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Optimal Operation Of Prototype Electrical Microgrid Via A Recurrent Neural Network For Linear Programming

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Abstract - *The aim of this paper is to minimize the power acquired from the utility grid and to maximize the power supplied by the renewable energy sources. The development and implementation of a new recurrent neural network for optimization as applied to optimal operation of an electrical microgrid, which is interconnected to the utility grid. The neural networks determine the optimal amount of power over a time horizon of one week for wind, solar, battery and electric car. In this paper to minimize the power acquired from the utility grid also cost of the power will be reduced. Simulation results illustrate that generation levels for each energy source over a time horizon can be reduced in an optimal form.*

Index terms : *Batteries, Electrical microgrids, linear optimization, multi agent system, neural networks, renewable energy sources.*

I. INTRODUCTION

A mathematical optimization problem is one in which some function is either maximized or minimized relative to a given set of alternatives. The function to be minimized or maximized is called the objective function and the set of alternatives is called the feasible region (or constraint region). Many systems, such as massively interconnected electric power grids, require solving large-scale linear programming problems in real time [1]. In such applications, existing sequential algorithms such as the classical simplex or the interior point methods are usually not efficient due to the limitation of sequential processing. In general, traditional algorithms may not be efficient since the computing time required for a solution is greatly dependent on the dimension and structure of the problems [2]. One possible and very promising approach to real-time optimization is to apply artificial neural networks. Because of the inherent massive parallelism, the neural network approach can solve optimization problems in running time at the orders of magnitude much faster than those of the most popular optimization algorithms executed on general-purpose digital computers [3]. This paper also presents the development of an electrical microgrid, which provides optimal levels of power over a time horizon. It is a typical optimization problem, in which a proposed objective function over a time horizon is minimized subject to different constraints. Various numerical optimization techniques [7], [8] have been employed to solve this problem. In the literature, there are works that seek to optimize the operation of power generation systems, using multilayer neural networks [5], [6]. The aim of this paper is to determine the optimal amounts of power supplied by each energy source in a microgrid prototype. For the solution of this global optimization problem by using RNN [14].

II. NEURAL NETWORK

Neural networks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an 'output layer' where the answer is output as shown in the graphic below

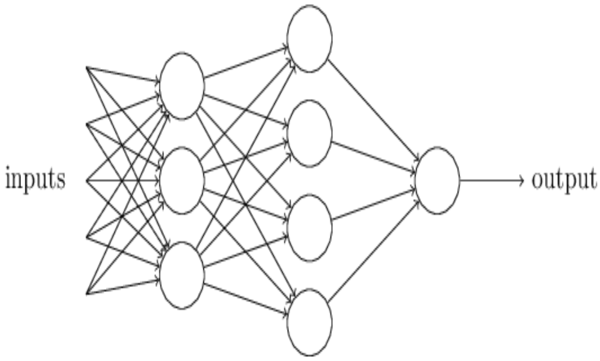

Fig.1. NEURAL NETWORK

Most ANNs contain some form of 'learning rule' which modifies the weights of the connections according to the input patterns that it is presented with. In a sense, ANNs learn by example as do their biological counterparts; a child learns to recognize dogs from examples of dogs.

Although there are many different kinds of learning rules used by neural networks, this demonstration is concerned only with one; the delta rule. The delta rule is often utilized by the most common class of ANNs called 'back propagation neural networks' (BPNNs). Back propagation is an abbreviation for the backwards propagation of error.

With the delta rule, as with other types of back propagation, 'learning' is a supervised process that occurs with each cycle or 'epoch' (i.e. each time the network is presented with a new input pattern) through a forward activation flow of outputs, and the backwards error propagation of weight adjustments. More simply, when a neural network is initially presented with a pattern it makes a random 'guess' as to what it might be. It then sees how far its answer was from the actual one and makes an appropriate adjustment to its connection weights.

III. NEURAL NETWORK FOR LINEAR PROGRAMMING

Consider a general linear programming problem with restrictions as follows:

Minimize $f(v) := c^t v$

(1)

Subject to $Av = b$

(2)

$$l \le v \le q$$

$$c \in R^n, v \in R^n, A \in R^{m\times n}, b \in R^m, l \in R^n, q \in R^n \qquad (3)$$

where v is a vector of decision variables; c is a vector of cost coefficients;b is a vector of right-hand-side parameters; and A is a constraint coefficient matrix, m<n. Let V denote the feasible region defined by (2) and (3), and let v=[v1,v2,……vn]^T denote on optimal solution, and T denotes the transepose operator. For practical reasons, we assume that the feasible region V is nonempty and the minimal objective function value cT v∗ is bounded. To solve this problem, we propose the following RNN , which consists of n massively connected artificial neurons. Each neuron represents a decision variable v. The state equations of the new RNN are given by

$$\dot{u}(t) = -\alpha A^T A v(t) + \alpha A^T b - \beta e^{-nt} c \qquad (4)$$

$$v_i(t) = \begin{cases} l_{i,} & if u_i(t) < l_i \\ q_i & if u_i(t) > q_i \\ u_i(t) & otherwise \end{cases}$$

i=1,2………n; $u \in R^n; \alpha, \beta, \eta \in R > 0$ (5)

Where u(t) is an n-dimensional column vector of instantaneous net inputs to neurons; v(t) is an n-dimensional column vector of activation states corresponding to the decision variable vector; u(0) and v(0) are specified. Equation (4) defines the dynamics of the neural network, in which the first two terms on the right side take into account the equality constraint (2) and the third term helps to minimize the objective function. Equation (5) defines the functions of activation to fulfill constraint (3).

The lowest and highest values for the vector of decision variables v are l and q, respectively; the state space of the RNN is defined as a hyper rectangle parallelogram V = [l, q], ∴ V ⊆V .

IV. ELECTRICAL MICROGRID OPTIMIZATION DESCRIPTION

The electrical microgrid under study is shown in Fig. 3. It is composed of the utility grid, wind and solar energy systems, a bank of batteries, and an electric car. The objective of the short-term generation scheduling problem is to determine the optimal amount of power supplied by the utility grid, the bank of batteries, the electric car, and the wind and solar energy sources over a time horizon. There are several works that perform optimization processes in energy systems.

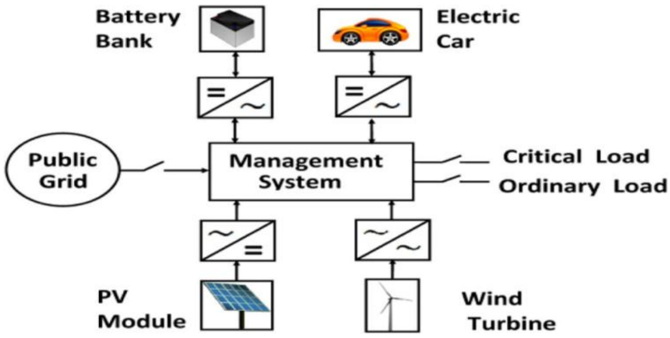

Fig.2. PROTOTYPE SCHEME

For obtaining the minimized cost of energy provided by the utility grid, the time horizon is divided into T time interval, and the short-term generation scheduling problem is formulated as follows:

$$\text{Minimize} \quad CT = \sum_{t=1}^{T} FC\left(P_{G,t}\right) \tag{6}$$

Where

CT total energy cost acquired from the utility grid over the time horizon;

FC energy cost of utility grid at each time interval;

$FC\left(P_G\right) = C_G P_G$

$P_{G,t}$ power from the utility grid at time t;

C_G cost per kilowatt from the utility grid over the time interval;

T number of considered time intervals.

This minimization is subject to the following constraints:

Power balance equation:

$$P_{W,t}(t) + P_{S,t} + P_{G,t}(t) \pm P_{EC,t} \pm P_{B,t}(t) = L_{C,t}(t) + L_{O,t}(t) \tag{7}$$

Where

$P_{W,t}$ Output power of the wind system at time t;

$P_{S,t}$ Output power of the solar system at time t;

$P_{EC,t}$ Input or output power of the electric car battery at time t;

$P_{B,t}$ Input or output power of the battery bank at time t;

$L_{C,t}$ Critical load power demand at time t;

$L_{O,t}$ Ordinary load power demand at time t.

V. MAS

A. OPERATION BASED ON MAS

Due to random variations in weather conditions, power generation from renewable sources is constantly changing. A multiagent system (MAS) is a coupled network of agents working together to solve problems, which are beyond the individual abilities of each agent . The general function of each agent is to collect information about its operation, to receive and execute instructions from the MAS, and to diagnose faults and monitor its operation and devices. The MAS functions are to specify the tasks to be performed by each agent and the coordinated control of the entire system based on the results of the requested actions and to evaluate the results of each agent's actions. Advantages of agents and MAS are autonomy, robustness, scalability, and flexibility among others . For the operation of the microgrid, we propose the following MAS: WA is the wind power generation agent, SA is the solar power generation agent, ECA is the electric car agent, BA is the battery bank agent, GA is the utility grid agent, CLA is the critical load agent, and OLA is the ordinary load agent.

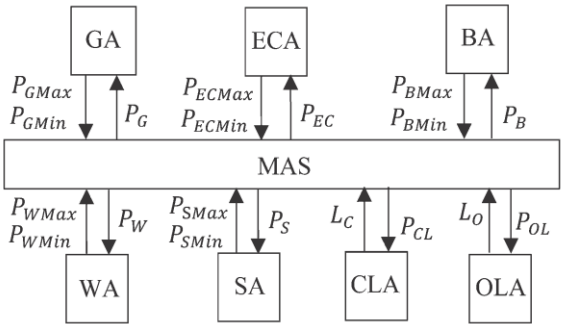

Fig.3. PRESENTS THE STRUCTURE OF THE PROPOSED MAS,

where

P_{WMax} Maximum wind electric power;

P_{WMin} Minimum wind electric power;

P_{SMax} Maximum solar electric power;

P_{SMin} Minimum solar electric power;

P_{GMax} Maximum utility grid electric power;

P_{GMin} Minimum utility grid electric power;

P_{ECMax} Maximum electric car power;

P_{ECMin} Minimum electric car power;

P_{BMax} Maximum battery bank power;

P_{BMin} Minimum battery bank power;

P_{CL} Critical load power;

P_{OL} Ordinary load power.

To solve the optimization problem, the agents send to MAS the following information:

• GA agent. Values of minimum and maximum power of the utility grid, which are determined according to the contract with the company.

• ECA and BA agents. Values of maximum and minimum power of the battery bank and the electric car battery at time t. These values are based on the state of charge (SOC) of the battery.

• WA and SA agents. Indicate the maximum power values of the wind and solar systems at time t, according to the predicted values of wind and solar radiation by prediction algorithms. The minimum power values are defined as zero.
• CLA and OLA agents. Predicted load demand value for each time t.

VI. AGENT FORMULATION

A. WIND ENERGY SYSTEM (WA)

The power output function with respect to the wind speed is taken from

$$P_{W,t} = \begin{cases} 0, & v_t < v_1 or v_t \geq v_3 \\ \psi(v_t), & v_1 \leq v_t < v_2 \\ P_{r,} & v_2 \leq v_t < v_3 \end{cases} \qquad i=1,2,\ldots\ldots T$$

(8)

where

$\psi(v_t)$ Wind-to-energy conversion function for wind power generation;

v_t Predicted wind speed at time t;

P_r Wind generator rated power output;

v_1 Wind generator cut-in wind speed;

v_2 Wind generator rated wind speed;

v_3 Wind generator cut-out wind speed.

B. SOLAR ENERGY SYSTEM (SA)

The power output function with respect to the solar radiation is taken from as

$$P_{S,t} = \begin{cases} P_{sn} \dfrac{(G_t)^2}{G_{std} R_c}, \; 0 < G_t < R_c \\ P_{sn} \dfrac{(G_t)}{G_{std} R_c}, \; G_t > R_c \end{cases} \qquad (9)$$

Where

G_t Predicted solar radiation at time t;

G_{std} Solar radiation in the standard environment set as 1000 W/m^2 ;

R_c Certain radiation point set as 150 W/m^2 ;

P_{sn} Equivalent rated power output of the photovoltaic (PV) generator.

It is noted that PV cell temperature is neglected. For both the WA and SA systems, adequate predictors should be included. In literature, works can be found in which solar power prediction is performed using different techniques.

C. BATTERY STORAGE AND DISCHARGE (BA AND ECA)

The batteries must satisfy the following constraints:

$$P_{BMin} \leq P_{B,t} \leq P_{BMax}$$

(10)

$$P_{ECMin} \leq P_{EC,t} \leq P_{ECMax}$$

t=1,2,….T

(11)

To avoid deep discharge of the batteries, levels are limited by the power minimum values defined in (10) and (11). We use the mathematical model in to simulate the battery operation. A description of the algorithm for obtaining the maximum and minimum values of electric power for the battery systems is included in the Appendix.

D. UTILITY GRID (GA)

Values of minimum and maximum power of the utility grid are determined according to the contract with the utility. Therefore, it must meet the following constraint:

$$P_{GMin} \le P_{G,t} \le P_{GMax}, \qquad t=1,2,\ldots\ldots.T$$

(12)

VII. PREDICTION PROCESS

The prediction process consists in obtaining the values of power demand, wind speed, and solar radiation for the next 15 min. Such process is based on the application of the neural network , which can predict time series. The neural network uses wavelet functions on its structure, and is trained using an extended Kalman filter (EKF). The structure is composed of an input vector; two hidden layers, where the first layer is constructed using the direct product of 1-D wavelets; and an output layer.

The EKF-based training algorithm is based on

$$K(k) = P(k)H^T(k)\left[R + H(k)P(k)H^T(k)\right]^{-1}$$
$$w(k+1) = w(k) + K(k)\left[y(k) - \hat{y}(k)\right]$$
$$P(k+1) = P(k) - K(k)H(k)P(k) + Q$$

(13)

where P(k) and P(k +1) are the prediction error covariance matrices at steps k and k +1, respectively; w(k) is the weight (state) vector; NW is the total number of neural network weights; y(k) is the measured output vector; ˆy(k) is the network output; o is the total number of outputs, K(k) is the Kalman gain matrix; Q is the state noise covariance matrix; R is the measurement noise covariance matrix; H(k) is a matrix where each entry is the derivative of one of the neural network output ˆyi, with respect to one neural network weight wj, as follows:

$$H_{ij}(k) = \left[\frac{\partial \hat{y}_i(k)}{\partial \omega_j(k)}\right]_{w(k)=\hat{w}(k+1)}$$

i=1,……..0j=1,………,NW (14).

Usually P, Q, and R are initialized as diagonal matrices, with entries Po, Qo, and Ro, respectively. In the following, prediction of power demand, wind power, and solar power is presented. Results in Figs. 4–6 are obtained by considering samples of one week for training the neural network. two weeks of power demand; their values are in kilowatts. Previously, it is mentioned that the prediction of wind speed and solar radiation is required; for practical purposes, in this paper, we use directly the prediction of wind and solar power.

VIII. OPTIMIZATION SOLUTION

Wind speed or wind power, solar radiation or solar power, and power demand must be known before the generation optimization problem can be solved. In addition, the power limits of the utility grid and the SOC of the batteries must be known as well. The optimization problem is formulated as follows**:**

Minimize $2P_G - 2P_W - 2P_S$

Subject to $P_G + P_W + P_S + P_B + P_{EC} = C_T$

$$P_{GMin} \le P_G \le P_{GMax}$$
$$P_{ECMin} \le P_{EC} \le P_{ECMax}$$
$$P_{BMin} \le P_B \le P_{BMax}$$
$$0 \le P_W \le P_{WMax}$$
$$0 \le P_S \le P_{SMax}$$

(15)

It is considered that $C_T = L_C + L_O$ In (15), we propose an objective function, which minimizes the power supplied by the utility grid and maximizes the power supplied by renewable energy sources, such as wind and solar agents. To formulate (15) as (1)–(3), we define

$$c = [2 - 2 - 200]^T$$
$$v = [P_G P_W P_S P_{EC} P_B]^T$$
$$b = [C_T]^T$$
$$A = [11111]$$
$$l = [P_{GMin} 0 0 P_{ECMin} P_{BMin}]^T$$
$$q = [P_{GMax} P_{WMax} P_{SMax} P_{ECMax} P_{BMax}]^T$$

(16)

The problem is ready to be solved by the RNN (4) and (5).

IX. SIMULATION RESULTS FOR PREDICTION

Here, we present simulation results corresponding to the application of the proposed scheme. The first-week data are used for training the neural network [12], and the second week data are used for testing. We use the information from the second week in Figs. 4, 5, and 6, for power demand, wind power, and solar power, respectively. The neural network parameters defined in the following are u, v, α, β, and η. Initial conditions u(0) and v(0) are set to zero at each instant, and the following values are used:

$$\alpha = 1 \times 10^6 \quad \beta = 1 \times 10^6 \quad \eta = 200 \times 10^3$$
$$P_{g\max} = 50kw \; P_{gMin} = 0kw$$

(17)

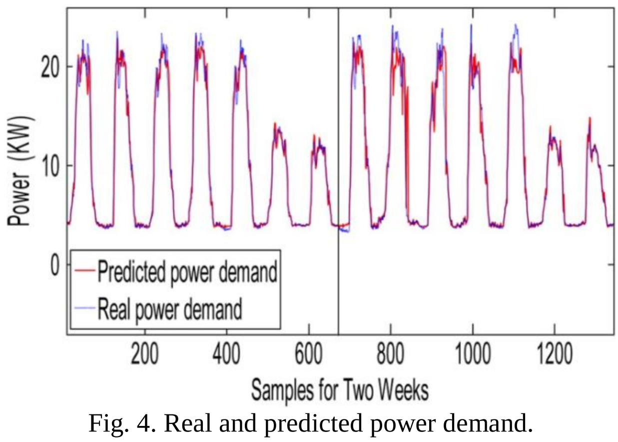

Fig. 4. Real and predicted power demand.

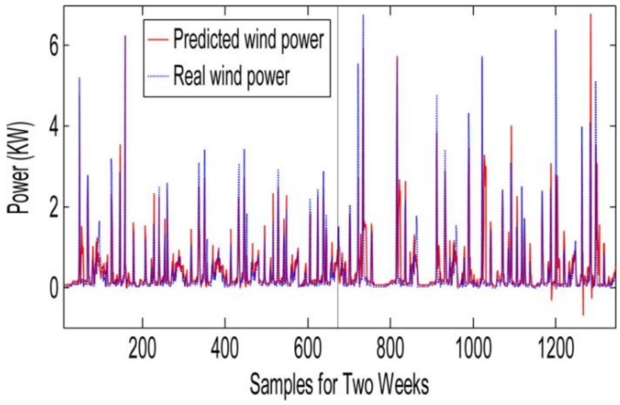

Fig. 5. Predicted and real wind power.

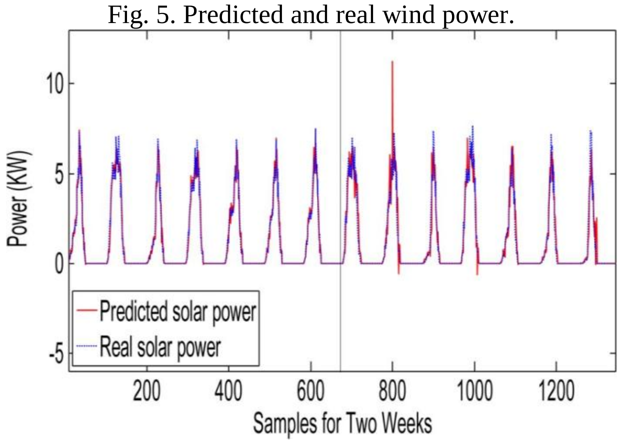

Fig. 6. Predicted and real solar power.

The Fig 4 shows the predicted power demand and real power demand in kw for the period of two weeks. Fig 5 shows the predicted and real wind power in kw for the period Of two weeks. Fig 6 shows the predicted and real solar power in kw for the period of two weeks.

X. CONCLUSION

In this paper, a novel technique based on [13], which employs a recurrent neural network has been proposed to achieve the optimal operation of a microgrid interconnected to a utility grid. A recurrent neural network is used to obtain the optimal solution to a microgrid. The references obtained are implemented to control a microgrid power distribution, in order to minimize the consumed power from the utility grid, maximizing the use of the renewable power sources. The results show that the algorithm determines the optimal power values for a time horizon of one day, for the wind, solar, batteries systems and the utility grid. As future work, we will make the physical implementation of the microgrid, in order to obtain experimental results.

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