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Applying Machine Learning to Enhancement the Level Energy-Based Smart Grid by the Renewable Environment

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Abstract: Beneficent the power grid (PG) of the electrical system and solar freightage rectifiers stay a confront. We intend to suggest the optimal design of the intelligent system with a smart grid for the efficient operation of the energy management system. This design is based on an interactive combination of machine learning with robust neural networks and control circuits. The best parameters of power grid and robust control are determined via optimization, where NN is tuned using genetic algorithm to achieve the optimal solution. Neural Network is used to enhance the robust control parameters for designing NN of the Machine learning system. The entire scheme is further tuned by hybrid energy parameters under various operating conditions to improve the power grid management performance in terms of charging and rectifying. Performing the proposed analog-implemented energy management controller is evaluated by interfacing it with a hardware prototype experimental application of dual photovoltaic (PV) system.

Keyword: Machine Learning, Smart Grid, Energy Level, RBF-ANN.

I. INTRODUCTION

1.1 Background

Recently, microgrid systems have shown promise to integrate multiple distributed systems based on renewable energy sources. Due to the arbitrary properties of energy sources such as wind energy and solar energy, the electrical properties of renewable energy sources are arbitrary, irregular and unreliable. It is attractive to integrate local production on the grid, but there are many existing and renewable energy sources. Planning Challenges, In addition, most electricity generation depends on the weather, so energy storage systems and/or emergency power-generation systems are an important part of small networks. Proper design and design is the first step in combined power. Optimization technology is a reasonable investment in energy management systems, providing economical and stable use of resources.

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Extensive research in the published literature shows that mathematical methods (such as evolutionary algorithms, inference, and non-classical algorithms) give better results than other traditional methods. By combining smart optimization algorithms the look like machine learning with adaptive technologies, optimization problems can be sought from several angles.

1.2 Machine Learning

Prediction | The various subfields were established during the forecast period. The problem of estimating energy demand can be a nonlinear time series. As the prediction continues, different subdomains are created. Due to some complex factors, the energy collection estimation problem can be an invisible estimation problem because it requires several aggregations and a high level of accuracy. To solve this problem, various time series and machine learning methods are presented in the literature. With developing neural network prediction methods, reinforcement learning technology is expected to increase the accuracy of random prediction and provide bi-directional communication between neurons.

Based on data, we have examined and expanded forecast monitoring methods and improved the use of energy estimation methods in uncertain structures. *Supervised energy prediction | We propose three new deep learning methods for supervised energy prediction. Overall, the thesis details the mathematical derivation of the proposed learning methods and a comparison with state-ofthe-art methods for energy prediction, such as artificial neural networks, recurrent neural networks, support vector machine, hidden Markov models and persistence method.

The methods are tested under different time horizons using various resolutions. Two datasets are used to validate our proposed methods at the building level, while another dataset collected to use to analyze the prediction accuracy at the aggregated level. Optimization | In the second part the potential benefits of strategic optimization at the building and aggregated level are proposed. The study is based on the assumption that optimal resource allocation for end-user models based on the daily profile of intelligent electrical devices is easily suitable for future energy models and variable sources such as wind and sun and meets these requirements. You can use important information to encourage comments. And requirements management software. Expect that you can solve the cost-saving problem to get a real-time response.

Besides this, there are major benefits of energy management system by machine learning for microgrid devices listed below: Increasing the ability to control energy production and transmission in modern methods. Provide voltage support along the line. Provides interactive power compensation in the speakers and when receiving the end of the line. Enhanced dynamic stability and stable state of system connections. An improvement in the power factor.

1.3.1 Microgrid:

Technically speaking, a microgrid is a low voltage distribution network located underneath the distribution station via a point of common coupling (PCC). Microgrids have many components, including Distributed Generators (DG), Distributed Energy Storage Device (DES), and controlled loads. The unique properties and dynamics of microgrid components pose unique challenges for the management and operation of networks. Depending on the type and degree of intrusion of the distributed energy resources (DER) and DES nodes into a particular microgrid, the required energy management plan can differ significantly from existing power supply systems. A typical microgrid works in two modes..[1]

In terms of power and energy, the network increasingly uses microgrid, but there is no single definition of how microgrid are identified and how to differentiate between microgrid. Unlike other conditions, such as open or microgrid, as the microgrid system becomes more complex parts of our global power systems, the need for general settings becomes increasingly important**.** In addition, we can divide microgrid into four main categories, depending on different criteria. The two most important criteria are: (1) when a microgrid is connected to a large network and (2) the output power that can transmit another important difference is the type and size of distribution in microgrids. However, many options are available, making it difficult to agree on criteria.

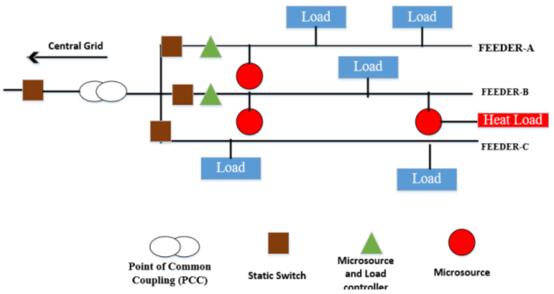

Figure 1 structureof Microgrid

Scales can be an important criterion. However, this is an ongoing process and there are many ways to consider it. Different standards can clearly distinguish between different size systems.

Finally, control is a potential difference and is manifested: In the past, standard keyboard products have been used to connect and disconnect large networks. Parallel Control Generator In various locations most of the remaining controls relate to pregnancy management. This is a very important question. However, with many options available, classification is difficult. The difference between dimensions (large or small) and network connections (connected or remote) leads to four types of microgrids that require further classification.

Microgrids connected to large networks such as military bases and large campus applications connected to traditional public services. However, they can operate in island mode. They have many generators and can have many complex deployments and controls on a microgrid.

A microgrid has only one generator set connected to the network. Usually, microgrids are in developing countries where networks are unreliable and often use unnecessary generators. It is not clearly distributed across the network. There may be other boot controls and other controls, but they start manually. Many people may not think about these microgrids. However, there are many other microgrids.

The smallest and most remote microgrid (e.g., island providers) has many generators and they are widely used. It can detect the smallest microgrid usually not the smallest generator. Elevator adapters should not be available to sell small items that can DC distributes. Billing innovations and payment methods can increase the workload of this microgrid.[2]

1.3.2 Energy Management System:

If there is more than one power source in the microgrid, the EMS must effectively control the flow of energy through the system. Ideally, EMS wants to maximize the consumption of renewable energy, minimize ESS loads, reduce energy costs, ensure the stability and reliability of the system, and distribute the loads in all situations.[3]. EMS can be implemented using a conventional rule-based strategy or an intelligent strategy, which is usually based on optimization algorithms. However, EMS, which works well for certain micro-networks, might not be optimized for other configurations. In addition, it is widely recognized that EMS can control the flow of energy within the system, depending on the objectives and criteria set by the users. This section explains some of the suggested EMS methods for different microgrid configurations[4].

Renewable energy microgrid is an effective method for the supply and demand ratio (SDR), especially when it has an energy store [5]. The main mission of EMS, which is composite as an ingredient of the Energy Storage System (ESS), is to improve ESS performance taking into account system limitations (including power consumption). "Taking into account many factors such as energy, energy consumption, and production as well as economic costs, network stability, battery status, or a combination of these goals." The term "economic cost" refers to production, including conversion, storage, import and export, total freight and energy costs, all energy consumption, and demand for a microgrid.[6]. The most widely accepted methods for successful EMS work with such objectives are rule-based regulation [7] and mathematical control based on the optimization associated with the model[5].

II. RESULT AND DESICCATION

For RBF-ANN, a fuzzy controller of the Sugeno type of first order with linear rules was used, the block diagram of which is shown in Fig.

The network representation of the fuzzy logic system shows that the backpropagation can configure parameters in membership functions and output rules. RBF inputs are high speed and light barrier inputs that pass through a wash filter to remove existing DC biases. The first escalation block assigns the actual input to certain membership functions. The second scale block is used to compare the output of the fuzzy output system with the actual output required. The fuzzy inference system consists of a fuzzification unit, a control table, and a tank unit, and a surgeon-type defuzzification unit.

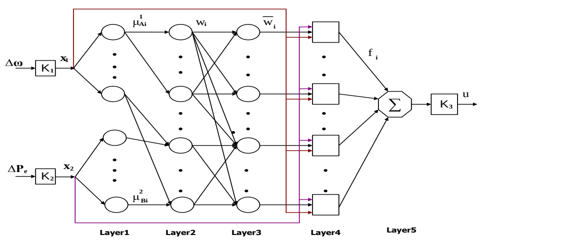

Fig. 2 structure of sugeno-fuzzy with RBF-ANN

The fuzzy control design is based on an understanding of the functional and control effects obtained from experience. The rules are created using the acceleration power of the generator (Pacc = power of the mechanical axis (Pm)), the power of the electric generator (Pe) and the speed deviation (Δω) as control variables.

It is difficult to measure Pm and sum. Due to the slow reluctance of the controller (regarding the response to excitation), Pm is assumed to be a constant from one sample to the next,

Therefore: ΔPm = Pm - Pmo is assumed to be zero. While ΔPe = Pe – Peo

You can switch from sample to sample. Pmo and Peo are the stationary values of Pm and Pe and Pmo = Peo, respectively. Pacc-Pm-Pe ≈ -ΔPe is used in developing the control function. Every fuzzy if - then first-order rule of Takage and the surgeon [12]:

IF X_1 is A_i and X_2 is B_i THEN $U_i = P_i\, X_i + q_i\, X_2 + r_1$

X_1, X_2 are input variables (Δω, ΔPe) and Ai, Bi are language variables, U_i shows the i_{th} rule, and {pi, qi, ri} is the resulting set of parameters. The node functions in each layer are of the same type. The function is described below:

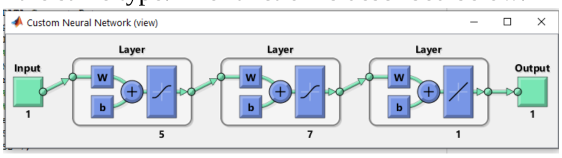

Fig. 3 Structure of ANN

Layer 1: Each node in this level works as a Gaussian membership.

$$y_i^1 = \mu_{Ai}\,(X_i) = e^{-\frac{1}{2}\left(\frac{X_i}{b_{ir}}-\frac{a_{ir}}{b_{ir}}\right)^2}$$

Xi is the input for point i, Ai is the linguistic name assigned to this node, and {ai, bi} is the Gaussian form of the MF parameters. y1i indicates the maximum degree to which this entry belongs to the linguistic description of Ai. with a maximum value of 1 and a minimum value of 0. When the values of these parameters change, the functions in Gussion form the forms of the functions of the membership. All functions that can be continuously distinguished, eg B. trapezoidal or triangular membership functions, are also capable candidates for node functions in this layer.

Layer 2: Every node on this level offers the possibility to remove the rules. The nodes therefore perform a fuzzy operation AND.

Layer 3: The nodes at this stage determine the normalized gravity of rule:

$$y_i^3 = W_i = \frac{w_i}{\sum_{i=1}^{n} w_i}$$

Level 4: The product of the node in this layer is a sequential influence of weighted aspect of the subdue control flux:

$$y_i^4 = f_i = W_i(p_i\, X_i + q_i\, X_2 + r_i)$$

Level 5: As for all incoming the yield signals, a hub in this layer computes the total output signals:

$$y_i^5 = \sum_{i=1}^{n} f_i$$

The training potential of the FLC was built up. To achieve the desired I/O assignment. These parameters are updated according to the training data and the gradient-based training method described below.

If the training data set has P inputs and the output layer has a node, measure the errors of the p_{th} input of the training data:

$$E_p = \frac{1}{2}\,(y_p - y_p^L)^2$$

Here y_p is the p_{th} component of the searched vector, and y_{pL} is the p_{th} component of the actual output vector. For each training information, a direct run is performed and then, from the output level, repetition is used to calculate (∂E_p)/(∂y_p) for all internal nodes. For the playback node:

$$\frac{\partial E_p}{\partial y_p^L} = -\left(y_p - y_p^L\right)$$

For the internal nodes in layer k:

$$\frac{\partial E_p}{\partial y_{i,p}^k} = \sum_{m=1}^{k1} \frac{\partial E_p}{\partial y_{m,p}^{K+1}} \quad \frac{\partial y_{m,p}^{K+1}}{\partial y_{i,p}^k}$$

If y_{ki}, p is the node output in the set of the k_{th} level with k points, and k1 is the number of nodes on the level (k + 1).

Assume that α is the network parameter specified for the adjustment:

$$\frac{\partial E_p}{\partial \alpha} = \sum_{y*\epsilon s} \frac{\partial E_p}{\partial y^*} \quad \frac{\partial y^*}{\partial \alpha}$$

Where S is the set of nodes whose output depends on α. The goal is to minimize the common mistake. E = ∑Ep General learning rule:

$$\frac{\partial E}{\partial \alpha} = \sum_{P=1}^{P} \frac{\partial F_p}{\partial \alpha}$$

$$\Delta\alpha(t) = -\eta\, \frac{\partial E}{\partial \alpha} + \beta\Delta\alpha(t-1)$$

The symbol β is represented as a pulse coefficient and Δα (t-1) is the change of α in the last step. An adaptive network is viewed as the superset of a multi-layer, high-performance neural network with controlled learning skills. The RBF-ANN network's directional nodes decide which nodes are connected. (7)

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Each nod has a specific function, and this function varies from node to node. The general I/O function determines the choice of each node to use based on the adaptive network achieved. RBF has adaptive parameters determined by the learning algorithm and must be updated to achieve the desired I/O assignment. Like ANN with a controlled learning algorithm, the adaptive network learning rule is based on gradient descent.

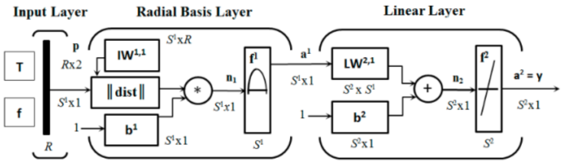


Fig. 4 A scheme of the framework of formed RBF-ANN

The block diagram formed of RBF-ANN is shown in Fig. . The grid is provided in Neural Network Toolbox for Matlab® Release 9.0.0.341360 R2016a, which contains several functions in RBF-ANN, which are quite algorithms Reliable and easy to use learning and modeling.

Performance graphs, regressions, and model errors were used to detail the quality of the ANN model.

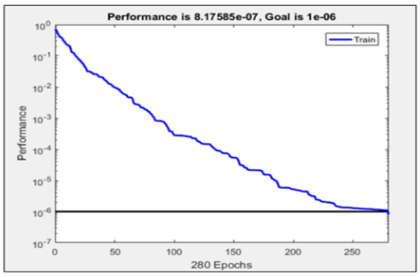


Fig. 1 RBF-ANN Training Plot

Fig. 1 shows an RBF-ANN performance graph showing how to mean squared error (MSE) is minimized during network training. The figure shows that the MSE of the training data decreases continuously during the training with no signs of excessive or inadequate adjustment. The best model performance was observed in the last 268th epoch of the training iteration cycle, with the corresponding final MSE being approximately 8.176 x 10^{-7}, which was lower than the target MSE equal to 1 x 10^{6}, indicating that the best training goal-setting function was matched.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_i^m)^2 \qquad (17)$$

Where y_i is target values, tanδ(T,f) is loss tangent and y_i^m is the network response to frequency (f) and temperature (T).

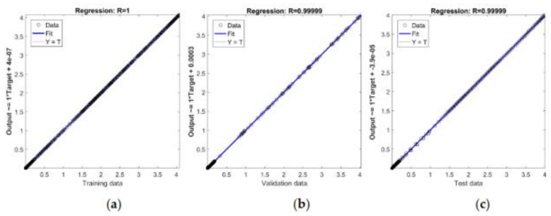


Fig. 2 Comparison of learning objectives with the learning outcomes of the network.

Moreover,

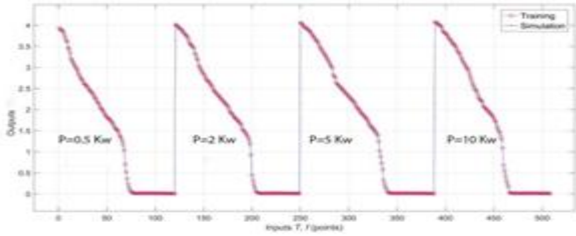
(a) Linear regression plot for training results.

(b) Linear regression plot for validation results.

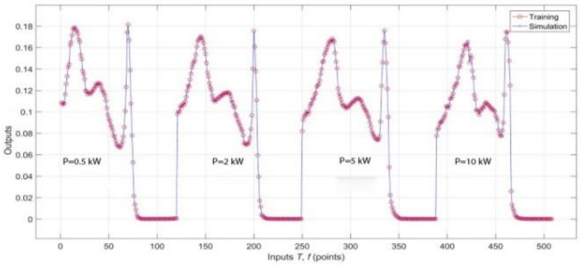
(C) Linear regression plot used to evaluate results.

III. DATA PRACTICALLY CONNECTED IN SMART GRID BASED NEURAL NETWORK:

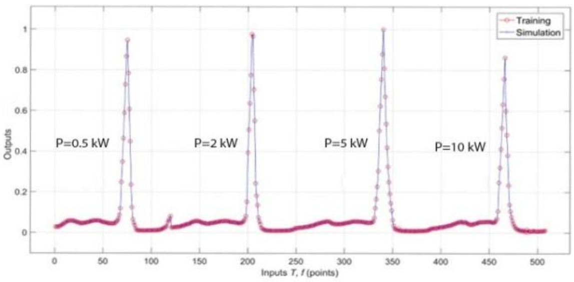
In the original data of this configuration can, we obtained at the kaggle website for area zone connected with main energy network and supporting a few auxiliary renewable sources to provide the network for basic forecasting value {Görgel, 2015 #95}. The forecasting load can be better correlation snice, the first and perhaps slowest step in developing a neural network is data preprocessing. Converting and extracting meaningful information from raw data takes a lot of time and, sometimes, a special data processing tool. This process can take up to eight-tenths of the entire design and implementation task . Preprocessing means transforming data to make it easier for the network to learn I/O relationships. The preprocessing can include mathematical operations such as normalization, classification, and statistical operations such as correlation and asymmetry. The main goal is to create a file that contains several input examples. If you are familiar with the application, you can collect data. For example, in a short-term load forecast, a load diagram always depends on past and future load and temperature data. Therefore, the input data file should contain the most correlated data on past temperatures and loads appropriately and format.



(a)



(b)



(c) tanδ(-) output

Fig. 3 the training target simulated with comparison output training

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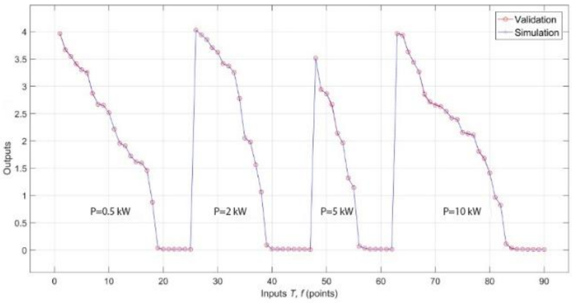
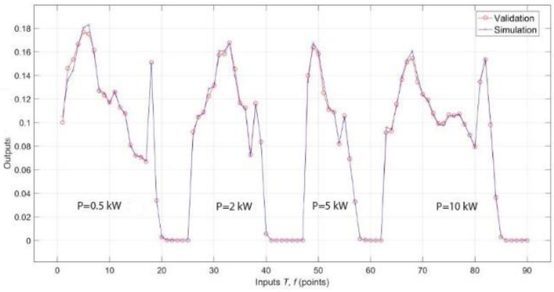
Fig. 3 (a-c) shows a comparison of the validation objectives with the validation results documenting the excellent interpolation capabilities of the model. A comparison of test outcomes and test results close is shown in Fig. 4 a-c. This shows that the RBF-ANN model analyzed doesn't only have wonderful definition and interpolation capabilities but also very good forecasting skills. Documentation of superior model interpolation capabilities is shown in Fig. 3 a-c. A similar comparison with the test objectives and results is shown in Fig. 4 a-c, That demonstrates the RBF-ANN model analyzed.



(a)



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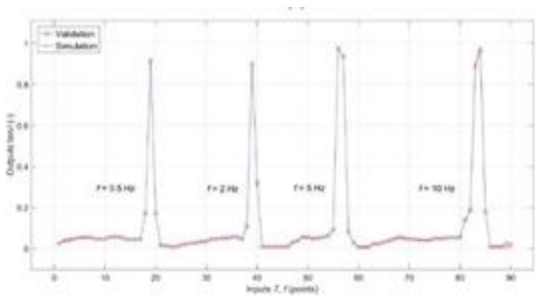
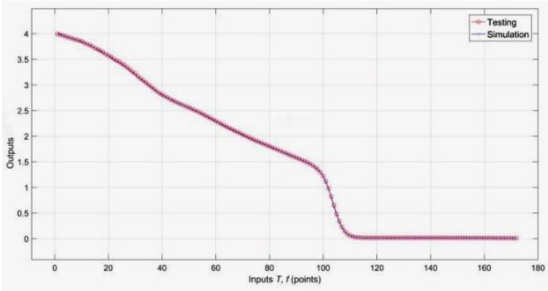


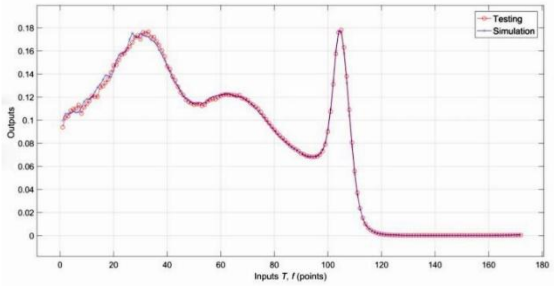
(c)

Fig. 4 The validation targets with simulation output points

Training, validation, and testing of a modified network seemed to have reduced the number of hidden neurons in the approximately of ideal model as well as the training time, i.e. about 18 percent and 23 percent conformable. Nonetheless, for the training and testing data, the linear correlation coefficient R has not changed although its value for the test data has increased. Consequently, the optimized RBF-ANN model has a slightly higher computing efficiency compared to other models, but this does not affect the overall model error, which remains at the same level, in practice.



(a)



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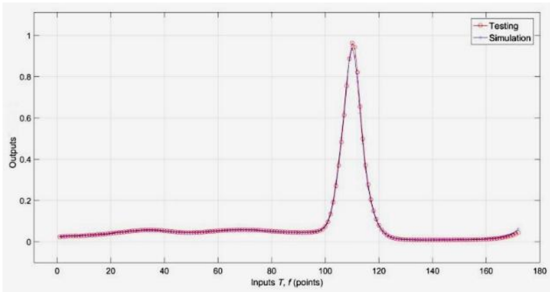
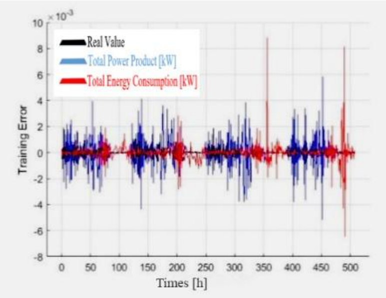


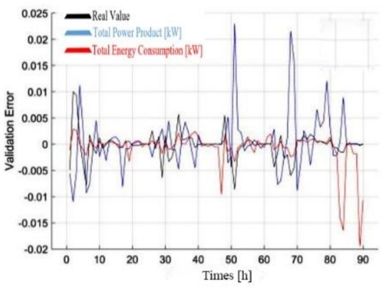
(c)

Fig. 5 The testing targets with outputs simulation

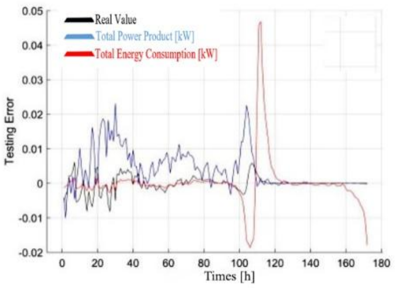
In this experiment, we develop a typical new neural network-based radial basic function for the reaction and damping characteristics of the PLC of PID control systems over the entire temperature range of their lifetime, and comprehensive energy production for errors in total energy consumption. Changes in the coefficient of accumulation, the coefficient of loss and losing shadow with temperature and frequency were simulated using a well-trained neural network model with a good radial base with a Gaussian radial base function that depends on the layer neurons hidden and linear transformation and neural output function. Excellent compatibility of data and experimental models, including all observed relaxation transitions, was found across the range of observed temperatures and frequencies. The functional radial basis function of the neural network has been confirmed to be an powerful technical intelligence tool for flexible computing to effectively predict the viscous behavior of thermoplastic elastomeric systems at close range based on experimental results to reduce errors.



Training plot



Validation Error Plot



Testing Error Plot

Fig. 6 Error Plot Network Data

Table 1 Optimal ANN parameters, Training and network Validation results, and RBF-ANN model tests.

	Data Division	Sample	MSE	R	Intercept
Training	0.92	1108	7.961X10-7	1	$5X10^{-7}$
Validation	0.18	177	-	0.99985	$3.1X10^{-4}$
Testing	0.999	361	-	0.99999	$3.8X10^{5}$

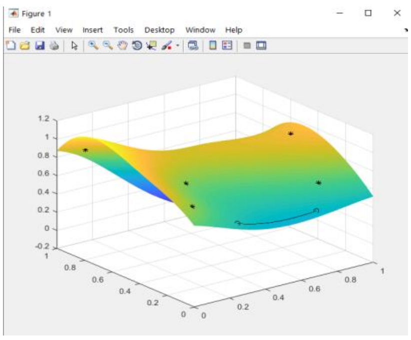


Fig. 7 Enhancement level of energy after applied RBF-ANN

IV. CONCLUSION

The machine learning module contains several instructions for improvement our system always uses the latest trained model to make its predictions. Operators must now decide when to retrain the model if they notice a drop in performance. We are developing a dynamic online algorithm that selects optimal or quasi-optimal models based on recent results from competing models. This next-generation ML engine aims to automate the system and eliminate assumptions that may affect performance. In addition, this can enable an interesting process of knowledge discovery as we learn to refer to the environment and system states with optimal model properties.

Besides, we frisk using our ML method to classify the root causes of failures. The neural network algorithm's first pass assesses each function individually for its ability to predict outages across the entire collection of feeder training data. We find that if these features are grouped into general categories (electrical characteristics, transformer tension, cable type, etc.), the top-ranked feature categories from the first PLC pass are successful leading indicators of corresponding actual causes of failure, with a lead time of about 6 days. For example, in our study, we see a rise in AVR test related features and an increase in it about a week before we see a corresponding rise in actual burnout-induced feeder failures. Further analysis of the relationship between ML-identified attributes and actual causes may lead to further improvements in device reliability and fault management processes.

A related question of forecasting that occurs with regard to our cooperation with the smart grid is to make quantitative predictions about the time-feeder fails and the corresponding components in the system. A combination of machine learning and statistical approaches like big data and real-time analysis can solve this complex problem. While we currently do not concentrate on this area of study, it is a part of our long-term study plans.

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