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Optimal Energy Demand Forecasting for Systems by Improved Manta Ray Foraging Optimizer: A Case Study in Taiwan

Haoran Fu [1,2,*]***, Huahui Li*** [2] ***, T. Ramayah*** [2,3,4,5]

[1] *School of Economics, Anyang Normal University, Anyang, 455000, China*
[2] *School of Management, Universiti Sains Malaysia, Minden, Penang 11800, Malaysia*
[3] *Department of Management, Sunway University Business School (SUBS)*
[4] *Fakulti Ekonomi dan Pengurusan, Universiti Kebangsaan Malaysia (UKM)*
[5] *Faculty of Economics and Business, Universiti Malaysia Sarawak*

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ABSTRACT

A new methodology is suggested in this study for providing an optimum energy demand forecasting for the future projections. The paper presents an improved version of manta ray foraging optimizer (iMRFO) for giving an optimum and suitable forecasting model. The model designing has been done on Taiwan as the case study. The optimized forecasting is performed based on three models, including linear, exponential, and quadratic models where their coefficients are optimized by the suggested iMRFO algorithm based on different affective factors containing yearly growth rate of the real GDP, yearly growth rate of the population, annual industry share in growth rate of GDP, annual rate of urbanization, and annual coal consumption. Simulation results showed that using the proposed-energy demand prediction technique based on iMRFO has higher accuracy and reliability prediction in the direction of the other compared methods from the literature, such as ACO, GA/PSO, basic MRFO-based, and multiple linear regression models. Two different scenarios have been measured for more analyzing the suggested method. The results finally show that energy intensity in Taiwan will decline in varying degrees based on both scenarios which indicates that additional growth of efficient strategies and actions is needed for ensuring that the target is accomplished.

Keywords: *Energy demand forecasting; scenario analysis; improved Manta Ray Foraging Optimization*

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1. INTRODUCTION

In today's world, it seems impossible to move towards economic development without considering energy [1]. In developing countries, energy, in addition to its role as a major factor of production, is also considered a source of national income [2]. Therefore, the need to move towards economic growth in developing countries on the one hand and the fundamental role of energy in this way on the other hand, shows the importance of recognizing energy demand in various economic sectors, especially industry [3]; Because one of the indicators of economic development of countries is increasing the share of industry in Gross Domestic Product (GDP). The main consumers of energy in the world are developed countries, so with economic growth and development and as a result of industrialization, the request for energy increments [4].

Taiwan is one of the developing countries which faced a general development in both energy consumption and economic aggregate [5]. Based on the statistics [6], the total electricity consumption updated monthly shows averaging 14,704.036 kWh mn from Jan 1982 to Jul 2020, with 463 observations.

As said by the official Taiwanese statistics, natural gas and coal account include about 38.18% and 37.32% of Taiwan's total primary energy consumption in 2019, respectively, whereas the

* Corresponding Author Email: *haoranfu@aynu.edu.cn*

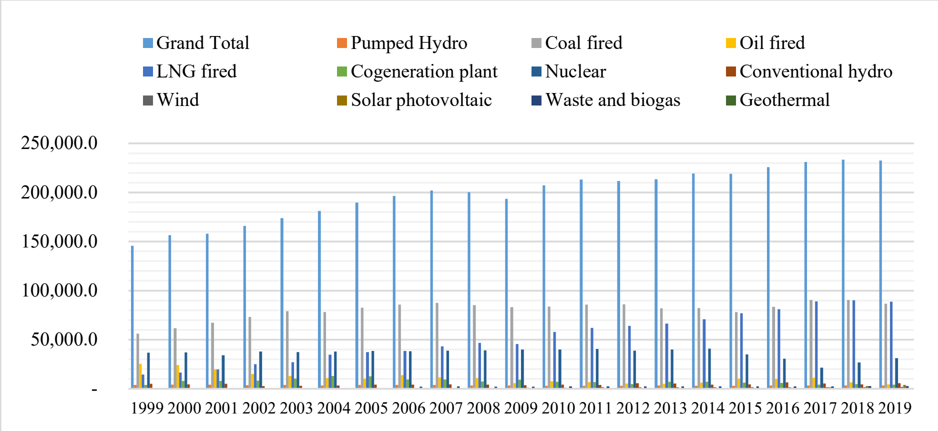

Fig. 1. Net Electricity Produced and Purchased of Taiwan Power Company (GWh) [7]

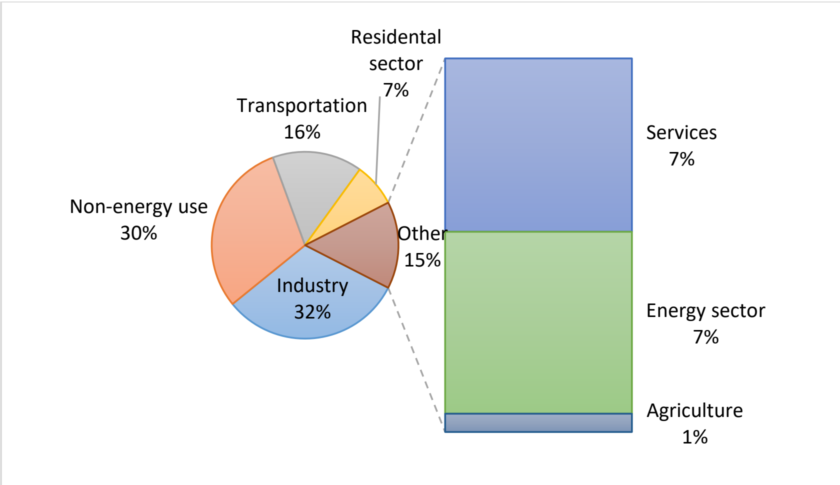

Fig. 2. Energy consumption by sector in Taiwan in year 2018 [8]

rest is mostly for oil with 1.9% and some other smaller amounts of different types such as hydro, geothermal, biogas, solar, and wind. Also, As stated by the Taiwanese government, the total necessity on energy imports has been about 98%. Fig. (1) shows the Net Electricity Produced and Purchased of Taiwan Power Company [7].

During 2019, the gross power production was about 274,058.7 GWh with 0.54% decreasing compared with 2018's. Fig. (2) shows the last updated share amount of each sector which is for 2018.

By considering the above cases, it is observed that the prediction of the energy demand growth in Taiwan can be so beneficial for the future planning [9]. Also, intense growth of the energy consumption in this country especially in recent decades may form an imbalance between demand and supply [10]. Alternatively, a long-term prediction needs to plan the future investment policies and guarantee the energy supply security of the country [11]. An important case for energy planning is to model the energy demand, concerning to recommending energy policies and strategies [12]. The prediction of the energy consumption is commonly a complicated task due to that is affected by the fast growth of the government decisions, technology, economy, and different aspects [13]. Accordingly, the precise approximation of power demand is a significant element for energy strategy makers.

Tran et al. [14] proposed a model for energy use forecasting in residential buildings by the

Evolutionary Neural Machine Inference technique (ENMIT). The model ensembled least squares support vector regression (LSSVR), and the radial basis function (RBF) neural network along with the symbiotic organism search (SOS) to achieve the optimal adjusted parameters. The model was validated by performing on a residential building in Ho Chi Minh City, Vietnam. The comparison results showed that the proposed method exceeds other state of the art models with higher accuracy.

Wu et al. [15] proposed a fractional order nonlinear grey Bernoulli technique to Five-Year prediction of the renewable energy use in China. For optimum adjusting of the method variables, Particle Swarm Optimization (PSO) algorithm was employed. The model indicated a high precision for all cases to prove the effectiveness of the method.

Wang et al. [16] proposed a model for residential solar energy use prediction in United States. The model was done by considering a series of encouragement policies. The method was based on a grey model based on buffer operator and data grouping. Genetic Algorithm (GA) was employed for giving optimal degree of buffering. Afterward, the model was analyzed and compared with by different types of grouping, echo state network, non-linear autoregressive neural network. Final results indicated that the average total percentage errors of the forecasted technique compared with five other models gives a higher effectiveness. Also, the solar energy use of the United States residents with leap growth feature was precisely predicted. Yan et al. [17] proposed a combination of long short-term memory (LSTM) neural network and the stationary wavelet transform (SWT) technique for energy use prediction of the individual households. The SWT lessens the instability and enhances the data dimensions, that accordingly developed the precision of the LSTM-based prediction. Simulation achievements showed that the suggested technique has the best results in comparison to some other state-of-art techniques.

Somu [18] suggested a hybrid long short-term memory networks and improved sine cosine optimization algorithm for energy consumption prediction of an academic building at Indian Institute of Technology. Also, the parameters of the LSTM were optimized by the proposed sine cosine optimization algorithm. Final results showed that the presented model has better efficiency toward the state-of-the-art models.

As can be observed from the new works in the literature, the application of the metaheuristics for predicting energy consumption has been exponentially increasing. However, each type of metaheuristics has its drawbacks and profits. The main purpose of this research is to design a modified version of Manta Ray Foraging Optimization algorithm for optimal estimation of the coefficients for three models of energy demand techniques, including quadratic, linear, and exponential, applied GDP, economic mechanism, population, rate of urbanization, and energy procedure as inputs of technique. These data from 2010 to 2018 is employed to improve and to test the techniques. The future power demand in 2015–2025 has been predicted under two scenarios, and a comparison of the achievements with some different estimating techniques.

2. PROBLEM STATEMENT

As aforementioned in the introduction section, using the basic model of metaheuristics usually have different drawbacks [19]. For example, they only consider the inputs, such as import and export statistics, population, GDP, by not considering the different influencing aspects of power demand [20]. This shortcoming leads us to present an efficient and more accurate technique, for optimizing the coefficients in the model equations with high effectiveness [21]. The current study proposed a new developed version of the – algorithm to improve the efficiency of the basic model for better coefficients optimization [22]. In addition, five factors, different from the economic measurements have been used as the model inputs [23]. The method of the estimation is based on a three-form model, including multiple linear (ED_{ML}), quadratic (ED_Q), and exponential (ED_{exp}) forms of equations which are indicated in the following, respectively:

$$ED_{ML} = w_0 + \sum_{i=1}^{T} w_i \times x_i \tag{1}$$

$$ED_Q = w_0 + \sum_{i=1}^{T} w_i \times x_i + \sum_{i=1}^{T} u_i \times x_i^2 + \sum_{i=1}^{T}\sum_{j=i+1}^{T} k_{ij} \times w_i \times x_i \tag{2}$$

$$ED_{exp} = w_0 + \sum_{i=1}^{T} w_i \times x_{ii+t}^{w} \tag{3}$$

where ED stands for energy demand, T describes the number of factors, x_i and x_j represent the i^{th} and the j^{th} affecting factors of the ED , w_0 , w_i , u_i , and k_{ij} represent the equation coefficients.

3. IMPROVED MANTA RAY FORAGING OPTIMIZER

Manta ray is a wonderful aquatic animal with smooth surface and millionth forms [24]. The manta ray has a 300 million-year living on the earth and is classified as the closest family to the sharks. The main food source for these animals are plankton, worm, shellfish, crabs, and small fish. The case of how these animals hunt their prey, is the main motivation for Manta Ray Foraging Optimizer (MRFO) which is introduced by Zhao et al. [25] in 2020. However, this algorithm is a newly introduced metaheuristic algorithm, it has a proper efficiency toward different types of algorithms.

In the following, a general explanation of the method will be explained. Also, a method is used for improving the efficiency of the algorithm. The main idea is to use the new algorithm for further efficient estimation of the energy demand.

3.1. The chain behavior

Based on the food chain law, the hunters move toward a position with a high density of the plankton population; This is considered as the most proper place for the manta rays. Once there is no suitable place with enough prey, the hunters attempt to swim and try another place with higher density of plankton. The manta rays have a head-to-tail strategy to make a bait chain.

The hunters renew the location by the most appropriate location prey with more population density of plankton during each iteration. Mathematically, this performance can be modeled by the following:

$$x_i^d(t+1) = \begin{cases} x_i^d(t) + r\times\begin{pmatrix} \left(x_{best}^d(t) - x_i^d(t)\right) \\ +\alpha\times x_{best}^d(t) - x_i^d(t) \end{pmatrix}, & i=1 \\ x_i^d(t) + r\times\begin{pmatrix} \left(x_{i-1}^d(t) - x_i^d(t)\right) \\ +\alpha\times x_{best}^d(t) - x_i^d(t) \end{pmatrix}, & i=2,\ldots,N \end{cases} \tag{4}$$

where, r defines a random value between 0 to 1 , $x_{best}^d(t)$ represents the population density for the plankton, $x_i^d(t)$ determines the position of the i^{th} and $x_{i-1}^d(t)$ the $(i-1)^{th}$ member at time t in d^{th} dimension. The α coefficient based on the algorithm is modeled below:

$$\alpha = 2r\times\left|\log(r)\right|^{\frac{1}{2}} \tag{5}$$

3.2. Cyclone behavior

After finding the proper position including intense plankton population, the manta rays arrange a long bait chain and swim in a spiraling motion in the direction of the prey. This behavior is known as storm. Based on this behavior, individuals swim based on two strategies: spiral moving and swimming on the way to the planktons. The storm behavior can be mathematically modeled as follows:

$$x_i^d(t+1) = \begin{cases} x_{best}^d + r\times\begin{pmatrix} \left(x_{best}^d(t) - x_i^d(t)\right) \\ +\beta\times(x_{best}^d(t) - x_i^d(t)) \end{pmatrix}, & i=1 \\ x_{best}^d + r\times\begin{pmatrix} \left(x_{i-1}^d(t) - x_i^d(t)\right) \\ +\beta\times(x_{best}^d(t) - x_i^d(t)) \end{pmatrix}, & i=2,\ldots,N \end{cases} \tag{6}$$

$$\beta = 2\exp\left(r_1\times\left(\frac{T-t+1}{T}\right)\right)\times\sin(2\pi r_i) \tag{7}$$

where, r_1 defines a random value in the range [0, 1], β signifies the weight coefficient, and T describes the iteration number.

Once the searching process is going on, the prey has been considered as a reference position. Then, storm behavior has been applied to the exploration term to obtain better random values. This can be modeled by the following equation:

$$x_{rand}^d = L^d + r\times\left(U^d - L^d\right) \tag{8}$$

$$x_i^d(t+1) = \begin{cases} x_{rand}^d + r\times\begin{pmatrix} \left(x_{rand}^d(t) - x_i^d(t)\right) \\ +\beta\times(x_{rand}^d(t) - x_i^d(t)) \end{pmatrix}, & i=1 \\ x_{rand}^d + r\times\begin{pmatrix} \left(x_{i-1}^d(t) - x_i^d(t)\right) \\ +\beta\times(x_{rand}^d(t) - x_i^d(t)) \end{pmatrix}, & i=2,\ldots,N \end{cases} \tag{9}$$

where, x_{rand}^d defines a random position, and L^d and U^d represent the lowest and highest amounts per limitations of the d^{th} dimension, respectively.

3.3. Somersault bait

In this step, based on somersault foraging, the prey situation is achieved based on leadership behavior. The hunter discovers for the leader and somersault to a different location. Therefore, the new locations are considered to obtain the best location. This behavior can be mathematically modeled by the following:

$$x_i^d(t+1) = x_i^d(t) + S \times \left(r_2 \times x_{best}^d - r_3 \times x_i^d(t)\right), \quad i = 1, 2, \ldots, N \tag{10}$$

where, S denotes the somersault bait that is considered to be 2, and r_2 and r_3 show two random amounts between 0 and 1.

Base on the distance reduction among member's positions, the disorder has been decreased. Consequently, the range of somersault forage has been reduced by increasing iterations.

3.4. Improved Manta Ray Foraging Optimizer

The Manta Ray Foraging Optimizer as a new metaheuristic technique has well outcomes to find solutions for the optimization problems. However, premature convergence is a limitation in some cases. In this paper, to propose a high potential optimization methodology, two modifications have been performed to the algorithm.

The first modification one is based on a popular technique, called opposition-based learning (OBL) method. Sometimes, there is a possibility to diverge from the initial solution than the optimal solution. Additionally, the worst-case scenario should be considered, when the initial solution is in the opposite direction to the optimal solution that makes the algorithm to work more on the optimization, or make it failed during the finding problem solution. Therefore, to give more efficient results in the algorithm population, the OBL mechanism has been applied by the following:

$$\overline{x}_i^d = x_i^{max} + x_i^{min} - x_i^d \tag{11}$$

where, $\overline{x}_i^d$ signifies the opposite position for the x_i^d, and x_i^{max} and x_i^{min} describe the upper and the lower limitations. Here, if $\overline{x}_i^d$ gives better results than , then $\overline{x}_i^d$ replaces with x_i^d.

Another term for modification is to use the self-adaptive mechanism. This term is a parameter adjustment for size regulation in the population. Defining the population size for optimization is a vital task. First, the initial population size is

Table 1. The variable settings for all of the analyzed algorithms

Algorithm	Parameter	Value	Algorithm	Parameter	Value
EPO [30]	$\vec{A}$	[-1.5, 1.5]	MRFO	r	0
	Temperature value (T')	[1, 1000]			
	f	[2, 3]			
	M	2		γ	0.7
	S	[0, 1.5]			
SHO [29]	l	[1.5, 2]	MVO [31]	Traveling distance rate	[0.6, 1]
	$\vec{h}$	[5, 0]		Wormhole existence prob.	[0.2, 1]
	$\vec{M}$	[0.5, 1]			

Table 2. The studied benchmark functions detail.

Function	Equation	Limitation	F^*	Dimension
Generalized Rosenbrock	$F_1(x) = \sum_{i=1}^{d}\left[100 \times \left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right]$	[-30,30]	0	30
Generalized Rastrigin	$F_2(x) = \sum_{i=1}^{d}\left[x_i^2 - 10 \times \cos(2 \times \pi \times x_i) + 10\right]$	[-5.12,5.12]	0	30
Hartman's Family	$F_3(x) = -\sum_{i=1}^{4} c_i \times \exp\left(-\sum_{j=1}^{d} a_{ij} \times \left(x_j - p_{ij}\right)^2\right)$	[0,1]	-3.32	3
Shekel's Foxholes	$F_4(x) = -\sum_{i=1}^{d}\left[(x_i - a_i) \times (x_i - a_i)^T + d_i\right]^{-1}$	[0,10]	10.1532	4

Table 3. The results of the verification compared to the benchmarks using the analyzed algorithms

Algorithm		f_1	f_2	f_3	f_4
EPO [30]	Min	7.96	0.06	0.0009	4.56
	Max	1.16e3	0.47e2	5.01	4.95
	Mean	0.73e3	2.53e2	2.12	4.68
	std	1.84e4	1.55e2	2.16	4.04
SHO [29]	Min	5.07	0.02	2.29	1.81
	Max	3.57e3	7.85	3.80	15.16
	Mean	0.13e3	5.49	2.92	9.11
	std	1.66e4	0.07	2.68	2.86
MVO [31]	Min	3.28	1.70e-5	3.19e-5	0.73
	Max	1.52e2	0.049	0.003	1.01
	Mean	68.67	0.002	0.0021	1.22
	std	4.39e4	0.005	1.20e-5	1.05
MRFO [25]	Min	0.15	81.26e-21	3.27e-10	6.92e-13
	Max	10.31	6.85e-20	1.89e-9	2.98e-12
	Mean	5.37	2.35e-20	3.16e-9	0.07e-12
	std	3.05	0.78e-17	3.93e-10	0.14e-13
iMRFO	Min	0.00	0.79e-21	2.58e-11	2.30e-15
	Max	2.93	1.59e-20	1.45e-10	9.58e-14
	Mean	1.40	2.13e-20	8.95e-10	3.57e-14
	std	0.83	1.22e-18	3.90e-11	4.78e-15

converted as follows:

$$x_i^d\left(t\right)=10\times N \tag{12}$$

where, N describes the number of variables.
Then, the new size of the population for the next iteration is as follows:

$$\overline{x}_i^{d+}=round\left(x_i^d\times\left(1+\delta\right)\right) \tag{13}$$

where, δ signifies a randomly uniform distribution value between -0.5 and 0.5 that describes a tunable parameter for changing the size of population.

Based on the case that whether the δ is negative or positive, the population size decreases or increases. If the size of new member is larger than the old one, ($\overline{x}_i^{d+}>\overline{x}_{i-1}^{d+}$), the present individuals are moved to the next iteration and the left over population is merited by the elitism. Contrariwise, if $\overline{x}_i^{d+}<\overline{x}_{i-1}^{d+}$, just the top members of the present individuals have been moved to the next iteration and the leftover are eliminated. Afterward, if the new population size is a smaller amount than the problem dimension, the new population size equals the problem variables number.

3.5. Algorithm verification

The effectiveness validation of the suggested improved Manta Ray Foraging Optimizer (iMRFO) algorithm was analyzed by analyzing four standard benchmark functions [26-28]. The results of the functions applied by the proposed iMRFO are then compared with four well-known metaheuristics, containing Spotted Hyena Optimizer (SHO) [29], Emperor Penguin Optimizer (EPO) [30], Multi-Verse Optimizer (MVO) [31], and the basic MRFO. The information about parameters in each algorithm are given in Table 1.

To give consistent results for the algorithms, they run independently for 35 times and their results are briefly given in Table 2. The iteration value and the population size for all of the analyzed algorithms are set 200 and 100, respectively. Table 2 tabulates the studied benchmark functions detail.

where, $a_i=\left[4,1,8,6\right]$, $c_i=\left[1,1.2,3,3.2\right]$, $d_i=\left[0.1,0.2,0.2,0.4\right]$, and

$$p_{ij}=\begin{bmatrix}0.37 & 0.12 & 0.27\\ 0.47 & 0.44 & 0.75\\ 0.11 & 0.87 & 0.55\\ 0.40 & 0.57 & 0.88\end{bmatrix}.$$

To do verification on the algorithm efficiency compared with the other analyzed algorithms, four measures including lowest value (min), highest value (max), average value (mean), and the standard deviation value (Std) of the studied benchmark functions are investigated. Table 3 tabulates the simulation results 0of the functions analysis.

As seen in Table 3, the presented iMRFO algorithm give the lowest value for all of the benchmarks. This shows that using the proposed method has more certainty than the other algorithms which has been compared. Also, with analyzing of the Std value of the algorithms, it has resulted that the suggested iMRFO algorithm has the lowest value among the other. This shows the proposed method higher reliability toward the other compared aalgorithms, even the basic MRFO algorithm.

4. THE DEMAND AFFECTED FACTORS FOR TAIWAN

Different factors effect on the energy consumption. For example, relative prices, per capita GDP, economic structure, lifestyles, and available technology [32]. Energy demand in Taiwan due to its energy shortage and several energy requirements in different cases is too complicated with lots of uncertainties [28]. This makes the forecasting task difficult for the energy scientists. In the following, some of the effective cases are explained briefly:

One of the affected factors of demand in Taiwan is population growth [33]. This factor. Generally, the total population in the country in addition to directly impact on the total energy consumed value, has also impression on per capita consumption [34]. Due to a rather large population in Taiwan, the population growth should be considered in the calculations and energy consumption forecasting.

Another important affected factor is economic growth. Lee et al. [35] specified that the economic growth in Taiwan contains a key part of the energy consumption. The economic growth is directly impressive by the GDP with a lower rate [33]. This index is affected by some different cases. First, Taiwan's economic growth due to its experiencing of urbanization and industrialization is increasing with high speed which is due to the higher industrial demand than the agriculture and energy consumption, and the higher demand of the urban zones toward the rural zones. Also, solid energy demand accomplishes the economic growth of Taiwan based on the consumption, exportation, investment.

Due to the high coal consumption of Taiwan, it can be considered as a significant and energy structure-based factor for this country. This importance is because of that Taiwan has ranked as 14^{th} in the world for coal consumption with about 6.4% of the world's total consumption [36]. However, coal energy has low productivity with high consumption, it produces a lot of environmental pollution. Recently, Taiwan attempt to regularly decreases the coal consumption with using more green energy sources. Hence, this factor can be considered as an important affected case in Taiwan.

On the other hand, Taiwan contains a significant part in the global economy such that it is placed as one of the topmost countries in exporting of merchandise [37]. According to the World Trade Organization, Taiwan is ranked as the 17th largest importer and 18th largest exporter of merchandise in 2018. Therefore, the economic structure can be considered as one of the affected factors of the forecasting.

The energy consumption in rural and urban zones are completely different. Due to the reason that urban population in Taiwan contains 78.6% of total population (2019) with 0.8% annual rate of change, it has the main share to the overall power demand. Therefore, the rate of urbanization can be also considered as another significant factors in forecasting the energy demand for Taiwan.

Likewise, price is a key demand-affecting factor which should be considered in the evaluations which contains both substitution and income effects and also the user operations. The arrangement structure of energy cost in Taiwan manages market cost. Consequently, Taiwan doesn't reflect the energy prices with its real energy demand and supply state of affairs. Accordingly, the present research doesn't consider an effected variable with energy demand.

Here, the overall energy use data have been evaluated in billion tce with considering caloric value measure, whereas the study analyzes GDP data in billion TWD. For using the urbanization rate in the study, it is well-described as the urban population ratio to the overall population (%). The population factor is set based on the yearly overall population of Taiwan. The share value of the coal use from the entire energy use (%) is set as the energy structure. The contribution of industrial added amount to GDP (%) is used to indicate the

Table 4. The optimized weights for the three models based on iMRFO

	ED_{ML}		ED_Q
w_0	-51347.4	w_0	60.145
w_1	-5.345	w_1	3.189
w_2	5837.1	w_2	-3.145
w_3	6275.8	w_3	72.52
w_4	4280.3	w_4	58.14
w_5	1.457	w_5	120.34
	ED_{exp}	w_6	0.0001
w_0	3.856	w_7	0.0027
w_1	29.24	w_8	0.0402
w_2	0.735	w_9	0.0218
w_3	-0.0061	w_{10}	-0.0095
w_4	1.2964	w_{11}	0.0185
w_5	0.0005	w_{12}	0.0214
w_6	5.172	w_{13}	36.276
w_7	0.0497	w_{14}	69.271
w_8	4.197	w_{15}	-15.37
		w_{16}	0.0001
w_9	0.0480	w_{17}	0.0000
		w_{18}	0.0000
w_{10}	4.1985	w_{19}	0.0010
		w_{20}	0.0003

economic structure, and the yearly data has been collected from [7].

5. ENERGY DEMAND FORECASTING MODEL APPLICATION

Three energy demand techniques for Taiwan including multiple linear (ED_{ML}), quadratic (ED_Q), and exponential (ED_{exp}) have been established using the suggested iMRFO. The proposed iMRFO-based Energy Demand Forecasting (EDF) model has been established by minimizing the mean absolute percentage error between the predicted and the observed values on training data, i.e.

$$E = \frac{1}{N} \times \sum_{k=1}^{N} \left| \tilde{z}(k) - z(k) \right| \times 100\% \tag{14}$$

where, $z(k)$ and $\tilde{z}(k)$ represent the observed and the forecast values, respectively.

The lengths of manta ray individuals have been changed based on the number of problem decision variables, such that ED_{ML}, ED_Q, and ED_{exp} have 6, 21, and 11 set of individuals. The initial manta ray population is in the range -10 and 10 for the magnitude of variables in the Taiwan EDF.

For optimal prediction of the weighing factors, iMRFO employs 22 years of the noticed data from 1997 to 2019. Here, the optimized weights for the three models based on iMRFO are given in Table 4. Fig. (3) shows the real and the predicted data for the three techniques between 2010 and 2018.

As can be observed from Fig. (3), all of the optimized models have appropriate fitting with the actual historical data. Also, to indicate the precision of the models' prediction, the mean total percentage error between the predicted and the observed values on training data from 2010 to 2018 are given in Fig. (4).

As can be seen from Fig. (4), the highest error rate of the data is 1.5%, that is obtained for the ED_{exp} model, that gives a completely promising forecasting rate for the data. To validate the higher potential of the suggested iMRFO-based EDF, its mean absolute percentage error in the training and testing data has been compared with some other well-known methods including ACO, PSO, PSO/GA, and basic MRFO -based algorithms and the results are tabulated in Table 5. The training data for the algorithms is established from 2010 to 2016 and the testing data is established from 2017 to 2018.

As can be observed from Table 5, the mean value (m) and the standard deviation value (Std)

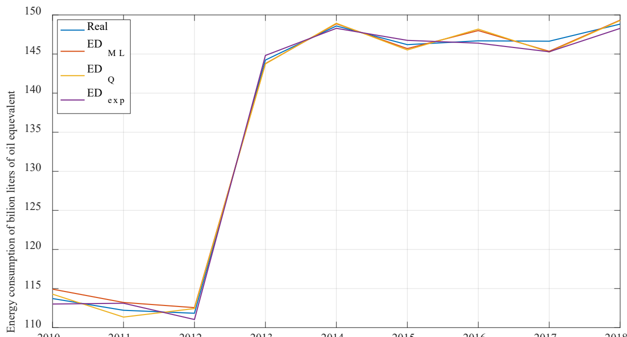

Fig. 3. The real and the predicted data for the three techniques between 2010 and 2018.

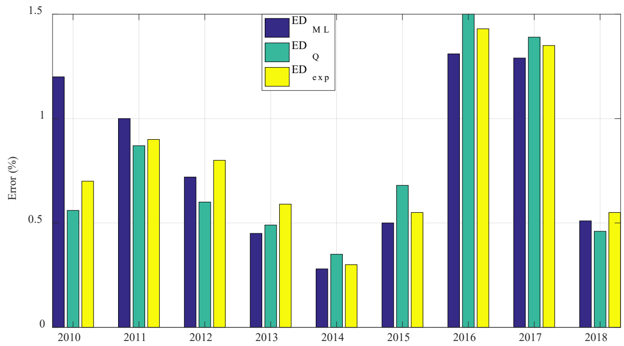

Fig. 4. The mean absolute percentage error between the predicted and the observed amounts on training data

Table 5. Comparison results of energy demand for different techniques

Technique	Optimizer	AVG R^2	Training set		Testing set	
			m (%)	Std	m (%)	Std
Multi Linear Regression	OLS	0.9994	1.41	0	1.09	0
	PSO	0.9869	6.32	0.0002	2.23	0.0001
	ACO	0.9946	2.50	0.00009	3.73	0.00009
Multiple Linear	PSO-GA	0.9856	5.47	0.0001	2.62	0.0001
	iMRFO	0.9996	1.24	0.00009	0.98	0.00009
	PSO	0.9887	4.39	0.0004	1.75	0.0003
	ACO	0.9893	1.81	0.0005	0.75	0.0004
Exponential	PSO-GA	0.9968	2.17	0.0002	1.18	0.0001
	iMRFO	0.9997	1.03	0.0002	0.61	0.0002
	PSO	0.9921	3.66	0.002	1.56	0.0018
	ACO	0.9979	2.39	0.0016	0.67	0.0015
Quadratic	PSO-GA	0.9943	2.83	0.0017	3.06	0.0016
	iMRFO	0.9997	1.05	0.0015	0.59	0.0012

of the error value in the training and the testing sets, along with the average R^2 of 35 independent runs. The results specify that the suggested iMRFO-based forecasting method has a higher prediction rate in both training and testing data toward the other comparative methods.

6. SIMULATION RESULTS

6.1. Scenarios overview

In this section, three scenarios including “A” as the business-as-usual scenario, and “B” as the planning and strategy scenario have been studied for specifying the forecasting potential of the suggested

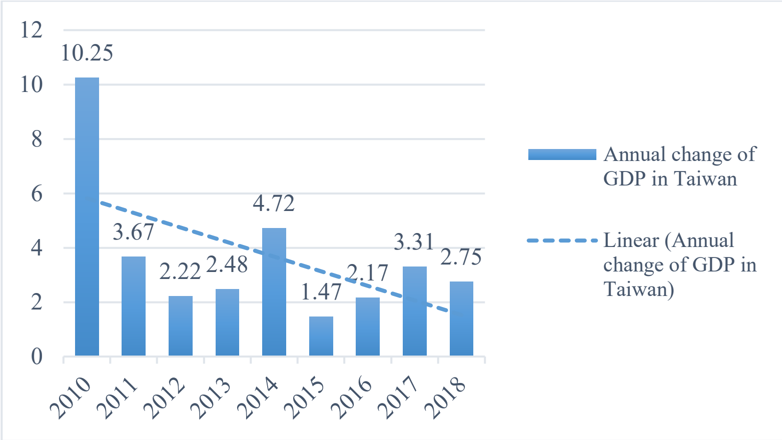

Fig. 5. The yearly growth rate of the real GDP in Taiwan from 2010 to 2018 [38]

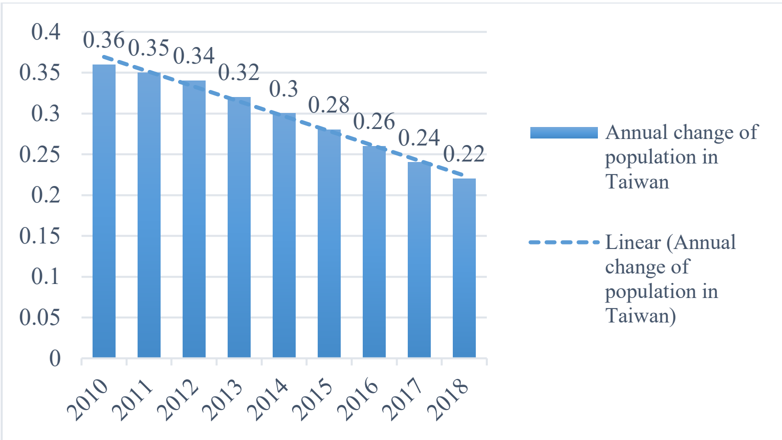

Fig. 6. The yearly growth rate of the population in Taiwan from 2010 to 2018 [39]

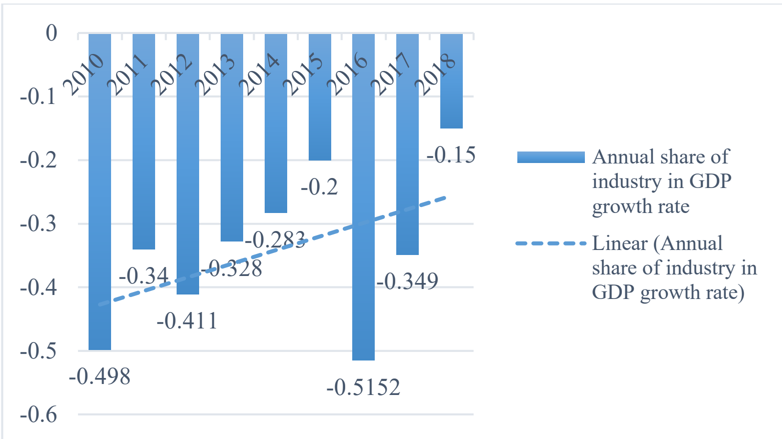

Fig. 7. The annual share of industry in GDP growth rate in Taiwan from 2010 to 2018 [39]

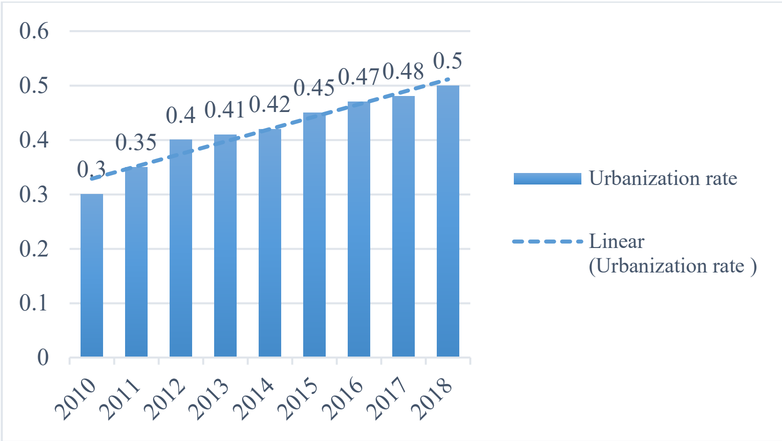

Fig. 8. The annual urbanization rate in Taiwan from 2010 to 2018 [39]

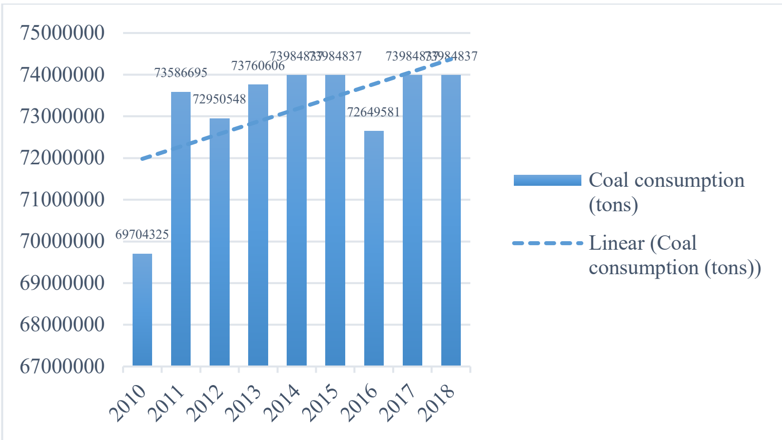

Fig. 9. The annual coal consumption in Taiwan from 2010 to 2018 [36]

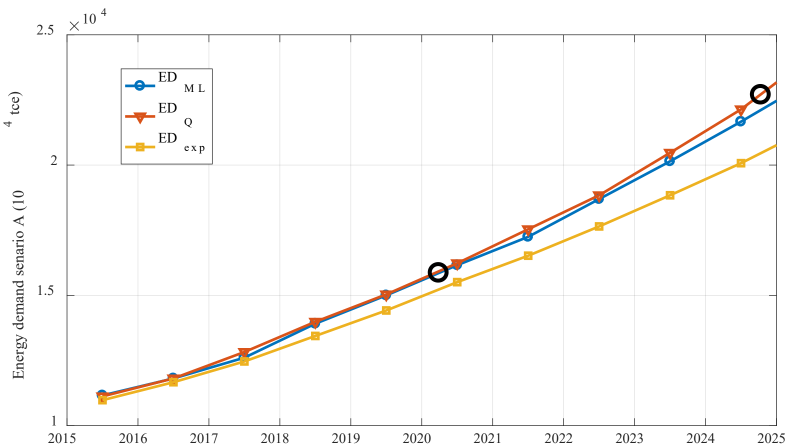

Fig. 10. Energy demand for scenario A

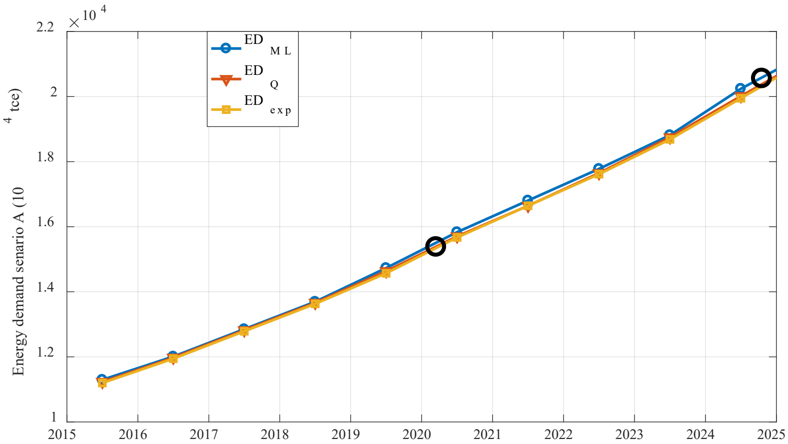

Fig. 11. Energy demand for scenario B

iMRFO-based energy demand forecasting. As aforementioned, five affected factors, i.e. growth of population, economic growth, rate of urbanization, coal energy share, and economic structure have been used for the analysis.

6.1.1. Scenario A

This scenario considers high economic process, such that past trends keep their movement with the future without new policies for environmentally friendly applications. This scenario considers the following assumptions for the studied affective factors:

The average annual GDP growth rate of Taiwan with 10.25% in 2010 has been reached to 2.75% in 2018 [38]. Based on the Trading Economics Organization and Fig. (5), the yearly growth rate of the real GDP in Taiwan from 2010 to 2018 has been shown.

GDP refers to the entire market price of all goods and services that are produced within a rustic per annum. it's a crucial measure of the economic strength of a rustic. In 2019, the annual rate of growth of the GDP in Taiwan was approximately 2.71%.

The population growth is the second factor that is considered for changing the dimension and of power demand structure both through its impression on economic growth and directly. Population growth reduced a little from 0.36% in 2010 to 0.22% in 2018 [39]. Based on the statistics, the population of Taiwan in 2017 has a rate of 0.24% increase from 2016 and in 2018 has a 0.22% increase from 2017. Fig. (6) shows the annual growth rate of the population in Taiwan from 2010 to 2018 [39].

Another factor, called economic structure is also considered for the analysis in this scenario. The average share of industry was reduced from 15.14% in 2010 to 0.41% in 2018. Based on Fig. (7), it is shown that Taiwan has accelerated the alteration of its industrial structure and the tertiary industry has expanded energetically. Based on the assumption in scenario A, industrial shares will keep its decreasing. Fig. (7) shows the yearly share of industry in GDP growth rate in Taiwan from 2010 to 2018 [39].

The next factor in scenario A is to consider the urbanization rate assumptions. Rural people in Taiwan have migrated to urban regions and increased the population of cities and towns with the rapid economic growth of the recent years. The average growth rate for annual urbanization was 0.8 percent in 2015 to 2018. The urbanization of Taiwan figures out an s-curve track qualified based on most developing regions in the same way. Fig. (8) shows the yearly urbanization rate in Taiwan from 2010 to 2018 [39].

After fast growth in 2012, growth is slowing down. In 2010-2018, the average growth rate of urbanization is assumed to be 2.0 percent.

The final factor for analysis is based on energy structure. However, as aforementioned, Taiwan has very small domestic resource of coal mines, it is one of the coal-dependent countries in the world. The average proportion of coal usage coal accounted for 29 of Taiwan's overall primary energy consumption in 2015, respectively. According to the Taiwanese government, total energy import reliance was around 98 percent. Fig. (8) shows the yearly coal

Table 6. Scenario setting

Senarios	Years	Yearly GDP growth rate (%)	Yearly population growth rate (%)	Yearly share of industry in GDP growth rate (%)	Yearly urbanization growth rate (%)	Yearly coal share growth rate (%)
A	2010-2017	9	0.55	-0.15	1.95	-0.09
	2018-2025	8	0.45	-0.25	1.75	-0.15
B	2010-2017	6	0.45	-1.27	1.58	-0.65
	2018-2025	5	0.35	-1.45	1.45	-0.75

Table 7. Index amounts by 2017 and 2025 in the various scenarios

Influencing factors	Years	Scenario A	Scenario B
GDP (10^9 Taiwan dollar)	2017	921.64	800.46
	2025	1425.13	1076.45
Population (10^4 persons)	2017	579.73	576.42
	2025	594.57	588.37
Share of industry in GDP (%)	2017	153.54	142.21
	2025	150.19	131.52
Urbanization rate (%)	2017	210.35	220.70
	2025	246.58	222.37
Coal portion in initial energy use (%)	2017	285.56	275.08
	2025	282.46	263.54

Table 8. The mean demand prediction in 2017 and 2025

Metric	Scenario A	Scenario B
Mean demand in 2017 (billion tce)	2.058	1.735
Average demand in 2025 (billion tce)	2.969	2.162
Energy intensity in 2017 (tce/10 thousand TWD GDP)	0.945	0.914
Energy intensity in 2025 (tce/10 thousand TWD GDP)	0.886	0.852

Table 9. Comparison results of the comparative forecasting results (Unit: million tce).

Origin	technique	Power demand in 2017	Power demand in 2025
IEA,2010	Trend analysis	1.788	1.831/19.13
Suo and wang	GM-BP-CEX	1.724	-
Zeng	Elasticity coefficient	1.578	-
Zhang	Leap	1.449	0.490
Current study	PSO-GA ED	1.952/1.629	2.863/2.055

consumption in Taiwan from 2010 to 2018 [36].

As can be observed from Fig. (9), energy demand in 2020 its going to be more than 4500 million tce in Scenario A. The highest forecasted amount by ED_Q is achieved 2300 million tce.

6.1.2. Scenario B

This scenario represents a move towards a further renewable energy direction through strategies and initiatives purposed at energy quality enhancement and energy use reduction. The scheme and strategy scenario is focused on anticipated and not yet achieved government policies and initiatives, which will be accomplish or chosen by 2017 or 2025.

This scenario doesn't consider the possible future policy decisions and new policies. This scenario has energy savings potentiality connected with proposed initiatives, unlike scenario A. Mostly, this scenario is based on Taiwan's 12th Five-Year Plan. The main assumptions of scenario B are given below:

First about economic growth, the 12th Five-Year Plan of Taiwan's Government of Republic of China [37] considers deeply transform the economic growth of the country by highlighting on quality upgrading in place of high economic growth rate. The consideration imagines an annual rate of economic growth equal to 4% in 2010–2017 and 5% in 2017–2025.

The second factor is to analyze the population growth. Scenario B considers that the mean growth rate in a year must be 0.3% in 2010–2017 and 0.2% in 2017–2025. These rates specify that the overall population in Taiwan should have been reached 23.83 million in 2018.

Economic structure is the other factor that should be analyzed. The future policy of the government is to quicken the structural modification of the Taiwan economy. Here, the tertiary sector sharing is particularly expected to increase, even though the construction and manufacturing are anticipated to be decreased. The 12th Five-Year Plan of Taiwan's Government of Republic of China [37] indicates that, from 34.1 percent in 2015 to 34.21 percent in 2018. To obtain this aim, the industrial share of the sector should have additional decreasing. The fourth factor, the urbanization rate show that the urbanization rate in Taiwan has a 0.8% annual rate of change from 2015 to 2020.

The estimated energy demand for scenario B is given in Fig. (10).

As can be observed, all kind models in scenario B in 2020 are above 4.0 billion tce. The lowest and the highest predicted values are 200.5 million tce and 200.9 million tce, respectively.

Finally, based on energy structure, and also according to the Taiwan attempts to decrease the CO_2 emissions, it has made tenacious efforts in emerging green energy sources, such as solar, wind, etc. to decreasing the fossil-based energy production. The 12th Five-Year Plan of Taiwan's Government of Republic of China [37] indicates that the green energy sources is an important purpose in energy development. The contribution of sustainable energy is aimed to obtain 3.99GW in 2015 to 5.82 GW in 2018.

To get the weight, the departure coefficient technique has been used, which is common in integration prediction, to achieve the mean demand estimate of the three formula types, which can be formulated as follows:

$$d_j = \frac{1}{M} \times \sqrt{\sum_{m=1}^{M} \left(z_{j_m} - \tilde{z}_m \right)}, \quad j = 1, 2, \ldots, k, \quad m = 1, 2, \ldots, M \tag{15}$$

where, $\tilde{z}_m$ describes the average predicted value for all k models at time t, z_{j_m} defines the predicted amount of the j^{th} model at t, and M represents the number of historical predictions. The weighs in this state is achieved as follows:

$$w_j = \frac{\sum_{j=1}^{k} d_j - d_j}{\sum_{j=1}^{k} d_j} \times \frac{1}{k-1} \tag{16}$$

Here, k is set 3 and M is set 20 and $w_j = [0.2415\, 0.2408\, 0.3157]$. The mean demand estimating of the three formulas in 2020 and 2025 is given in Table 8.

Although, if the adjustment of economic growth is further improved by Taiwan, the service industry will establish and the industry contribution will be decreased. Also, on the word of the 12th Five-Year Plan of Taiwan's Government of Republic of China [37], the goal line of renewable sources in electricity generation share is 20% by 2025 [40]. The results show that energy demand in scenario B reduces from 323 million tce in 2020 to 80.7 billion tce in 2025 in comparison to Scenario A. Thus, Taiwan's power strength in the two studied scenarios would decrease to varying degrees. Table 9 provides a comparison of the projections for Taiwan's energy demand with sone other related state of the art methods.

Which shows the superiority of the current methodology toward the others.

7. CONCLUSIONS

This paper provided a new optimization methodology for energy demand estimation by five demand-affecting factors including yearly growth rate of the real GDP, yearly growth rate of the population, annual industry share in the rate of GDP growth, annual rate of urbanization, and annual coal consumption for Taiwan. The optimization method is based on an improved version of Manta Ray Foraging Optimizer (iMRFO). Simulations indicated that using the suggested iMRFO-based power demand prediction technique gives higher precision and consistency prediction results toward the other compared methods from literature, including ACO, GA/PSO, basic MRFO-based, and multiple linear regression models. Two different scenarios were considered to more analyzing the proposed method. The final concluded that energy intensity in Taiwan will decline in varying degrees based on both scenarios. This concluded that additional growth of efficient strategies and actions is needed for ensuring that the target is accomplished.

8. ACKNOWLEDGEMENTS

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