FRONTIER ENERGY SYSTEM AND POWER ENGINEERING
ISSN: 2720-9598

Optimization of Double Exponential Smoothing Using Particle Swarm Optimization Algorithm in Electricity Load

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Abstract

Electricity load forecasting plays a critical role in ensuring the efficient allocation of resources, maintenance optimization, and uninterrupted power supply. The double exponential smoothing (DES) method is widely used in forecasting time series data due to its adaptability and robustness, particularly in handling linear trends without seasonal patterns. However, determining the optimal value of the alpha parameter in DES is crucial for accurate forecasting results. This study proposes the use of the Particle Swarm Optimization (PSO) algorithm to optimize the alpha parameter in DES for electricity load forecasting. PSO is a computational method that iteratively improves candidate solutions by moving particles in the search space based on simple mathematical formulas. By optimizing the alpha parameter using PSO, we aim to enhance the accuracy of short-term electricity load forecasts. Our results demonstrate that the PSO-optimized DES approach achieves a Mean Absolute Percentage Error (MAPE) of 2.89% and an accuracy of 97.11%, indicating significant improvements in forecasting performance. While the PSO algorithm provides promising results, future research may explore the application of other metaheuristic algorithms, such as the whale or orca algorithms, to further enhance the optimization of DES parameters for electricity load forecasting. This study contributes to the advancement of forecasting techniques in the power industry, facilitating more efficient power generation and distribution planning.

Keywords

Electricity Load, Double Exponential Smoothing, Forecasting, PSO

INTRODUCTION

The quantity of power used or required at a specific time and location is referred to as the electricity load. In order to guarantee there is a sufficient supply of power to fulfill demand, electric utilities carry out this crucial planning role [1]. Energy service providers must plan to allocate resources efficiently, optimise equipment maintenance, and avoid potential disruptions in electricity supply. In the process of making a plan, a reference is needed so that the planning objectives are as expected. One reference that can be used is the results of electricity load forecasting. Electricity load forecasting is the process of estimating future electricity demand based on historical and probabilistic data, which is used for long-term planning and short-term operational decisions [2]. The double exponential smoothing approach is one of the most widely used forecasting techniques.

Double exponential smoothing, also known as second-order exponential smoothing, is a forecasting technique used to handle trends in time series data. The method is particularly useful when the data exhibits a linear trend but no seasonal pattern [3]. The double exponential smoothing method has been implemented in various fields because it is adaptive and robust [4], simple and intuitive [5], less sensitive to outliers and noise [6], and improved accuracy [7]. Determining the value of the alpha parameter is a crucial step in the double exponential smoothing method, because it can affect the accuracy of the forecasting results. The alpha parameter has a value between 0 and 1 [8]. In order to produce forecasts with high accuracy, an optimization algorithm is needed to determine the most optimal alpha value. Therefore, this study used the Particle Swarm Optimization (PSO) algorithm to find the value of the alpha parameter in the double exponential smoothing method. Particle Swarm Optimization (PSO) is a computational method used to optimize a problem by iteratively trying to improve a candidate solution. It involves a population of candidate solutions, called particles, which move around in the search space according to simple mathematical formulae. The particles' movements are influenced by their local best known positions and are also guided toward the best known positions in the search space, which are updated as better positions are found by other particles [9]. The advantage of the PSO algorithm in determining the optimal parameters for different approaches has been demonstrated by several research, among which are Particle swarm optimization-based tuning technique for PI controllers [10]. The PSO algorithm is used to optimize the controller parameters to achieve better performance. PSO-based machine learning methods for predicting ground surface displacement induced by shallow underground excavation method [11]. In this study, the PSO algorithm is used to determine the optimal hyperparameters or random parameters in four machine learning methods, namely back-propagation neural network (BPNN), extreme learning machine (ELM), support

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ISSN: 2720-9598

vector regression (SVR), and random forest (RF). The performance of the PSO-based ML methods is compared in terms of fitness function, time cost, and prediction accuracy. The Improved Particle Swarm Optimization Method: An Efficient Parameter Tuning Method with the Tuning Parameters of a Dual-Motor Active Disturbance Rejection Controller [12]. This paper proposes an improved particle swarm optimization method (IPM) to alleviate the difficulty in parameter setting for a dual-motor active disturbance rejection controller. The IPM is shown to be an efficient method for parameter tuning.

So the first novelty in this research is the use of the PSO algorithm to determine the optimal alpha parameter in the double exponential smoothing method and the second is the double exponential smoothing method optimized with the PSO algorithm, implemented in the electricity load forecasting problem. In this study, the double exponential smoothing with PSO approach was used to anticipate the short-term electrical load. Short-term load forecasting (STLF) aims to predict electrical load demand in the near future, typically within a few hours to a few weeks. It is crucial for scheduling operations and production planning in the power industry, as it helps utility companies and dispatchers to manage power generation and distribution more efficiently. STLF is essential for maintaining a balance between electricity supply and demand, ensuring grid stability, and reducing operational costs [13].

RELATED THEORY

Double Exponential Smoothing

The exponential smoothing method is a forecasting method based on the use of analyzing the pattern of the relationship between the predicted variable and the time variable which is a time series [3]. The exponential smoothing method is a development of the moving averages method. In this method, forecasting is done by repeating the calculation continuously using the latest data. Each data is given a weight, the newer data is given a greater weight. The moving average method is easy to calculate but this method gives equal weight to each data. To overcome this, the exponential smoothing method is used. In the exponential smoothing method, the weight given to the existing data is α for the latest data, α(1-α) for older data, $α(1-α)^2$ for older data, and so on. The value of α is between 0 and 1. The closer to 1 means that the most recent data is given more attention. more attention is paid to the most recent data [14]. One method of exponential smoothing is double exponential smoothing. The following are the processes involved in utilizing the double exponential smoothing approach to determine forecasting results:

1. Determining the first smoothing (S'_t)
$$S'_t = \alpha X_t + (1-\alpha) S'_{t-1} \tag{1}$$
2. Determining the second smoothing (S''_t)
$$S''_t = \alpha S'_t + (1-\alpha) S''_{t-1} \tag{2}$$
3. Determining the magnitude of the constant (a_t)
$$a_t = 2S'_t + S''_t \tag{3}$$
4. Determining the magnitude of the slope (b_t)
$$b_t = \frac{\alpha}{1-\alpha} S'_t - S''_t \tag{4}$$
5. Determining the forecasting value (F_t)
$$F_{t+m} = a_t + b_t m \tag{5}$$

where X_t is actual data S'_t is single smoothing value, S''_t is double smoothing value[15].

Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a stochastic optimization algorithm inspired by the collective behavior of bird flocks or fish schools. PSO is a computer approach that uses a population of candidate solutions known as particles to optimize a problem by iteratively attempting to enhance a candidate solution based on a specified measure of quality [16]. Compared to other optimization techniques, PSO offers a number of benefits: simplicity [17], flexibility [18], adaptability [19] and robustness [20].

ISSN: 2720-9598

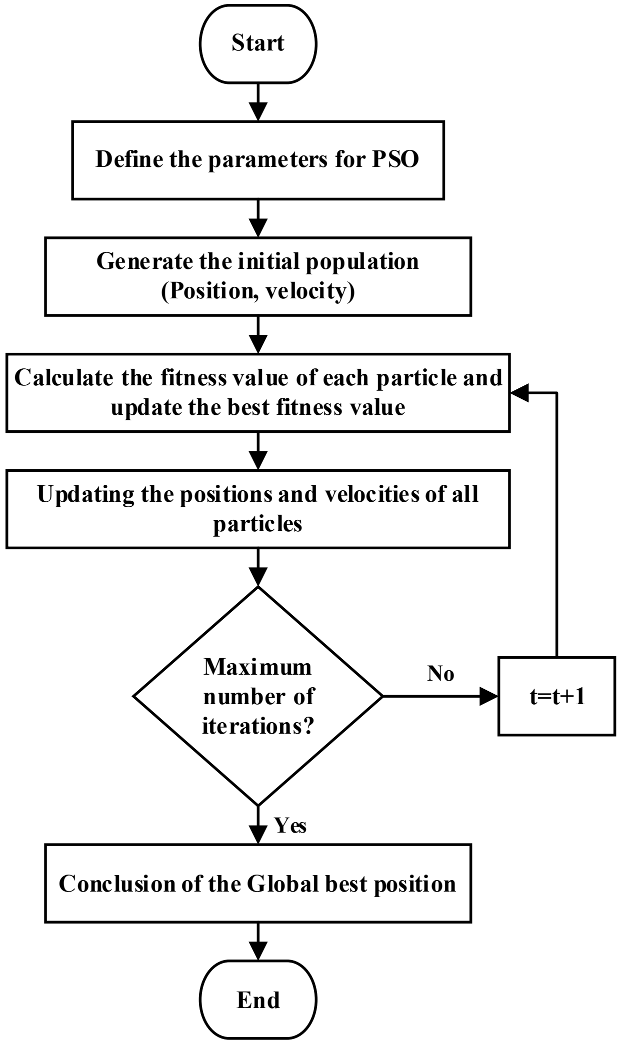

Figure 1. Flowchart of PSO Algorithm

The Particle Swarm Optimization (PSO) algorithm is shown in the following steps:

1. Set up the acceleration constants (cognitive and social characteristics) and other algorithmic constants, such as the number of particles and iterations.
2. Start the solution with the initial location and velocity data from the solution space.
3. Assess each particle's fitness.
4. Update the pbest and gbest, the personal and global bests.
5. Update each particle's location and velocity.
6. Repeat step 3 until the termination condition is satisfied, which might be a maximum number of iterations or a suitable fitness value [21].

PROCEDURE

A. Dataset

The dataset used in the research is electricity load data taken from the web https://data.open-power-system-data.org/time_series/. The data is aggregated by country, control area or supply zone. The geographical coverage includes the European Union and some neighbouring countries. All variables are provided in hourly resolution. This version of the package contains only data provided by TSOs and power exchanges through ENTSO-E Transparency, covering the period 2019-mid-2020 with a total data set of 15,337. Some of the data used in this study are shown in Table 1 below.

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TABLE I
Electricity Load Data

No	Date	Electricity Load
1	2019-01-01 00:00:00	6075
2	2019-01-01 01:00:00	5852
3	2019-01-01 02:00:00	5619
4	2019-01-01 03:00:00	5324
5	2019-01-01 04:00:00	5273
6	2019-01-01 05:00:00	5439
7	2019-01-01 06:00:00	5517
8	2019-01-01 07:00:00	5948
9	2019-01-01 08:00:00	6204
10	2019-01-01 09:00:00	6544
11	2019-01-01 10:00:00	6884
12	2019-01-01 11:00:00	7064
13	2019-01-01 12:00:00	7062
14	2019-01-01 13:00:00	7041
15	2019-01-01 14:00:00	6938
⋮	⋮	⋮
15333	2020-09-30 21:00:00	6661
15334	2020-09-30 22:00:00	6336
15335	2020-09-30 23:00:00	5932
15336	2020-10-01 00:00:00	5628
15337	2020-10-01 01:00:00	5395

B. Performance Evaluation

Mean Absolute Percentage Error (MAPE) is one measurement that may be used to verify the forecasting's results [22]. The formula for MAPE is as follows:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{D_{t+1} - S_{t+1}}{D_{t+1}}\right| \times 100\% \quad (6)$$

The forecasting accuracy is computed using the MAPE value. The forecasting results improve with a decreased MAPE value. The following Table 2 displays the MAPE accuracy criterion [23].

TABLE II
The MAPE Accurate Criterion

Criteria	The limit of MAPE Percentage
Very Good	< 10%
Good	10% - 20%
Reasonable	20% - 50%
Not Accurate	>50%

C. PSO Algorithm for Tuning Alpha Parameter of Double Exponential Smoothing

The steps or procedure involved in adjusting exponential smoothing parameters using the PSO algorithm are as follows:

1. Define the parameters of the PSO, such as the population size, maximum number of iterations, inertia weights, and the acceleration coefficients c_1 and c_2
2. Define initialization for starting position and speed.
3. Determine the starting PBest and GBest values as well as the fitness value
4. By entering electricity data and processing it using the exponential smoothing technique formula, the fitness value is determined. The MAPE formula is used to express the fitness value, and the lowest value is chosen
5. Update the velocity and location data.
6. In the event that the iteration does not reach its maximum iteration, PBest must be updated by designating as the new PBest the particle with the lowest fitness value, or MAPE.

ISSN: 2720-9598

RESULT

In this research, there is no need to determine the optimal alpha by trial and error, because the alpha value with the smallest MAPE is determined by the PSO algorithm. From the results of calculations using Matlab with 10 trials, each trial determined the maximum number of iterations is 50, the following alpha and MAPE values were found:

TABLE III
The MAPE value of each alpha

No	Alpha value	MAPE (%)	Iteration time (second)
1	0.4871	2.900912	188.7791
2	0.4735	2.893927	184.3682
3	0.5	2.915891	184.75
4	0.4976	2.912891	187.6185
5	0.4735	2.893927	188.1117
6	0.4735	2.893927	191.5573
7	0.4832	2.897696	195.7238
8	0.4975	2.912806	195.8678
9	0.4735	2.893927	195.6949
10	0.4735	2.893928	181.9062

From the 10 trial calculations shown in Table 3, it can be observed that the smallest MAPE value is generated by alpha 0.4735, which is 2.893927%. Figure 2 illustrates how the value of the parameter α begins to converge at iteration 14, with a calculation duration of approximately 182 seconds, the highest number of iterations employed in this investigation was 50.

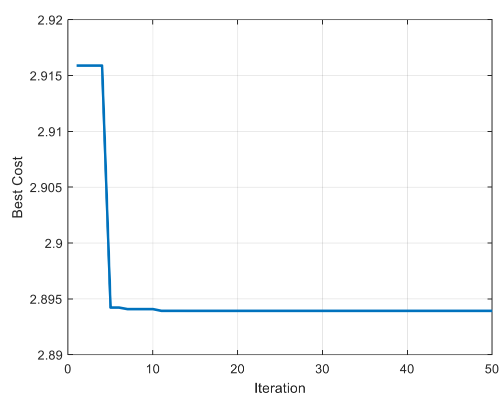

Figure 2. Iteration Graph of Double Exponential Smoothing with PSO

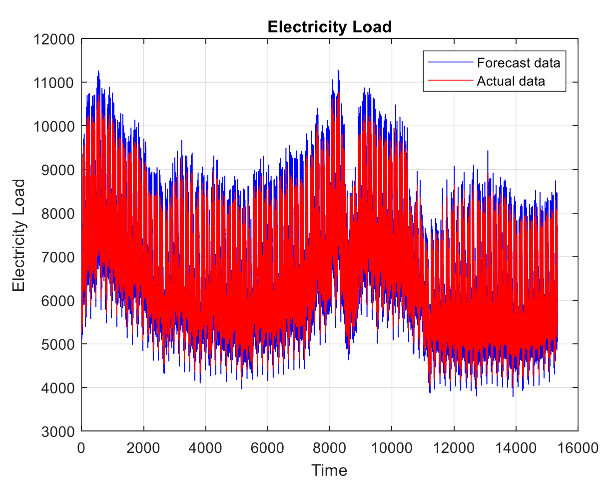

Figure 3. Comparison Graph of Actual Data and Forecasting Data Using PSO Algorithm

ISSN: 2720-9598

The line connecting the actual and forecasted data is quite close, as seen in figure 3. As can be seen, the error between the actual and forecasted data is quite minimal (2.893927%) when the optimal alpha is used. Then the results of electricity load forecasting using the optimal alpha from the above calculations, shown in Table 4.

TABLE IV
Electricity Load Forecasting

No	Date	Electricity Load	Electricity Load Forecasting
1	2019-01-01 00:00:00	6075	
2	2019-01-01 01:00:00	5852	5863.819
3	2019-01-01 02:00:00	5619	5581.978
4	2019-01-01 03:00:00	5324	5232.787
5	2019-01-01 04:00:00	5273	5108.143
6	2019-01-01 05:00:00	5439	5267.755
7	2019-01-01 06:00:00	5517	5424.259
8	2019-01-01 07:00:00	5948	5896.592
9	2019-01-01 08:00:00	6204	6281.482
10	2019-01-01 09:00:00	6544	6692.782
11	2019-01-01 10:00:00	6884	7095.419
12	2019-01-01 11:00:00	7064	7330.09
13	2019-01-01 12:00:00	7062	7333.589
14	2019-01-01 13:00:00	7041	7253.781
15	2019-01-01 14:00:00	6938	7086.411
⋮	⋮	⋮	⋮
15333	2020-09-30 21:00:00	6661	6831.926
15334	2020-09-30 22:00:00	6336	6408.574
15335	2020-09-30 23:00:00	5932	5982.938
15336	2020-10-01 00:00:00	5628	5633.8
15337	2020-10-01 01:00:00	5395	5367.306

CONCLUSION

Based on the research above, it can be concluded that the PSO algorithm can be used in conjunction with the Double Exponential Smoothing method to determine the optimal alpha with a MAPE of 2.893927% and an accuracy of 97.11%. This means that researchers can reduce the time required to calculate electricity load forecasts using the Double Exponential Smoothing method by utilizing the PSO algorithm. Nevertheless, the PSO algorithm's optimal alpha calculation results take a while to complete. Thus, other metaheuristic algorithms, such as the whale or orca algorithms, might be suggested by researchers to find the ideal alpha in the Double Exponential Smoothing approach.

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