A Power Aware Long Short-Term Memory with Deep Brief Network Based Microgrid Framework to Maintain Sustainable Energy Management and Load Balancing

N. Gowtham[1,*], V. Prema[2], Mahmoud F. Elmorshedy[3,4], M. S. Bhaskar[3] and Dhafer J. Almakhles[3]

[1]*Department of Electrical and Electronics Engineering, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal, India*
[2]*Department of Electrical and Electronics Engineering, B.M.S. College of Engineering Bengaluru, India*
[3]*Renewable Energy Lab, Department of Electrical Engineering, College of Engineering, Prince Sultan University, Riyadh 11586, Saudi Arabia*
[4]*Electrical Power and Machines Engineering Department, Faculty of Engineering, Tanta University, Tanta 31733, Egypt*
E-mail: gowtham.n@manipal.edu; premav.eee@bmsce.ac.in; smahajan@psu.edu.sa; dalmakhles@psu.edu.sa; mahmoud.elmorshedy@f-eng.tanta.edu.eg.
[*]*Corresponding Author*

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Abstract

Microgrids are seen as the future of reliable, sustainable and green energy source for myriad applications. The increasing dependence on microgrid also adds challenges on reliable management of power supply to vividly variant consumers, the major chunk being households coupled with an unprecedented rise in the demand for EV charging. This study aims at presenting a

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deep Long Short-Term Memory with Deep Brief Network model to reliably predict the grouped energy load and solar energy outcome in a community microgrid. A cutting-edge hybrid metaheuristic algorithm will be taken into consideration for optimizing the load dispatch of community microgrids that are connected to the grid. Three different scheduling scenarios are evaluated to establish an ideal dispatching design for a grid-linked community microgrid with solar elements and energy storage systems feeding electricity loads and charging electric vehicles. The prediction outcomes are integrated into the model to accommodate the uncertainties associated with solar energy outcome and residential energy load and EV charging to achieve a supply-demand equilibrium. The objective of the proposed model is to obtain an energy-efficient system capable of balancing the load and power of microgrid system which remains unperturbed by the aforesaid oscillations.

Keywords: Load forecasting, LSTM-DBN, RDHH, electrical vehicle, community microgrid.

1 Introduction

The need for energy and the demand for optimised power consumption has increased with technological developments, and urbanization. In recent times, there has been a revolutionary change in the structure of conventional distribution systems. The beginning of distributed energy sources as well as cutting-edge metering, interaction, and regulation innovations at the distribution system, has changed the traditional distribution networks into multi-microgrid systems that are typically quicker, more manageable, and much more reliable. There may be a wide range of electricity energy buyers in multi-microgrid systems [1, 2].

The present study is primarily concerned with how to maximise energy efficiency and grid resiliency while minimising the impact of uncertainty [2]. To ensure the hybrid system operates optimally and securely, the hybrid ac/dc microgrids EMS requires a more generalised Model of energy flow and co-ordination method [3]. To increase system stability and efficiency, electric vehicles (EVs) in microgrids may be a useful energy source [4]. To fully utilise this type of evolving electricity source, significant additional restrictions, and EV prototype are needed. Ref. [5] presents an optimization technique for flattening the load profile and shifting peak load from one time to another, considering the characteristics of the load curve, the needs for electric vehicle movement and the hourly energy cost structure. Along with reducing operating costs, the method is directly proportionate to net consumption and it also reduces overhead. On an annual basis, the strategy is extrapolated further. Coordination between the grid and EVs is required to prevent peak load times for EV market penetration to reach more than 10% [6]. A distribution system with multi-microgrids that uses a bi-level coordinated optimum energy management (OEM) paradigm. In this structure, decisions are made at two levels: the top level is handled by the distribution system operator (DSO), and the lower level is managed by the microgrids on their own. In addition, an interactive system based on a leader and several followers a dynamic game calls Stackelberg is offers to increase the usefulness of both sides [7, 8].

Contribution of this work:

- Deep LSTM with DBN (LSTM-DBN) model is created to predict the total in a community microgrids, the energy load and solar power outcome are both measured.
- Hybrid metaheuristic algorithm (Red Deer optimization and Harris Hawks optimization (RDHH)) approach that will be taken into consideration for optimising the energy community microgrid load distribution.

LSTM, DBN, and ANN are used to evaluate the RDHH-LSTM-DBN. These analyses can be performed with at least five days' worth of load data.

2 Literature

Kumar, D et al. [9] utilized the LSTM RNN to forecast solar and wind energy used to regulate load frequency in a remote microgrid. Deep learning methodology based on LSTM-RNN has been used for variable step series to series prediction of PV and wind power. With the help of memory cells in an LSTM network, this method trains, forecasts, and updates RNN states. In contrast to RNN-based forecasting, LSTM-based forecasting does not experience vanishing/exploding gradient issues. In comparison to the other reviewed techniques, The RMSE for predicting solar radiation with RNN-LSTM is also found to be extremely low. The RMSE acquired with LSTM-based wind speed forecasting is found to be the lowest among all the evaluated methods. Erenoğlu, et al. [10] used the best microgrid energy management systems considering energy storage, load management, and clean energy electricity production. Requirement versatility and ESSs can be used in combination to guarantee the autonomous energy supply in stand-alone microgrids while maintaining the level. The developed framework's primary goal is to investigate the impacts of flex source materials on the procedure of the distribution network from various perspectives. The suggested MILP model is evaluated to see if it can reduce division power loss during the energy microgrid procedure. For the purpose of minimising branch total losses and various other losses, all the aforementioned units were developed using a MILP framework. Yu, H., et al. [11] discussed to reduce electricity costs and flatten power load profiles, an integrated smart home using EV and PV technology uses a two-stage energy management strategy. This study provides a smart home energy management method that incorporates an electric car with or without solar power generation. The suggested technique allows for control over how much energy is taken in by the grid-connected EV and/or Solar panels and how much power is put into the load from the EV to guarantee that household electricity expenses are kept to a minimum and the profile of the consumer is flattened. The results demonstrate that it is possible to reduce household electricity bills while also flattening the power load profile.

Jain, R. et al. [12] studies of the forecasting's effect mistake on market characteristics is illustrated in this research by relating load forecasting to the energy market. Utilization of specifics such as cost of energy, benefit to society, and energy dissipation are subjected today's real economic assessments. This work elaborates on the impact of RES's intermittent nature on system parameters. Higher LMP based on ranking methods are used to determine the best site for RES-based distributed generation. The goal of the optimal energy management challenge is to reduce the overall cost of generating while accounting for the sun's production variance. Rao, et al. [13] utilized machine learning techniques, Day-ahead peak load predicting in urban community subsystem microgrid. To figure out the best stack predictive modelling in cluster microgrid, this paper utilizes a few machine-learning algorithms, including linear regression (quadratic), SVM, LSTM, and ANN. The efficiency of these methodologies is assessed by calculating a few variables such as RMSE, R-square, MSE, MAE, MAPE, and calculation time. This leads to the conclusion that the ANN produces accurate forecasting results. E. Harmon et al. [14] proposed an optimization methodology involving a diffusion-based algorithm which is based on quasi distributed approach with wide area internet and works on local wireless network. M. Moghimi et al. [15] proposed a communication platform for Multi-Microgrid Energy Management System with communication protocols in a hierarchical architecture. This platform has an internet of Things gateway which helps to connect multiple Microgrids. S. Yao et al. [16] proposed a

Markov decision process strategy with integrated service restoration which coordinates the scheduling of Mobile Energy Storage Systems along with resource dispatching of microgrids.

V. Suresh et al. [17] have proposed a forecasting system that is based on a deep learning model and the architecture is LSTM. This involves statistical analysis of performance over several runs and is bound to address reliability and running time issues. Y. Vilaisarn et al. [18] proposed an optimization method under resilience condition. This methodology is utilized for planning of microgrids. Y. Huang et al. [19] proposed a deep reinforcement learning (DRL) based microgrid formulation method. This method can integrate open DSS and can interact with the use of optimal control policies. Z. Zhang et al. [20] explained the bi-layer scheduling method for microgrids based on deep reinforcement learning which can accomplish the objectives economically and in an environment-friendly manner. H. H. Goh et al. [21] investigated a mechanism that was capable of enhancing the training of agents with expert interference. This mechanism was later called as multistage reward mechanism (MSRM) R. Yan et al. [22] have proposed a data-driven method for distributed frequency control of islanded microgrids based on multiagent quantum deep reinforcement learning (DRL). This method combines the conventional DRL framework with quantum machine learning. H. Cimen et al. [23] proposed a new energy disaggregation approach based on adversarial autoencoder (AAE) to create a generative model and enhance the generalization capacity. The proposed method has a probabilistic structure to handle uncertainties in unseen data. A Dridi et al. [24] proposed an innovative reinforcement learning architecture to implement distributed energy management systems for microgrids. The learning architecture is based on novel reinforcement learning and on time series prediction. Herman Zahid et al. [25] have proposed a smart energy network framework for regional microgrids to ensure self-sufficiency and energy wheeling.

Zhiping Cheng et al. [26] proposed a framework with day ahead scheduling and intraday adjustment layers. This framework is economical if the microgrid is operating for longer duration. Subrata K. Sarker et al. [27] have proposed voltage control techniques with two stage and multi objectives to enhance the stability of the hybrid microgrids over renewable energy integration. T. Narasimha Prasad et al. [28] proposed a droop control strategy with power management. In this methodology AC-DC microgrids are controlled with the use Adaptive neuro-fuzzy inference system (ANFIS) controller and Proportional Integral Derivative (PID) controllers. Zilong Zhao et al. [29] proposed a forecasting method to predict uncertainties in the microgrid.

This forecasting method is based on probability and includes statistical, and data driven algorithms. Hamidat et al. [31] Zadehbhageri et al. [32] Choja. H et al. [33] proposed improved fuzzy based control techniques and ANN based torque control techniques for doubly fed induction generators and highlighted the effectiveness of the proposed models.

3 Proposed Methodology

A deep LSTM with DBN model is created to forecast aggregated load energy and PV energy outcome in a community MICROGRID. During this time, three distinct planning situations are used to determine a perfect load-shedding prototype for an energy society MICROGRID, which involves residential energy loads, photovoltaic panels, EVs, and ESS. The predicted results are incorporated into the model to help the supply-demand balance by accounting for the uncertainty of both household energy load and solar output energy. Here, a novel hybrid metaheuristic algorithm approach will be taken into consideration for improving society's load dispatch microgrids that are connected to the grid.

3.1 Framework for Forecasting

3.1.1 Design framework

The operation status of home appliances, which is very instantaneous and volatile, is reflected in the residential power demand, making the energy demand account non-linear and transient. As an outcome, the predictive model must be capable of modeling the non-linearity and consistency of the load power characteristics, in addition to the account for the time derivative of the information. When particularly in comparison to the residential load power characteristics, the PV outcome power posts show some regularity and repeatability. However, PV wattage is influenced by the environment. More precise forecasting is needed to encourage the use of solar electricity and minimise waste.

3.2 Deep Brief Network (DBN)

DBN can be used to complete supervised learning tasks to create classification or regression models as well as unsupervised learning activities to lower the dimensionality of feature space. Figure 1 depicts the DBN structure [30]. There are no connections between the components for each layer. An RBM

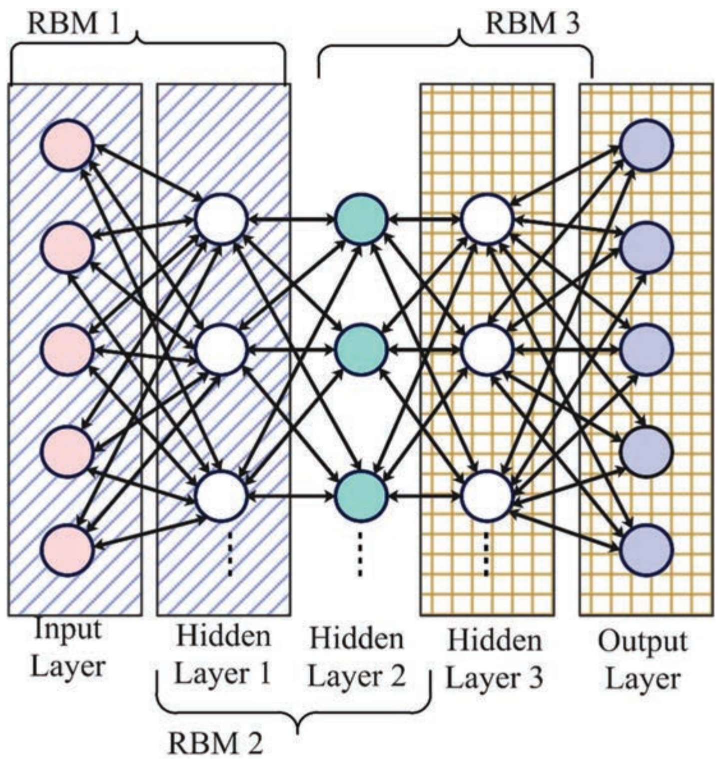

Figure 1 DBN architecture.

is a type of neural network that can learn the probabilistic model over a given data. The DBN pre-training operation considers each successive couple of strands in the MLP to be an RBM, with a joint distribution characterised as,

$$P_{\frac{H_i}{V_o}}(H_i/V_o) = \frac{1}{Z_{H_i,V_o}} * e^{(V_o{}^T W_N H_i + V_o{}^T b + a^T H_i)} \tag{1}$$

$$P_{\frac{H_i}{V_o}}(H_i/V_o) = \frac{1}{Z_{H_i,V_o}} * e^{(V_o{}^T W_N H_i + V_o - b)^T (v_o - b) + a^T H_i)} \tag{2}$$

where H_i represent the input hidden layer, V_o is the output visible layer and hidden neuron weight.

An RBM's objective is given by:

$$L(a, b, W_N) = \sum \log P_{H_i/V_o}(P_{H_i/V_o}) \tag{3}$$

According to the gradient approach, the objective function's gradients are used to update the parameters (such as a, b, and W_N). The probability distribution function's gradients can be expressed as follows:

$$\frac{P_{\frac{H_i}{V_o}}(H_i/V_o)}{\partial W_{q,p}} = \langle (V_o)_p (H_i)_p \rangle_{P_{H_i/V_o}(H_i/V_o) -} \langle (H_i)_p \; (V_o)_q \rangle_{recon} \quad (4)$$

$$\frac{P_{\frac{H_i}{V_o}}(H_i/V_o)}{\partial a_i} = \langle (V_o)_p (H_i)_p \rangle_{P_{H_i/V_o}(H_i/V_o) -} \langle (V_o)_p \rangle_{recon} \quad (5)$$

$$\frac{P_{\frac{H_i}{V_o}}(H_i/V_o)}{\partial W_{q,p}} = \langle (V_o)_p (H_i)_p \rangle_{P_{H_i/V_o}(H_i/V_o) -} \langle (H_i)_p \rangle_{recon} \quad (6)$$

where $\langle (V_o)_p (H_i)_p \rangle_{P_{H_i/V_o}(H_i/V_o)}$ is the expected actions of the conditional probability distribution in relation to the raw input data and $\langle (H_i)_p (V_o)_q \rangle_{recon}$ is the anticipated ith-step reconstruction of the distribution.

Through alternating Gibbs sampling, we may apply contrastive divergence to determine what to predict from the rebuilt distribution. Later, the modifying formulas which are applied are listed as follows:

$$(W_N)_{p+1} = (W_N)_p + \eta (\langle (V_o)_p (H_i)_p \rangle_{P_{H_i/V_o}(H_i/V_o) -} \langle (H_i)_p (V_o)_q \rangle_{recon} \quad (7)$$

$$a_{p+1} = a_p + \eta (\langle (V_o)_p (H_i)_p \rangle_{P_{\frac{H_i}{V_o}}(H_i/V_o) -} \langle (H_i)_p (V_o)_q \rangle_{recon} \quad (8)$$

$$b_{p+1} = b_p + \eta (\langle (V_o)_p (H_i)_p \rangle_{P_{\frac{H_i}{V_o}}(H_i/V_o) -} \langle (H_i)_p \; (V_o)_q \rangle_{recon} \quad (9)$$

3.3 DBN and Long Short-Term Memory (LSTM)

LSTM is an advanced, strong neural network that can analyse and predict data on a regular basis. However, in the face of increasing adaptable data sets, it is difficult for LSTM to keep the precision of prognostications solely based on the time series of a prior load. When confronted with the problem of multiple factors influencing load flow analysis, DBN was able to address the problems of the internal factors of the load being not evident and the addendum of a hidden units by using the RBM pile to officially typify the

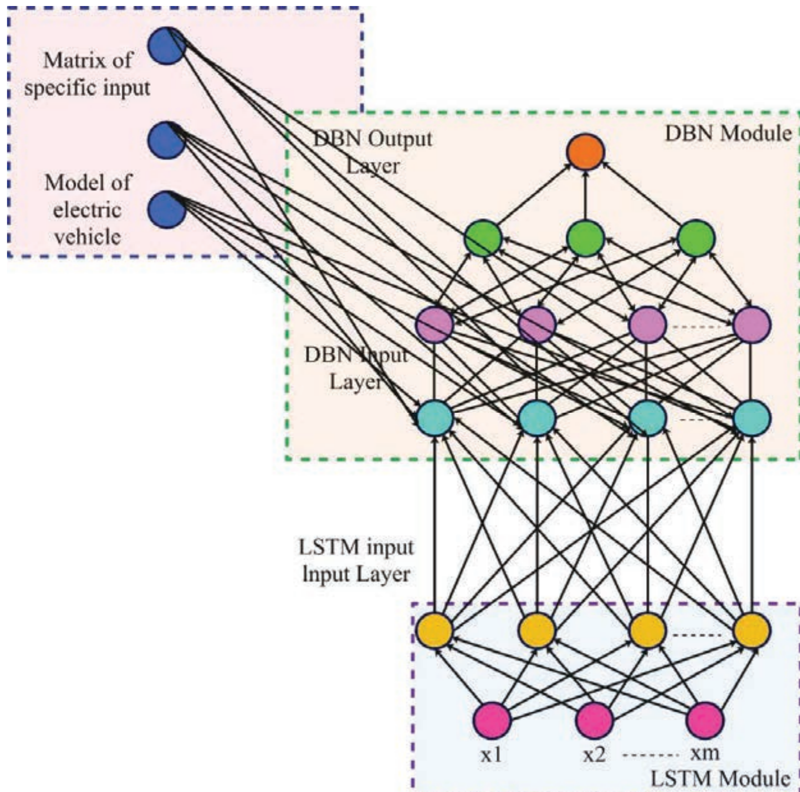

Figure 2 LSTM-DBN.

hierarchy of the connection among input and result features. For the forecasting model, LSTM and DBN are integrated to enhance the two neural network techniques. Both the processing and training of historical load data employ LSTM. The artificially filtered specific influencing factor matrix is merged with the learned output matrix with the concept function, these matrices are concatenated to create a new function. Its function is to link two parameter groups; if the object is a parameter, add the element to the array as the DBN network's input and the forecasted value as the network's output. It not only enhances the precision of the load under the impact from several complex factors, but it also quickly reveals the inherent factors of the load to improve prediction efficacy.

Data from historical load is used as the input for Because it has a higher education ability for period input, LSTM is preferred. Due to the actor's discrete and intrinsic characteristics not being clear, LSTM is not appropriate. These characteristics, such as day type and holidays, are therefore managed as distinct factors. When contemplating how EVs affect grid load, it is simple to see how climate data such as temperature, weather extremes, smog, snowfall, and so on can affect EV load factors such as daily trip range and accepted standard. The above said elements, along with former day sort as well as holidays, are designed as factors to create a particular factor input vector. Before merging with the LSTM output vector via the are together function, key aspects must be got to add to the composite information processing. The following formula should be used to normalise the continuous factors (such as weather):

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{10}$$

3.4 Optimization Model

This section created the best load shedding prototype for an energy community MICROGRID with ESS, EVs, and solar, and power loads.

3.5 Red Deer Optimization

The RD optimization algorithm is a technique for precisely reproducing the red deer's behaviour, skills, and characteristics. The RD optimization technique, like some other meta-heuristic methodologies, employs random initialising. The "male red deer" and the "hinds" are the two primary categories into which the red deer algorithm is often divided. The population's best RDs are recognised as male RDs, and the remaining RDs are supposedly referred to as hinds.

The male RD roaring engages in the first phase of the RD optimization procedure. The roaring period is divided into "stags" and "commanders" based on the roaring power. Also present were harems formed by a number of hinds, RDs roaring and fighting, and hinds in harems. The population's harems are categorised according on the male RDs' abilities, such as their strength, roaring, grace, and combat.

3.5.1 Phase 1: Initial generation

In the initial stage, an array is shaped to maximise the variable values. The "Red Deer" moniker refers to the RD array used in the RD optimization process. Assume Z is the workable option for the relevant results area in the

N VAR size optimization process conveyed in Equation (11).

$$Red_D = [X_1,\ X_2,\ z_3 \ldots X_{N_{VAR}}] \tag{11}$$

Every directional value is symbolized by X in the previous equation, and Red D represents the red deer. As a result, the associated with implementation regarding every RD is calculated in the section that follows.

$$F(Red_D) = f[X_1,\ X_2,\ z_3 \ldots X_{N_{VAR}}] \tag{12}$$

where $F(Red_D)$ is the functional value of the RD.

3.5.2 Phase 2: Male RD roaring

The process of roaring is how male RDs typically attract female RDs. The male RDs attempt to improve their grace quality as well in order to achieve the greatest possible outcome. Therefore, Equation (13) is used to update the RDs' locations.

$$male_{new} = \begin{cases} male_{old} + a_1 * (UB - LB) * a_2 + LB \\ male_{old} - a_1 * (UB - LB) * a_2 + LB \end{cases}$$

$$\begin{aligned} & male_{old} - male_{rand} - \frac{a_2}{male} + a_1(UB - LB)2a_2male_{old} \\ & \quad = (male_{old} - male_{mean}) - a_2(LB + a_3(UB - LB) \end{aligned} \tag{13}$$

It is important to make a smooth transition from exploration to exploitation. In this case, a change is anticipated between the various simulated exploitative behaviours based on the prey's escaping energy factor E, which drops sharply during the escaping behaviour. Equation computes the prey's energy (14).

$$E = 2E_o \left(1 - \frac{t}{T}\right) \tag{14}$$

The lower and upper limits of the search area are depicted by UP^L and LO^L. signifies the random values y_1, y_2, y_3 $\rightarrow$ [0, 1]. [0, 1].

3.5.3 Phase 3: Top male commanding officers' choice

One of every, in overall, man RD is different from the others because of their strength, attractiveness, etc. To determine how many commanders and stags there are overall, use the calculation below.

$$commanders\colon N_C = Round[\delta \cdot N_M] \tag{15}$$

$$Stags\colon N_S = [N_M - N_C] \tag{16}$$

where N_C, N_S and N_M is the number of male RDs, stags, and commanders, correspondingly.

δ – initial value of the RD algorithm, where $\delta \to$ [0 and 1].

3.5.4 Phase 4: Male generals and boars' fight

In order to achieve the commanding officer has two innovative solutions. and the stag fight. The mathematical formulation of two novel solutions is produced in Equation (24).

$$N^1{}_W = \left[\frac{C+2}{2}\right] + q_{r1} * [(UP_L - LO_L)]q_{r2} + LO_L] \tag{17}$$

$$N^2{}_W = \left[\frac{C+2}{2}\right] + q_{r1} * [(UP_L - LO_L)]q_{r2} + LO_L] \tag{18}$$

The two newly created solutions are denoted from the equation above as N_W^1 and $N_W^2 2$ respectively. The random values q_{r1}, $q_{r2} \to$ [0, 1] are denoted by q_{r1} and q_{r2}, respectively. A and B, respectively, stand in for the male RD stags and commanders.

3.5.5 Phase 5: Harem formation

The current hinds are proportionally divided among the commanders to create the harems. Therefore, the multitude of hinds in the n-th harem as a whole is denoted by nH_M,

$$nH_M = Round[N_p * N_H] \tag{19}$$

where N_p and N_H are normalised power and overall number of hinds.

3.5.6 Phase 6: Colonel copulating with regard to % hinds

The RMD, like other living creatures, mates with the female red deer, and this task is managed to carry by the captain based on the percentage of hinds.

$$nH^N_{M(MATING)} = Round[\delta * nH^N_M] \tag{20}$$

$nH^N_{M(MATING)}$ – mating of the commander of the nH^N_M.

The RD algorithm's starting point is denoted by the symbol δ, where [0, 1].

3.5.7 Phase 7: Colonel copulating in relation to % hinds

This stage involves the harem C being randomly chosen to mate with a certain percentage of hinds, and as a result,

$$nH^{B}_{M(MATING)} = Round[\delta * nH^{B}_{M}] \tag{21}$$

where $nH^{B}_{M(MATING)}$ is a representation of the overall number of hinds in the commander's harem at the time of mating.

3.5.8 Phase 8: Mating of a stag and a neighbouring hind

This stage involves mating a single stag with a nearby hind. Calculating the distance is important in order to identify the neighbouring hind. Hence,

$$D_J = \left[\sum_{K=k} \left(S_K - H^{J}_{N(K)}\right)^2 \right]^{0.5} \tag{22}$$

S_K and $H^{J}_{N(K)}$ – stag value & hind value.

3.5.9 Phase 9: Upcoming century choice

To choose the next generation, it is important to adhere to two different schemes. The initial plan entails asking the commanders and stags for their best practical solutions. The remaining population of the next generation is specified by the second scheme. In addition, the fitness competition or the roulette wheel mechanism are used to choose the upcoming century.

3.5.10 Phase 10: Requirements for the end

The end requirement specifies the overall number of iterations to be performed at a given time interval in order to arrive at the most optimum solutions.

3.6 EV Charging Model

Grid linkage for the neighbourhood microgrid EVs can participate in microgrid load dispatch by either charging or discharging to function as a load or a power supply. To obtain microgrids, EV must take into account their daily drivers spacing, charging time, and trying to charge load. Lognormal distribution governs the daily running distance (r_d) of EV ($\log -N(\mu_1, \sigma_1^2)$ which can be expressed as

$$F_{Distance}(r_d) = \frac{1}{\sqrt{2\pi\sigma_1 r_{d1}}} \exp\left(-\frac{(\ln r_d - \mu_1)^2}{2\sigma_1^2}\right) \tag{23}$$

Driving distance affects how often an EV needs to be charged. In this study, it was also assumed that the amount of electricity used to charge an EV was equivalent to the amount used each day. A normal distribution was used to define the last return time of an EV (i.e.t $N(\mu_2, \sigma_2^2)$. which can be formulated as

$$F_t(r_{d2}) = \begin{cases} \frac{1}{\sqrt{2\pi\sigma_2 r_{d2}}} \exp\left(-\frac{(r_{d2}+24-\mu_2)^2}{2\sigma_2^2}\right), & 0 < r_{d2} \le \mu_2 - 12 \\ \frac{1}{\sqrt{2\pi\sigma_2 r_{d2}}} \exp\left(-\frac{(r_{d2}+24-\mu_2)^2}{2\sigma_2^2}\right), & \mu_2 - 12 < r_{d2} \le 24 \end{cases} \tag{24}$$

Because the everyday beginning recharge time and EV driving range are self-reliant from one another, the Ev's load characteristics can be determined using an arbitrary test. The EV charging model is subject to some limitations, such as charge/discharge limitations and capacity restrictions.

(1) constraints on EV capacity.

$$CS_j^{mini} \le CS_j \le CS_j^{maxi} \tag{25}$$

CS_i is the CS of *CSi* *i*-th EV, displays the lesser bounds CS_j^{mini}, displays the upper limits CS_j^{maxi},

(2) EVs' capacity constraints after leaving the microgrid.

$$CS_{tj} \le CS_j^{min} \tag{26}$$

(3) Start charging restrictions of EVs.

$$P_j^{mini} \le P_j^{EV} \le P_j^{maxi} \tag{27}$$

P_j^{EV} – The j-th EV is powered by Evs or emptying.
P_j^{mini} and P_j^{maxi} – lower and upper limit.

3.7 Objective Function

EVs' action or task mode could provide peak usage movement while also lowering everyday costs. The main goal of the proposed model is to obtain an energy-efficient system. Furthermore, the suggested model can keep a microgrid system's load and power balance balanced, allowing the system to ignore a microgrid oscillation.

(1) The main power grid and microgrid's transaction costs are best described as

$$cost_1 = \sum_{t=1}^{T} |P(t)| s_t \tag{28}$$

(2) The expense of EV devaluation can be voiced as

$$cost_2 = \sum_{j=1}^{m} \left(\frac{cost_r}{E_1} \int_{t_{j1}}^{t_{j2}} |P_j^{ev}| dt \right) \tag{29}$$

(3) The ESS declining balance cost is described as continues to follow:

$$cost_3 = \sum_{k=1}^{m} \left(\frac{cost_s}{E_2} \int_{t_{k1}}^{t_{k2}} |P_k^{ess}| dt \right) \tag{30}$$

(4) The expense of removal of pollutants can be voiced as

$$cost_4 = \sum_{l=1}^{l} (cost_k - \alpha_k) \tag{31}$$

Model constraints

In this section, the model's constraints will be discussed. These constraints include those relating to the model's ability to regulate energy demand and supply the ability of the transmitting line joining the microgrid to the bigger electric grid, and the ESS's capacity and charge/discharge restrictions. Each constraint's description can be found in the section that follows.

(1) Constrained balance of supply and demand for electricity

$$T_p + T_{p_{evs}} + T_{p_{ess}} = T_{p_{load}} \tag{32}$$

T_p – Transfer of energy from the microgrid to the bigger electricity network

(2) Capacity constraints of ESS.

$$CS_k^{mini} \leq CS_k \leq CS_k^{maxi} \tag{33}$$

(3) ESS start charging constrictions.

$$T_{p_k}^{mini} \leq T_{p_k}^{EV} \leq T_{p_k}^{maxi} \tag{34}$$

(4) Transmission capacity constraints.

$$-P^{max} \leq P \leq P^{max} - T_p^{mami} \leq T_p \leq T_p{}^{mini} \tag{35}$$

4 Result and Discussion

In this section, the obtained results based on the proposed model is discussed in detail. Specifically, the energy management, load balancing, prediction-based analysis in terms of actual vs predicted, power generation-based analysis, error-based comparison such as MAE, MAPE, and RMSE, and R-Square and correlation are mainly considered for performance analysis. At last, the obtained results are tabulated and discussed as follows. Table 1 shows the energy management values for proposed RDHH-LSTM, LSTM, DBN, and RNN. Meanwhile, the proposed RDHH-LSTM model has the lowest values for all the metrics, indicating that it has the best performance among the four models. The LSTM model has relatively high MAE, MAPE, and RMSE values compared to the proposed RDHH-LSTM model, indicating that it has a lower prediction accuracy. The DBN and RNN models have even higher values for these metrics.

Table 2 shows the load balancing for proposed RDHH-LSTM, LSTM, DBN, and RNN. Further, the performance measures, such as Correlation and R-square, for the suggested and current approaches are shown in Figure 3. In addition, Figure 4 shows the demand power vs number of data output graph. RDHH-LSTM model have the best performance across all metrics, followed by LSTM, DBN and RNN in that order. The lower values of MAE, MAPE, and RMSE for RDHH-LSTM indicate that it is making less error on average.

Moreover, the performance measures, such as actual value and predicted value, for the suggested and current approaches are shown in Figure 5.

Table 1 Energy management

Items	MAE	MAPE	RMSE	Correlation	R-square
PROPOSED RDHH-LSTM	1.517652	2.396952	1.770291	0.999998	0.999996
LSTM	6.595447	3.498051	7.731174	0.999967	0.99993
DBN	9.055709	6.851737	10.94171	0.999933	0.99986
RNN	13.79479	17.05602	17.99173	0.999842	0.999621

Table 2 Load balancing

Items	MAE	MAPE	RMSE	Correlation	R-square
PROPOSED RDHH-LSTM	2.23968	0.001943	2.825832	0.999907	0.999784
LSTM	6.648418	0.005759	7.725946	0.999206	0.998383
DBN	8.743133	0.007575	10.60776	0.998563	0.996951
RNN	14.19964	0.12321	18.52855	0.996263	0.990697

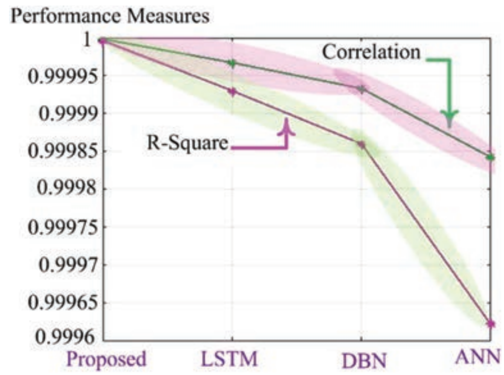

Figure 3 Comparison of correlation and R-square.

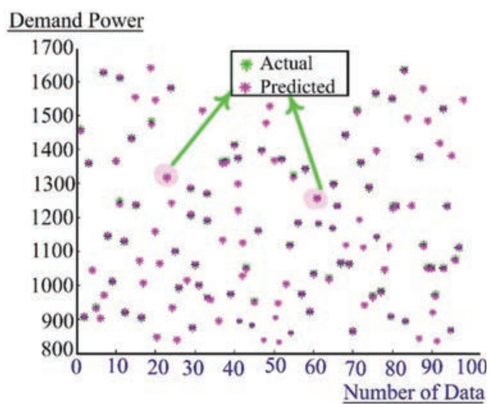

Figure 4 Comparison of actual and predicted value.

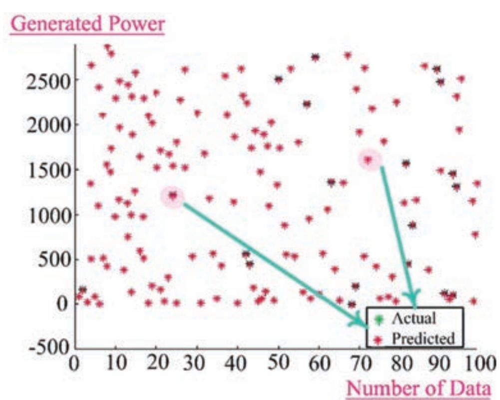

Figure 5 Generated power vs amount of data.

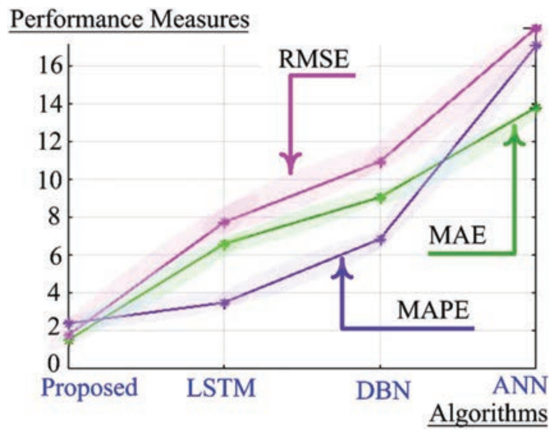

Figure 6 Comparison of MAE, MAPE, and RMSE.

Besides, the performance measures, such as MAE, MAPE, and RMSE, for the suggested and current approaches are shown in Figure 6.

5 Conclusion

A DRNN-LSTM model was suggested in this study to forecast the short-term output of PV power and the total residential power load. The DRNN-LSTM model was evaluated using two actual datasets. The DBN-LSTM model outperforms the MLP network, according to the forecasting results. Because conventional prediction models have constraints in designing complex non-linear issues and therefore can account for data time dependence, it conducted sometimes better in predicting aggregate data residences power to the load with a MAPE of 0.00195%. As a result, the proposed DBN-LSTM model enables extra exact brief forecasting to endorse proper load allocation of society microgrids. Moreover, in this article, the RDHH-LSTM-DBN is assessed alongside LSTM, DBN, and ANN to start investigating the best extremely heavy in a grid-linked community microgrid. With load data spanning at least five days, these evaluations can be performed. This article also investigated the optimal load shipment in an energy community microgrid, and the RDHH-LSTM-DBN were evaluated with LSTM, DBN, and ANN. The load shedding improvement used the predicting results of the proposed DRNN-LSTM framework to account for the uncertainty of both PV output voltage and residential power load in order to encourage interplay and stability between demand and supply. Finally, the load-shedding model was optimised using the RDHH optimization algorithm. The simulation results show that EES as well as EVs can switch peak demand, boost solar power usage, and lower daily costs. Additionally, the topic of EV charging was covered. It demonstrates how the coordinated charging mode will cause EV charging loads to shift from expensive periods to inexpensive periods, lowering overall costs and enhancing power system stability.

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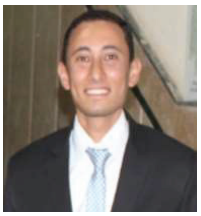
Biographies

N. Gowtham received bachelor's degree in Electrical and Electronics Engineering from the Vidyavardhaka College of Engineering, Mysuru, in 2011, M.Tech. degree in Microelectronics and Control Systems from the Dayananda Sagar College of Engineering, Bengaluru, in 2013, and Ph.D. degree in Electrical Power Quality from Visvesvaraya Technological University, Belagavi in 2020. He was a Research Fellow with IIT Delhi. He worked with Bosch Automotive Electronics, Bengaluru. Currently he is working as an Associate Professor with the Department of Electrical and Electronics Engineering, Manipal Institute of Technology, Bengaluru. He has published books and book chapters. He has authored more than 20 research papers in reputed conferences and journals. His research interests include applications of power electronics to power systems, power quality, integration of RE into LV/MV grid, and engineering education.

V. Prema was born in Thiruvananthapuram, Kerala, India. She received the B.Tech. degree in electrical engineering from Calicut University, in 2001, and the M.Tech. degree in power electronics and the Ph.D. degree in electrical engineering from Visvesvaraya Technological University, in 2005 and 2018, respectively. She has 21 years of teaching and industry experience. She is currently working as an Associate Professor with the B.M.S. College of

Engineering, Bengaluru. She has authored more than 40 papers in various journals and conferences. Her research interests include renewable energy, forecasting, and power electronics.



Mahmoud F. Elmorshedy was born in Gharbeya, Egypt, in 1989. He received the B.Sc. and M.Sc. degrees in electrical engineering from Tanta University, Egypt, in 2012 and 2016, respectively, and the Ph.D. degree in electrical engineering from the School of Electrical and Electronic Engineering, Huazhong University of Science and Technology, China, in 2020. He started working as a Teaching Assistant with the Department of Electrical Power and Machines Engineering, Faculty of Engineering, Tanta University, in 2013, where he was promoted to an Assistant Lecturer, in June 2016. He is currently working as an Assistant Professor (On academic leave) with the Department of Electrical Power and Machines Engineering, Faculty of Engineering, Tanta University. His current job is a Postdoctoral Fellow with the Renewable Energy Laboratory, College of Engineering, Prince Sultan University, Riyadh, Saudi Arabia. His research interests include linear induction motor, predictive control, power electronics, and renewable energy.

M. S. Bhaskar received the bachelor's degree in electronics and telecommunication engineering from the University of Mumbai, Mumbai, India in

2011 and a master's degree in power electronics and drives from the Vellore Institute of Technology, VIT University, India in 2014, and Ph.D. in Electrical and Electronic Engineering, University of Johannesburg, South Africa in 2019. He is with Renewable Energy Lab, Department of Communications and Networks Engineering, College of Engineering, Prince Sultan University, Riyadh, Saudi Arabia. He was a Post-Doctoral researcher with his Ph.D. tutor in the Department of Energy Technology, Aalborg University, Esbjerg, Denmark in 2019. He worked as a Researcher Assistant in the Department of Electrical Engineering, Qatar University, Doha, Qatar in 2018–2019. He worked as a Research Student with Power Quality Research Group, Department of Electrical Power Engineering, Universiti Tenaga Nasional (UNITEN), Kuala Lumpur, Malaysia in Aug/Sept 2017. He has authored 150 plus scientific papers with particular reference to DC/DC and DC/AC converter, and high gain converter, and received the Best Research Paper Awards from IEEE-GPECOM'20, IEEE-CENCON'19, IEEE-ICCPCT'14, IET-CEAT'16. He is a senior member of IEEE, IEEE Industrial Electronics, Power Electronics, Industrial Application, Robotics and Automation, Vehicular Technology Societies, Young Professionals, various IEEE Councils, and Technical Communities. He is a reviewer member of various international journals and conferences, including IEEE and IET. He received the IEEE ACCESS award "Reviewer of Month" in Jan 2019 for his valuable and thorough feedback on manuscripts, and for his quick turnaround on reviews. He is an Associate Editor of IET Power Electronics (UK), IET The Journal of Engineering (UK), Springer – Green Technology, Resilience, and Sustainability, River Publisher – Distributed generation and Alternative energy, Journal of Power and Energy Engg., Scientific Research and Topic Editor of MDPI Electronics, Switzerland.

Dhafer J. Almakhles received the B.E. degree in electrical engineering from the King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia, in 2006, and the Master's (Hons.) and Ph.D. degrees from The University of Auckland, New Zealand, in 2011 and 2016, respectively. Since 2016, he has been with Prince Sultan University, Saudi Arabia, where he is currently the Chairperson of the Communications and Networks Engineering Department and the Director of the Science and Technology Unit. He is also the Leader of the Renewable Energy Research Team and the Laboratory at Prince Sultan University. His research interests include the hardware implementation of control theory, signal processing, networked control systems, and sliding mode.