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Forecasting the Effect of Renewable Energy Consumption on Economic Welfare: Using Artificial Neural Networks

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Abstract

Energy as a production process input has an effective role on economic indicators such as gross domestic production (GDP). Limitations in fossil fuel and nuclear energy sources urge utilizing renewable energies. In this paper, the impact of renewable energy consumption on economic welfare indicators (i.e. GDP, GDP per capita, annual income of urban households, and annual income of rural households) is investigated. For this purpose, 41 annual data sets are collected, from 1971 to 2011, mostly from Iran's Statistical Yearbook and Iran's Balance Sheet. Artificial neural networks (ANNs) are used for forecasting the effect of renewable energy consumption on economic welfare indicators. Advantages in using the proposed ANN-based method are demonstrated by comparing its results with the multi-layer regression (MLR) model. The comparison between the artificial neural network and the multi-layer regression model demonstrates that the artificial neural network has more accurate results than the multi-layer regression model. Both ANN and MLR models show significant effect of using renewable energies on the economic welfare. Results demonstrate the importance of using the proposed model for policy makers in implementing new policies for renewable energies. The ANN prediction results show that GDP, GDP per capita, annual income of urban households, and annual income of rural households will grow by 35.63%, 62.59%, 167.61% and 143.19%, respectively, from 2007 to 2016.

Keywords: Economic welfare, renewable energy consumption, artificial neural networks, multi-layer regression model

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Introduction

Energy is one part of technical and economic society progress. Energy consumption is one of the inputs of the production function and depends on the level of country's economy. Energy sources are divided into three categories: fossil fuels, renewable energy sources and nuclear energy sources. In each country, the optimal decision about which sources should be used, depends on the economic, social, environmental and security conditions. Respect to population increasing, limitation in fossil fuel and nuclear energy sources, and energy consumption increasing; governments should not only depend on ordinary energy sources. In addition, environmental impacts of fossil fuel like greenhouse gases, have harmful results such as acid rain and global warming.

The renewable energy sources (i.e. solar, wind, wave, biomass and geothermal energy) don’t have those problems. They are replenish naturally, don’t have harmful environmental impacts, distribute everywhere in the world and need cleaner technologies. Using renewable energies leads to diversify the country's energy portfolio, minimizes fossil fuel consumption so it can be exported to other countries or it can be converted to useful products. As a result, needing clean energies is undeniable and they should be replaced with fossil fuel sources.

In developed economies, promoting renewable energy sources in order to strengthen the energy security of supply and control their greenhouse gas emissions has been done. Therefore international policies and programs have been assigned a special role to renewable energy sources for global sustainability development. Renewable energies are abundant and reliable, if they be developed properly, as sustainable energy sources; they would play an important role in achieving economic growth.

This research has been done to Iran. History of renewable energy in Iran returns to 17th century, when Sheikh Bahaei used biogas of bath waste as a bath fuel in Esfahan, but seriously developing and using renewable energies started at 1975, when Department of Energy conducted extensive studies to identify potential sources of geothermal energy in Iran. Investments in the renewable energy sector is growing and a good potential for wind, solar, biomass, geothermal energy and fuel cell technology is predicted for Iran.

Many researches have been done in field of modeling the relationship between energy consumption and income in emerging economies, (Fang, 2011; Sadorsky, 2009). They show that in most of countries, there is a positive relationship between energy consumption and GDP. Some of them find that energy consumption contributes to economic growth both directly and/or indirectly, others that economic growth determines energy consumption, others that energy consumption and GDP are interdependent and there is bidirectional causality among them or there is no causality relation among variables (Fang, 2011).

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Apergis and Payne (2010) use panel cointegration test to examine the casual relationship between renewable energy consumption and economic growth for 13 countries within Eurasia. They find that there is a long-run relationship between real GDP, renewable energy consumption, real gross capital formation and labor force. Aqeel and Sabihuddin (2001) investigate the casual relationship between energy consumption, economic growth and employment in Pakistan by using techniques of Granger causality. They find that economic growth leads to growth in petroleum consumption, but neither economic growth nor gas consumption affect each other. Asafu-Adjaye (2000) uses cointegration and error-correction modelling techniques for estimating the causal relationship between energy consumption and income for four countries. He finds that from energy to income, there is unidirectional Granger causality for India and Indonesia, and bidirectional Granger causality for Thailand and Philippines. Azade et al. (2013) use Artificial Neural Networks for optimum estimation and forecasting of renewable energy consumption by considering environmental and economical factors. The outcome of their paper provides policy makers with an efficient tool for prediction of renewable energy consumption. Baranzini et al. (2013) investigate the relationships between energy consumption and economic growth in Switzerland. The results show that there exist robust long-run relationships going from real GDP toward heating oil and electricity consumption. The results imply a possible decoupling between GDP growth and energy consumption, so that energy conservation policies are not necessarily expected to have a negative impact on Swiss economic growth. Belke et al. (2011) examine the long-run relationship between energy consumption and real GDP for 25 OECD countries. Causality tests show that there is a bidirectional causal relationship between economic growth and energy consumption and results indicate that energy consumption is price inelastic. Chien and Hu (2007) use data envelopment analysis (DEA) for analyzing the effects of technical efficiency of 45 economies. Labor, capital stock and energy consumption is their inputs, and GDP is their only output. They conclude that increasing the use of renewable energies improves an economy's technical efficiency, but for traditional energies is vice versa. In addition, OECD countries have higher technical efficiency compared to non-OECD economies, but non-OECD economies have a higher share of renewable energies in their total energy supply. Ekonomou (2010) uses artificial neural networks (ANNs) in order to predict the Greek long-term energy consumption. He compares the produced ANN results for years 2005-2008 with the results produced by a linear regression method and concluded that ANN is an accurate tool for the Greek long-term energy consumption prediction problem. Ermis et al. (2007) analyze the world green energy consumption through artificial neural networks. They find that world green energy consumption will be on average 32.29% of total energy use between 2005 and 2025. The world green energy and natural gas consumption will continue increasing after 2050, while world oil and coal consumption are expected to remain relatively stable after 2025 and 2045, respectively. They also conclude that The ANN approach appears to be a suitable method for forecasting energy consumption data and should be utilized in efforts to model world energy consumption. Fang (2011) assesses the role of both the amount and share of renewable energy consumption in economic welfare in China and uses Cobb-Douglas production function. Results show that increasing in renewable energy consumption will increase GDP, GDP per capita, per capita annual income of urban households and rural households, but the impact of renewable energy consumption share, negatively affects economic welfare growth and is insignificant. Inglesi-Lotz

(2013) estimates the impact of renewable energy consumption to economic welfare by employing panel data techniques and concludes that the influence of renewable energy consumption is positive and statically significant. Lee (2005) uses panel unit root, heterogeneous panel cointegration and panel-based error correction models for re-investigated the causal relationship between energy consumption and GDP in 18 developing countries. The results show that long run and short run causalities run from energy consumption to GDP and indicate that in developing countries, energy conservation may harm economic growth. Lehr et al. (2012) analyze implications of renewable energy investment on labor market in Germany under different assumptions. They find that the expansion of RE in Germany has positive impacts on employment and gross employment will increase from 340 thousand in 2009 to between 500 and 600 thousand in 2030. Sadorsky (2009) estimates two empirical models of renewable energy consumption and income for a panel of emerging economies. Results show that increase in real per capita income have a positive and statically significant impact on per capita renewable energy consumption. Salim et al. (2014) examine the dynamic relationship between renewable and non-renewable energy consumption and industrial output and GDP growth in OECD countries. They find that OECD economies still remain energy-dependent for their industrial output as well as overall economic growth and expansion of renewable energy sources is a viable solution for addressing energy security and climate change issues, and gradually substituting renewable to non-renewable energy sources could enhance a sustainable energy economy.

In this field of research, some studies have been done in Iran and published in Persian. They use econometric methods for their research. Some of them are as follow:
Aghaei et al. (2012) use panel co-integration method for investigating the relationship between energy consumption and economic growth. They find that there is a positive relationship between them and increasing energy consumption leads to economic growth in Iran. Aminifard and Daneshmand-shiraz (2013) study the impact of clean energies on economic welfare. They use Engel-Granger model and mean square method for their research and find that there is a long-run relationship between their inputs and outputs, in other words in long-run term, renewable energy consumption has positive impact on economic welfare. But in short term, renewable energy has no relationship with income of rural households and weak relationship with income of urban households. In a research, Fotros et al. (2011) study the impact of economic growth on renewable energy consumption in OECD and non-OECD countries. They use panel unit root test and panel cointegration test. They find that in long-run term there is cointegration between economic growth and per capita renewable energy consumption, and in OECD countries the effect of economic welfare on per capita renewable energy consumption is more than non-OECD countries. Fotros et al. (2012) also investigate the impact of renewable and non-renewable energy consumption on economic growth in developing countries. They find that there is cointegration between variables and also non-renewable energy consumption has greater coefficient than renewable energy consumption, so they have more impact on economic growth.

One of the factors that can contribute to renewable energy consumption is economic welfare. Economic welfare is the level of quality of living standards in an economy, (Fang, 2011). Indicators of a country's economic welfare at national level could be: gross domestic production (GDP) and gross domestic production per capita; and at individual level could be: per capita annual income of urban households and the per capita annual income of rural households.

In this paper, the effect of renewable energy consumption on economic welfare in Iran has been considered. For this purpose, artificial neural network (ANN)-feed forward method is used. The results of the ANN model are compared respect to the regression model. Some inputs are inserted in the model which have not been considered before, such as Iranian papers in field of renewable energies as technology factor, and the research and development (R&D) expenditure of renewable energies as a new input variable.

Prediction tools

Multiple linear regression

The relationship between two or more variables is used in many engineering and scientific problems. A useful linear statistical technique for predicting the relationship between a dependent variable and several independent variables, is multiple linear regression (MLR). The MLR model is based on least square errors which minimize the sum of square-differences between observed values and predicted values. Formula and the model equation is as follow:

$$Y = \propto_0 + \propto_1 X_1 + \cdots + \propto_i X_i + \cdots + \propto_n X_n + \varepsilon \qquad (1)$$

where Y indicates dependent variable, X_i indicates independent variables, $\propto_i$ is unknown parameter and should be estimated and ε is the error term.

Artificial Neural Network

Artificial Neural Networks (ANNs) are non-linear mapping structure based on the function of human brain. In 1943, Mc-Culloch-Pitts proposed a model of computing elements, called Mc-Culloch-Pitts neurons, which performed weighted sum of inputs to these elements followed by a threshold logic operation. Combination of these computing elements was used to realize several logic computations (Jha). They are powerful tools for modeling, especially in field of economy, energy and environment when the underlying data relationship is unknown, so to find the relation, the network is trained with experimental data. Compared to other mathematical models in modeling complex systems, ANNs consume less time. They can perform a range of tasks such as data mining, classification, process modeling and pattern recognition.

ANNs consist of neurons and layers. Each neuron in each layer has a weight which strengths the connections. In a multilayer ANN model, the first layer consists of input units which are known as independent variable and the last layer contains output units which are known as dependent variables. Between the first layer and the last layer, hidden layers are located.

Multilayer feed forward neural network or multilayer perceptron (MLP) is very popular because they are easy to use, fast and require little memory. In a MLP, in each layer there is no connection between neurons and the information is transferred from layer *i-1* to layer *i*. In this paper, this kind of network is used. The equation of MLP model can be written as follow:

$$y_t = \propto_0 + \sum_{j=1}^{n} \propto_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-1} + \beta_{0j}\right) + \varepsilon_t \qquad (2)$$

where *n* is the number of hidden nodes, *m* is the number of input nodes, *f* is a sigmoid transfer function, $\propto_j$ is a vector of weights from the hidden nodes to output nodes and β_{ij} are weights from the input to hidden nodes. $\propto_0$ and β_{0j} are weights of arcs leading from the bias term which have values always equal to 1. Eq. (2) indicates a linear transfer function which is employed in the output node as desired for forecasting problems, (Azadeh et al, 2013).

In this research, the outputs are GDP, GDP per capita, per capita annual income of urban households and per capita annual income of rural households, which used in each model as the only output. The inputs are elucidated in next section.

Data

The required data are provided for 41 years from 1971 to 2011 from Iran's Statistical Yearbook, Iran's Balance Sheet and Renewable Energy Organization of Iran. The number of papers and thesis are collected from Iranian University libraries and these websites: http://www.sciencedirect.com, http://www.civilica.com, http://www.sid.ir.

SPSS software is used to predict MLR models and MATLAB Neural Network Toolbox is used to develop ANN models. In ANN models, experimental data are divided into three groups randomly: 70% as training data set, 15% as validation data set and 15% as testing data set to predict economic welfare, because a neural network is generally created in three phases as: training, validation and testing. All the outputs are measured in Iran's national currency: *Rial*.

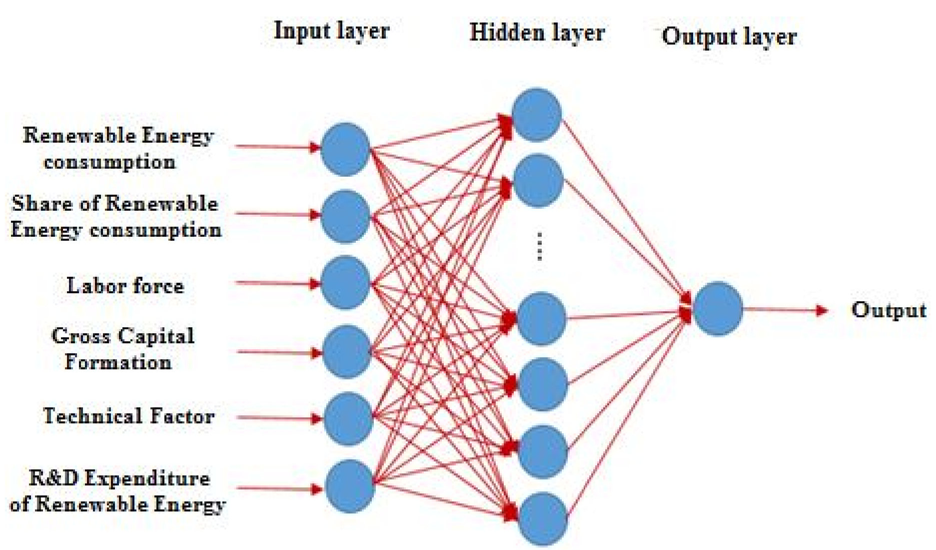

Fig.1. MLP neural network model

Methodology

Performance evaluation

To assess the validity of the ANN and MLR prediction models and provide the best result, some quality parameters are used like: the mean absolute error (*MAE*), the root mean square error (*RMSE*) and the coefficient of determination (R^2). The model with lower *MAE* and *RMSE* and higher R^2 values, represents the more accurate prediction result. The *MAE*, *RMSE* and R^2 equations are represented as bellow:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |P_i - A_i| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - A_i)^2} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - A_i)^2}{\sum_{i=1}^{n} {A_i}^2} \tag{5}$$

where P_i is the predicted value, A_i is actual value and n is the total number of data.

MLR model and results

Cobb-Douglas production function

In this research, the MLR model is based on Cobb-Douglas form of production function which is used by Fang (2011). This function is widely used to represent the relation between some inputs and an output. At first, this concept was proposed by Knut Wicksell. Charles Cobb and Paul Douglas tested the function against statistical evidence in 1928. Finally, the function took the following form:

$$Q = A\, L^{\alpha} K^{\beta} \tag{6}$$

where Q is output or total production; L is labor input ; and K is capital input. A represents total factor productivity; α, β are the output elasticity of labor and capital, respectively.

The omission of technical changes is a problem with the original specification of the functional relationship. In 1973, Handsaker and Douglas noted that taking account of technical change in this equation is necessary, (Fraser, 2002).

In this paper's model, the variables to quantify the impacts of renewable energy consumption on economic welfare are: total renewable energy consumption, share of renewable energy consumption, gross capital formation, labor force, technical factor and the budget specified to research and development of renewable energies. For technical factor and to indicate the research status, the number of Iranian papers and educational thesis in field of renewable energy, are used.

To find the relationships between variables, the regression model is used. So the log form of a Cobb-Douglas is as:

$$ln\, Y_i = \alpha\, ln\, REC + \beta\, ln\, SREC + \gamma\, ln\, K + \delta\, ln\, L + \rho\, ln\, T + \theta\, ln\, B + \mu \qquad (7)$$

where Y_i (i=1, 2, 3, 4) are: GDP, GDP per capita, per capita annual income of urban households and per capita annual income of rural households; *REC* is total renewable energy consumption; *SREC* is share of renewable energy consumption; K is the gross capital formation as a proxy of capital input; L is the number of employees as a proxy of labor input; T is the number of Iranian papers and educational thesis in field of renewable energy as technical factor; B is the R&D expenditure of renewable energies; $\alpha, \beta, \gamma, \delta, \rho, \theta$ are unknown parameters to be estimated; and μ is the error term.

Regression model results

To indicate the relationships between the amount and share of renewable energy consumption with GDP, GDP per capita, per capita annual income of urban households and per capita annual income of rural households, the multi-layer regression models are used and they are calculated by SPSS software. The results are as follow:

- Model 1: GDP production function

The prediction model with 94.2% R-squared value, is:

$$ln\, GDP = 0.716\, ln\, REC - 0.784\, ln\, SREC - 0.492\, ln\, L + 0.081\, ln\, K + 0.054\, ln\, T - 0.117\, ln\, B + 8.314 \qquad (8)$$

- Model 2: GDP per capita production function

The prediction model with 72.6% R-squared value, is:

$$ln\, GDPP = 0.474\, ln\, REC - 0.594\, ln\, SREC - 0.642\, ln\, L + 0.105\, ln\, K + 0.070\, ln\, T - 0.170\, ln\, B + 5.916 \qquad (9)$$

- Model 3: Urban household production function

The prediction model with 98.7% R-squared value, is:

$$ln\, Y_3 = 2.046\, ln\, REC - 1.963\, ln\, SREC - 1.110\, ln\, L + 0.387\, ln\, K \qquad (10)$$

where Y_3 represents per capita annual income of urban households.

- Model 4: Rural household production function

The prediction model with 99% R-squared value, is:

$$ln\, Y_4 = 2.042\, ln\, REC - 1.843\, ln\, SREC - 1.282\, ln\, L + 0.296\, ln\, K + 0.137\, ln\, B \qquad (11)$$

where Y_4 represents per capita annual income of rural households.

For urban households, the p-value for T, B and the constant before omitting them are 0.165, 0.875 and 0.912, respectively and for rural households, the p-value for T and the constant before omitting them are 0.987 and 0.174, respectively.

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Table.1. The MLR model results

independent variables	depended variables			
	GDP	GDPP	Urban households	Rural households
REC	0.716** (0.000)	0.474** (0.010)	2.046** (0.000)	2.042** (0.000)
SREC	-0.784** (0.000)	-0.594** (0.003)	-1.963** (0.000)	-1.843** (0.000)
L	-0.492** (0.011)	-0.642** (0.012)	-1.110*** (0.053)	-1.282** (0.023)
K	0.081** (0.001)	0.105** (0.001)	0.387** (0.000)	0.296*** (0.070)
T	0.054** (0.022)	0.070** (0.027)		
B	-0.117** (0.000)	-0.170** (0.000)		0.137** (0.000)
constant	8.314** (0.000)	5.916** (0.000)	-0.012* (0.988)	0.757* (0.720)
R-squared	0.942	0.762	0.987	0.990
F-statistics	77.995	12.8	590.592	588.568
P-value	0.000	0.000	0.000	0.000

Numbers in parenthesis are p-values.
* Not significant
** Significant at 95%-99% level
*** Significant at 90% level

The statistic indexes (R-squared, F-statistics, P-value) show that estimations are acceptable. Respect to regression results, renewable energy consumption, share of renewable consumption, labor force and gross capital formation are statically significant in all models, and technology factor is insignificant at individual level. According to table1, economic welfare has positive relation with REC and negative relation with SREC, and the effects are higher for urban and rural households than that for GDP and GDP per capita.

By expanding renewable energies, the countries dependence on fossil fuels will be reduced, thus these fuels can be exported to other countries and the incomes would be used for some purposes such as producing goods and services that cause improvement on economic welfare, so the impact of REC on economic welfare would be positive.

Some reasons may exist that cause the negative relation between SREC and economic welfare: First of all is cost factor. Households are sensitive to prices and renewable energies have high initial expenditures, if the households have to pay more for energy consumption like heating, lighting, etc. which are from renewable energies, they prefer to use conventional forms of energy to pay less.

The other reason is energy policies. Some policies should be implemented to develop renewable energies such as new laws, government subsidies or economic encouragement, supporting from renewable energy projects, etc. To gain the best result, there should be consistency and coordination to implement the policies.

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ANN model and results

To design the ANN model, feed-forward back-propagation network type is used and several possible architectures are tested with one and two hidden layer designs. In one-layer design 6 to 21 hidden neurons are inserted. In two-layer design 6 hidden neurons in the first hidden layer and 6 to 18 hidden neurons in the second hidden layer are inserted. To test the process, 70% of data are randomly selected by the software. All training algorithms are tested for each output but the Levenberg-Marquardt (LM) and Bayesian Regulation (BR) algorithms have better results than other training algorithms. In order to quantify the performance of ANN models, quality parameters are used. Table 2 shows the results of training different networks:

Table.2. The results of training different networks

output	algorithm	number of hidden neurons	iteration	RMSE	R^2	MAE
GDP	BR	6	30	16235	0.9972	7849
	LM	6	8	18908	0.9962	14338
	BR	9	30	18561	0.9963	7783
	LM	9	22	19645	0.9959	9324
	BR	**12**	**30**	**6428**	**0.9996**	**4100**
	LM	12	24	10344	0.9989	4841
	BR	15	30	6089	0.9996	4148
	LM	15	6	25542	0.9930	9378
	BR	18	30	32390	0.9888	11295
	LM	18	14	42102	0.9810	18021
	BR	21	30	6707	0.9995	4502
	LM	21	12	21213	0.9952	12228
	BR	6-6	30	15161	0.9975	11761
	LM	6-6	8	21240	0.9952	17320
	BR	6-12	30	7642	0.9994	5981
	LM	6-12	14	16077	0.9972	8120
	BR	6-18	30	9364	0.9991	6873
	LM	6-18	6	36236	0.9860	21486
GDP per capita	BR	6	25	241	0.9980	167
	LM	6	21	405	0.9943	285
	BR	**9**	**25**	**195**	**0.9987**	**143**
	LM	9	10	413	0.9941	297
	BR	12	25	368	0.9953	258
	LM	12	6	474	0.9922	228
	BR	15	25	240	0.9980	176
	LM	15	12	327	0.9963	227
	BR	18	25	200	0.9986	143
	LM	18	17	292	0.9970	196

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output	algorithm	number of hidden neurons	iteration	RMSE	R^2	MAE
	BR	21	25	254	0.9977	140
	LM	21	12	260	0.9977	191
	BR	6-6	25	247	0.9979	181
	LM	6-6	6	436	0.9934	312
	BR	6-12	25	359	0.9955	246
	LM	6-12	16	371	0.9952	246
	BR	6-18	25	248	0.9979	159
	LM	6-18	12	340	0.9960	233
Per capita annual income of urban households	BR	6	25	265632	0.9993	137703
	LM	6	7	3401081	0.8929	2085479
	BR	**9**	**25**	**122483**	**0.9999**	**57172**
	LM	9	6	1787736	0.9704	1324379
	BR	12	25	229011	0.9995	42811
	LM	12	10	1163684	0.9875	965693
	BR	18	25	568525	0.9970	122530
	LM	18	7	1133812	0.9881	288522
	BR	21	25	465151	0.9980	101789
	LM	21	8	1094456	0.9889	951441
	BR	6-6	25	585969	0.9968	147255
	BR	6-12	25	841019	0.9935	215085
	LM	6-12	5	2083816	0.9598	1662450
	BR	6-18	25	1798048	0.9701	457223
	LM	6-18	13	275183	0.9993	84523
Per capita annual income of rural households	**BR**	**6**	**25**	**129248**	**0.9994**	**94018**
	LM	6	7	1844638	0.8748	1063194
	BR	9	25	633518	0.9852	135509
	LM	9	6	1675249	0.8968	751477
	BR	12	25	230138	0.9981	60587
	LM	12	10	584862	0.9874	321026
	BR	18	25	238465	0.9972	64897
	LM	18	7	1656111	0.8991	1303958
	BR	21	25	273439	0.9973	61836
	LM	21	8	597769	0.9869	330149
	BR	6-6	25	194571	0.9986	57928
	BR	6-12	25	331187	0.9960	71437
	LM	6-12	5	831163	0.9746	445009
	BR	6-18	25	521554	0.9900	111968
	LM	6-18	13	1078591	0.9572	326688

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For all outputs the BR algorithm has better performance than the LM algorithm. The best model for all outputs consisted of one input layer with six input neurons, one hidden layer, and an output layer with one output neuron. The best network structure for each model highlighted in table 2 is: (6-12-1) for GDP, (6-9-1) for GDP per capita, (6-9-1) for per capita annual income of urban household, and (6-6-1) for per capita annual income of rural households. These structures have the highest coefficient of determination (R^2) and the lowest *RMSE* and *MAE* values among other tested networks, so these are selected as the best solution for each output.

Sensitivity analysis

In order to show the effect of the inputs (especially renewable energy consumption and share of renewable energy consumption) on the outputs and check the validity of developed ANN models, the best model for each output is retrained. For this purpose, each input is withdrawn one at a time while the others aren't changed and the model is retrained. Sensitivity analysis is conducted by calculating the *MAE* values which is shown in Fig 2.

The base line for each chart is *MAE* value of the best ANN model. According to the obtained results, each input variable has positive effect on desired output because the *MAE* value after withdrawing each input is higher than initial state. So it can be judged which one is the most significant parameter.

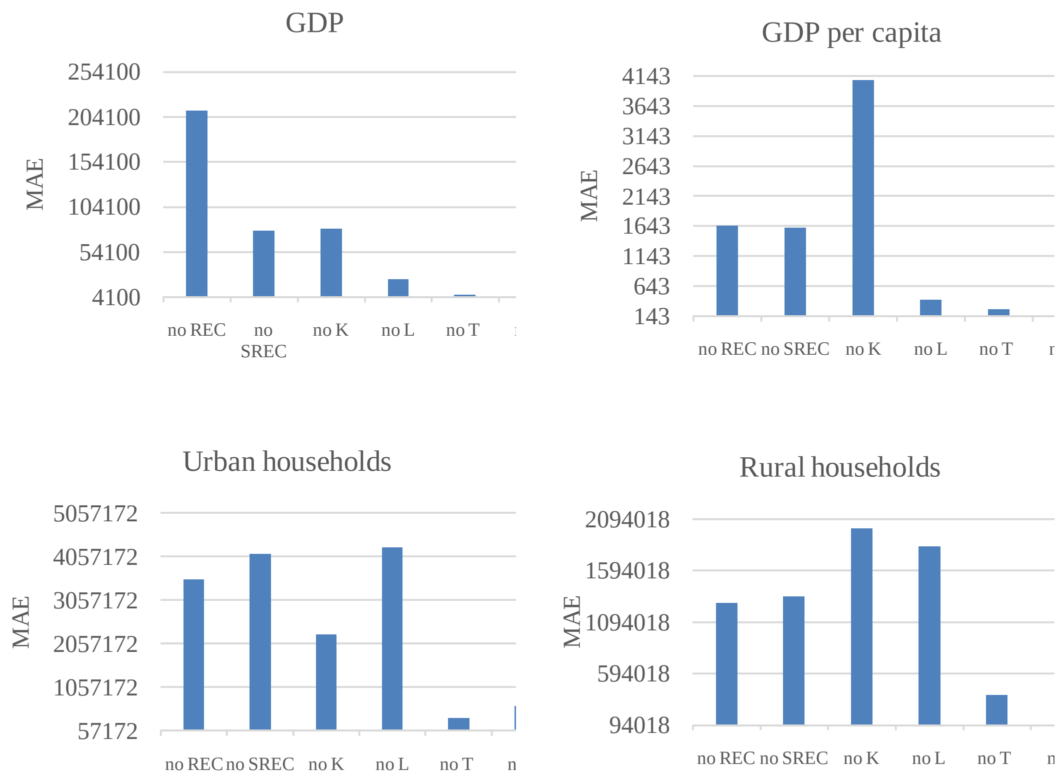

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Fig.2. The MAE values for sensitivity analysis

For GDP, renewable energy consumption has the highest and technology factor has the lowest effect. Share of renewable energy consumption and gross capital formation also have significant effects on GDP.

For GDP per capita, gross capital formation is the most and the R&D expenditure of renewable energies is the least effective factor. Renewable energy consumption and share of renewable energy consumption are also effective factors.

For per capita annual income of urban households, labor force has the highest and technology factor has the lowest effect on the output. Renewable energy consumption and share of renewable energy consumption are also effective factors.

For per capita annual income of rural households, gross capital formation is the most and the R&D expenditure of renewable energies is the least effective factor. Renewable energy consumption and share of renewable energy consumption also have significant effects on per capita annual income of rural households.

So it can be concluded that renewable energy consumption and share of renewable energy consumption are factors with significant effects on the economic welfare in Iran, and the R&D expenditure of renewable energies and technology factor (number of renewable energy papers and dissertations) don't have significant effects on economic welfare.

Comparison between MLR and ANN models

In this paper, the MLR and ANN methods are used for forecasting the effect of renewable energy consumption on economic welfare (i.e. GDP, GDP per capita, per capita annual income of urban households and per capita annual income of rural households) in Iran. To show which one is better, their *RMSE*, R^2 and *MAE* values are compared and the results are shown in table 3.

Table.3. The comparison between MLR and ANN models

Output	Method	RMSE	R-squared	MAE
GDP	MLR	16897	0.942	13805
	ANN	6428	0.9996	4100
GDPP	MLR	492	0.762	381
	ANN	195	0.9987	143
Urban households	MLR	571997	0.987	296097
	ANN	122483	0.9999	57172
Rural households	MLR	1458915	0.990	715202
	ANN	129248	0.9994	94018

It can be seen that the accuracy of the ANN model is higher than the MLR model, so the predictions values of the ANN model will be near the real values. By taking into account all the inputs, the ANN prediction results show that GDP, GDP per capita, annual income of urban households, and annual income of rural households will grow by 35.63%, 62.59%, 167.61% and 143.19%, respectively from 2007 to 2016.

Conclusion

Energy as a production process input has an effective role on economic indicators. In Iran fossil fuels are the main source of energy, but environmental impacts of fossil fuels such as greenhouse gases, have harmful results which encourage countries to develop their renewable energy consumption. Few studies have been conducted in Iran which consider the effects of renewable energies. So in this paper, the multi-layer regression model (MLR) and artificial neural network (ANN) are used to investigate the effect of renewable energy consumption on economic welfare.

The MLR model shows that economic welfare in Iran has positive relation with REC and negative relation with SREC and the effects on households are higher than the effects on GDP and GDP per capita. It may be because of sensitivity of households respect to price changes.

For ANN model, the best network structure for each output is: (6-12-1) for GDP, (6-9-1) for GDP per capita, (6-9-1) for per capita annual income of urban household and (6-6-1) for per capita annual income of rural households. To show the effect of the inputs on the model's outputs and check the validity of developed ANN models, one input is withdrawn each time and the best model is retrained. The Results show that renewable energy consumption and share of renewable energy consumption are significant factors for Iran's economic welfare, and the R&D expenditure of renewable energies and technology factor (number of renewable energy papers and dissertations) don't have significant effect on economic welfare.

The comparison between MLR and ANN prediction results indicates that the ANN model has more estimation accuracy because for ANN, the R^2 value is higher and *RMSE* and *MAE* values are lower than the MLR model. So the ANN predictions will be nearer to the real values.

Both of MLR and ANN models confirm each other that the amount and share of renewable energy consumption are important factors which have significant effect on economic welfare at national and individual levels in Iran. So Iranian energy policy makers should focus on these effective factors and some policies should be implemented to develop renewable energies such as new laws, government subsidies or economic encouragement, supporting from renewable energy projects, etc. and to gain the best result, there should be consistency and coordination to implement the policies. The cost effect of renewable energies should be reduced to encourage different sections like households or production departments to use this kind of energy in order to conventional forms of energy.

The ANN prediction results show that GDP, GDP per capita, annual income of urban households, and annual income of rural households will grow by 35.63%, 62.59%, 167.61% and 143.19%, respectively from 2007 to 2016. Also the inflation has effect on

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growth of these factors. The prediction values of economic indexes, like GDP and household's income, can be useful for predicting other economic variables.

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