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ORIGINAL RESEARCH

OELF: short term load forecasting for an optimal electrical load forecasting using hybrid whale optimization based convolutional neural network

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Abstract
Over the past few decades, models have been developed to accurately predict electrical charges. Long-term electricity forecast is the expansion of electrical equipment company management in the future. The short-term forecast for fuel and unit maintenance provides the information needed to systematically manage the unit's day-to-day operations and commitments. In this paper, we present the best in-class estimation method (OELF) to overcome micro grid problems. The proposed OELF system uses a hybrid convolutional neural network (CNN) and improved whale (IWO) to meet demand and facilitate economic growth. The main purpose of the CNN-IWO algorithm is to calculate the maximum demand for the micro grid and optimize the controllable load capacity for each project test. By investing in materials that reduce the performance of the micro grid, we can adjust the load on the micro grid and increase the controllable load. Therefore, OELF system for expanding micro grid expansion must carefully design cost control and load control strategies. The result showed that the performance of proposed OELF system is very effective in terms of mean MAPE and mean RMSE. The results clearly shows the average mean MAPE of proposed OELF system is 7.24%, 6.02% and 8.27% lower than the existing fuzzy based system in terms of 2 days, 1 days and 1 h ahead precision. The average mean RMSE of proposed OELF system is 9.37%, 8.34% and 5.41% lower than the existing fuzzy based system in terms of 2 days, 1 days and 1 h ahead precision.

Keywords Optimal electrical load forecasting (OELF) · Improved whale optimization (IWO) · Electric load · Forecast load

1 Introduction

Load forecasts are extremely important for the production, transmission, distribution and distribution of electrical energy (Deng and Ren 2003; Huang and Shih 2003). Responsible forecasting is a major issue and changes in the planning and management of power companies. The purpose of load forecasting is to model the power load forecasting required for accurate planning and running a profitable company. Load forecasting is important for electricity suppliers to make important decisions in the electricity market, load transfer, voltage regulation, network connectivity upgrades, and technology network expansion. Long-term electrical load prediction (Liao and Niebur 2003) is used to provide an estimate to the equipment operator for extension, equipment purchase, or contract requirement. Pearson's connection coefficient can be applied to the climate and burden datasets for load determining if the dataset range is adequately little to introduce a direct relationship. Long-term forecast (El-Sharkh and El-Keib 2003) can be planned for fuel consumption and savings in components (Baczyski and Parol 2004). Short-term forecasting (Sfetsos 2003) is used to run day-to-day operating systems and provide the information needed to encourage access. Includes descriptions of devices used by consumers, location size, age of equipment, technical changes, consumer behavior, and power use at the end of the population and facts and simulation models. In the event that the air temperature also, load datasets are confined to a set number of weeks during the colder season (winter), at that point there gives off an impression of being a negative direct connection between air temperature also, load. In the

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event that the air temperature and burden datasets are limited to a set number of weeks during the sultrier season (summer), at that point there seems, by all accounts, to be a positive direct relationship between air temperature and burden.

Micro grid systems are connected to public or independent grids, usually consisting of a combination of renewable and non-renewable energy; energy storage systems (ESSs), controllable or disposable, such as batteries or flywheels (Chakraborty et al. 2007; Amjady et al., 2010; Kanchev et al 2011; Chen et al 2011). More specific, a CNN is used as a function approximate to estimate the state-action value function or Q-function in the supervised learning step of fitted Q-iteration (Claessens et al. 2016). Due to the temporary nature of renewable resources such as wind or solar, it is difficult to accurately predict wind or solar energy. These forecasts depend on the weather forecast. Of course, the estimation of any data based on the estimation of other parameters leads to additional inaccuracies, although the relationship between input and output can be determined by various means. The success of intelligent grid arrangement depends on the quality of the data in the grid (Palma-Behnke et al 2013). This is especially true for state-of-the-art grid control systems, where reliable and accurate network information is in high demand from system operators. One of the major requirements of smart grids is to predict future power loads. As we know, electricity cannot be stored efficiently to store large amounts of energy. Therefore, the network operator should ensure that the volume produced over a given period of time is sufficient to meet the load without significantly exceeding the requirements (Jiang et al. 2013). Accurate power load estimates can not only provide relevant information to network operators to reduce maintenance costs, but also ensure reliable power system planning and operation. Point estimation is the most traditional technique, providing the most accurate prediction of future loads for each step within a project framework (Zhang et al 2016). Instead of providing a single value estimate, the distance estimation method attempts to establish the lower and higher constraints of future projections related to a given probability, called the confidence interval (Saez et al 2015). Unlike these two types of prophecy; Probability estimates can be evaluated by establishing the probability of the expected outcome (Shakya et al 2016). It can provide full details of possible future distribution needs, which are specific requirements in grid management. Although calculating the probabilities for each possible estimate requires additional effort, additional data is very useful to help to fully understand the reliability of the service. However, it is not possible to predict next year's maximum load with similar accuracy, due to inaccurate long-term weather forecasts (Cerne et al. 2018).

Contributions-Optimal electrical load forecasting (OELF) system is proposed to solve upper micro grid problems based on improved whale optimization (IWO) system. The main purpose of continuous OELF system is to calculate the maximum load requirements in the micro grid and to control the load using the best capacity setting settings. In results and discussion, we analyze the performance of proposed OELF system with the existing fuzzy based system in terms of mean MAPE and mean RMSE. As a result, it indicates that the performance of the specified OELF system is average MAPE and average RMSE. The results clearly show that the average MAPE of the specific OELF system is 7.24%, 6.02%, and 8.27% lower than the ambiguous base system based on 2 day, 1 day, and 1 h forecasts. The average RMSE current of the proposed OELF system is 9.37%, 8.34%, and 5.41% lower than the current obscure system with 2 days, 1 day, and 1 h accuracy.

The rest of this document is summarized as follows: Sect. 2 describes the related work. Section 3 shows the problematic approach and proposed model. Section 4 describes proposed OELF system. Section 5 shows the simulation results. Finally, concluded the paper.

2 Related works

He et al. (Hong et al. 2014) Chebshev proposed a random neural backward propulsion (CBP) network algorithm based on map quality. To improve the accuracy of the algorithm, the self-optimization format correction method is used to eliminate the aggressive occurrence of the network. An additional partial period optimization process, including a chaotic sequence, increases the weight and value of the network limit (Huang et al. 2004). With a band of [− 1, 1], the stupidity of the chaotic variable can reduce the binary trend of the network, increase the learning speed and greatly improve the predictive ability of the algorithm proposes to overcome the problem of duplication saturation. However, the calculated results are redundant or inconsistent because the non-related model is sensitive to the choice of weight, limit value and topology structure.

Pan et al. (2017) CSFPA calculates the potential of a self-optimization switch in each iteration. The best starting weights and requirements of BPNN are given by the CSFPA optimization results. The performance of this method is validated by real-world charging datasets from two different energy markets.

Li et al. (2018) in some developed cities, a data-driven linear clustering (DLC) was introduced to solve the long-term system weight prediction problem caused by weight variation. A large amount of material weight is used at annual intervals and must first be adjusted using the proposed linear cluster method. In the future, optimal autoregressive integrated moving average (ARIMA) models will be built for the summer series in each specific cluster. Summarize all ARIMA forecasts and get the results of the system load forecast. Error Analysis and Application Protocol Result results show that the DLC method can theoretically and practically minimize random prediction errors while ensuring the accuracy of the model.

Gendeel et al. (2018) proposed an artificial neural networks (NNs) model with variation mode decomposition (VMD) for predicting short-term wind speeds. In order not to reduce the static wind speed rating, the V historic wind speed was degraded by various VMD intrinsic mode functions (IMFs). The NN inverse distribution was adopted with Lewenberg-McCard to create sub-models according to the different characteristics of each IMF. Sub-models corresponding to different IMFs are superior for obtaining wind speed forecasting models. This predictive model for wave-related decomposition and empirical mode decomposition was compared with NN. Performance was evaluated on the basis of three measurements: maximum absolute error, median square error, and correlation coefficient.

Wang et al. (2018) Probable damage estimates, with the exception of the probabilistic load forecasting (PLF) method, are proposed to model baseline estimates. This method uses data related to large historical data to predict signal estimates. This estimate is used as an add-on element to indicate the distribution of exceptions to predict the data. Combine point estimation and distribution of the remaining exceptions to produce a final probability estimate. Detailed case studies obtained from a set of generally available weight data with multiple strings, comparing projects of different factors and quantitative response patterns, illustrate the advantages of this approach.

Eibl et al. (2018) a problem of weight estimation has been explored by energy suppliers as to whether the secret smart data obtained is useful. Energy producers will then be able to build a solid, stable, and secure facility based on the equipment guarantees provided for the power generator and the different types of housing. The first step is to estimate the weight of the energy supplier based on the smart measurement data with the required encryption certificate. In addition to designing and evaluating different personalities for weight estimation, members' perceptions can be understood using different recognition skills;

Luo et al. (2018) The Vanilla standard was introduced in GEFCom 2012 for very short-term load forecasting (VSTLF). For broken load data, real-time discrepancies can be cleared by replacing the estimated time clock with the latest slide simulation. Compare the Anomaly Detection Method for VSTLF. If not, there are three other options for comparison. According to extensive testing of ISONE data with simulator changes, the anomaly spy method is better than the two most used spy methods and the most advanced spying method. The framework provides a basis for differences in estimates for future research.

Gan et al. (2018) use of input instability and output variables Propose an innovative approach to probability load estimates. It turns out that the model works better than standard models. This gives better results than other common methods, such as hot coding used in previous publications. Investment methods demonstrate the ability to manage inputs that improve projected performance. Further studies are needed to improve the structure of the network with advanced techniques, such as deep neural networks, and to use intercepted information to practice design. It is able to retrieve more confidential information and assess the burden by looking at it from different angles.

Wu et al. (McPherron and Siscoe 2004) have introduced system that prediction intervals (PIs) can produce lower upper bound estimation (LUBE) forecasts based on numerical weather prediction (NWP) wind speeds. PI fuel is required for operation charged search system (CSS) is used to correct LUBE components. This part of the forecast combines the characteristics of the risk forecast, including real-time probabilities and the NWP model to generate data from various petrol stations in Taiwan while testing this operation.

Rafiei et al. (2018) A hybrid model has been developed that can predict potential electrical loads, including generalized extreme learning machine (GELM) for training an improved wavelet neural network (IWNN), vibration processing, and bootstrap training. Vision and hearing problems are considered a workload. Bootstrap technology is used to detect ambiguities and bombs related to data sound and pattern prediction. An accurate sample has been obtained which results in accurate, precise and accurate predictions. The power and speed of the right way of writing will definitely affect the e-commerce market.

3 Problem methodology and system model

3.1 Problem methodology

Wang et al. (2017) has developed an extended three-phase design plan for measuring loads in a separate micro grid using application expansion, capacity development and operational efficiency. The Latin hyperlink sampling method is used to generate load demand conditions. The controllers are also built into the extension, which can be closed again as needed and the grain update is used to confirm the design result. Demand for critical generation and loads is usually a short-term view. Any prediction made in a series of hours or days in advance can be divided into short-term predictions. Because loads and generation are dependent on a variety of climates, historical estimates, special events, time of day, numerical weather prediction (NWP), used devices or related seasonal data are the tools used for short data-time and generation. Many viewers use the NWP as the main tool for generational viewing. The problem with this approach is that generational estimates are based on weather forecasts, which can lead to more errors.

Many methods of separation use statistical or artificial intelligence methods such as transformation, networking, abstract thinking and professional systems. Both methods, end-of-life and so-called economic use are widely used for medium and long-term budgeting. Various methods, including the so-called solar system, different types of stress, time periods, network position, mathematical statistics, abstract memory, and specific systems, are designed to study the load. For continuous improvement, the optimal electrical load forecasting (OELF) has been developed for micro grid. The following is a summary of OELF's system:

The CNN-IWO hybrid algorithm is used to meet load requirements, and to enable economic development.
The main purpose of the CNN-WHO algorithm is to measure the maximum demand of the micro frame to provide the maximum controlled load capacity adjustment for each designer test set.
The micro grid load can be controlled according to regulatory requirements and the control load can be improved, reducing micro grid operating efficiency by reducing the cost of the machine.
Therefore, in order to maximize micro grid amplitude, the controllable cost and load control strategy must be carefully modeled in our OELT system.

3.2 System model of OELF system

Figure 1 shows a sample of the proposed OELF system. The left side shows the traditional distributed energy system, which provides combined heating and energy, in addition to heating and cooling. In addition, the side has a normal distributed power system, which includes more elements, its first column source On the other hand; the second column is the power supply system. Energy and the third column are by application. This means that the supply section includes not only conventional energy such as natural gas, but also renewable energy, such as boil and solar energy. In addition to cooling, heating and energy, fresh water and carbon products are also included on the application side. The intermediate system provides power supply from a single machine for the integration of multiple devices (energy storage).

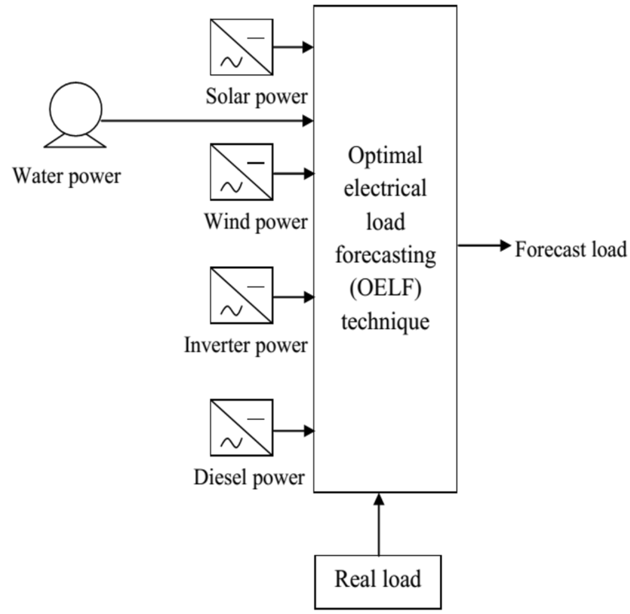

Fig. 1 System model

4 Optimal electrical load forecast (OELF) using hybrid CNN-IWO

Whale optimization (Nasiri and Khiyabani 2018) is a metaheuristic algorithm designed by the expert chain of criticalness, and what's continuously the looking for after bit saw in diminishes wolves. It is inspired by a special method of humpback whale hunting called balloon preparation. The whale can sense the distance between it and the animal and change the game. It has been suggested that mountain whales can grow up to a distance of about 15 feet, covering large bubbles. The ultimate flow of the balloon and the first bubble will increase simultaneously to form a cylinder or air cavity tube. We like to get tired like a giant spider moving the game at a sharp angle and moving the game in the middle. So the swimming whale swallowed the egg almost into its mouth and throat inside the bubble circle. According to the above description, the behavior of "wolf" and "whale" can be divided into three categories: walking, walking, walking on nails and hunting. After identifying the leader, the runners are divided into three categories: chasing, beating and beating the victim. According to the OELF method, the ivory wheel assembly is taken from a standard whale repair test, and sales measure the size of the wildlife in this modern way. Management begins with the warrior. Make decisions in life without a doubt. As a knee-jerk reaction, the dove population is a good study of the country's appearance. For example, three well-used balloons, Alpha Beta and Delta, are used to cover the entire public domain. Finding a solution represents the beginning of an attack. In particular, the World Health Organization has used a lot of attitude. The mathematical picture of the development algorithm consists of three stages: the tracking part, the wallet part, and the attack part. The mathematical model of these three behaviors like search for prey, encircling prey, and bubble-net foraging behavior of humpback whales are mentioned below terms. And the mathematical model is based on these three behaviors. In simulating an air conditioning system, two proposals are made based on the rotating circuit and the air conditioning system. These searches can be called learning platforms, the main purpose is to find better solutions. The process of hitting the ball can be called a violation, its main purpose is to use this complete solution. Rotational behavior is mathematically organized as follows

$$X_d(t+1) = X_p(t) + A..D \tag{1}$$

where A and C are coefficient vectors and t is the iteration number. X shows the location of the wolf. The parameter D represents as,

$$D = \left| C.X_p(t) - X(t) \right| \tag{2}$$

The parameter C is represented as,

$$C = 2r_2 \tag{3}$$

Contribute is the alpha where the beta and delta are hunted occasionally. The alpha, beta and delta demonstrates that the best position and gives solution established on the priority established on the current location and the urgency of the agents the data is updated with the best search agents. The position updating is formulated as

$$A = 2A.r_1 - a \tag{4}$$

The r_1 and r_2 are the random vectors in the value between [0, 1]. The distance of each wolves is represented as

$$D_\alpha = \left| C_{\}1} - X_\alpha - X \right|, D_\beta = \left| C_2 - X_\beta - X \right|, D_\delta = \left| C_3 - X_\delta - X \right| \tag{5}$$

$$X_1 = \left| X_\alpha - A_1..D_\alpha \right|, X_2 = \left| X_\beta - A_1..D_\beta \right|, X_3 = \left| X_\delta - A_1..D_\delta \right| \tag{6}$$

The fitness solution is represented as

$$X_d(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{7}$$

The t is the number of iteration and alpha is the best solution vector.

$$\alpha = 2 - \frac{t.2}{\text{max iteration}} \tag{8}$$

The searching for after closes by striking the prey, this headway watches out for the abuse design. It is done by reducing the estimate of 'a' directly from 2 to 0. To maintain a stable separation from neighbors, a basic step is used to drive the wolves out of the country. This theory of evolution keeps purpose beyond temptation. The use of different estimates and results produced by reducing the specific estimates from 2 to 0 confirms the relationship between assessment and study. This change is professional because half of the print follows the test time |A| · 1 when the remaining circuit is given the dissolution of |A|< 1. This change is part of the value of the findings. In general, A < 1 estimates require high-level animal leaders in estimates |A|> 1 requires them to separate from it. In general, each wolf has a N-focused process from memory N. Each internal component is a vector d. Each purpose is a vector. Wolf N people work together to find the best performance for customers. Proper user configuration is indicated by the correct location of the facility.

To name the utility value for all the nodes are the position and the energy are the two parameters applied in whale maximization algorithm. The nearest position node and maximum energy consumption are chosen as alpha and the service users. The fitness solution defined as follows:

$$X_d(t+1) = \frac{(X_1 + X_2 + X_3..)}{3} + \frac{(Y_1 + Y_2 + Y_3....)}{3} \tag{9}$$

Recalling the genuine goal to change the alliance clients to render the connection clients and non-advantage clients, incredible relationship to non-advantage clients inside the sight and sound cloud client gathering, engaged utility estimation of every client in the mixed media cloud client amass is figured and masterminded, and a short cross later the ideal number of the association client is picked are accumulated. To applying the lessen wolf propel tally is depicted by the brought together utility. The estimation figures begin with each middle point made on the division, lead and same media affiliations. Set up on the measure of past what many would consider conceivable the record gets spitted from the connection clients to the non-advantage clients. IWO estimation is associated with process the utility respect. The utility has been set up by the diagram estimations, for example, centrality utilizes and position of clients in the structure. The inputs of proposed IWO algorithm is predicted maximum and minimum solar power $\left(\max_{sp}, \min_{sp}\right)$, wind power (Wp), initial battery charge $\left(C_i\right)$, battery bank voltage $\left(V_i\right)$, current $\left(I_i\right)$, diesel power $\left(D_p\right)$, water consumption (Wc), water tank level $\left(L_{WT}\right)$ and measured load $\left(P_l\right)$. From this, the objective function is formulated as follows:

$$F(x) = \delta_t \sum_{t=t_0}^{T} \left(C_{Sp}(t) + C_{Wp}(t) + C_{Dp}(t) \right) + C_{L_{wt}} \sum_{t=t_0}^{T} C_{Wc}(t) + C_{Pl}\, \delta_t \sum_{t=t_0}^{T} P_l(t) \tag{10}$$

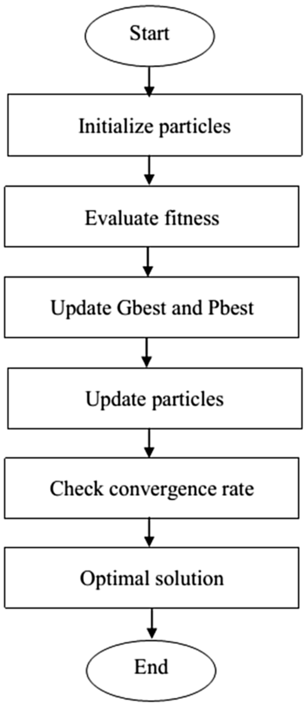

Fig. 2 Workflow of proposed CNN-IWO algorithm

where $C_{Sp}(t)$, $C_{Wp}(t)$, $C_{Dp}(t)$ represents the cost function of solar, wind and diesel power at a discrete time-step δ_t; $C_{L_{wt}}$ is the cost of un-served water, $C_{Wc}(t)$ is the water consumption level;

$$x_i^t \leftarrow n_t + \delta(m_t - n_t);\, t = 1, 2, \ldots, n \tag{11}$$

$$f_b = \min \left\{ f(x_i)\,;\, i = 1, 2, \ldots, n \right\} \tag{12}$$

$$f_w = \max \left\{ f(x_i)\,;\, i = 1, 2, \ldots, n \right\} \tag{13}$$

$$V = \max_{t \in \{1, \ldots, n\}} (m_t - n_t) \tag{14}$$

When V is empty, people switch points the other way; otherwise opt for unplanned and better schemes. Increased chasing and x_i evaluating behaviors can be seen as family behaviors. When V is idle, the algorithm uses the search behavior and selects a separate point, i.e. the index is specially selected and the point x_i is moved to it if the position is positive $f(x_r) < f(x_i)$. The animation guide shows the following:

$$\text{direction}_i = x_r - x_i \tag{15}$$

Point t_i, it is called swarming behavior.

$$\text{direction}_i = x_{\min} - x_i \tag{16}$$

Moving to a specific location, that is, on the other hand, is carried out by the unit and takes the allowable movement of fixed upper and lower boundaries. Details of the new t_i routes were selected for the next purpose according to the conditions.

$$x_i = \begin{cases} t_i; & \text{if } f(t_r) < f(x_i) \\ x_i; & \text{otherwise} \end{cases} \tag{17}$$

After optimize the time varying constraints of each vehicle node compute own strength (V_s) as follows:

$$V_s = x_1 + x_2 + \cdots \tag{18}$$

The processing steps of proposed IWO algorithm are given in Fig. 2 and the pseudo code of the same is given in Algorithm 1.

Algorithm 1: Pseudo code of proposed OELF using CNN-IWO algorithm

Input: S_p, W_p, D_p, W_c, L_{WT}
Output: Real load, forecast load

```
Begin
Extract power at T time period
Definesolar, wind, inverter, diesel, water power
For each iteration do
Find: difference, threshold solution
Find: initial population
Find: best and worst solution
If V = empty
Population movement = random
Else
Population movement = select from visual scope
End
Calculate new population
If new population > initial population
Solution = initial population
Else
Solution = initial population
End
End
Forecast load = V_s
end
Return: forecast, real load
```

5 Result and discussion

In this section, the planned OELF performance using the CNN-IWO algorithm is analyzed in the experimental micro grid. All instructions are used using MATLAB R2013a Intel Core i5 2.39 GHz with 8 GB of memory. Optimal electrical load forecasting (OELF) technology is proposed to solve upper micro grid problems based on improved whale optimization (IWO) system.

For a fair comparison, the maximum iterations (max. iterations) of the IWO algorithms set to 50, and the size of population *Xp* is set to 5. The other parameters are listed in Table 1. The main purpose of continuous OELF technology is to calculate the maximum load requirements in the micro grid and to control the load using the best capacity setting settings. Micro grid configuration has been simplified for a single bus system. To evaluate the technical performance of the OELF method the error measurements generated by Root mean square error (*RMSE*) and mean absolute percentage error (*MAPE*). *RMSE* is a term often used to distinguish between the predicted values of the model values and the actual environmental laws stored and represented as follows:

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{\left(\mathrm{Real}_i - \mathrm{Forecast}_i\right)}{N}} \tag{19}$$

$$MAPE = \frac{100}{N} \sum_{i=1}^{N} \left| \frac{\mathrm{Real}_i - \mathrm{Forecast}_i}{\mathrm{Real}_i} \right| \tag{20}$$

The data center is divided into training, validation and testing. Types are trained by the training center and their training error is calculated according to the established certificate. The central network of error sites of the test site was selected for the final performance evaluation in the test information area. In addition, all models used the standard stop during training, hindering training if the *RMSE* and *MAPE* verification data did not change during the 50 sessions. In these cases, the short-term load concept plays an important role in the micro grid capacity control system for use without the tools available.

Comparisons are made with *RMSE* and *MAPE* guidelines, one hour, 24 h and 48 h. In this case, fatigue is only considered. Parliament *Ts* was moved to the next level of property theory. This is done with advanced problem-solving techniques, creating estimates of the weight of the next *N* hours of each step, using real-time data. As mentioned, different teachers offer different theories using different theories that can adapt to the capabilities of their homes and show different levels of accuracy, leading to natural differences between them. Estimates provided by different networks. Such forms give the public speaker the freedom to know and appreciate the best combination. Also, the overall player is equally high in all household scales with very few errors, and secondly, the final budget collection to identify and follow a good home reader. In Fig. 3 shows an example of the performance of the OELF system verification data type and existing load limits the use of a surprising type. Figure 4 shows the difference between the actual and expected weight in the OELF design process and the weight previously used for Fuzzy's benefit. The plan clearly demonstrates the development of OELF system strategies, much lower than the existing ambiguity type.

Tables 2 and 3 show weather errors on MAPE and RMSE for up to one hour, one day and two days before the power outage, using the training and training strategies we mentioned above these days 7, 15 and 30. In each case, three types are used, trained for 30, 60 and 90 days. The pictures show the errors of the different types during the test. For each type, MASE and RMSE for all services are set. The

Table 1 Parameter settings for IWO algorithm

Parameter	Value
X_p	5
Max. iterations	50
α	[0, 2]
f_b	0.09
F_w	0.04
m_t	1
n_t	−1

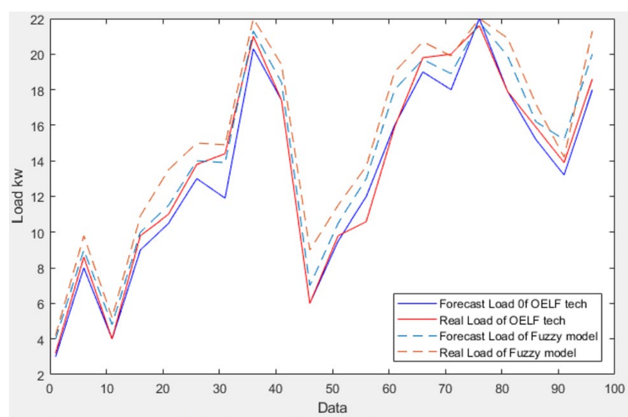

Fig. 3 Validation set of real and forecast load

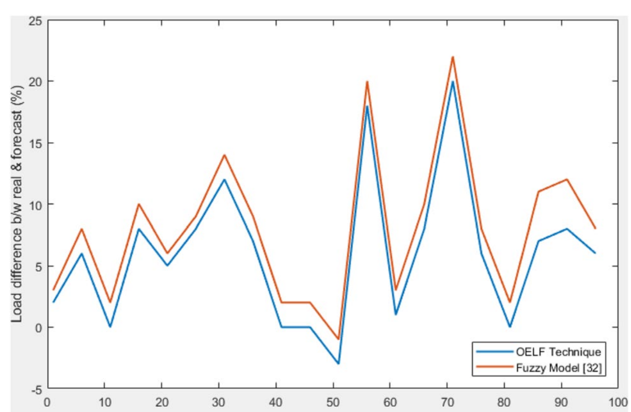

Fig. 4 Difference between real and forecasted load

Table 2 Performance analysis of Mean MAPE (%)

Predictor	Data for training (days)	Training frequency (days)					
		7		15		30	
		Fuzzy (Luo et al. 2018)	OELF	Fuzzy (Luo et al. 2018)	OELF	Fuzzy (Luo et al. 2018)	OELF
2 days ahead	30	15.9003	14.122	15.6955	14.698	16.1343	14.927
	60	15.5700	14.107	15.4568	14.654	15.5245	14.541
	90	14.1630	14.137	14.1987	14.023	14.2569	14.124
1 day ahead	30	15.5260	14.789	15.2391	14.001	15.6270	14.078
	60	15.2763	14.203	15.2345	14.0025	15.2777	14.005
	90	13.9682	14.001	13.9801	14.142	14.0975	13.789
1 h ahead	30	15.5171	13.784	15.6394	13.994	16.2135	13.546
	60	15.4031	13.457	15.4151	13.854	15.4399	13.487
	90	14.4017	13.278	14.3877	13.472	14.5323	13.247

OELF-proposed system

Table 3 Mean RMSE (kW) for real time training

Predictor	Data for training (days)	Training frequency (days)					
		7		15		30	
		Fuzzy(Luo et al. 2018)	OELF	Fuzzy(Luo et al. 2018)	OELF	Fuzzy(Luo et al. 2018)	OELF
2 days ahead	30	1.7949	1.654	1.7848	1.5544	1.7938	1.654
	60	1.7761	1.623	1.7653	1.6241	1.7781	1.687
	90	1.6956	1.610	1.6959	1.5987	1.7051	1.634
1 day ahead	30	1.7210	1.541	1.7195	1.5784	1.7788	1.6123
	60	1.6837	1.574	1.6798	1.5487	1.7034	1.6045
	90	1.6564	1.384	1.6560	1.5100	1.6713	1.649
1 h ahead	30	1.4447	1.3244	1.4453	1.4987	1.4795	1.547
	60	1.4234	1.347	1.4249	1.4875	1.4390	1.598
	90	1.4256	1.2012	1.4243	1.457	1.4291	1.567

OELF-proposed system

OELF system evaluates all data components for comparison. The most measurable results are found in experimental and experimental studies. It shows good points with RMSE of 0.0812, MAE of 0.0412, and average 0.127. Comparison is done with RMSE and MAPE guidance, one hour, 24 h and 48 h per step, real-time data is used. As mentioned, different teachers present different theories using different theories that best fit the capabilities of their homes and show different levels of accuracy, showing the natural differences between these estimates provided by different networks.

When, 2 days ahead predictor, the average mean MAPE of proposed OELF system is 7.16%, 3.97% and 10.597% lower than the existing Fuzzy based predictor for the training periods as 30, 60 and 90 days receptively. When, 1 day ahead predictor, the average mean MAPE of proposed OELF system is 4.357%, 5.19% and 9.07% lower than the existing Fuzzy based predictor for the training periods as 30, 60 and 90 days receptively. When, 1 h ahead predictor, the average mean MAPE of proposed OELF system is 5.0607%, 6.955%, and 12.786% lower than the existing Fuzzy based predictor for the training periods as 30, 60 and 90 days receptively.

When, 2 days ahead predictor, the average mean RMSE of proposed OELF system is 7.207%, 11.106% and 9.807% lower than the existing Fuzzy based predictor for the training periods as 30, 60 and 90 days receptively. When, 1 day ahead predictor, the average mean RMSE of proposed OELF system is 8.936%, 8.27% and 8.12% lower than the existing Fuzzy based predictor for the training periods as 30, 60 and 90 days receptively. When, 1 h ahead predictor, the average mean RMSE of proposed OELF system is 5.73%, 5.58% and 5.32% lower than the existing Fuzzy based predictor for the training periods as 30, 60 and 90 days receptively.

6 Conclusion

We proposed an optimal electrical load forecasting (OELF) system to overcome complexity and precision problems in the micro grid. The proposed OELF system used the hybrid CNN-IWO algorithm to calculate the optimal load, also known as predicted load. The CNN-IWO algorithm is used to calculate the maximum load requirement of the micro grid to complete the predicted load with the optimal capacity settings of the controllable loads for each planning test set. The methodology has been assessed in a subjective reproduction, involving a heterogeneous group of thermostatically controlled burdens, that lone offer their operational air temperature, while their envelope temperature stays covered up. The calculated loads on the micro grid are regulated in accordance with legal requirements and the controllable loads are used. The operational performance of the micro grid can be improved through less investment in the plant. Analysis of performance and results has shown that the proposed OELF system is effective over existing prior art systems.

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