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Forecasting and Comparative Analysis of Energy Consumption in Iran and the United States: Divergent Trends and Policy Insights

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ABSTRACT

This paper explores the energy consumption (EC) of Iran and the United States as representatives of developing and developed countries. It introduces an innovative hybrid forecasting model that combines Principal Component Analysis (PCA), Support Vector Regression (SVR), Particle Swarm Optimization (PSO), and Autoregressive Integrated Moving Average (ARIMA) to predict EC trends for both countries until 2030.This approach fills a gap in the existing literature by integrating both advanced forecasting techniques and a comparative policy analysis, focusing on two countries with vastly different economic structures and energy policies. The model leverages key socio-economic indicators such as GDP, population, and energy trade data to generate accurate forecasts, with a mean absolute percentage error of 2.25% for Iran and 1.55% for the U.S. Through a comparative analysis, this study highlights the role of the "EC-economic growth nexus" and "Human development index" in explaining the disparities in per-capita EC between the two countries. It also identifies key challenges in Iran's energy sector, such as its energy tariff system, energy-intensive industries, and limited access to energy-efficient technologies, offering critical policy recommendations to improve energy efficiency.

Keywords: Energy consumption, Forecasting, Energy policy, Iran, The United States, ARIMA, Support vector regression

1. INTRODUCTION

Energy plays a crucial role in economic growth and national development, influencing foreign policy strategies, economic stability, and international security. Ensuring a sustainable energy supply has become a major concern for governments worldwide as noted in Fetanat, Khorasaninejad & Shafipour (2021). While extensive research has been conducted on energy forecasting and policy analysis, significant gaps remain in understanding the long-term energy consumption trends of countries with vastly different economic structures and energy policies.

A key challenge in energy forecasting is the lack of comprehensive studies that integrate both forecasting

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techniques and comparative policy analysis. Most existing studies either focus on forecasting future energy consumption trends or analyze policy impacts on energy efficiency, but few combine both approaches. Additionally, while various forecasting methods such as Box-Jenkins models, Grey models, and machine learning techniques have been employed, there remains a need for more robust hybrid models that improve accuracy and provide deeper insights into policy implications.

This study focuses on Iran and the United States, two countries with contrasting energy landscapes. Iran holds a critical position in the global energy market, with the world's third-largest oil reserves and the second-largest natural gas reserves. The Iranian economy heavily depends on the export volume and prices of these energy resources, reflecting its prominent role as an oil and gas exporter as asserted by Yazdan, Behzad & Shiva (2012). On the other hand, the United States plays a strategic role in the global energy market due to its membership in NAFTA, its status as a G7 nation, and its position as one of the five permanent members of the United Nations. The United States is also notable for its significant energy consumption and greenhouse gas emissions, further underscoring its importance for study and comparison as noted by Dogan & Turkekul (2016). Moreover, the political relationship between Iran and the United States can significantly impact global oil prices, as demonstrated by Ruiz Estrada, Park, Tahir, et al. (2020). Consequently, analyzing the historical and projected future energy trends of these two influential countries is of substantial interest, which serves as the primary focus of this study.

Figure 1 highlights the significant disparities in energy trends between Iran and the United States, representing a developing and a developed country, respectively. The ratio of energy use per capita to GDP per capita from 1990 to 2015 shows that while the United States has successfully increased its GDP with a declining trend in energy consumption, Iran's higher GDP during the same period has been accompanied by a substantial increase in energy usage.

To address the existing research gap, this paper proposes a hybrid forecasting model that integrates Principal Component Analysis (PCA), Support Vector Regression (SVR), Particle Swarm Optimization (PSO), and Autoregressive Integrated Moving Average (ARIMA) to predict energy consumption trends in Iran and the U.S. until 2030. By combinig these forecasting methods with a comparative analysis, this study provides valuable insights into Iran’s energy trends and highlights some policy recommendations for this country as a major oil and gas exporter, with an energy-intensive economy while having high subsidies and low energy efficiency.

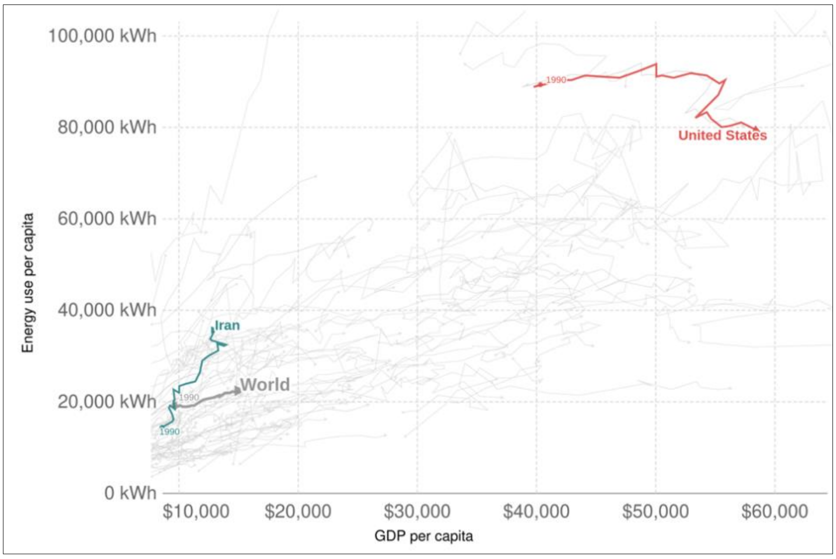

Fig. 1 GDP per capita vs. Energy use, 1990-2015 [*https://ourworldindata.org/energy*]

The paper is structured as follows: Section 2 reviews related studies on energy consumption forecasting and policy analysis. Section 3 outlines the theoretical background and presents the proposed hybrid forecasting method. Section 4 discusses numerical results, followed by a comparative analysis of Iran and the U.S. in Section 5, where barriers to Iran's energy efficiency improvement and potential policy solutions are examined. Finally, Section 6 concludes the study and offers recommendations for future research.

2. LITERATURE REVIEW

As the economy continues to grow rapidly, energy-related challenges have attracted increasing attention from researchers across various fields, leading to extensive efforts to analyze current trends and predict future developments. The studies conducted in this domain encompass a wide range of perspectives, considering different energy types such as fossil fuels, electricity, and renewables, as well as sector-based or national-wide forecasting, short-term or long-term forecasting, various predictors, and a variety of forecasting methods like Box-Jenkins, Grey model, and machine learning as can be found in Wang, Wang & Wu (2022), Wei, Li, Peng, et al. (2019), Mat Daut, Hassan, Abdullah, et al. (2017) and Ghalehkhondabi, Ardjmand, Weckman, et al. (2017). Since energy management trends and policies at the national level are aimed to be investigated in the current study, the review of the related literature will be limited to those studies forecasting annual energy consumption (EC) at the national level.

In energy consumption (EC) forecasting, two main types of predictors are commonly used. The first type relies on time series data, where future values are predicted based on past trends. This approach, known as the time series method, often uses Box-Jenkins models introduce by Box, Jenkins & Reinsel (1994) and Grey models by Julong (1989). The second type involves regression-based methods, which use independent variables or indicators as predictors. These methods include fuzzy regression, Support Vector Regression (SVR), Artificial Neural Networks (ANNs), and their various adaptations.

Several studies have employed the time series approach to forecast annual EC. For instance, Khan & Osińska (2023) utilized various types of Grey models to forecast Total EC, as well as the consumption of oil, gas, coal, hydroelectric, nuclear, and renewable energy in Brazil and India. Jiang, Yang, Li, et al. (2021) employed a hybrid method combining fuzzy time series and an improved chaotic electromagnetic field optimization algorithm to forecast the total EC, oil, coal, and gas consumption in China. Moreover, Samu, Asumadu Sarkodie, Fahrioglu, et al. (2020) utilized Box-Jenkins models to forecast the total EC in Zimbabwe for the period 2013-2030. Additionally, Ma & Wang (2019) utilized hybrid methods combining Box-Jenkins and Grey models for the EC forecasting of South Africa, while Yuan, Liu & Fang (2016) employed similar hybrid methods for the EC forecasting of China. Table 1 provides a summary of additional studies that focus on the EC forecasting of various countries.

In the context of annual EC forecasting for a country using a regression-based approach, socio-economic indicators like gross domestic product (GDP), population (POP), energy import (IMP), and energy export (EXP) are frequently employed as independent variables in several studies as considered by Hu, Nozari, et al. (2025), Zeng, Zeng, Choi, et al. (2017), Liu, Fu, Bielefield, et al. (2017). However, in order to forecast using a regression-based approach, it becomes necessary to have future values of the independent variables, which need to be estimated or forecasted. To address this requirement, different techniques have been utilized in the literature. These techniques include leveraging known national or international forecasts, assuming some growth rates, assessing various scenarios, forecasting the future values of predictors, or employing a combination of these techniques.

In Liu, Fu, Bielefield, et al. (2017), a gated recurrent neural network was applied to forecast Chinese primary energy consumption considering GDP, POP, IMP, and EXP as inputs to the network. In this study, the forecast of Chinese GDP published by the International Monetary Fund was employed. For POP, an approximation of the annual growth rate was calculated based on the prediction of the World Population Prospects for China's population by 2030. Due to the uncertainty of the import and export trade volume, four possible scenarios were considered. Rabbani, Ghoreyshi, Rafiei, et al. (2012) employed international forecasts of these variables from the International Monetary Fund and the World Bank for POP, GDP, cost of crude oil, and annual oil production.

An ANN supported by adaptive differential evolution was applied by Zeng, Zeng, Choi, et al. (2017) for EC forecasting of China based on its annual GDP, POP, IMP, and EXP. In this study, the utilized technique for estimating the future values of independent variables is based on considering some growth rates. For example, the average annual GDP growth rate was assumed to be 7% according to China's five-year plan. For the average annual growth rate of import for 2014-202, 3.4%, the same as for 2012-2013, was utilized. Szmelter-Jarosz et al.,(2024) assumed that the growth rates for POP and GDP, inputs of the proposed recurrent neural network, are the same as the last growth rate factor in the actual data. In another study that employed GDP as the only independent variable for forecasting the total EC of China conducted by Ji (2016), a constant growth rate of 7% determined by the government as the target annual GDP growth was applied.

In another study, Movahed, et al. (2023) utilized a combined technique for estimating the future values of predictors. In this study, GDP, POP, urbanization rate, the share of industry in GDP, and the share of coal in primary EC are independent predictors for China's primary EC forecast. The growth rates of these variables, except GDP and coal consumption, have been considered based on the target rates mentioned in China's national population development plan and Energy Outlook 2030. Four scenarios were investigated for GDP and coal consumption growth rates, and the corresponding EC for each scenario has been forecasted.

Another technique employed in the literature is forecasting the future values of predictors. In Eder & Provornaya (2018), energy intensity, serving as the sole predictor of EC, was forecasted using trend analysis across various economies, including developing/developed countries in Europe, China, Central and South America, and North America. However, in some other studies, the primary focus is on proposing forecasting methods without suggesting specific techniques for estimating or predicting future values of independent variables as studied by Hu, Wang, Peng, et al. (2020) as well as Bushehri, Mohammad Mehdi, Khavari, et al. (2022).

As mentioned, many regression-based methods for EC forecasting lack forecasts for upcoming values of independent predictors and instead rely on estimations from national or international sources. While this approach is commonly used in the literature, it has certain drawbacks. Firstly, when estimations for each predictor are obtained from different organizations or data sources with varying assumptions and estimation methods, inconsistencies may arise. Moreover, there might be some correlations between predictors, as highlighted by Hu, Wang, Peng, et al. (2020). Consequently, using these predictors as inputs to the forecasting methods without considering their correlation can impact the accuracy and reliability of the forecasts.

To address these limitations, the current study tackles these issues by employing Box-Jenkins methods to forecast future values of each independent variable rather than relying on some estimations. Additionally, Principal Component Analysis (PCA) is applied to the independent variables to transform them into uncorrelated predictors. These transformed predictors are then utilized in a Support Vector Regression model (SVR), with Particle Swarm Optimization (PSO) employed to determine the optimal set of kernel functions and SVR parameters. By incorporating these techniques in a proposed framework, we aim to enhance the accuracy and reliability of the EC forecasts and overcome the limitations associated with traditional approaches. After forecasting the EC of Iran and the United States till 2030 using the proposed framework, a comprehensive comparison of the actual and forecasted energy-related trends in these countries will be provided.

Table 1 Summary of some related studies

Reference	Predictor	Energy type to be forecasted	Forecast period	Country	Methodology
Khan & Osińska (2023)	Time series of the past values	Total EC, oil, gas, coal, hydroelectric, nuclear, and renewable	2020-2024	Brazil India	Nonlinear Grey Bernoulli model; Nonlinear Grey Bernoulli model with PSO; and Standard Grey model
Bushehri, Mohammad Mehdi, Khavari, et al. (2022)	Sustainable development indicators	Total EC	-	Iran	Hybrid genetic algorithm and SVM
Wang, Wang & Wu (2022)	Time series of the past values	Total EC	2020-2025	China	Grey multi-variable model
Jiang, Yang, Li, et al. (2021)	Time series of the past values	Total EC, oil, coal, and gas consumption	2009-2017	China	Hybrid of fuzzy time series and Improved chaotic electromagnetic field optimization algorithm (ICEFO)
Samu, Asumadu Sarkodie, Fahrioglu, et al. (2020)	Time series of the past values	Total EC	2013-2030	Zimbabwe	ARIMA
Hu, Wang, Peng, et al. (2020)	GDP, POP, IMP, EXP	Total EC	2010-2015	Turkey	Bagged echo state recurrent network
Ma & Wang (2019)	Time series of the past values	EC	2017-2030	South Africa	Hybrid of ARIMA and nonlinear Grey model
Castro Verdezoto, Vidoza & Gallo (2019)	Different scenarios of economic growth and efficiency policies	Energy consumption and demand	2010-2030	Ecuador	Using LEAP for future projection
Zhou & Chen (2019)	Time series of the past values	Total EC	217-2021	China	Error correction and decompose-ensemble strategy combined with regression and triple exponential smoothing
Wang, Li & Li (2018)	GDP, POP, urbanization rate, share of industry in GDP, coal share of primary EC	Primary EC	2017-2030	China	Optimized SVM by a self-adaptive multi-verse optimizer
Zeng, Zeng, Choi, et al. (2017)	GDP, POP, IMP, EXP	Total EC	2014-2020	China	ANN supported by adaptive differential evolution
Liu, Fu, Bielefield, et al. (2017)	GDP, POP, IMP, EXP	Primary EC	2016-2021	China	ANN with gated recurrent unit
Xie, Xiao, Hu, et al. (2017)	Time series of the past values	EC, petroleum and gas consumption	2014-2020	China	Group method of data handling based on auto-regressive model
Ji (2016)	GDP	Total EC	2011-2015	China	Variable asymptote Boltzmann model
Barak & Sadegh (2016)	Time series of the past values	Total EC	-	Iran	ARIMA-ANFIS (adaptive neuro-fuzzy inference)
Yuan, Liu & Fang (2016)	Time series of the past values	Primary EC	2014-2020	China	Hybrid of ARIMA and Grey model
Zhao & Guo (2014)	Time series of the past values	Total EC	-	China	Hybrid of generalized regression ANN, PSO and cultural algorithm
Rabbani, Ghoreyshi, Rafiei, et al. (2012)	POP, GDP, cost of crude oil, annual oil production	EC	2010-2015	The U.S., Japan, Canada, Australia	Bi-objective fuzzy linear regression model
Avami & Boroushaki (2011)	POP, GDP	Total EC	2007-2011	Iran	Recurrent neural networks

3. METHODOLOGY

The hybrid method proposed in this study comprises four modules, each serving a specific purpose. The first module utilizes ARIMA to forecast individual socio-economic indicators as independent time series. These forecasts are then used as EC predictors in subsequent steps. The second module employs Principal Component Analysis (PCA) to transform the predictors into uncorrelated principal components (PCs). The third module utilizes Support Vector Regression (SVR) to forecast the EC Lastly, the fourth module, Particle Swarm Optimization (PSO), is responsible for finding the optimal set of kernel function and SVR parameters. In the following sections, each of these modules will be explained in more detail.

3.1 Autoregressive Moving Average (ARMA)

Autoregressive Moving Average (ARMA) is a known method based on Box–Jenkins time series forecasting models which uses predicted variable and residual errors as the regressors, noted by Pandey & Basu (2020). When data show evidence of non-stationarity, some differentiating steps are needed. To forecast a time series, several ARIMA models should be investigated. In the literature, the Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (BIC), given in Eqs. (1) and (2), are frequently used to choose the best ARIMA model. In these equations, k is the number of free parameters of the model to be estimated, L is the maximum likelihood function of the model, and N is the number of observations. The model with the least AIC and/or BIC is preferred for forecasting as explained by Sen, Roy & Pal (2016).

$$AIC = 2k - 2\ln(L) \tag{1}$$

$$BIC = -2\ln(L) + kln(N) \tag{2}$$

3.2 Support Vector regression (SVR)

Initially designed for classification tasks, the support vector machine (SVM) is a learning method grounded in structural risk minimization. Subsequently, the capability for regression analysis of nonlinear functions was introduced by formulating it as a convex quadratic optimization problem, leading to the development of SVR as noted by Ghasemi-Marzbali (2020). The objective of SVR is to estimate a linear regression function, denoted as $f(x) = w^T x + b$, where $x_i \in R^n$ represents the input data vector, w denotes the weight vector, and b corresponds to the bias. The estimation is obtained by solving Eq. (3).

$$\min \frac{1}{2} w^T w + C\sum_{i=1}^{n}\left(\xi_i^+ + \xi_i^-\right)$$
$$s.t. \begin{cases} y_i - \left(w^T x + b\right) \le \varepsilon + \xi_i^+ \\ \left(w^T x + b\right) - y_i \le \varepsilon + \xi_i^+ \\ \xi_i^+, \xi_i^- \ge 0 \end{cases} \tag{3}$$

Where ε represents the tube size, ξ_i^+ and ξ_i^- are the distance between actual values and the corresponding boundary values of ε-tube and C is the regularized constant. By introducing Lagrange multipliers, the estimation function will be turned into Eq. (4), where $\alpha_i^+, \alpha_i^- \ge 0$ are Lagrange multipliers satisfying $\alpha_i^+ \times \alpha_i^- = 0$. Solving the corresponding dual function will determine the optimal values of these multipliers.

$$f(x)=\sum_i\left(\alpha_i^+-\alpha_i^-\right)x_i^Tx+b \tag{4}$$

In the case of nonlinear regression, x_ix_j in Eq. (5) is replaced by a kernel function. The Gaussian radial basis function (RBF), Eq. (5), and polynomial kernel, Eq. (6), are the most known kernels for nonlinear applications.

$$K\left(x_i,x_j\right)=\exp\left(-\frac{x_i-x_j^{\ 2}}{2\sigma^2}\right) \tag{5}$$

$$K\left(x_i,x_j\right)=\left(x_ix_j+1\right)^p \tag{6}$$

Apart from choosing an appropriate kernel function for a given data, setting the parameters of the kernel and finding the optimal or near-optimal values of C and ε in the SVR model can substantially impact the model's ability for accurate forecasting.

3.3 Proposed Hybrid Method

The proposed hybrid method consists of different steps. Firstly, for each indicator, the ARIMA model with the least AIC and BIC is utilized to forecast the future values of that indicator until 2030. Given the possibility of correlations among these indicators, it becomes valuable to project them into an uncorrelated space. Principal component analysis (PCA) is a statistical modeling technique that identifies correlations between variables and summarizes the dataset using particular linear combinations of the variables, called principal components (PCs) as noted by Platon, Dehkordi & Martel (2015). In PCA, the significance of a PC is determined by its corresponding eigenvalue, which indicates the amount of total variance that can be explained by that PC A detailed description of the PCA method can be found in the study conducted by Kong, Liu, Shi, et al. (2015).

There are two approaches to determine the optimal number of PCs. The first one is based on the overall variance explained by the PCs (cumulative eigenvalues of PCs). Using those PCs that cumulatively explain 95% of the overall variance of the data, for example, was employed by Platon, Dehkordi & Martel (2015). The second approach involves optimizing an objective function, where PCs will be added consecutively until adding another PC worsens the objective function's value. Consequently, that PC and all the remaining PCs would be excluded. An example of applying this procedure can be found in the study of Sousa, Martins, Alvim-Ferraz, et al. (2007). In the current study, the second approach will be used to decorrelate independent variables (IMP, EXP, POP, and GDP) with the objective of minimizing forecast error.

In the literature, different methods are employed setting the SVR kernel's parameters and finding the optimal or near-optimal values of C and ε to find the best set of values for these parameters. Utilizing a population-based optimization algorithm is among the most frequent ones as mentioned by Hong (2009), Che (2014), Zhang, Deb, Lee, et al. (2016). The current study will use PSO, a known population-based algorithm, in this regard. In this algorithm, each particle has a velocity and a position, updated by Eqs. (7) and (8), respectively. In these equations, c_1 and c_2 are constant, r_1 and r_2 are random numbers and $\bar{w}$ is the inertia weight. $pbest_{id}(t)$ is the best solution found by an identical particle in iteration t and $gbest(t)$ is the best solution of all particles as noted by Kiran (2017).

$$v_{id}(t+1)=\bar{w}v_{id}(t)+c_1r_1\left[pbest_{id}(t)-X_{id}(t)\right]+c_2r_2\left[gbest(t)-X_{id}(t)\right] \tag{7}$$

$$X_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \tag{8}$$

This study will examine RBF and polynomial kernels while PSO is applied to find the best set of parameters. Based on try and error, a population of 30 particles starts the optimization process, and the maximum iteration is set to 50. The values of c_1 and c_2 are also set to 1.5 and $\bar{w}$ is set to 0.9. Figure 2 gives the pseudo-code of the proposed hybrid method called SVR-based. In this pseudo-code, the kernel parameter for the polynomial function is p and for RBF is σ. This hybrid method is implemented in Matlab R2017a.

```
1. Forecast the future values of input data by appropriate ARIMA models.
2. Apply PCA method on the input data (actual and forecasted) and convert them to PCs.
3. Separate PCs into training and testing subsets.
   3.1. For each PC
      3.1.1. If the last MAPE is increased compared to the previous MAPE
            3.1.1.1. Add the PC to the input dataset.
            3.1.1.2. While iteration<maximum iteration of PSO
               3.1.1.2.1. For each particle
                     - Train the SVR with the determined combination of kernel function
                       parameter and SVR parameters (C and ε).
                     - Forecast training subset by the trained SVR.
                     - Calculate MAPE, fitness function, of each particle.
                     - Update pbest_id of each particle.
               3.1.1.2.2. End For.
               3.1.1.2.3. Update gbest
               3.1.1.2.4. Update position and velocity vectors of all particles.
            3.1.1.3. End While.
      3.1.2. Determine the best combination of the kernel function and SVR parameters (the best
             solution found by PSO) based on MAPE.
      3.1.3. End If.
   3.2. End For.
4. Determine the optimal set of PCs as input data.
5. Forecast future values of the time series using optimal set of PCs and trained SVR with optimized
   kernel parameters by PSO
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Fig. 2 The pseudo-code of the SVR-based method

4. NUMERICAL RESULTS

In this section, the proposed method is applied to the EC-related data of Iran and the U.S. to investigate its performance and provide EC forecasts for conducting a comparative analysis of these countries.

4.1 Implementation details

For Iran, the annual EC, GDP, POP, IMP, and EXP are collected from the website of the Office of Energy and Electricity Planning, Ministry of Energy (MoE) of Iran. The data from 1967 to 2006 is taken to fit the model, and the remaining data (2007-2021) are used to evaluate the methods. For the U.S. and due to more available data through the World Bank website, corresponding data of 1949-2008 are considered for model fitting and 2009-2021 data for forecasting performance evaluation. Afterward, the EC will be forecasted for 2022-2030 for these countries.

In the literature, different criteria are used to quantify a forecasting method's performance as a measure of accuracy. Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are among the most frequently used criteria, as employed by Qin & Li (2020), Torabi, Hashemi, Saybani, et al. (2019), and Wang, Li & Li (2018). These criteria are introduced in Eqs. (9) to (11). In the current paper, these criteria are reported for all the forecasts. However, MAPE, which is stated in percent and is comparable, will be used as the main criterion to determine the best models.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(x_t - \hat{x}_t\right)^2}{N}} \tag{9}$$

$$MAE = \frac{\sum_{i=1}^{N}\left|x_t - \hat{x}_t\right|}{N} \tag{10}$$

$$MAPE = \frac{\sum_{i=1}^{N}\left|\frac{x_t - \hat{x}_t}{x_t}\right|}{N} \times 100\% \tag{11}$$

In addition to the proposed SVR-based method, some other forecasting methods are implemented in the current study for comparison purposes. ARIMA is the first method in this regard, which is implemented by investigating several ARIMA models and choosing the most appropriate model with the least AIC and BIC criteria by considering the EC as a time series. The second implemented method is regression where the actual and forecasted values of IMP, EXP, POP, and GDP are used to fit a linear and quadratic regression function on the EC. The study conducted by Haouraji, Mounir, Mounir, et al. (2020) is an example of employing regression for EC forecasting purposes. The last method for comparison is a hybrid method similar to the proposed one, while SVR is replaced with Multilayer Perceptron (MLP). MLP is an artificial neural network widely used in forecasting, especially for energy-related applications as noted by Zolfaghari & Sahabi (2019). In the current study and according to trial and error, the MLP network consisted of one hidden layer with nine computational neurons in this layer.

4.2 Forecasting

As mentioned, the first step of the proposed hybrid method is to forecast the future values for each of the independent predictors (IMP, EXP, POP, and GDP) as individual time series using ARIMA. Table 2 gives the most fitted ARIMA models based on the least AIC and BIC. For example, ARIMA(2,1,3) provides the most accurate forecasts for the annual IMP of the United States. It is worth noting that this step also follows the same fitting and forecasting time intervals as the other steps. So, 1967-2006 and 1949-2008 are taken for fitting the model for Iran's and the United States' IMP, EXP, POP, and GDP, respectively.

Table 2 Fitted ARIMA models and the values of performance criteria for independent variables' forecasting

	Independent Variable	**IMP**	**EXP**	**POP**	**GDP**
Iran	Model	ARIMA(0,1,0)	ARIMA(2,0,2)	ARIMA(2,1,2)	ARIMA(0,1,1)
	AIC	4.374965	9.281331	13.996415	27.72376
	BIC	4.452932	9.512982	14.230315	27.84071
The U.S.	Model	ARIMA(2,1,3)	ARIMA(1,2,3)	ARIMA(3,1,4)	ARIMA(2,2,2)
	AIC	3.228658	1.954461	-0.41848	12.76459
	BIC	3.457137	2.151896	-0.12472	12.96202

Afterward, PCA is employed to transform these independent variables into uncorrelated predictors for the subsequent steps of the proposed forecasting method, according to the pseudo-code given in Figure 2. Consequently, the forecasted values of EC for the periods 2007-2030 and 2009-2030 are illustrated in Figure 3 for Iran and Figure 4 for the United States.

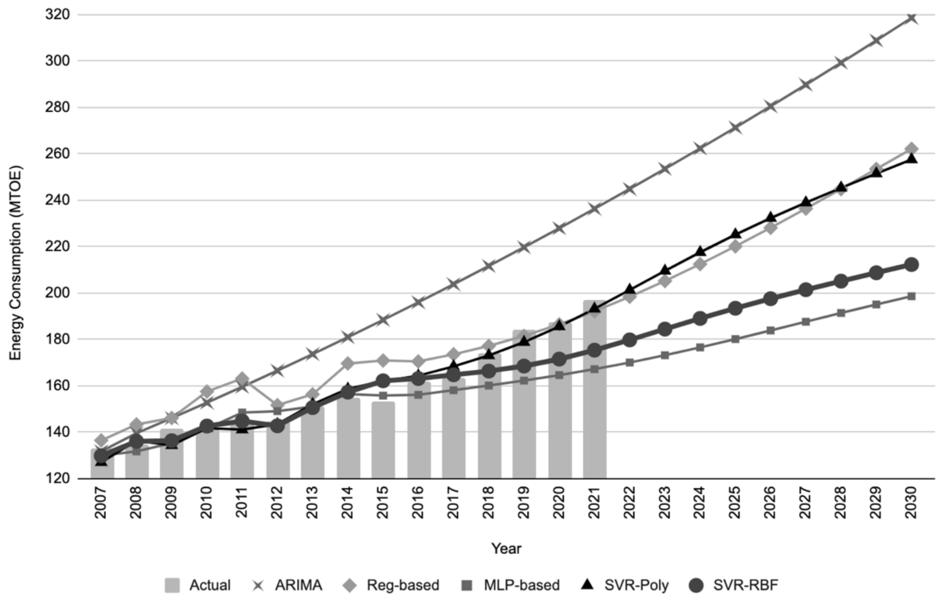

Fig. 3 Comparison of forecasting methods applied on the EC of Iran

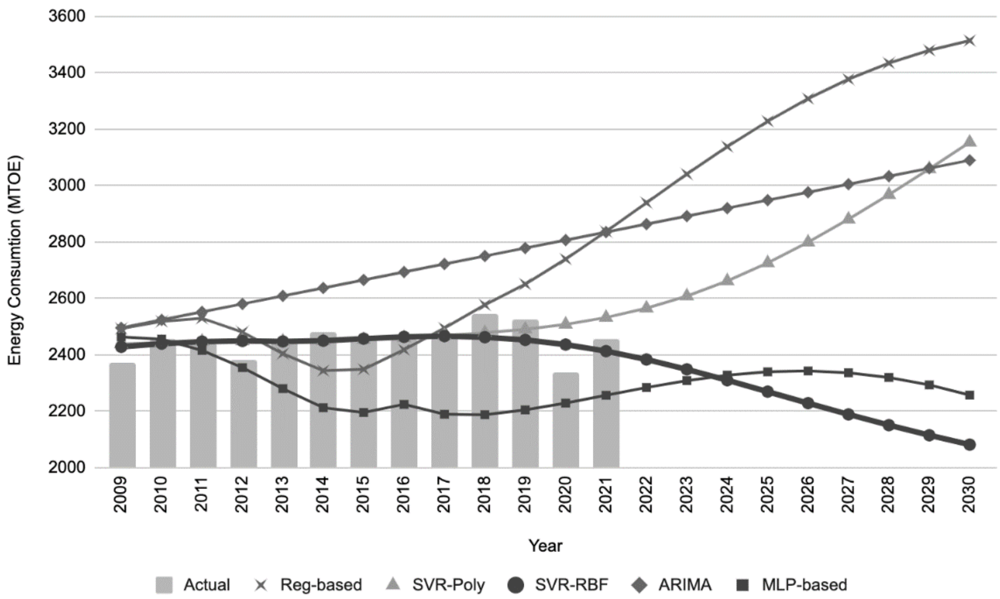

Fig. 4 Comparison of forecasting methods applied on the EC of the U.S.

In order to evaluate the reliability and statistical significance of the forecasted EC values, the Wilcoxon rank sum test is utilized. This test compares two sets of data to determine if they originate from continuous distributions with equal medians. The results of the Wilcoxon test for the forecasted values of Iran and the United States are displayed in Table 3 and Table 4, respectively. As shown in Table 2, all the p-values obtained from the Wilcoxon test for each pair of comparisons exceed the predefined significance level of 5%. Therefore, the null hypothesis cannot be rejected. This indicates that all the methods are theoretically reliable and valid for forecasting EC in Iran. However, for the United States, the ARIMA and MLP-based methods, as highlighted in Table 3, do not produce reliable forecasts as the null hypothesis is rejected. This implies that these methods do not originate from distributions with equal medians when compared to the actual values of the United States' EC and, consequently, the Reg-based and SVR-based methods. Therefore, these methods must be excluded and will not be considered for the subsequent comparisons.

Table 3 P-values of the Wilcoxon rank sum test for Iran

Method		**Actual**	**ARIMA**	**Reg-based**	**MLP-based**	**SVR-based**	
						Polynomial	**RBF**
Actual		-	0.094	0.094	0.931	0.816	0.931
ARIMA		0.094	-	0.605	0.077	0.077	0.077
Reg-based		0.094	0.605	-	0.063	0.077	0.050
MLP-based		0.931	0.077	0.063	-	0.050	0.931
SVR-based	**Polynomial**	0.816	0.077	0.077	0.050	-	0.796
	RBF	0.931	0.077	0.050	0.931	0.796	-

Table 4 P-values of the Wilcoxon rank sum test for the U.S.

Method		**Actual**	**ARIMA**	**Reg-based**	**MLP-based**	**SVR-based**	
						Polynomial	**RBF**
Actual		-	0.00004	0.54570	0.01420	0.73040	0.60480
ARIMA		0.00004	-	0.00029	0.00004	0.00004	0.00004
Reg-based		0.54570	0.00029	-	0.01420	0.73040	0.73040
MLP-based		0.01420	0.00004	0.01420	-	0.02440	0.01420
SVR-based	**Polynomial**	0.73040	0.00004	0.73040	0.02440	-	0.93140
	RBF	0.60480	0.00004	0.73040	0.01420	0.93140	-

Table 5 provides an overview of the performance measures associated with EC forecasting for Iran and the United States. It is important to note that the MLP-based and SVR-based methods incorporate PSO, a population-based algorithm, resulting in varying forecasts in each run. As a result, the average values of performance criteria from 15 runs of these methods are reported in this table.

When considering MAPE as the primary performance criterion for comparison, the SVR-based method demonstrates the most accurate forecasts for both Iran and the United States. Specifically, for Iran, the Polynomial kernel yields the best results with a MAPE of 2.25%. On the other hand, for the proposed SVR-based method, employing the RBF kernel leads to EC forecasts with a MAPE of 1.55% for the United States.

It is worth noting that in the existing literature, there is a greater emphasis on reporting the Mean Absolute Percentage Error (MAPE) or other performance measures for the fitting dataset compared to the unseen testing data. This may be attributed to the limited available data for EC forecasting, which often leads researchers to work with smaller datasets that do not allow for a separate unseen test dataset. However, in the present study, we have distinct datasets for fitting and testing purposes, allowing for an evaluation of model performance on unseen data. So, to ensure a fair comparison, we implemented the ARIMA, Reg-based, and MLP-based methods using the same fitting and testing data in our study.

As a result, the proposed SVR-based method not only demonstrates an excellent forecast in terms of MAPE, as stated by Wang, Wang & Wu (2022), but also exhibits superior performance compared to other implemented methods. This establishes the SVR-based method as a reliable and accurate forecasting approach for energy-related applications.

Table 5 Performance measures for different forecasting methods (Bests in **bold**)

Country	Metric	ARIMA	Reg.	MLP	SVR-Poly	SVR-RBF
Iran	RMSE	28.28	10.12	12.16	**4.26**	8.73
	MAE	24.7	8.44	8.21	**3.49**	5.85
	MAPE%	14.96	5.59	4.71	**2.25**	3.38
The U.S.	RMSE	-	173.99	-	62.19	**50.12**
	MAE	-	128.87	-	42.17	**37.77**
	MAPE%	-	5.31	-	1.75	**1.55**

5. DISCUSSION

This section presents a comparative analysis aimed at explaining the disparities in EC values and trends between Iran and the United States. It includes an examination of both EC per capita and energy intensity in these countries, providing insights into the factors driving the differences. Afterwards, based on the discussed characteristics of the EC trends in Iran, the main barriers hindering the enhancement of Iran's energy efficiency are addressed, and some policies, based on a comprehensive examination of Iran's energy plan, are recommended.

5.1 Comparative analysis of EC per capita

Figure 5 illustrates the actual and forecasted values of the EC per capita for Iran and the United States. As illustrated in this figure, there is a substantial disparity in their EC per capita. The EC and economic growth nexus could be an explanation for this disparity. The causal relation between a country's EC and its GDP has been extensively explored in the literature. The study conducted by Arto, Capellán-Pérez, Lago, et al. (2016) is an example in this regard. However, although energy consumption has a positive impact on economic growth, the reverse relationship is not necessarily true as explained by Aslan, Apergis & Yildirim (2014). In other words, energy is considered an essential input for economic growth, but increasing energy efficiency can weaken this association, as observed in the case of the United States studied by Shahbaz, Zakaria, Shahzad, et al. (2018). Figure 6 demonstrates that Iran's GDP per capita is significantly lower than that of the United States, which could be considered a major factor contributing to the substantial difference in their energy consumption per capita.

Moreover, according to the definition provided by the United Nations Development Program, the Human Development Index (HDI) is a summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and having a decent standard of living. It has been found that there is a strong correlation between the EC and living standards. However, after hitting a high HDI, there is a saturation point where the EC changes can barely affect living standards as discussed by Arto, Capellán-Pérez, Lago, et al. (2016). As illustrated in Figure 7, although Iran's HDI is approaching that of the United States, there remains a notable disparity. This strong correlation could also be considered another explanation for the different EC levels observed in these countries.

Hence, the distinction depicted in Figure 5 can be mainly attributed to both economic growth and human development, although there may additional contributing factors exist. In summary, EC per capita of the United States exhibits a declining trend as a result of transitioning towards a more energy-efficient and less energy-dependent approach to economic growth, coupled with achieving a high level of human development. On the other hand, Iran is gradually approaching the United States through a steady upward trajectory, although there remains a considerable gap between the two nations.

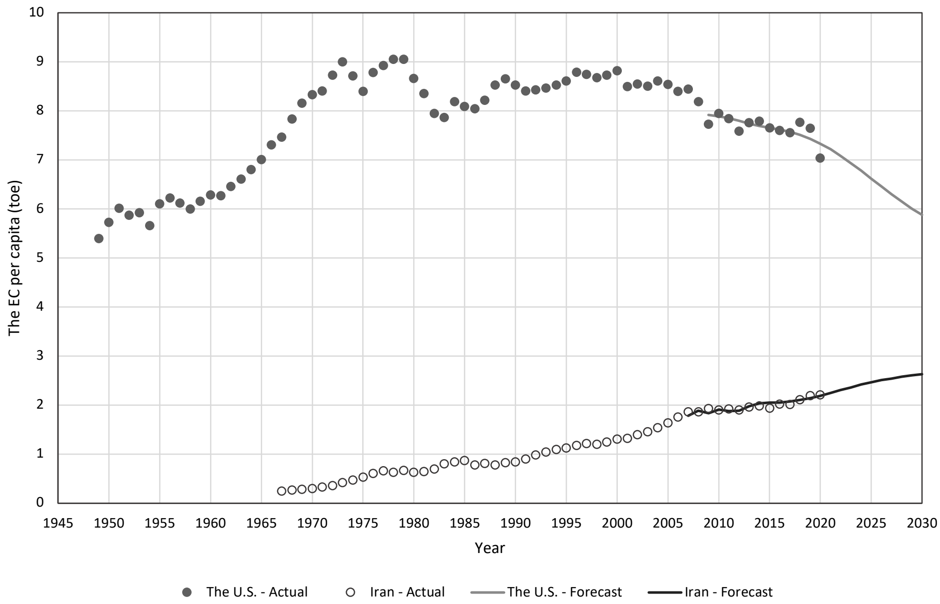

Fig. 5 Actual and forecasted values of the EC per capita of Iran and the U.S.

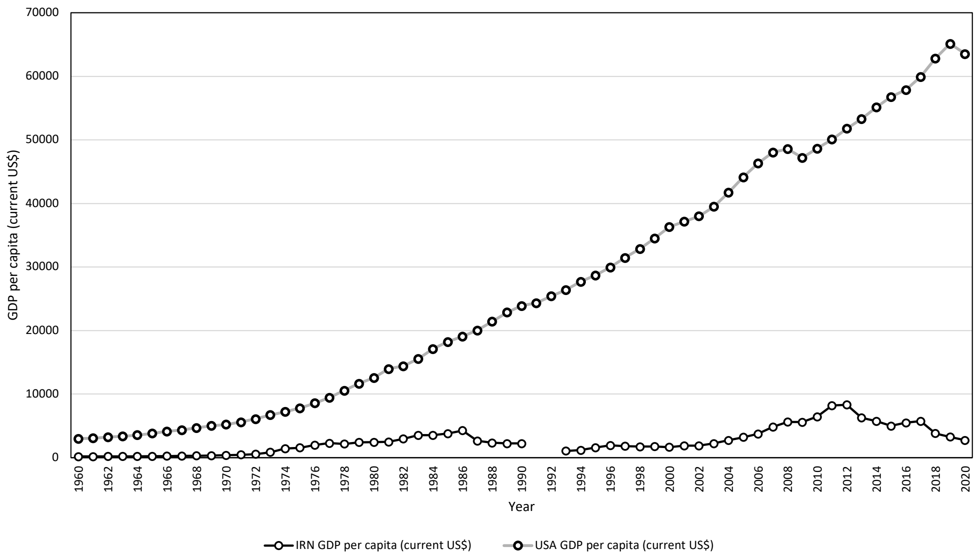

Fig. 6 GDP per capita of Iran and the U.S. [Ref.: The World Bank website]

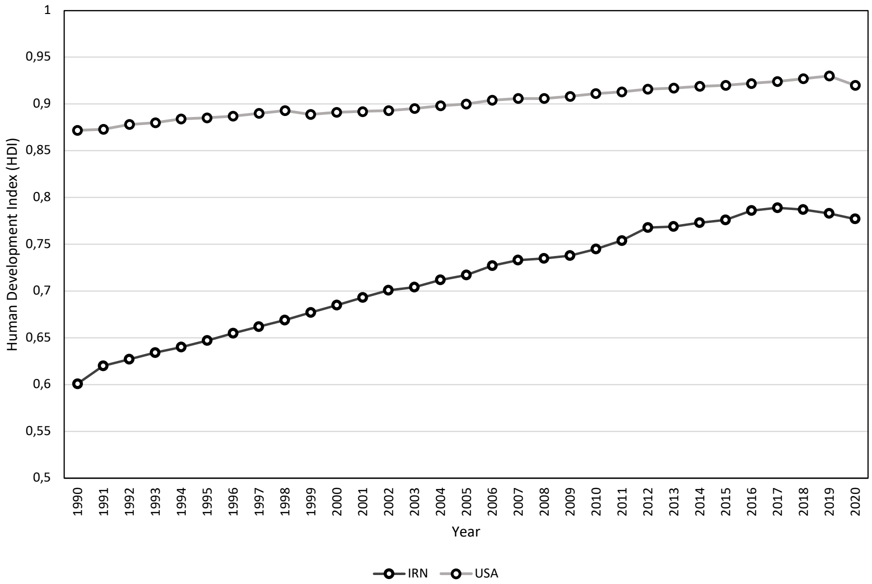

Fig. 7 Human Development Index (HDI) of Iran and the U.S. [Ref.: United Nations Development Program website]

5.2 Comparative analysis of energy intensity

Energy intensity is a commonly used measure in energy trends analysis that mainly focuses on a country's energy inefficiency. Energy intensity is defined as the ratio of total annual energy consumption to the annual GDP as noted by Dargahi & Khameneh (2019) and Pati (2021). Various countries have been actively working towards reducing their energy intensity and decoupling economic growth from energy consumption. Notably, developed nations have been more successful in this endeavor compared to developing countries. As depicted in Figure 8, the United States, categorized as a developed country, has consistently achieved a downward trend in energy intensity, which is a desirable continuous reduction over time.

Contrarily, Iran's energy intensity does not show a consistent downward trend and has instead experienced fluctuations over time. Notably, its lowest energy intensity levels were achieved during the period of 2011-2012, bringing it closer in alignment with the United States. A more detailed examination reveals that these fluctuations can be attributed to the dynamics of oil prices. Given Iran's status as a prominent global exporter of oil and gas, its economy is heavily reliant on energy export. Consequently, Iran's income from energy exports, a big share of its GDP, is dependent on the prices in the global energy market. This dependency can be justified by comparing Iran's GDP and the OPEC oil price, as depicted in Figure 9. Notably, the years 2011 and 2012 witnessed the highest prices for the OPEC oil basket, consequently resulting in the highest recorded GDP value for Iran, and accordingly, Iran's energy intensity approached values similar to those of the United States. However, following the decline in oil prices, Iran's energy intensity experienced an increase and is forecasted to continue this trend, at least till 2030, as shown in Figure 8. Although a relatively stable trend has been forecasted for years ahead for Iran, international political decisions such as intensifying Iran's sanctions or OPEC oil and gas supply policies can impact this trend.

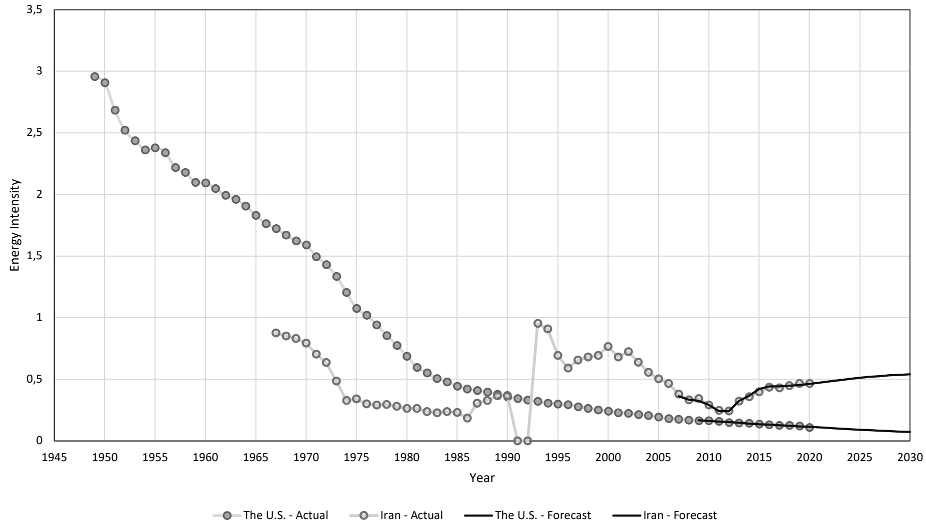

Fig. 8 Actual and forecasted values of energy intensity of Iran and the U.S.

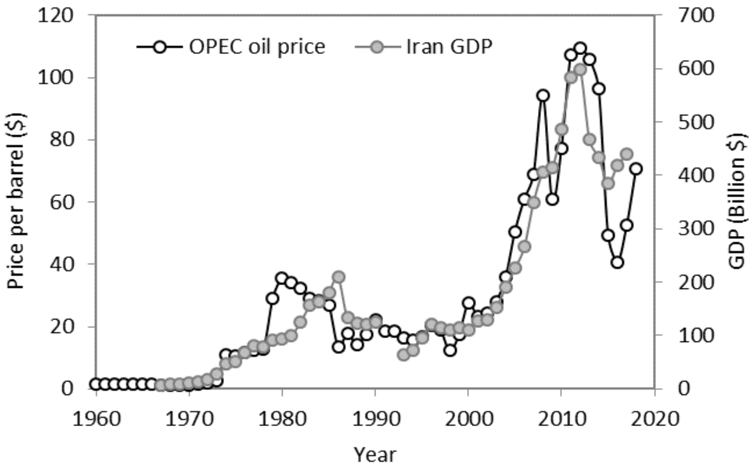

Fig. 9 Comparative time series of Iran GDP and OPEC oil price [Ref.: OPEC website]

5.3 Policy discussion

According to the energy-related trends discussed in Iran, there are notable economic growth opportunities that can be pursued by focusing on the energy sector, which holds a critical position in the country's economy. However, sustainable economic growth hinges upon the establishment of an energy-efficient economy, where economic growth is not necessarily achieved by consuming more energy. This section aims to outline the main barriers hindering the enhancement of Iran's energy efficiency and provides recommendations for policies based on a comprehensive examination of Iran's energy plan. These proposed policies are intended to provide a deeper understanding of Iran's energy market and explore potential opportunities for collaboration and investment. Energy tariffs, multi-carrier energy system, energy-intensive industries, service economy, and energy-efficient technologies are topics in this regard.

Energy tariff system

Based on the 2018 report from the International Energy Agency, Iran ranks third worldwide in terms of the share of subsidies in its GDP, accounting for 15%. Furthermore, Iran holds the first position globally in terms of the net amount of subsidies, with a substantial $69.2 billion dedicated to subsidizing fossil fuel consumption and electricity. These subsidies present a significant barrier to improving energy efficiency and contribute significantly to the rising trend of EC. As highlighted by Khojaste-Sarakhsi, Ghodsypour, Fatemi Ghomi, et al. (2018), modifying Iran's energy tariff system stands out as the primary and most critical strategy to adverse this trend. The "Iran subsidy reform plan," enacted by the Iranian Parliament in 2010, was implemented as one of the strategies to overcome this issue, resulting in a positive impact on reducing EC. However, due to its major adverse effect on the country's inflation rate, the implementation of the subsequent phase of this plan has been postponed. This inflation, along with a considerable devaluation in Iranian currency that happened due to economic sanctions resulted in a considerable reduction of the relative energy price compared to other goods and services. Consequently, due to the lack of financial incentives, many of the energy efficiency advancements achieved through the implementation of the "Iran subsidy reform plan" became ineffective.

Therefore, redefining the energy tariff system with the least negative effect on the inflation rate is necessary. This must be based on a comprehensive economic analysis and a comprehensive understanding of consumers' behavior when facing the new energy tariff system. This redefinition is the first and maybe the most critical step toward energy-efficient consumption in this country.

Multi-carrier energy systems

The utilization of multi-carrier energy systems has witnessed a growing trend across various applications. The ability to switch between different energy sources, such as electricity, gas, and thermal energy, offers the potential to meet energy demands in a more reliable manner as discussed by Noussan & Jarre (2018). In Iran, the presence of well-established energy grids enables widespread access to electricity and natural gas throughout the country. While the availability of a multi-carrier energy system presents an opportunity, the concurrent enhancement of energy efficiency in these energy carriers has encountered several challenges due to financial and technological limitations in this country.

In Iran, the Ministry of Petroleum oversees natural gas and liquid fuels, while the Ministry of Energy is responsible for electricity. As a result, energy-related policies are developed and implemented by two separate ministries with different approaches aimed at optimizing their own area of responsibility. An integrated policy would involve considering various factors such as the economy, government structure, behavioral and social responses, and available infrastructure to enhance energy efficiency. By aligning policies, regulations, and investments to create synergy and maximize the overall energy efficiency of the country, Iran can effectively benefit from the potential advantages of a multi-carrier system.

At the operational level, there exist numerous opportunities for investors to capitalize on the multi-carrier energy system in this country. One such opportunity is investing in gas-fired power stations, particularly those equipped with combined heat and power (CHP) technology to generate electricity in these stations and subsequently feed it into the electricity grid, helping better management of peak loads. This investment aligns with the goal of ensuring a reliable and sustainable energy supply for Iran's government while also providing economic benefits for investors.

Energy-intensive industries

Energy-intensive industries are characterized by substantial energy consumption, constituting a significant portion of their production costs. This high energy demand has led developed countries to relocate such industries to non-developed countries, often due to less stringent environmental regulations and/or lower costs of resources or labor as mentioned by Lan, Malik, Lenzen, et al. (2016). In Iran, several industries are classified as energy-intensive and contribute significantly to its overall EC. The steel industry is one of them. According to the World Steel Association report (World Steel Association 2018), Iran ranked as the ninth largest net steel exporter in 2017. While the United States maintained its first rank among net steel importers, Iran has increased its exports, changing its rank to the seventh largest net exporter in 2018 and 2019 according to World Steel Association (2019) and World Steel Association (2020).

Moreover, energy-intensive industries have another downside regarding their embodied energy, which refers to the energy consumed throughout the entire industrial chain to obtain products. The embodied energy encompasses the required energy for manufacturing associated materials, workshops, and equipment and the energy needed for services like transportation and healthcare. This indirect energy

consumption is much greater than the direct energy consumed in processing as highlighted by Tang, Gong, Xiao, et al. (2017).
Given the substantial levels of direct and embodied energy consumption, exporting energy-intensive products can be seen as a form of implicit energy export without monetary compensation. Furthermore, as these products are manufactured using subsidized energy, they may compete with energy-efficient counterparts from other countries without sufficient focus on enhancing energy efficiency or managing their greenhouse gas emission. Accordingly, it is crucial to examine the trade-off between costs and benefits associated with energy-intensive industries and implement energy-efficient policies that can have a positive impact on Iran's GDP.
Meanwhile, to address the substantial workforce employed in energy-intensive industries, creating alternative jobs is necessary. Investors and practitioners can capitalize on Iran's cost-effective labor by establishing alternative employment opportunities. Moreover, investing in renewable energy generation is highly recommended in Iran, given its exceptional potential for hydropower, wind energy, and solar power. With approximately 300 sunny days per year covering two-thirds of its land area and an average solar radiation of 2200 kWh per square meter as noted by Aghahosseini, Bogdanov, Ghorbani, et al. (2018), the renewable energy market offers a perfect opportunity to create alternative jobs while promoting sustainable development through the production of green energy.

Service economy
The service sector has gained significant attention in the modern economy, marking a shift from manufacturing-based economies that began in the mid-20th century as discussed by Barrett & Davidson (2008). Developed countries such as the U.S., Great Britain, Netherlands, and France have experienced an increased share of the service sector in their GDP during the last third of the 20th century according to the study conducted by Plotnikov & Volkova (2014). As energy plays a vital role in manufacturing, transitioning to a service-based economy would result in a reduced dependence on energy for GDP growth. In the case of Iran, which has a young and educated workforce, empowering the service sector emerges as one of the most practical strategies for achieving financial and energy-related advantages. Therefore, prioritizing the establishment of service-oriented enterprises in Iran would be a great opportunity. Specifically, placing Information Technology (IT) at the forefront is highly recommended, as IT services can be globally offered. Moreover, given the devaluation of Iran's currency in recent years, operating a business in the country proves to be cost-effective when compared to nations with stronger currencies, particularly in IT-related industries, considering Iran's highly skilled human resources.

Energy-efficient technologies
Iran has been facing challenges in accessing energy-efficient technologies and knowledge due to international economic sanctions. These restrictions have had an impact on different aspects of Iran's energy system, ranging from extraction/mining/utilization, treatment and conversion, transportation/transmission, and distribution to import/export-related issues and energy end-use as discusses by Ghadaksaz & Saboohi (2020). As a result, the replacement of outdated technologies with energy-efficient alternatives has been slowed down in some sectors. Considering Iran's growing population, projected energy consumption trends, and the financial burden of the sanctions, ensuring a secure energy supply in the coming years poses a significant challenge. However, empowering the national research and development (R&D) of this country or developing strategic alliances with other countries can help Iran overcome these limitations. This approach presents an opportunity for international practitioners and investors to contribute by supplying energy-efficient technologies, investing in domestic manufacturing, establishing assembly lines within Iran, or even exporting these technologies to the country.

6. CONCLUSION

The aim of this study was to compare the EC of Iran and the United States, considering their statuses as representative examples of developing and developed countries, respectively. To achieve this, a hybrid method combining principal component analysis (PCA), SVR, particle swarm optimization (PSO), and autoregressive integrated moving average (ARIMA) was employed to forecast the EC of both countries until 2030. These forecasts were based on historical data on key socio-economic indicators, including gross domestic product (GDP), population, and energy import and export. The numerical results demonstrated the effectiveness of the proposed method, with a mean absolute percentage error of 2.25 % for Iran and 1.55% for the United States.

Subsequently, several comparisons and analyses were performed based on the forecasts. Firstly, the actual and forecasted values of EC per capita and energy intensity were compared between Iran and the United States, revealing a substantial disparity between the two countries. It was observed that the difference in per capita EC could be attributed to the concepts of "The EC and economic growth nexus" and "Human development index." Examining the trends in energy intensity further confirmed that the United States has successfully achieved a consistent decrease in energy intensity over time, whereas Iran has not. Therefore, there is a need for a more comprehensive investigation into Iran's energy sector to identify the barriers hindering Iran's energy efficiency improvement. Although the energy intensities of Iran and the United States were approaching each other until 2012, the most significant factor contributing to this decreasing trend was traced back to the economic growth facilitated by the continuous increase in oil prices in the global energy market.

Finally, the main barriers to improving Iran's energy efficiency were discussed, and some potential opportunities were mentioned. Accordingly, Iran's energy tariff system, unfavorable application of a multi-carrier energy system, numerous energy-intensive industries, undeveloped service economy, and limited access to energy-efficient technologies were discussed to have a significant adverse impact on Iran's energy efficiency.

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