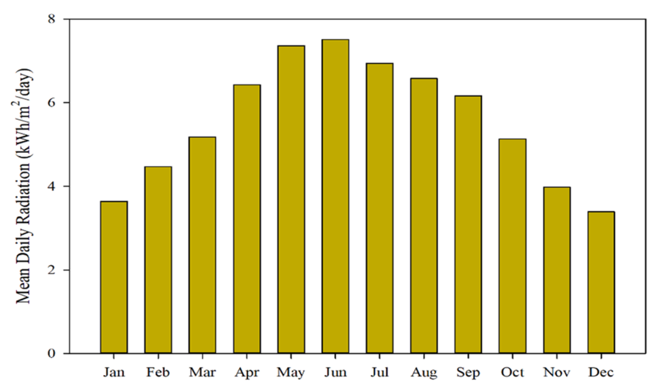

Fig. 2. Average annual monthly solar radiation in Qeshm island – 2018 (kWh/m2/day) [31].

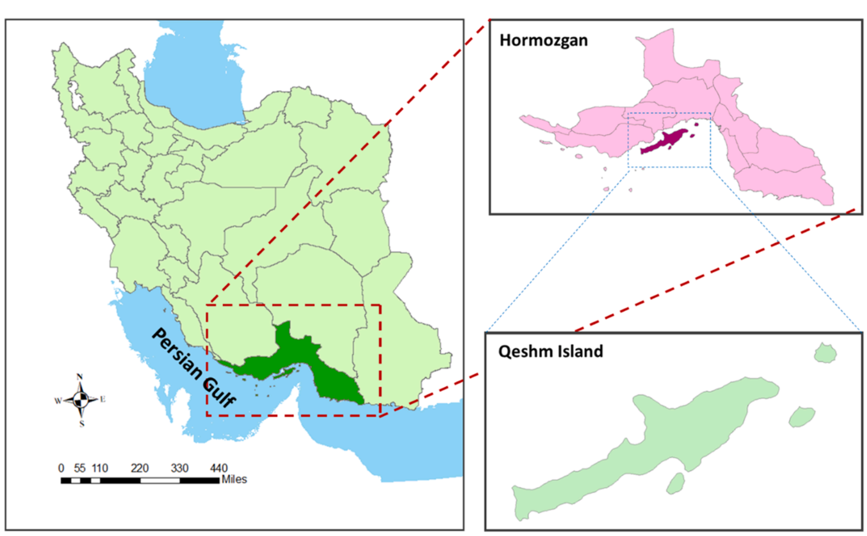

Fig. 1. The exact location of Qeshm island (Hormozgan Province, Iran).

Fig. 3 illustrates the sectoral electricity consumption of Qeshm island, starting from 2001 with an overall amount of >230,000 (MWh). As can be seen, electricity consumption increased about 5 times during the mentioned period.

Qeshm island currently has three thermal power plants with a total capacity of 173 MW as well as a 10 MW solar power plant. In this way, the nominal capacity of the power plants installed on this island reaches 183 MW. The details of the island power plants are provided in Table 2. These power plants are responsible for supplying a part of the island's energy needs, while by connecting the island's power grid to the national power grid, the rest of the island's needs are supplied through energy imports.

Qeshm Island, as the biggest island in Iran, is of great importance and its selection as the case study area may be justified as follows:

- *Strategic Location and Unique Environmental Conditions*: Qeshm Island, located in the Persian Gulf, is the largest island in Iran and possesses unique environmental and geographical characteristics that make it a significant case for studying sustainable energy planning. Its strategic location offers an excellent setting for examining the integration of renewable energy systems in a semi-arid climate with high solar irradiation and consistent wind patterns.
- *Energy Independence and Sustainability Challenges*: Qeshm Island faces challenges typical of remote and isolated regions, such as reliance on imported fossil fuels. These factors make the island a representative example of the challenges faced by other islands in transitioning to sustainable energy solutions. The study aims to explore how Qeshm Island can reduce its dependency on external energy sources and move toward greater energy self-sufficiency.
- *Abundant Renewable Energy Resources*: The island has considerable potential for harnessing renewable energy, particularly solar energy, given its high solar insolation. By focusing on Qeshm Island, the study aims to explore the feasibility and optimization of renewable energy systems in a region that could greatly benefit from such a transition.
- *National and Regional Importance*: As an island of national strategic importance, Qeshm has been the focus of various development initiatives by the Iranian government, including those aimed at promoting sustainability and renewable energy. The island's selection reflects its relevance to broader national policies on energy transition and sustainable development.

2.2. Study process

The process of this paper consists of five different steps, depicted in Fig. 4. As the first step, the energy consumption data collection of the island has been done—in particular electrical energy and gasoline consumption. With the data collected in the first step, ARIMA, as a forecasting model is used to predict the energy consumption in 2030 as one of the inputs of the third stage, i.e., energy modeling. In this stage,

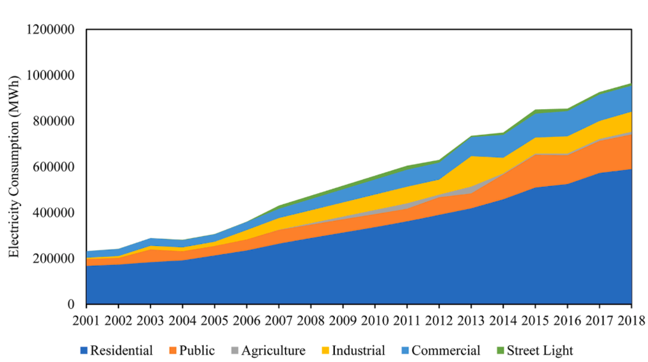

Fig. 3. Electricity consumption trend in Qeshm island regarding different sectors [31].

Table 2
Installed powerplants of Qeshm island (2018) [32].

Powerplant	Type	Capacity (MW)	Fuel	Gross Generation (GWh)	Owner
Jask	Thermal	53	Natural Gas	2	Government
Mapna	Thermal	50	Natural Gas	232	Government
Pasargad Qeshm	Thermal	70	Natural Gas	186	Private Sector
Toula	Solar	10	–	17	Private Sector

EnergyPLAN software is used to analyze the energy system. The fourth part assesses the modeling outputs by the multi-criteria decision-making approach. Then, the desired scenario is selected in the last step from the obtained results.

2.2.1. Data gathering

The electric energy consumption of Qeshm island, as well as the amount of gasoline distributed in the fuel distribution stations of the island between 2001 and 2019, have been taken into consideration as input data.

2.2.2. Demand forecasting

There are various methods in order to forecast energy demand. In this paper, a time series analysis method, namely the ARIMA model, has been implemented to forecast the electrical energy and petrol consumption for the year 2030. RapidMiner Studio is used in order to implement this step.

2.2.3. Energy modeling

EnergyPLAN software is a combinatory simulation program aiming to find the optimal integration of energy systems. While the program calculates hourly information regarding various criteria like energy consumption during a year or even more, it provides a platform for economic, technical, and environmental analysis for both present and future. In this paper, EnergyPLAN is used to model the energy system of the island in the base year as well as the target year, i.e., 2030.

2.2.4. Decision-making

In this research, the MCDM modeling has been implemented in order to determine the best scenario. For defining the MCDM problem, criteria like total primary energy supply (TPES), total annual cost (TAC), CO_2 Emission, and the share of renewable energy resources (RES) have been taken into consideration. The decision matrix consisted of the alternatives of 4 scenarios as well as the base condition for all the defined criteria. In order to solve the MCDM problem, at first BWM method is utilized to find the weights of the different criteria. Then by implementing the WASPAS method, the MCDM problem is solved, and the scenarios are ranked by their level of importance.

2.2.5. Final discussion

Finally, the best scenario could be discussed from various aspects ranging from environmental to economic ones. The best scenario can be considered in planning the energy policy of the island and can help authorities to take practical steps.

3. Demand forecasting

ARIMA model, used to forecast time series is known as a conventional statistic method. In the ARIMA (p, d, q) model, p refers to AR (auto-regression) order, d stands for I (integration) factor which is the differencing order and q is the order of MA (moving average) [33]. The mathematical structure of the ARIMA (p, d, q) model is as follows:

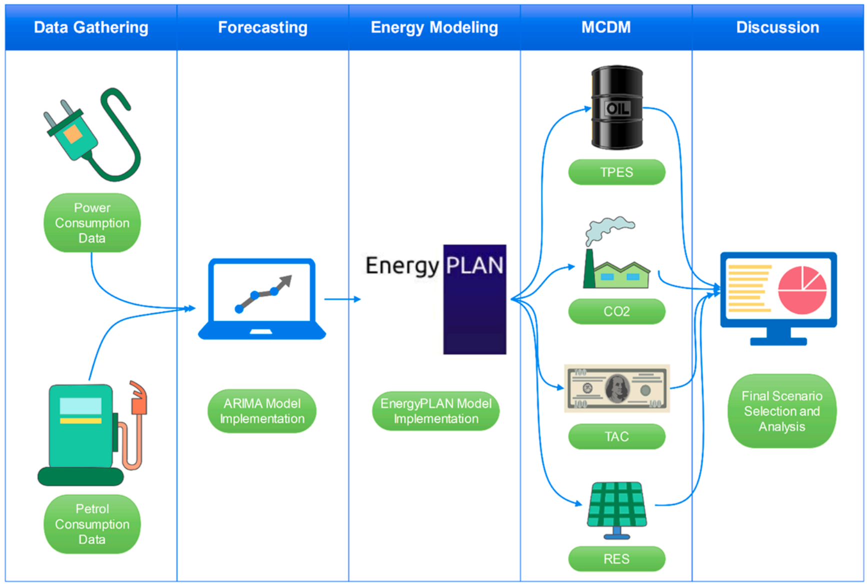

Fig. 4. Study process flow diagram.

$$X_t - \alpha_1 X_{t-1} - \ldots - \alpha_p X_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \quad (1)$$

Where α_i are the parameters of the autoregressive part of the model, θ_i are the parameters of the moving average part and the ε_i are error terms.

To predict the time series data by the ARIMA model, first, the stationarity of the time series is checked by different methods. The cumulative average explanation model based on the iterative process of Box-Jenkins includes the stages of identifying the modern structure, estimating the modern unknown parameters, determining the accuracy of the model fit, and forecasting with the selected model [34].

According to the trend in the power and gasoline consumption data, it can be seen that the time series is not stationary. Therefore, it is

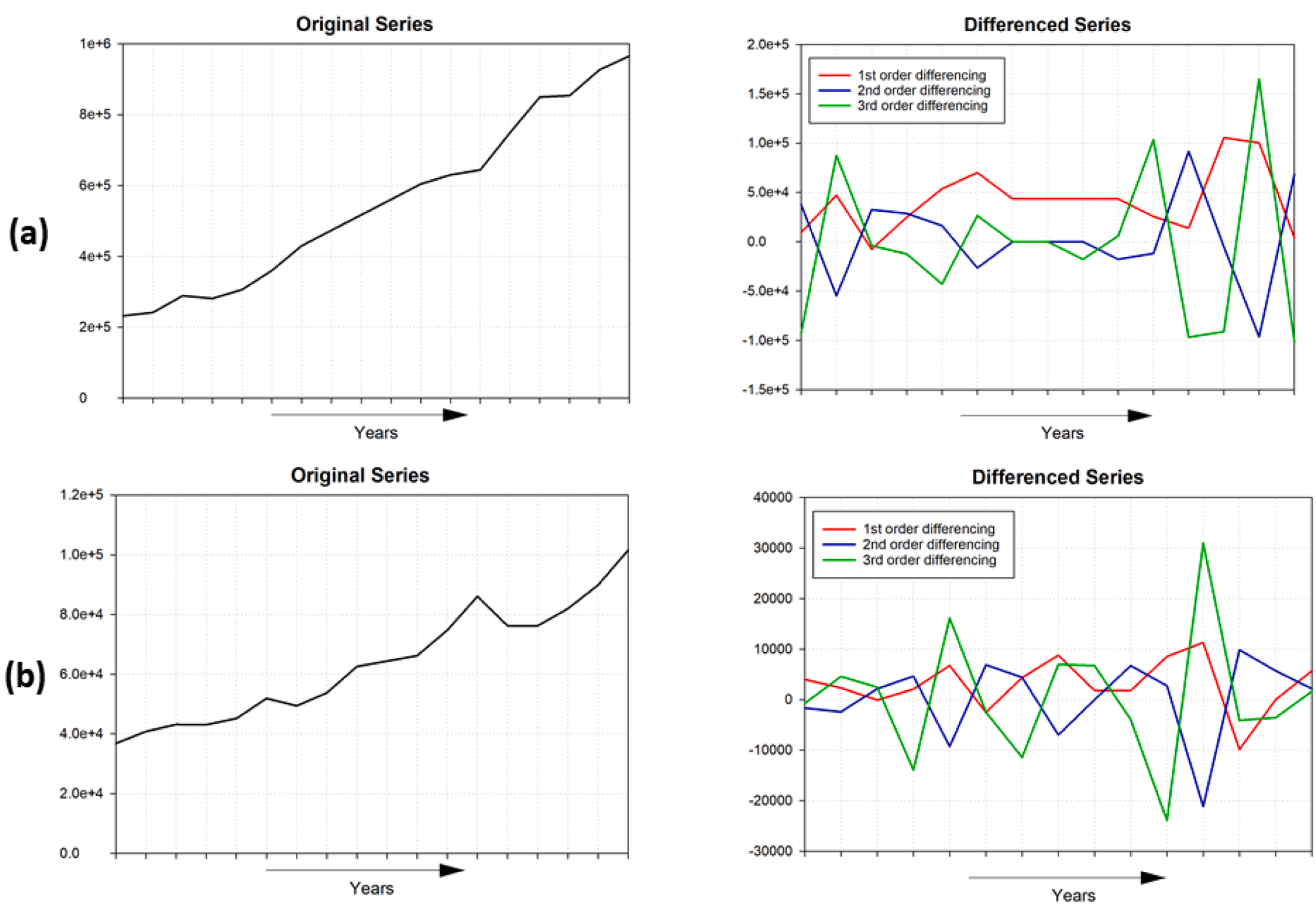

Fig. 5. The original time series and its corresponding differentiated series; (a) Power; (b) Gasoline.

necessary to determine the order of differentiation in these time series first. Fig. 5 shows the original time series along with the corresponding differentiated series up to 3 times. As can be seen in this figure, up to 2 differentiating can help to make the time series stationary.

In the next step, the order of p and q terms should be estimated. ACF and PACF graphs can be used to find the trend of the time series to estimate these terms. By analyzing these graphs, it is possible to determine the type of time series in terms of AR and MA sections. In order to maintain brevity in the article, the corresponding graphs have been drawn for the two-order differentiated series. This issue is shown in Fig. 6. As seen in Fig. 6, the downward trend of the graph in the initial lags is more in the ACF diagram than in the PACF diagram. Therefore, the type of time series in both cases of power and gasoline is mainly of the moving average type. Therefore, to perform ARIMA, the priority is on MA section.

As said previously, in ARIMA model forecasting there are always problems of selecting appropriate values for the orders p and q. Though fitting high-order models mostly results in a small estimated white noise variance, reducing white noise is not only related to the mean squared error of the forecasts, it also depends on errors coming from the estimation of the parameters of the model. In this regard, the Penalty Factor to control the over numbering of the parameters is implemented. In this research we use the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to select predictors for regression [35]:

$$AIC = -2 \ln (\pounds) + 2k \tag{2}$$

$$BIC = -2\ln (\pounds) + k \ln(n) \tag{3}$$

In both of these criteria, £ is the maximum of Likelihood function, k is the number of parameters, and n is the number of observations. By minimizing the AIC and BIC, the most suitable ARIMA models to forecast the electrical load and petrol consumption of Qeshm island in 2030 are selected.

In order to obtain the order of terms of the ARIMA model, a two-level optimization model based on grid search has been conducted in RapidMiner software. Fig. 7 shows the schematic of this model. After receiving the input data (time series), the "Optimize Model Parameters" block evaluates all the values defined for the ARIMA terms and executes the "ARIMA" block at level 2. In order to measure the optimality of the model, the AIC index has been used as the main evaluation criterion. Thus, the model with the lowest AIC is selected as the best-fitting model.

According to the model presented in Fig. 7, the ARIMA models with smaller prediction criteria (AIC) should be selected. For the electricity forecast, the best model is ARIMA (0, 2, 2), having the minimum values of AIC and BIC. As the petrol forecast is considered, the most suitable model is ARIMA (0, 2, 5). Regarding the best orders obtained, the best calculated ARIMA models for electricity and petrol consumption are given in Table 3. According to the prediction models presented in Table 3, Fig. 8 shows the trend of increasing power and gasoline consumption.

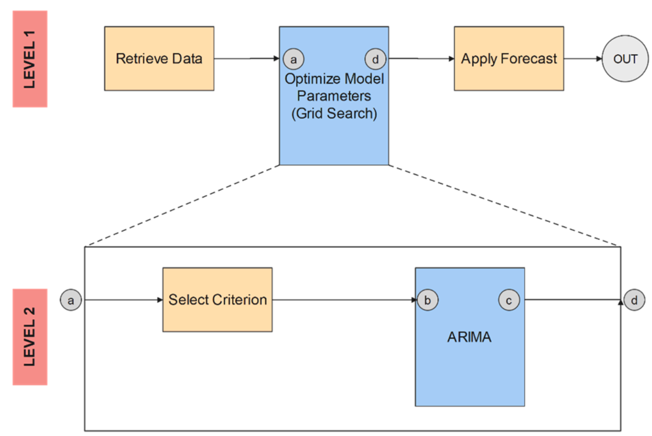

Fig. 7. Two-level grid search optimization model for ARIMA implementation.

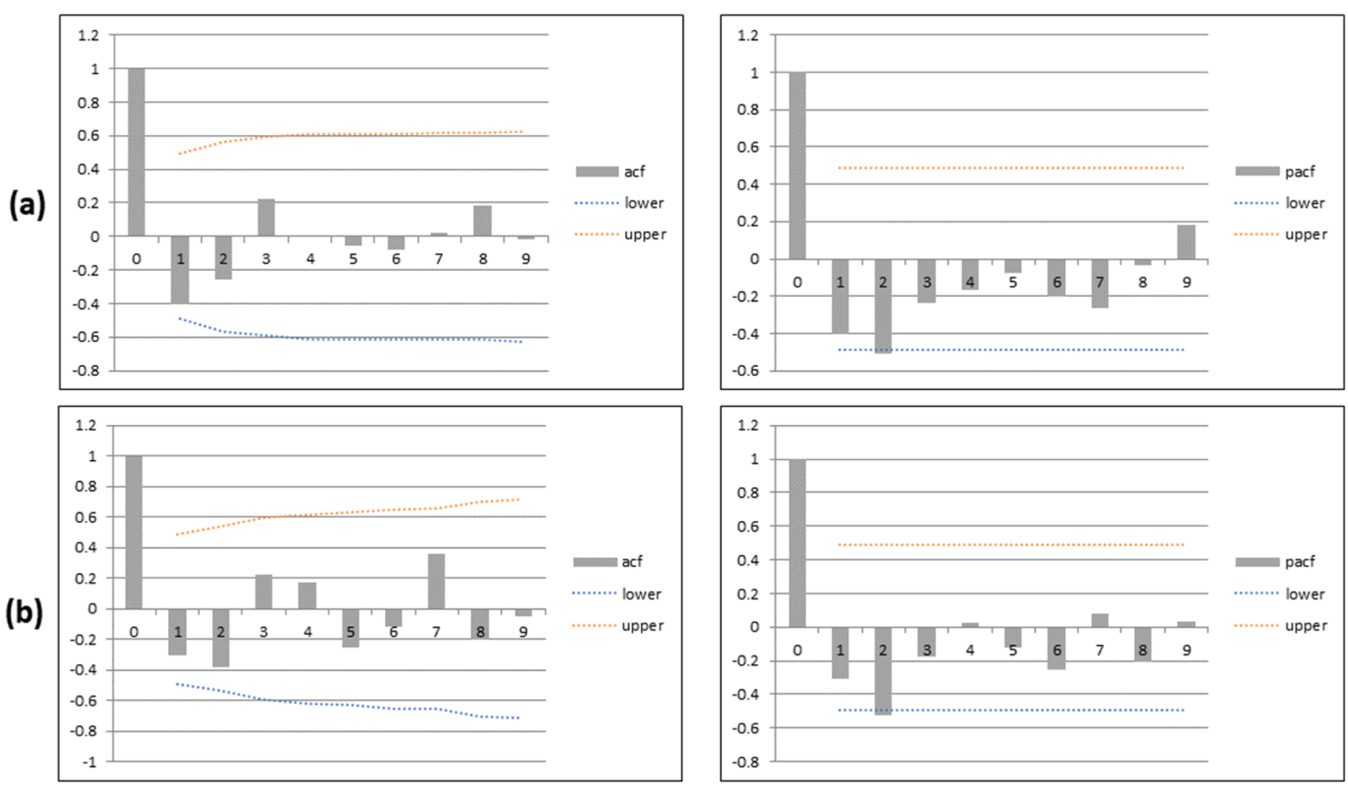

Fig. 6. ACF and PACF plots for (a) power and (b) petrol.

Table 3
The best forecast models (having the least values of AIC and BIC) for electricity and petrol consumption.

	Best forecast model	Equation	AIC	BIC
Electricity Consumption Forecast	ARIMA (0,2,2)	$Y_t = 1846.9377 + \varepsilon_t - 0.9986\varepsilon_{t-1} + 0.1224\varepsilon_{t-2}$	385.690	388.781
Petrol Consumption Forecast	ARIMA (0,2,5)	$Y_t = 482.6835 + \varepsilon_t - 0.7671\varepsilon_{t-1} - 0.8387\varepsilon_{t-2} + 0.8882\varepsilon_{t-3} - 0.1998\varepsilon_{t-4} + 0.2848\varepsilon_{t-5}$	328.366	333.774

4. Multi-criteria energy planning

4.1. Energy modeling

In this paper by undertaking various scenarios based on increasing the share of PVs and Electric Vehicles, reducing carbon emission is discussed. The PV plants planned for construction are shown on the Qeshm island map in Fig. 9.

The EnergyPLAN software is an advanced energy system analysis tool providing solutions for energy systems. Its special focus is on sustainable energy resources and integrating them into various resources and balancing the suppliers considering the demand load side [36,37]. Moreover, it is an input-output model that uses data on system energy conversion capacities and efficiencies and the availability of fuels and renewable energy inputs. It calculates how the power needs of the system are met under set constraints and strategies hour by hour. In this regard, it should be said that some distribution trends for different parameters are entered into the model in the form of text files in 8784 lines (hours). In these distributions, regardless of the values, each line is considered as a proportion to the total sum and is valued according to the total capacity entered in the software. Fig. 10 depicts the used annual hourly distribution trend for electricity consumption and solar energy generation of the island. Fig. 11 also shows the distribution trend for EV charging pattern through a 24-hours interval which is expanded through the whole year for the simulation.

In this case study, all the assumptions are logically based on potential investments that may occur in the near future and their impacts on the energy mix of the island and also on the demand side in the transportation sector. According to official statistics, in the year 2018, the overall installed thermal powerplants were 173 MW, besides the available PV powerplants amounting to just 10 MW. In this way, the nominal 183 MW capacity was just in charge of supplying the island's electricity demand. Hence, the island imported electricity to cover all its needs. Moreover, in the transportation sector, the energy need in this year is entirely provided by fossil fuels, especially petrol.

For future scenarios, the mixture of the most possible conditions in the transportation and power sectors is taken into consideration. At first, the base scenario has been discussed in which no change in both sectors has occurred, and the energy consumption growth has been supplied with no change on the supply side. However, given that licenses for 195MW have been issued and a 500 MW thermal powerplant is planned to be constructed, the possibility of adding the additional power to the energy mix of the island is not out of mind. In the transportation sector, three assumptions of zero, 20 %, and 50 % share of EVs have been considered for the Energy modeling. All proposed scenarios for power and transport sector are presented in Table 4.

As illustrated in scenario 1, known as S1, only the thermal Power plant was added to the energy system, and 100 % of the energy demand of the transportation sector was met by petrol. For scenarios 2–4, known as S2, S3, and S4, the proposed solar PV powerplants were added to the electricity mix of the island. Their difference is in supplying the transportation sector, which has no EV, like S1 and S2, 20 % for S3, and 50 % for S4. By changing the share of EVs in the last scenarios, the impact of less petrol consumption has been scrutinized in the following parts.

On the whole, in this study, it can be said that possible future policy changes and technological developments were considered to analyze the energy scenarios of Qeshm island. The scenarios include increasing the share of renewable energies and electric vehicles with the aim of reducing fossil fuel consumption and reducing CO2 emissions. The study is intended to seek whether these changes lead to improving the efficiency of energy systems and reducing fuel costs and greenhouse gas emissions or not? These different scenarios were designed with a focus on increasing the share of renewable energy (such as installing new solar power plants) and increasing the share of electric vehicles in the island's transportation system. Future trends, which include the growth of renewable energy production technologies and the increase in the penetration of electric vehicles, will lead to a reduction in fossil fuel consumption, a reduction in fuel costs, and a reduction in greenhouse

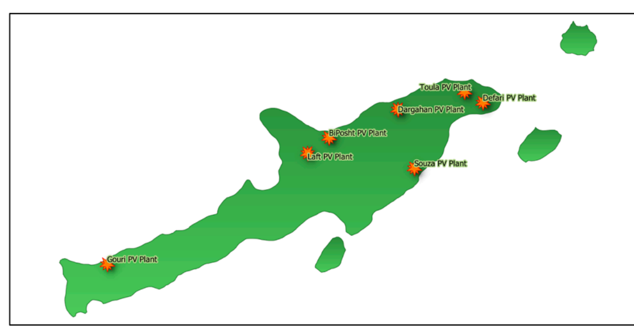

Fig. 9. Location of prospect PV powerplants.

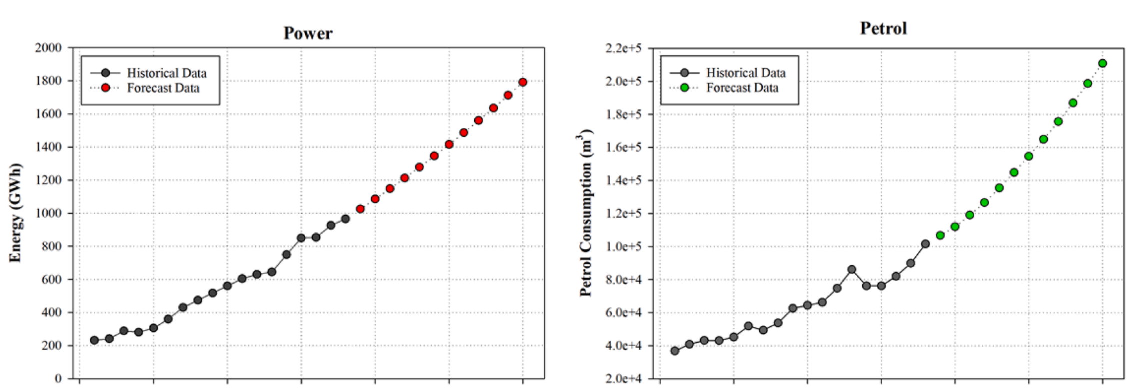

Fig. 8. Electricity and petrol consumption forecast.

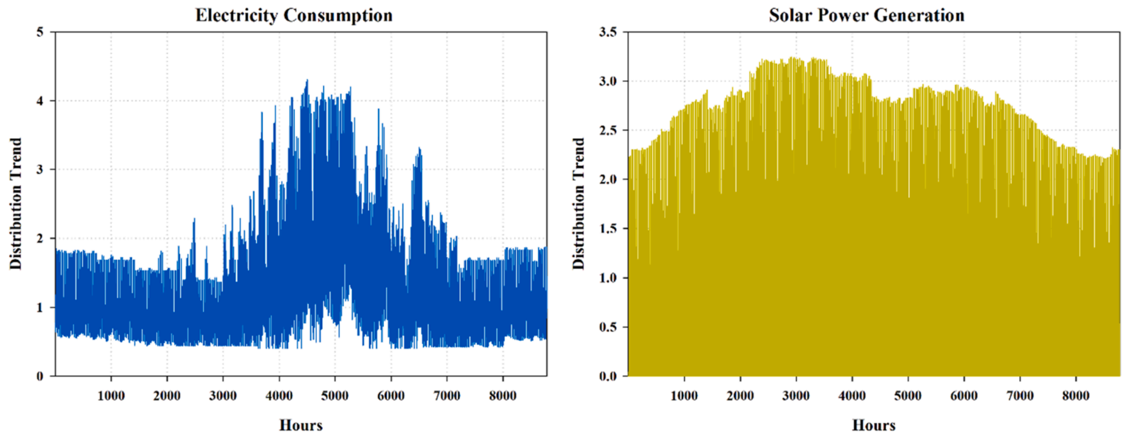

Fig. 10. Annual hourly distribution trend for electricity consumption and solar generation used in EnergyPLAN.

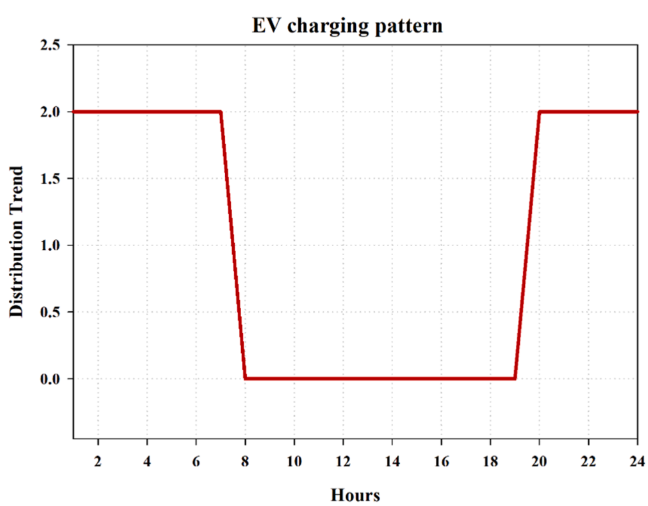

Fig. 11. Daily distribution trend for EV charging used in EnergyPLAN.

Table 4
Details of scenarios for power and transport sectors.

Scenario	Description	
	Power sector (MW)	Transport sector (%)
Base	PP: 173 PV: 10	Petrol: 100 EV: 0
S1	PP: 673 PV: 10	Petrol: 100 EV: 0
S2	PP: 673 PV: 205	Petrol: 100 EV: 0
S3	PP: 673 PV: 205	Petrol: 80 EV: 20
S4	PP: 673 PV: 205	Petrol: 50 EV: 50

gas emissions. Hence, scenarios with the highest share of solar energy and electric vehicles may show significant improvements in energy system efficiency and sustainability of the Qeshm island.

For both thermal and PV powerplants, the costs of investment, and Operation and Maintenance, and their lifetime has been provided in Table 5, which is used in the following model to evaluate the various scenarios. Also, the CO_2 content of the two main energy carriers in this paper, i.e., petrol and natural gas, were considered equal to 71.7 and 57.9 kg/GJ, respectively. The petrol and natural gas fuel prices are also considered as 7.4 and 0.025 EUR/GJ, respectively. Although no CO_2 tax and environmental external costs have been specified yet for the Iranian

Table 5
Cost details for different power generation technologies [38].

Technology	Investment cost (M EUR/MW)	Lifetime (year)	O&M cost (% of Inv.)	Efficiency (%)
Thermal powerplant	0.74	25	3.32	35
Solar PV	0.69	25	1.28	18

energy system, but this study assumed 7 euros per tons of CO_2 as tax, based on [38].

4.2. MCDM analysis

4.2.1. Criteria weighting system

As a practical systematic approach, Multi-Criteria Decision Making (MCDM) contributes to the process of decision-making [39]. Since the modern MCDM has been funded from 1950–1960, many various practical methods in this regard have been introduced by mathematicians. All of these methods have their own strengths and weaknesses [40]. The definition of the MCDM problem is generally shown in following matrix:

$$A = \begin{array}{c c} & \begin{array}{cccc} c_1 & c_2 & \cdots & c_n \end{array} \\ \begin{array}{c} a_1 \\ a_2 \\ \vdots \\ a_m \end{array} & \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mn} \end{pmatrix} \end{array} \tag{4}$$

Where $\{a_1, a_2, \ldots, a_m\}$ is a set of feasible alternatives, $\{c_1, c_2, \ldots, c_n\}$ is a set of decision-making criteria, and $p_{ij}$is the score of alternative i with respect to criterion j. In such MCDM problems, the final goal is to choose the best alternative.

In this paper, the Best-Worth Method (BWM) model is used for weighing the criteria. The BWM method is one of the new techniques of multi-criteria decision-making, presented by Jafar Rezaei in 2015 [41]. In this method, the best and worst indicators are selected by the decision-maker and a pairwise comparison is made between each of these two indicators (best and worst) and other indicators; Then a maximum-minimum problem is formulated and solved to determine the weight of different indicators. This method, compared to other MCDM methods requires less-comparative data and leads to more robust comparisons.

After determining the criteria set, first, the most important and the least important criteria should be determined among all the indicators, which are called *best* and *worst*. Then the pairwise comparison of the best criterion with other criteria and other criteria with the worst criterion should be formed in the form of two matrices. The best-to-others vector is determined by the Sa'ati scale from 1 to 9, where 1 denotes equal importance and 9 means extremely more important. This is stated Eq. (5):

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}) \tag{5}$$

Where a_{Bj} indicates the preference for the best criterion B over criterion j. In the same way, the preference of all the criteria over the worst criterion using the same scale should be determined, resulting to others-to-worst vector as in Eq. (6):

$$A_w = (a_{1w}, a_{2w}, \dots, a_{nw})^T \tag{6}$$

Where a_{jw} stands for the preference of the criterion j over the worst criterion w.

Now the aim is to find optimal weights vector $(w_1^*, w_2^*, \dots, w_n^*)$, such that the maximum absolute differences $|\frac{w_B}{w_j} - a_{Bj}|$ and $|\frac{w_j}{w_W} - a_{jW}|$ for all j is minimized. This can be translated to the following optimization model to be solved:

$$\begin{aligned} &\min \max_j \left\{ \left|\frac{w_B}{w_j} - a_{Bj}\right|, \left|\frac{w_j}{w_W} - a_{jW}\right| \right\} \\ &s.t. \\ &\sum \dot{w}_j = 1 \\ &w_j \geq 0, \text{ for all} j \end{aligned} \tag{7}$$

The BWM has been implemented using the opinions of three experts. In order to increase the accuracy and validity of the results, each of the experts weighted the criteria independently. Then, the results of these processes were combined using BWM and through consensus and collective agreement among three experts. This multi-step approach allowed us to avoid potential biases that may arise from relying on one person's opinion. As a result, the final weights have been determined in a way that best represents the different and complementary views of each expert.

4.2.2. Scenario ranking system

As an efficient decision-making tool, Weighted Aggregated Sum Product ASsessment (WASPAS) is known for its accuracy and simplicity. This method is a combination of WSM (weighted sum model) and WPM (weighted product model) but also enhanced in function and widely accepted [42]. WASPAS method first suggested by [43] at 2012 and since then applied widely in various scientific papers to solve MCDM problems and find the optimal alternatives. In the last decade new WASPAS approaches like: Grey WASPAS, Fuzzy WASPAS, WASPAS-IT2FSs, WASPAS-IVIF, and WASPAS-SVNS have been introduced [44].

In this method like other methods, a decision matrix should be defined in the form of Eq. (7). Besides, the decision maker provides the weight of decision-making criteria $\{w_1, w_2, \dots, w_n\}$, which is obtained by BWM method in this paper. Then the normalized decision matrix should be calculated using Eqs. (8) and 9 for positive and negative decision criteria, respectively:

$$p_{ij}^* = \frac{p_{ij}}{\max\limits_i p_{ij}}; \ i = 1, \dots, m, \ j = 1, \dots, n \tag{8}$$

$$p_{ij}^* = \frac{\max\limits_i p_{ij}}{p_{ij}}; \ i = 1, \dots, m, \ j = 1, \dots, n \tag{9}$$

Where the p_{ij}^* illustrates the normalized value of the decision matrix of the i_{th} alternative and j_{th} decision criteria. After normalizing the decision matrix, the Additive Relative Importance for each alternative will be calculated using the following equation:

$$Q_i^{(1)} = \sum_{j=1}^{n} r_{ij}^* . w_j ; i = 1, \dots, m \tag{10}$$

Where w_j is the weight of decision criteria and $Q_i^{(1)}$is an indicator for additive relative importance for the i_{th} alternative. Then, the Multiplicative Relative Importance is calculated for each alternative using Eq. (11):

$$Q_i^{(2)} = \prod_{j=1}^{n} \left(r_{ij}^*\right)^{w_j}; \ i = 1, \ \dots, m \tag{11}$$

The joint generalized criterion (Q_i) aiming to integrate the additive and multiplicative methods is calculated by Eq. (12):

$$Q_i = \frac{1}{2}(Q_i^{(1)} + Q_i^{(2)}) = \frac{1}{2}\left(\sum_{j=1}^{n} r_{ij}^* . w_j + \prod_{j=1}^{n} \left(r_{ij}^*\right)^{w_j}\right); \ i = 1, \dots, m \tag{12}$$

By ranking the Q values obtained from Eq. (12) in a descending order, the highest value has the first rank and so on.

5. Results and discussion

5.1. Energy modeling results

The energy modeling in this paper has been done by EnergyPLAN software. The forecasted electricity consumption of Qeshm island as well as the possible future scenarios for energy production, both based on statistical information and future plans of the Hormozgan Province have been prepared as an input for the software. Various software models have been developed to model energy systems. Meanwhile, the EnergyPlan software model is considered an efficient tool in this field, which provides researchers with valuable facilities in modeling the supply and demand side, different energy consuming sectors, different energy production and conversion technologies, etc.

Different scenarios that were considered for energy supply capacity in 2030 along with the percentage of electric vehicle share, lead to different results in the modeling output. From various outputs of the software, Figs. 12–17 provide some details, which will be discussed, and finally, in the next step, the alternatives will be classified, and the best one will be chosen using MCDM method introduced previously.

Fig. 12, shows the Total Primary Energy Supply of the base and four scenarios. It clearly indicates that S4 has less amount of TPES, considering that S4 has the highest share of both solar power generation and EVs. Besides, as the ratio of renewable power generation and EVs

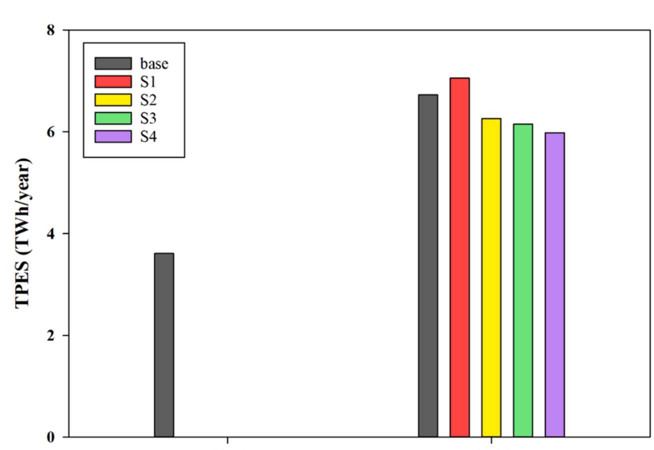

Fig. 12. TPES for scenarios in 2018 and 2030.

consumption fell in scenarios 3, 2, and 1, the amount of TPES rose dramatically, illustrating the fact that the better scenarios for the TPES have an inverse relation with the consumption of fossil fuels for power generation and transportation in the Qeshm island. S1 has no share of EVs in the transportation sector and no improvement in installing PV powerplants, and the highest amount of TPES is associated with this scenario. This clearly shows the bilateral relation of natural gas and petrol consumption with TPES amount. In other words, the worst situation in the TPES index is related to the scenario S1, where almost all the island's electricity is provided through fossil sources and all its transportation needs are provided by petrol vehicles. The difference in the amount of this scenario with other scenarios clearly shows the place of greening of energy sources and electrification of the transportation network in reducing primary energy consumption. From another perspective, even if the proposed 500 MW thermal powerplant will not be installed on the island (which is the condition of the base scenario), the TPES has a lower amount compared to S1. Therefore, investing in just a thermal powerplant is detrimental compared to importing the needed electrical energy to meet the island's demand based on comparing the amounts of TPES.

Regarding middle scenarios, by transition from S2 to S3, even though the installed solar powerplants have the same amount as the optimal scenario, just by increasing the percentage of the EVs, a commensurate drop in the TPES has been obtained from the model. In fact, there is a significant difference in the amount of TPES index between S2 and S3 scenarios. This shows that a one-sided approach to energy transition and one-sided attention to the development of renewable resources, while the electrification of the transportation network is neglected, cannot lead to the greatest gains in reducing primary energy consumption. Additionally, the same happened when both of these scenarios were compared to S4, considering the uprising trend of EV consumption.

The dramatic drop obtained from S1 to S2 is clearly the result of the reduction in natural gas consumption in thermal powerplants and the increase in the share of solar energy. In addition, to the S4 scenario, although the electricity consumption increases (due to the increase in the share of electric vehicles), this is largely compensated by the decrease in gasoline consumption and leads to a decrease in the TPES level.

Fig. 13 shows the total annual cost of different scenarios for 2018 and 2030, illustrating that in the best case, the total cost will approximately be doubled in amount for 2030. In this figure, like the previous one, the fourth scenario has less value and is optimal in terms of costs and expenses. As the transportation sector for base and scenarios S1 and S2 has the same condition and consumes just petrol, the uprising trend results from installing the thermal powerplant for the jump between base and S1 and the cost of installing the solar powerplants for the S2. However, from the highest costs that occurred in scenario S2, by increasing the share of EVs and thereby decreasing the petrol consumption, the trend reversed to a descending one ending to the minimum amount of the probable scenarios, i.e., S4. This result shows that just having a decent share of the energy mix for renewable energy resources has no economic affordability, but when the percentage of EVs rose, the uprising trend of the costs broke to the optimal scenario.

By comparing Figs. 12 and 13, it can be seen that with the transition from S1 to S2, although the amount of TPES decreases, this reduction does not cover the costs of installing renewable powerplants, and the costs in scenario S2 are higher than in S1. Meanwhile, with the electrification of cars, the TAC trend is aligned with the TPES trend and decreases. Again, this asserts that a holistic view of the energy system can guarantee its sustainability.

As far as CO_2 emission goes, Fig. 14 shows the amount of CO_2 in a million tons per year by 2030 for all the five alternatives, which all are more than that of 2018. The increase in energy consumption over the course of this period caused the overall growth of CO_2 emission for all the probable scenarios. But as the share of solar PV powerplants and EVs upraised, the CO_2 emission drops to the lowest point, which is occurred in our model in specific scenario S4. This graph has some details illustrating the effectiveness of renewable energy resources in the electricity mix of the island, which could be clearly seen in the gap between S1 and S2. However, the importance of implementing the EV fleet into the transportation system in reducing CO_2 emissions should not be overlooked, delivering the optimal scenario from the perspective of CO_2 emissions reduction in S4.

In fact, by examining the emission reduction trend in Fig. 14, and considering scenarios from S1 to S4, it can be concluded that the development of renewable resources has a much greater impact on the reduction of carbon dioxide emissions than the expansion of electric transportation.

Figs. 12 and 14 should show a similar trend and behavior. This is because the emission rate is directly proportional to the primary energy consumption. With the transition from scenario S1 to S4, with the reduction of primary energy consumption (here, natural gas and gasoline), the amount of emission will also decrease.

Fig. 15 shows that by incrementing the installed PV powerplants in the last three scenarios, the share of renewable energy resources will jump over 7 percent from lower than 1 % in base and scenario S1. The contribution of renewable energy resources in 2018 was <1 %. It nearly halves as no new PV powerplants have been installed in base and S1, and the electricity demand rose over the research period. The big jump between S1 and S2 occurred as 195 MW PV powerplants were added to the electricity mix of the island. In addition, the slight growth starting from S2 to S4 has happened as the share of petrol in these scenarios decreased to half of its consumption in the base and first two scenarios. Lastly, as the offspring of constructing the PV powerplants and with little help

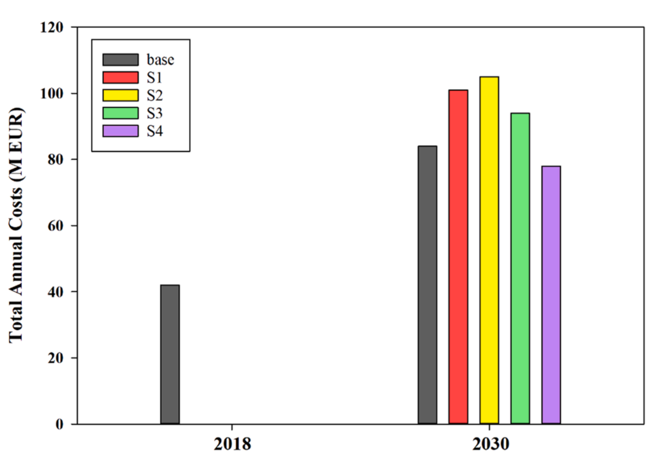

Fig. 13. Total annual costs for scenarios in 2018 and 2030.

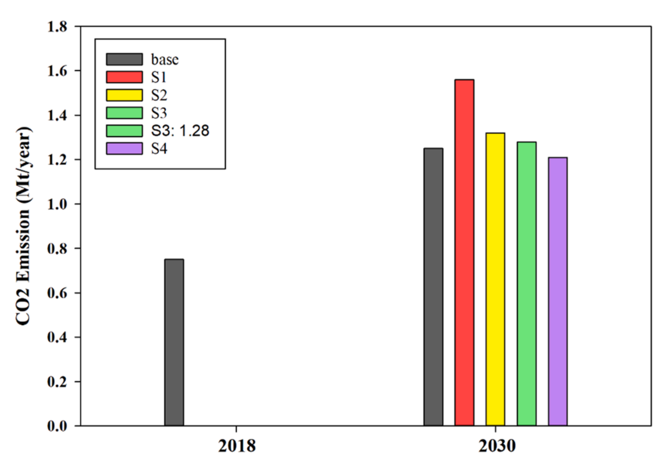

Fig. 14. CO_2 emission for scenarios in 2018 and 2030.

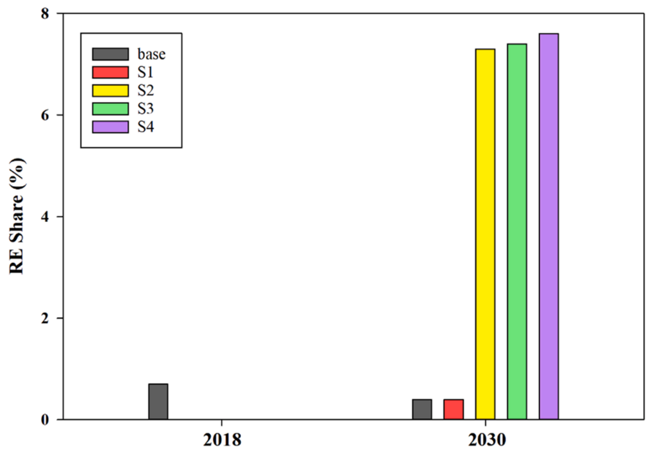

Fig. 15. Renewable energy share in primary energy consumption for scenarios in 2018 and 2030.

from the higher share of EVs in the transportation sector, S4 exceeded the other rival's percentage of renewable energy resources and conquered the best stage compared to other scenarios, followed closely by scenarios 3 and 2, respectively. In fact, although the share of renewable resources is alike in scenarios S2 to S4, due to the increase in the share of electric transportation from S2 to S4, and basically the electrification of the island's energy system, the share of gasoline consumption in the primary energy consumption of the island has decreased, while the share of renewable resources has increased. Besides, considering the reduction of gasoline consumption, and with the replacement of electric vehicles due to higher efficiency, as seen in Fig. 12, the TPES of the whole island is decreasing. Therefore, by reducing the overall amount of primary energy consumption, the share of renewable resources will naturally increase.

Here too, same as with the CO_2 emission, the main game-changer has been the development of renewables, which has changed the game in a big way. Meanwhile, the development of electric cars has acted as a kind of facilitator in this field.

A detailed share of energy carriers in the total primary energy supply is shown in Fig. 16, illustrating the dominance of natural gas in the mix of primary energy supply, followed by petrol used in the transportation sector for both the 2018 and 5 probable alternatives discussed for 2030. This figure shows that just in scenarios 2 to 4, a small amount of energy will be exported. In case of taking no action to improve the power production, be it a thermal powerplant construction or installing PV powerplants, the island will be in need of Importing energy carriers to supply its dweller's demand. The share of solar energy in 2018, base, and S1 are negligible, while in scenarios 2–4, its proportion is significantly higher but still in the third stage after natural gas and petrol. Another point while considering this proportional column diagram is the decreasing trend of petrol consumption between S2 and S4 echoed by the increasing trend of natural Gas consumption as the percentage of EVs in these three scenarios are 0, 20 %, and 50 %, respectively for S2, S3, and S4.

In Fig. 16, by comparing scenarios S2 to S4, it can be observed that the difference occurred in the share of natural gas is due to the increase in electricity consumption (caused by electric vehicles) which must be partially supplied in thermal powerplants. In other words, natural gas has somehow replaced gasoline in these scenarios, because the share of gasoline consumption has decreased while the share of electricity consumption has increased. In fact, in the transportation sector, the island's needs have shifted from petrol to electricity (and supply through natural gas in the powerplant).

The detailed costs of different scenarios in Fig. 17 show the expenses in million Euros for 2018 and 2030′s scenarios, including fuel costs, investment, operation, and maintenance. The petrol is leading the expenses in both base and target years. In all four different scenarios, investment costs have the second stage, followed by operation and maintenance and CO_2 emissions in the next steps. However, the base and 2018 proportions are partially different. In both of them, CO_2 has the second stage surpassing the investment in third place for 2018 and fourth place after importing for the base. In S2 to S4, the power export has little income, while in 2018, and base reversely, the import of energy calls for higher expenditure from local authorities.

It is also important to review, compare and analyze the overall economic scenarios. This includes the overall costs of each scenario, including investment costs, operational and repair costs (O&M) and fuel costs. Hence, the scenarios should be compared using the cost-benefit evaluation method, which indicated the best choice from an economic point of view.

In the base scenario, it is assumed that no significant changes will be made in the current energy system of the island and the demand growth will be met only by using the existing grid and resources. The operating costs of this scenario are high and include the costs of importing energy and fossil fuels, which leads to an increase in long-term costs. In scenario S1, a new 500 MW thermal power plant was added to the system, having a high capital cost. Operating costs also increase due to high consumption of natural gas and maintenance costs. Although the initial capital costs are significant, in the long run the costs due to the consumption of fossil fuels and the emission of pollutants make this scenario economically inefficient.

In scenario S2, 195 MW of solar power plants were added to the system, which has moderate capital cost and low operating cost. By reducing the consumption of natural gas and fossil fuels, this scenario leads to long-term economic savings. Reduced fuel costs and higher system efficiency make this scenario one of the attractive economic options. Regarding S3, this scenario achieves a significant improvement in fuel cost savings with an increase of 195 MW of solar power plants and a 20 % share of electric vehicles. Capital and operating costs are still low, and the reduction of fuel costs and the reduction of pollutants help to

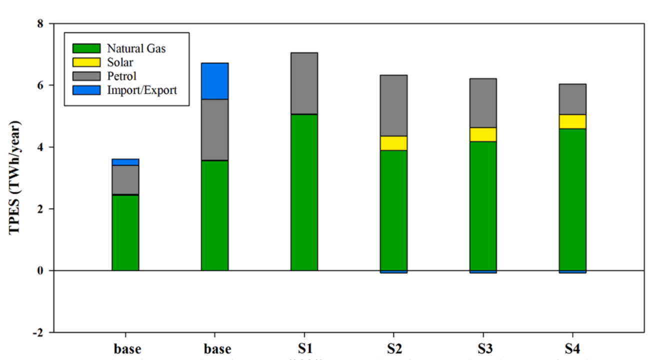

Fig. 16. TPES breakdown.

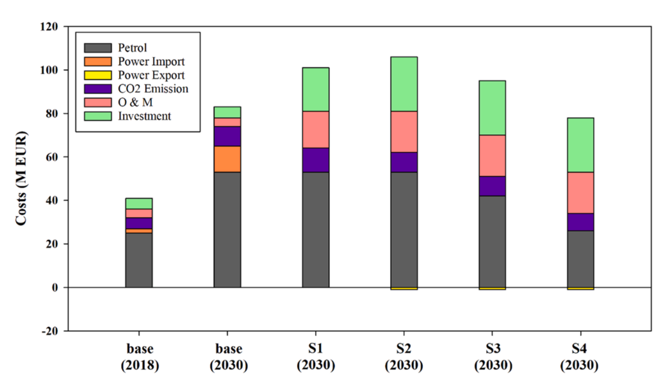

Fig. 17. Total costs breakdown.

improve the economic situation of the scenario. Finally, this scenario S4 offered the best economic results by combining the largest share of solar power plants and electric vehicles. Capital costs are significant due to the need for new EV infrastructure, but the long-term savings in fuel costs and reduced emissions make this scenario an economically viable option.

Analysis of financial and technological barriers of these scenarios is also of great importance, since the implementation of the proposed scenarios may face some financial and technological challenges.

From a financial point of view, high initial investment costs for building solar power plants and electric vehicle infrastructure are among the key obstacles. In addition, the lack of financial facilities and restrictions on access to foreign investment can slow down the implementation of projects. To deal with these obstacles, it is suggested to provide support policies and tax incentives for investors and to use public-private partnership models. It is also recommended to establish joint ventures with private and international companies to reduce investment costs. For the development of EVs, it is suggested that the government encourages the private sector to invest in this field by providing incentives and financial facilities.

From a technological point of view, the need to improve the charging infrastructure of electric vehicles and upgrade the power grid to accept renewable energies are among the important issues. To solve these problems, it is recommended to hold technical training courses and invest in new infrastructure. The creation of smart networks and the use of new energy management technologies can also contribute to the efficiency and stability of the system.

5.2. MCDM results

As mentioned earlier, BWM is one of the methods of weighting the decision criteria based on the opinion of experts who are proficient in the subject. This method, which is somehow derived from the well-known AHP method, by reducing the amount of pairwise comparisons, imposes less burden on the experts to make decisions and greatly reduces the number of calculations. On the other hand, expert opinion-based methods, compared to data-based methods, such as CRITIC or Shannon's entropy, have the risk of encountering inconsistency of matrices due to the wrong judgment of decision makers.

For the process of BWM, first, the best and the worst criteria should be defined based on the expert's comment. Then all the criteria should be compared to the best criterion in the so-called best-to-others vector. The results of this pairwise comparison is shown in Table 6. Following the method, the next step is comparing others to the worst criterion and writing the numbers in the others-to-worst vector, which is provided in Table 7.

In this BWM model, the optimal weights have been calculated in the scale of 100 instead of 1, which is defined in our model. After finding the best and worst criteria and the numbers defining the preference of one criterion over the others, the BWM model will be optimized, and optimal weights for all four criteria will be calculated via the optimization model. The optimized weights resulting from the BWM model are shown in Table 8.

After determining the weights by BWM, the decision matrix of MCDM is written as presented in Table 9, which shows all five alternatives with their values derived from the energy modeling phase. It is evidenced that these variable alternatives have no common dimensions and scopes to be compared, and this is exactly why the problem should be considered as MCDM one.

The WASPAS method is a combination of two models: WSM (weighted sum model) and WPM (weighted multiplication model). This method has more accuracy compared to independent methods. Based on the weights calculated by the BWM method and by implementing the WASPAS formulas represented previously, this MCDM problem could be solved by calculating the $Q_i^{(1)}$ and $Q_i^{(2)}$. Then the amount of Q_i has been calculated, and all the scenarios are ranked by their value, as can be seen in Table 10. Through this MCDM method, the best scenario will be the S4 which has the highest share of both PV powerplants in its Electricity mix and EV share in its transportation sector. When compared to S3 and S2, which both have the same condition regarding the power generation capacity, the value of higher EVs share will be more highlighted. The second and third rank has been conquered by S3 and S2, respectively, and a big gap is seen between them and S1 and base. This clearly conveys an important message about the importance of installing the PV powerplants on the island and their vital role in upgrading the condition of the alternative in this study. However, the worst stage is occupied by S1, illustrating that only constructing the thermal power plant will be intensively destructive. It simply means that investing no money in the proposed power plant projects, which is the base energy system alternative, has been better than S1, in which a 500MW thermal power plant is proposed to be constructed to cover the uprising electricity demand of the island. In other words, it means that diversity in both the power supply and transportation sector enhanced the situation of the scenario.

6. Conclusion

In this paper, following the latest trends in energy systems and the transportation sector, five different scenarios for Qeshm island have been discussed. This research is based on available official data on

Table 6
Pairwise comparisons of the most important criterion over other criteria.

Best to Others	TPES	CO2	TAC	RES
TPES	1	2	4	3

Table 7
Pairwise comparisons of the least important criterion over other criteria.

Others to the Worst	TAC
TPES	4
CO2	3
TAC	1
RES	2

Table 8
Final weights of criteria.

Weights (%)	TPES	CO2	TAC	RES
	46.551724	25.862069	10.344828	17.241379

Table 9
The decision matrix based on energy modeling.

	TPES	CO2	TAC	RES
base	6.72	1.25	84	0.4
S1	7.05	1.56	101	0.4
S2	6.26	1.32	105	7.3
S3	6.15	1.28	94	7.4
S4	5.98	1.21	78	7.6

Table 10
Values of Additive and Multiplicative Relative Importance, Joint Generalized Criterion and final ranks of scenarios.

Scenarios	$Q_i^{(1)}$	$Q_i^{(2)}$	Q_i	Final Rank
base	0.769733277	0.560991134	0.665362205	4
S1	0.684426245	0.508277286	0.596351766	5
S2	0.924219626	0.921733847	0.922976736	3
S3	0.950843303	0.949809466	0.950326384	2
S4	1	1	1	1

energy consumption of the Qeshm island and the prediction of energy demand in 2030 on the island using the ARIMA model. The EnergyPlan software has been used to model these various scenarios. These scenarios are based on 0, 20 %, and 50 % for the percentage of the EVs used in the transportation sector of the island besides the construction plans of new powerplants; i.e., 500MW thermal and 195MW PV. A mixture of these alternatives to each sector has been considered to analyze the future condition of each scenario. Finally, comprehensive comparisons from various aspects have been conducted on all the scenarios from the detailed and overall overview. The criteria discussed in this paper are TPES, CO2 emission, TAC, and RES share, for all different scenarios and base alternatives. After comparing all alternatives from the determined criteria, a general comparison has been made. In this regard, BWM is used to define the weight of each criterion in the MCDM problem, and then the problem was solved by employing the WASPAS method. Finally, all the alternatives for 2030 have been ranked.

This model illustrated that for the year 2030, the best scenario is S4, which has the largest share of solar energy and electric vehicles among the examined scenarios. Replacing fossil-fueled cars with EVs tends to be environmentally friendly in terms of CO_2 Emissions reduction and energy intensity. This matter is attractive as it is possible that the electricity supplied to the EV may not be from a renewable resource. It means that even using the extracted electricity from fossil fuels like natural gas for EVs can benefit the island environmentally.

From the economic aspect, the scenario with the lowest investment cost has the highest priority as it is more affordable. This means that integrating solar power into the island's energy mix and EVs into the transportation sector would be the most justified scenario, economically. This is highly satisfying that the first-ranked scenario (from the general overview) has the highest rank in each subcategory discussed in this research.

Comparing the S1 and base alternative showed that investing in just a thermal power plant generally is the least logical decision for the island's energy supply system, though without which the island may be in need of importing electricity. Moreover, from the perspective of each criterion, S1 is the worst in 3 out of 4 aspects showing the detrimental prospect of this scenario in our analysis.

As an extension of the current research, the following subjects can be mentioned: a) using machine learning methods instead of time series analysis in order to predict energy consumption trends, b) implementing a Generation Expansion Planning (GEP) optimization model instead of just modeling, in order to achieve an optimal energy system in the future; c) applying a thorough sensitivity analysis, regarding various influential factors and assessing the potential outcomes of that on the energy system performance of the island; d) putting more emphasis on the development of energy storage technologies, smart grids, and load management plans; e) focusing on multi-objective analysis and nonlinear optimization to provide more comprehensive solutions for designing sustainable energy systems; and finally f) conducting techno-economic research with more details on the island such as the optimal siting and sizing of electric vehicle charging stations.

CRediT authorship contribution statement

Mohammad Hasan Ghodusinejad: Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Conceptualization. **Hossein Yousefi:** Writing – review & editing, Validation, Supervision, Project administration, Formal analysis, Data curation. **Mohammad Sotoodeh:** Writing – review & editing, Writing – original draft, Resources, Investigation, Data curation.

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

Data will be made available on request.

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