Journal of Scientific & Industrial Research
Vol. 82, February 2023, pp. 287-296
DOI: 10.56042/jsir.v82i2.70255

Industry 4.0 Based Efficient Energy Management in Microgrid

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Received 29 May 2022; revised 15 September 2022; accepted 07 October 2022

Industry 4.0 which includes new technologies such as artificial intelligence, machine learning, and the internet of things etc. has brought the revolution in the field of energy management of a microgrid. Energy management is the backbone of a microgrid that needs to be controlled efficiently for a low system failure. There are a lot of issues, such as the intermittent nature of generation, proper voltage distribution, and harmonics, which may arise while implementing an energy management for a microgrid. Machine learning establishes the core of industry 4.0 and is one of the best-suited methods to mitigate such challenges in the current industry 4.0 scenario. In this paper, a Back Propagation Neural Network (BPNN) based machine learning approach is applied for forecasting of a photovoltaic (PV) generation in a microgrid to deal with its intermittent nature for efficient energy management. Further, a firefly optimization technique is utilized to mitigate the harmonics in the voltage. This model is implemented on a real dataset of a solar power plant in Delhi, India. The proposed approach achieves the results of high precision, recall, and accuracy, which shows the efficiency of the system to monitor and regulate uncertainties in the PV microgrid systems.

Keywords: BPN, Distributed power resources, Energy management, Machine learning

Introduction

A microgrid is a mid-scale and limited energy structure that can separate from the outdated utility grid and run independently. The capability to keep working formerly means a microgrid structure can work as an emergency power backup system to repair the grids that lead to extensive power failures. Without any huge structure to preserve or restore, a microgrid is effectually toughened against tornados or natural tragedies.[1] The strong point about microgrids is that they can easily integrate various dispersed power resources into the network, which are clean sources in terms of energy. Since the power at multiple places varies with weather conditions, it's suitable to attract influence when they are present and in that condition when they are absent.[2] The efficient features of backup and stability help the microgrid system stable to provide reliable resources.[3] The protection of the microgrid system is very difficult for system maintenance, and it must be created within the microgrid systems. The microgrid system's challenging situation is short circuits that must be controlled for the different operations.[4,5]

The major changes and transitions in manufacturing and industrial process with new innovative technology are the main reason for the industrial revolution. The 1st industrial revolution began in 1784, using machines powered by water and steam. The 2nd industrial revolution began in 1870 by discovering electricity and steel production. The 3rd industrial revolution started in 1969 by finding electronic automation computers.[6] The new technologies are currently implemented in the 4th industrial revolution by discovering cyber-physical systems that connect the real world with the virtual digital world. Industry 4.0 is a new phase in the industrial revolution that introduce intelligent networking of machines for an industry with the help of information and communication technology. Machine learning is a new technology that establishes the core of industry 4.0. Several machine learning-related techniques play a significant role in an efficient energy management system.[7]

Currently, research is going on in energy level management and efficient resource generation. In PV-based microgrid systems, the distribution of the load is a critical task in managing the resources. Most of the research is done in controlling the microgrid system's activities.[8] Still, very little work is done in the forecasting process using predictive modeling, which can provide future solutions for the optimum power quality distribution process.[9] A microgrid structure provides various generation sources that deal

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with electricity, warming, and freezing conditions to the end-user. These bases are separated into two major sets, i.e., thermal energy sources, which include heat and power generators, and renewable generation units, such as solar turbines.[10]

Microgrid systems have different components like consumption, energy storage, and common coupling point. In this system, consumption deals with the elements that use electricity, warm and cooling elements ranging from a single procedure to the illumination and buildings systems, commercial areas, etc. Electricity depletion can be improved in well-regulated loads according to the system's difficulties.[11] It contains energy-storing components that can accomplish multiple purposes, such as confirming power value, including occurrence and voltage instruction, smoothing the productivity of renewable power components, providing backup control for the arrangement, and playing an essential role in optimization of the cost and building blocks.[12] It contains all electrical, density, gravitational, and heat storage expertise. When several residual energies with various measurements are accessible in a microgrid system which is preferred to organize their charging and discharging phases such that reduced power storage does not release faster than larger measurements. This can be accomplished under a synchronized control of power storage centered on their charging state.[13] If various power storage structures based on different technologies are recycled, they are measured by an exclusive controlling unit that can be well known by the energy management system and ordered controlled architecture, ensuring the best operations in the emergency phase.[14] Common coupling points are the main grid connection points that are the backbone of the microgrid systems. The system of a microgrid that is not connected or having a coupling point is known as isolated microgrids, which regularly exist in remote communications where there is no feasibility in the interconnection of the main grid because of some constraints related to technical aspects.[15]

Problem Statement

The improvement in microgrid systems is a never-ending process. There are some power management problems in the microgrid systems that need continuous enhancements in the system. The power equipment connected to the microgrid systems can cause grid failure at any time due to heavy voltage harmonics. Microgrids are not available to back up the system during grid failures which can cause unnecessary complexities in the system. Also, the power-sharing capability is a complex situation in these systems due to some transitions in the energy levels during the forecasting process. So that's where the machine learning models are required, which gives necessary facilities during a grid down situation. Also, the power network security issue is not yet resolved in the microgrid systems, which can reduce the synchronization capabilities among the Distributed Generators (DG's) to provide the optimum power level at the target locations. So still, efficient predictive modeling is required to predict the energy levels for the industrial revolution.[16] The proposed approach will solve the problems of efficient modeling of the system and reduce the uncertainties in the forecasting process of the microgrid systems for the industrial revolution.

Related Work

This section covers the valuable research done in the microgrid forecasting processes for the industrial revolution. It will give good insights into the state-of-the-art research for the effective modeling of microgrid systems. Nowadays, the energy market is unbalanced due to the demand and flexibility in energy supply. However, precise prediction and demand scheduling are the biggest challenges in the energy management system. For efficient energy management, the significant features of data series in terms of load using neural processes are used to obtain a group of relevant features. These features are analyzed using the electricity data demand of an active microgrid system in China.[17] Then, the typical energy management methods functional to the microgrid, with centralized mechanism, decentralized controller, and distributed schemes, were applied.[18] Various energy management approaches have been proposed in the past to facilitate the finest and economically controlled energy flows using microgrid networks. These approaches are carefully supervised for the flow of power by estimating renewable energy generation processes, the accessibility of energy at storage sequences, and raising the appropriate method of operation. This makes the procedure efficient and economical.[19] For efficient energy management, a network based on the IEEE bus distribution arrangement involves wind energy system generation, photovoltaic system, and energy storage arrangement connected with countless loads. Moreover, the optimization algorithms are used to minimize the loss of power, improve the system's voltages, and optimize various distributions under the worst production condition when there is a high electricity demand.[20,21] For improving worst production conditions, steady power supplies are used to control the voltage supplies in the microgrids. The other solution is the management of the loads and a stable action by converting a voltage-controlled unit at the main grid. These solutions shows that the microgrids can function stably during grid failures.[22] For the distributed energy controlling actions in microgrid system's various optimized models have been used in the past. The suppliers and users of power are modeled as independent agents, capable of assembling local load to make the most of their profit in a microgrid atmosphere. For each merchant, an absence of data on traders and other merchants creates experiments for the best decision-making for their return maximization.[23,24]

Research Gap

After reviewing the related works based on various works done in the PV microgrid scheduling and modeling of the microgrid systems, there are still research gaps in the ongoing scenarios of the development of microgrids. Various works are done on energy management, but these issues still arise due to the stochastic nature of the distribution process and the risk of grid silence. Also, the forecasting model is not so accurate to enhance the dynamic responses of the microgrids. These forecasting models will help achieve the optimum power forecasting and generation of the loads. So, these need to be adequately trained using automation and error-free computations. So, the proposed work puts light on a similar process to enhance the power forecasting model to increase the system efficiency of the microgrid power systems. This paper introduces a hybrid intelligent technique to minimize the forecasting error and energy consumption for industrial revolution. This paper deals with the microgrid energy management issues to reduce forecasting errors and energy consumption.

Materials and Methods

Proposed Work

The proposed work consists of the optimization and supervised machine learning prediction model to efficiently use renewable energy sources in microgrid systems. The harmonic mitigation is done using a hybrid combination of the static VAR compensator and firefly swarm optimization. Then the backpropagation neural network is used to efficiently train the system to predict the energy levels. The energy levels are considered the main source because it is the main resource to be given to the target location when the demand increases.

Dataset

The dataset taken is the real energy generation dataset from the microgrid plant, Delhi, India, from January 2020 to December 2021, on which the processing is done, and the model is trained. It is the time-series data of the energy generation based on hourly temporal resolution, which are trained on 70% of the whole data and 30% of the test data. The 70% is trained using BPNN, and 30%, is considered as unknown data and used for predicting the energy levels based on which the future energy levels will be controlled. The two years of data records is used which are sufficient to test the model.

Specifications Initializations & Deployment

After dataset configurations, the next step is to initialize the configurations of the DG's and the intermediate nodes used for the resource passing elements to the target locations. This is to be configured properly because the whole processing will be done on their evaluated power levels.

Static VAR Compensator & Optimization

A static VAR compensator is a process of the controlled reactor of parallel combination and immovable shunt capacitor. The thyristor switch is the significant component that is used in the SVC as a reactor controller. The thyristor is the device used as the control unit through which the voltage uses an inductor and the flowing current uses the inductor device. The reactive power using the inductor can be measured. So, it is capable of more negligible modification of reactive power without any delay in time intervals. So overall, system stability is improved using this process, and the system power factor is stabilized in the proposed system. So, it used the arrangements in the proposed system such as: Thyristor controlled reactor, Thyristor-switched capacitor, Self reactor, Thyristor controlled fixed capacitor, Thyristor switched reactor.

After applying the static VAR compensator process, the population is created using a static VAR compensator, which controls the load distribution process and reduces the harmonics on the proposed model. The optimization is done using several iterations that evaluate the best possible solutions in terms of harmonic reductions, which reduces the unnecessary voltage hikes in the system.

Model Training and Validation

This is the very significant and last process of our proposed system. It is the supervised learning approach using a feedback process to reduce the training errors, which helps reduce the classification loss in terms of cross-entropy. If the entropy increases, the disorder also increases, which must be reduced for a stable system. The BPNN is used for the proposed work because it is having a high response and reaction time and is fast in decision making and information passing using the sigmoid activation function. By doing this, BPNN performs the fine-tuning process of weight updations. The Fig. 1 shows the BPNN network along with connected weights and inputs. The loss errors are evaluated as Eq. (1):

$$L_{errors} = A(x) - P(x) \qquad \ldots (1)$$

where, A(x) is the actual output and P(x) is the predicted output. Using the above process, the variance among the data points can also be estimated. The overall network is the collaboration of the function compositions and multiplication of the matrix stated in Eq. (2).

$$P(x) = f\{L\}(W\{L\}f\{L-1(W\{L-1f\{1(W\{1\}x)))\} \qquad \ldots (2)$$

where, P(x) is the predicted output and W(x) is the weight which is used as the connection unit with the other neurons of hidden layers, output layers and f are the function compositions.

Proposed Methodology Flow

The proposed work shows the efficient regulation of the energy prediction model using machine learning and optimization scenarios-based industry 4.0. The various characteristics of the model can be controlled by fine-tuning for better performance. Firstly, the specifications will be initialized for the microgrid environments then the deployment of the nodes and DG's are evaluated. In the proposed approach, the PV source is considered as the plant, which is an energy or power generation unit. After deployment, the harmonics or voltage analysis is done, which is a crucial part of the proposed work. After that energy consumption scenario is regulated through the performance of the output powers of the DG's can be estimated. After that static var compensator is used to control the overload and harmonics in the microgrid systems. Once it is done, the next step is to perform the optimization scenario, which is done using the swarm intelligence approach, i.e., firefly optimization, which manages the distribution of the load among the components of the microgrid system. Then back propagation neural network is evaluated for the self-learning supervised modeling, which reduces the distortions and harmonics, which is an important step in the training of the system. The main concentration that needs to be given in the training process is the overfit and underfit of the model, which needs to be taken care of

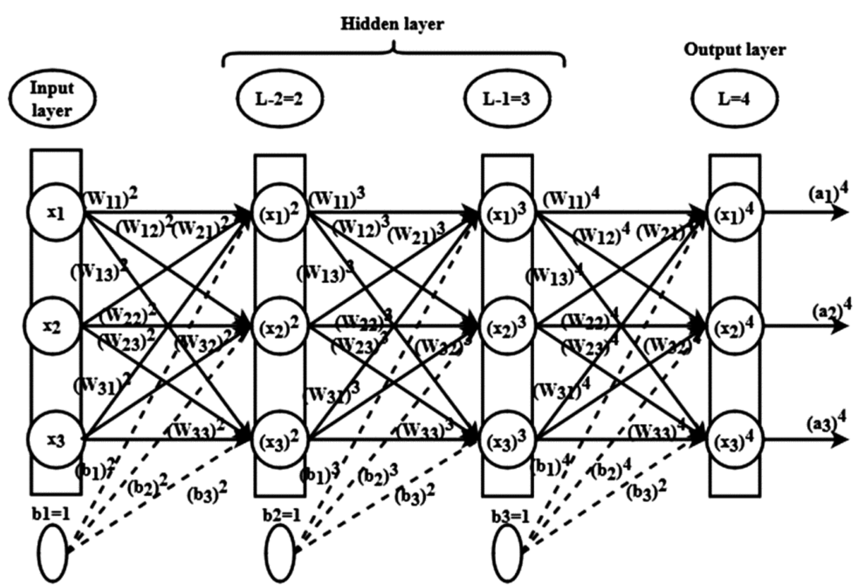

Fig. 1 — Back propagation neural process, with connected weights and inputs

using regularization processes. Once the model training is completed, the prediction on the energy levels based on the past data and training process is evaluated, giving high true positive and true negative rates. The proposed workflow block diagram is shown in Fig. 2, and the specification of the system requirements are presented in Table 1.

Proposed Algorithm

Step 1: Initialize the specifications of the microgrid systems, such as: MaxV(x), MinV(x), MaxP(x), MinP(x), V_g, PowR(x). Where MaxV(x), MinV(x) is the maximum and minimum voltage levels of the DGs, and MaxP(x), MinP(x) is the maximum & minimum power of the DG's and V_g is the voltage gain, and PowR(x) is the power reactance in the KW.

Step 2: Input T(x) such that T= T_1, T_2…….T_N as training data and generate the data framing for the processing.

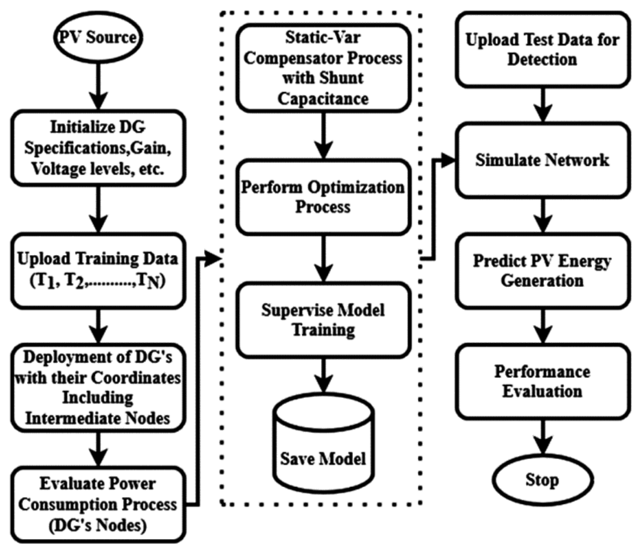

Fig. 2 — Proposed flow diagram

Table 1 — System requirements

Parameters	Values
DG voltage	10 KV
DG power	150 KW
Number of DGs	5
Power reactance	750 KV
Energy	0–1000 Joules
Min. phase voltage	10V
Max. phase voltage	50V
Hourly sessions	24
Training epochs	100
Number of hidden neurons	5–10
Simulator	MATLAB

Step 3: Deploy the DG's such that,fori=1 to N. DG(x)Such that

$$DG(x) = DG_1, DG_2, \ldots\ldots..DG_N \quad \ldots (3)$$

where N is total number of DG's.

Step 4: Evaluate the DG'senergies.So each has homogeneous energies initially.

For i = 1 to N

$$DGE(x) = E(n) \quad \ldots (4)$$

Step 5: EvaluateDGPow(x) &NPow(x)

$$DGPow(x) = Pow(n) \text{ € } MaxV(x) \& MinV(x) \quad \ldots (5)$$

$$NPow(x) = Pow(N(x)) \text{ € } MaxP(x) \& MinP(x) \quad \ldots (6)$$

Step 6: Perform the static var compensation process to regulate the voltage levels and process tuning. i.e.,

$$SV(x) = SVFunc\{DGPow(x), NPow(x), DGE(x), Vg, PowR(x), T(x)\} \quad \ldots (7)$$

Step 7: Perform an optimization scenario to optimize the microgrid system performance to evaluate the system's performance. While (CurrIter(p) < MG(g)i.e., Maximum generation & for all instances.

If({INT{np} > INT{jp}}). Vary T(x) i.e., holding to R(d) € D(s) i.e., distance move T(x) from np to jp ;

Estimate T(n) and update INT(x).

end if

Best fit instances selections.

End While

Step 8: Implement the train-test splitting process

N_D = {T(N_x)}, where 70%→ training data and 30%→test data & generate a training model.

Step 9: Initialize the BPNN model to perform convolutions.

$$T(errors) = Act(x)-Pred(x) \quad \ldots (8)$$

where, Act(x)→ actual output and Pred(x)→ is the predicted output.

The resultant training and prediction outcome is the association of the process's functional structures and feedbacking process and is given below.

$$Pred(x) = func\{g\}(W\{g\}func\{g-1\}(W\{g-1\} func\{1\}(W\{1\}(x)))) \quad \ldots (9)$$

where, Pred(x)→ predicted output and W(x)→ weight as connection unit among hidden layers and output layers and functions. Function compositions and fit transform produce the configuration feedback model with updated weights.

Step 10: Upload Test data

$$T_S = \{T_{S1}, T_{S2}, T_{S3}, T_{S4} \ldots T_{SN}\} \quad \ldots (10)$$

Step 11: Load the trained model and perform classification on T_{SN}.

Step12: Evaluate the performance of the proposed model in terms of precision, recall & accuracy rate.

Results and Discussion

This section covers the proposed work implementation and related studies which used machine learning approaches for energy management. The proposed work is evaluated using a MATLAB environment. The MATLAB simulator is used because it is well suited for analyzing complex procedures and having huge instruction set to overcome the problems of the computations of the complex problems. The result of the proposed approach and the comparative studies of related works are discussed below.

The main contribution of related studies is summarised in Table 2, which includes energy management related issues based on different categories and applications. Deep learning and machine learning approaches are discussed, which are used for residential and commercial purposes and reduce the cost by 14% compared to other techniques.[25,26] The neural network and time series techniques are used for energy consumption and demand forecasting for residential and commercial applications.[27,28] The energy forecasting related issues are highlighted for efficient energy management.[29–31] As best of my knowledge, the related studies are not discussed the evaluation criteria, which is an essential factor in finding the best fit model in the case of energy forecasting. The proposed work has discussed the evaluation criteria for precision, recall, and accuracy.

The distributed generator microgrid environment generation in which the distributed generators are deployed, which are energy generation units are presented in Fig. 3. Distributed generators are the units through which power or energy will be transmitted in the distributed environments. The black colour nodes are also deployed, which acts as a medium for transferring the power through nodes located at different x-locations and y-locations. The intermediate nodes are deployed to have smooth transmission among the DG's to the target locations because DG's are responsible units for transmitting the power or energy at larger distances. The target locations can be the buildings, receiving power units, base stations, residential areas, etc.

The voltage harmonics analysis, which is responsible for generating the distortions in the microgrid systems is shown in Fig. 4. It can be estimated how much overloading and underloading of the voltages concerning the generated power is taking place. This is one of the significant steps of the analysis on the deployed system because if it's not properly done or evaluated, then it will be very difficult to maintain the voltage levels in the microgrid systems. The control of the voltage harmonics is a crucial part of power generation units in the power systems, which need to be controlled or scheduled efficiently.

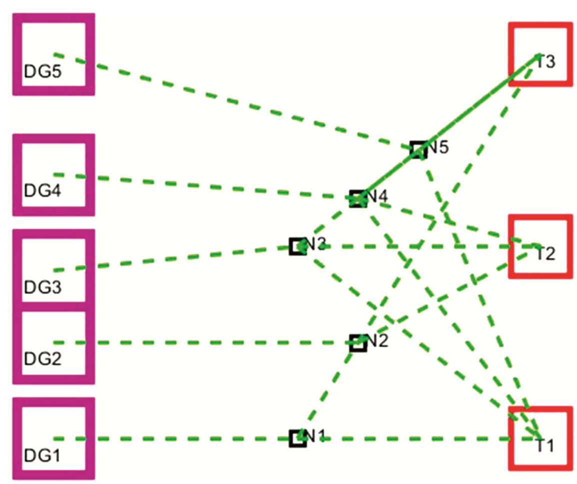

Fig. 3 — Distributed simulation scenario

Table 2 — Related studies which used machine learning approaches for energy management

Forecasted Model[Ref]	Objective	Applications	Year
Deep reinforcement learning[25]	Hybrid energy management	Commercial	2021
Deep learning[26]	energy management	Residential	2021
Neural Network[27]	Forecast the energy consumption	Residential	2020
Time series approaches[28]	Energy demand forecasted	Commercial	2020
Deep neural network[29]	Load forecasting	Residential	2019
Hybrid Model[30]	Energy management	Microgrid	2019
Ensemble learning model[31]	Energy demand forecasting	Residential	2019

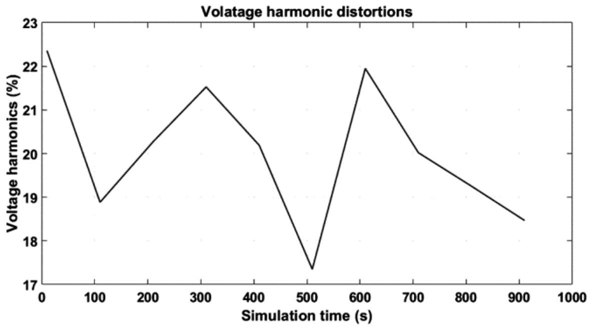

Fig. 4 — Voltageharmonics

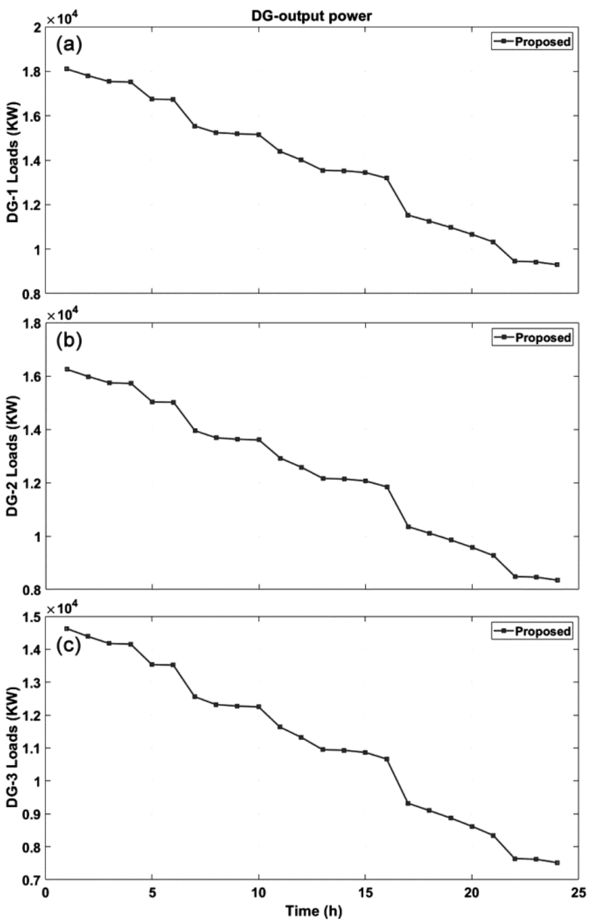

Fig. 5 — DG's output power

The DG's output power which is evaluated in the proposed work is presented in Fig. 5. It's a significant parameter which shows how much power one DG is generating and what should be the amount of power that needs to be distributed among the DG's. It can be seen that the DG output power is near about the same for all distributed generators, which shows the precision of the generation of the powers. Through this significant parameter, it can be estimated that the fuel costing and complexities of the output

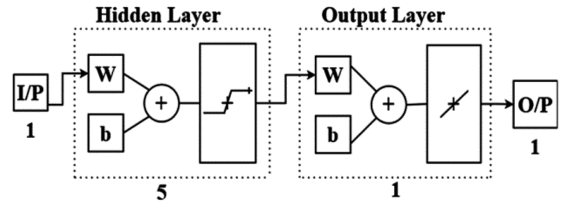

Fig. 6 — BPNN training model

Table 3 — Training performance

Unit	Starting value	Stopped value	Target value
Epoch	0	100	100
Time	—	0:00:02	—
Performance	4.81e + 03	0.253	0.0100
Gradient	1.25e + 04	4.25	1.00e-07
Mu	0.00100	0.00100	1.00e + 10
Validation checks	0	0	6

power of the DG are maintained because DG is a complex structure of the microgrid systems, and it consumes power to generate resources to the target locations.

The backpropagation training process is the prediction model shown in Fig. 6. The back propagation feedback process is used in the proposed approach, which trains the network and increases the validation process to achieve low losses and training errors. Also, the BPNN model has a high response and reaction time, which increases the execution time to compute the model based on the training set and the layers generated in the BPNN. It's a neural structure in which the data based on energy levels needs to be predicted for the time series predictions of the energy levels. By doing this, the energy levels for the microgrid systems can be maintained. They can be changed as per the requirement based on the trained data, which is well known by supervising learning process with low classification error rates. The training performance of the BPNN model is shown in Table 3. Training of the data has been done by selecting the input parameters.

When the current or voltage moves from one source to another, the standard deviation in the microgrid energy management system is shown in Fig. 7. This is another case among the DG's in the microgrid structures that when the load deviates from a lower value to the larger value, then the load is distributed among the components of the microgrid systems. It can be seen from the above figure that the deviation among the load is decreasing which shows that the proposed system can generate distributed load so that there will no fluctuations which results in low

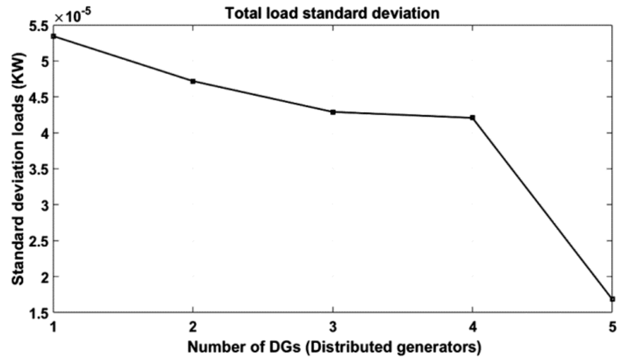

Fig. 7 — Load deviation

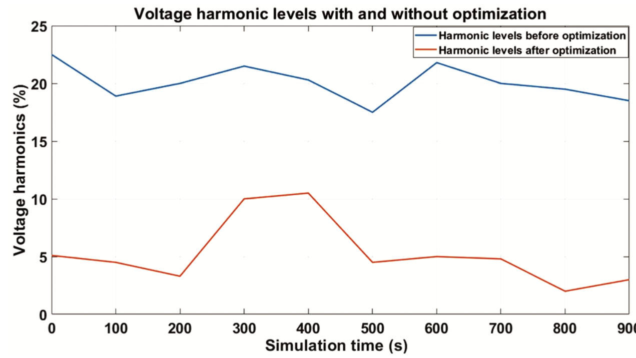

Fig. 9 — Harmonics levels before and after optimization

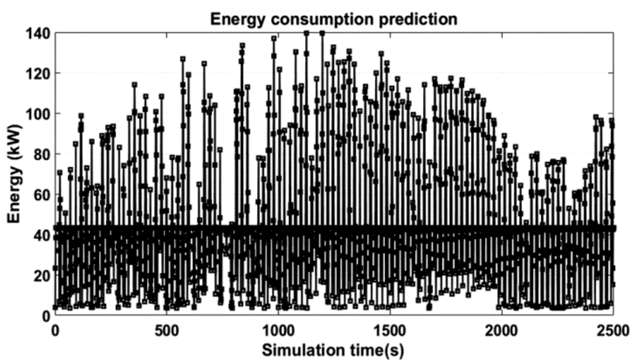

Fig. 8 — Energy generation prediction

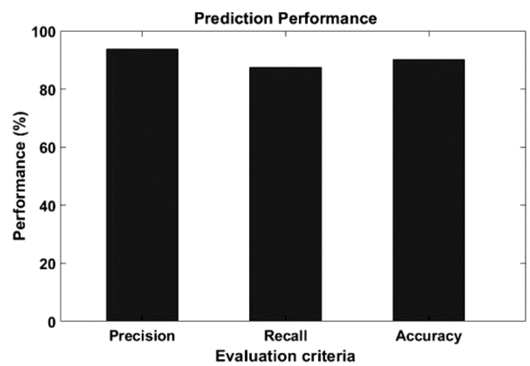

Fig. 10 — Performance evaluations

harmonics and distortions. This will also maintain the energy levels in the microgrid systems.

The predicted energy levels from the PV microgrid systems can be seen from Fig. 8. These energy levels are predicted on real-time data from power plant data. Firstly, the data is normalized and split into 70% of the training data and 30% of the test data. Then 70% of data is trained using optimization and BPNN trained model, and then predictions are performed on the 30% test data through which the energy levels are predicted. The BPNN is organized in the form of layers from the input layer to the hidden layer and then hidden to the output layer. Then the updations are done in MATLAB in an iterative manner, generating the feedback looping, and the performance is evaluated on the updated weights data. In this manner, it will reduce the loss functions, which are a cross-entropy loss. The cross-entropy loss is the disorder performance during the training and testing phase.

The comparison between voltage harmonics levels before and after optimization is shown in Fig. 9. Reduction in the harmonics can cause uncertainties in the microgrid systems. It's one of the crucial steps in scheduling and forecasting energy levels. It can be seen from Fig. 9 that the harmonics reductions are reaching 3% approx., which is evaluated after optimization from 17% approx., which is before optimization and can be analysed easily. This is a significant step in the distribution and scheduling process through which resource levels can be managed and controlled efficiently.

The performance evaluations of the proposed work are shown in Fig. 10, which is measured in terms of precision, recall, and accuracy. It can be noticed that the proposed model achieves high precision, recall, and accuracy. These performance parameters must be high for accurate predictions because the sensitivity and specificity model are completely dependent on them. The precision shows that how precise and positive predictive, and if the positive predictions are high, then the model predictions among the energy levels based on the training of the data will also be high. The recall shows the fraction of relevancy as compared to the relevant data which is already present, which also must be high for high-performance evaluations. This also shows that the predicted results through our proposed model are true positives and true negatives. If the precision and recall of the prediction are high, then the model's accuracy also increases, which is our desired output. So, accuracy shows that the proposed model is achieving high true positives and true negatives concerning the low false positives and false negatives.

Conclusions

In the proposed work, the PV modeling is done using an optimization and machine learning approach based on industry 4.0. As a microgrid system is a huge and complex structure for energy generation and resources, it is essential to control the uncontrolled voltages in terms of harmonics for the energy level generations, which needs an optimization process. Flexible operational management is a crucial part of the microgrid systems, which help balance the load among various resources and generate bulk power systems. It also helps in the forecasting process of energy levels. So, the proposed work is well suited for achieving good and appropriate results in optimizing the microgrid systems and also reduces the forecasting load losses by training the backpropagation neural network. This will produce a supervised energy management model based on industry 4.0 for the microgrid systems to make good implementation on the energy-based renewable resources. The future scope of our proposed work can be the implementation based on deep learning methods such as CNN and GAN networks. This can increase more feasibility of our proposed systems.

Nomenclature

A(x)	Actual output
BPNN	Backpropagation neural network
CNN	Convolution network
DG's	Distributed generators
F	Function compositions
G(x)	Predicted output
GAN	Generative adversarial network
L_{errors}	Loss errors
MaxP(x)	Maximum power
MaxV(x)	Maximum voltage
MinP(x)	Minimum power
MinV(x)	Minimum voltage
Mu	Momentum update
P(x)	Predicted output
PowR(x)	Power reactance
PV	Photovoltaic
SVC	Static var compensator
V_g	Voltage gain
VAR	*Volt ampere reactive*
T(x)	Training data
W(x)	Weight

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