2014-07-06

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Sánchez-Torres, J.D.; Loza-López, M.J.; Ruiz-Cruz, R.; Sánchez, E.N.; Loukianov, A.G., "A recurrent neural network for real time electrical microgrid prototype optimization,"Neural Networks (IJCNN), 2014 International Joint Conference on, Beijing, China, 6-11 July 2014, pp.2794,2799.

A Recurrent Neural Network for Real Time Electrical Microgrid Prototype Optimization

Juan Diego Sánchez-Torres, Martin J. Loza-Lopez, Riemann Ruiz-Cruz, Edgar N. Sanchez and Alexander G. Loukianov

***Abstract*— The aim of this paper is to present a new class of recurrent neural networks, which solve linear programming. It is considered as a sliding mode control problem, where the network structure is based on the Karush-Kuhn-Tucker (KKT) optimality conditions, and the KKT multipliers are the control inputs to be implemented with fixed time stabilizing terms, instead of common used activation functions. Thus, the main feature of the proposed network is its fixed convergence time to the solution, which means, there it is a time independent to the initial conditions in which the network converges to the optimization solution. The applicability of the proposed scheme is tested on real-time optimization of an electrical microgrid prototype.**

I. INTRODUCTION

THE use of conventional power sources in the current electrical network operation has been related with problems as gradual depletion of fossil fuel resources, poor energy efficiency and environmental pollution. As an approach to solve these problems, a new trend of generating power locally at distribution voltage level has been increasingly applied. This kind of active distribution networks, which include different renewable and non-conventional energy sources and various loads, are commonly known as *microgrids* [1]. For most of the cases, the sources integrated to the microgrid are natural gas, biogas, wind power, solar photovoltaic cells, fuel cells, combined heat and power systems, micro-turbines and Stirling engines. For the successful operation of a microgrid, different optimization problems must be solved in order to obtain the best performance of the system. Due to the network operation conditions, these optimization procedures are performed off-line.

On the other hand, these massively interconnected electric power grids presents problems as the time varying load demand and the no-conventional/renewable sources availability, requiring to solve large-scale real-time optimization procedures, most of them in the form of linear programming. For such applications, sequential algorithms as the classical simplex or the interior point methods are often proposed. However, those traditional approaches may not be efficient since the computing time required for a solution is greatly dependent on the problem dimension and structure.

One promising alternative is the use of dynamical systems which can solve real-time optimization. This class of systems were introduced by Pyne [2], where it is highlighted the unusual flexibility of this proposal because the system constantly seeks new solutions as the parameters of the problem are varied. Another major contribution to this set of solutions is the use of systems with sliding modes, as proposed by Korovin and Utkin [3], providing finite time convergence to the problem solution. Further extensions of the mentioned schemes were presented by Chua [4], Hopfield and Tank [5], [6], Brockett [7], Chong [8] and Ferreira et al. [9] for linear programming, Kennedy and Chua [10] for nonlinear programming and, finite time approaches [11]–[14]. Some of these systems were presented as the solution to a controller design problem [15], [16] (including the case of sliding mode control [17], [18]), in the form of circuits [19], [20] or under the computational paradigm of the so-called artificial neural networks (ANN) where are known as recurrent neural networks (RNN) as it is shown by Wang and Xia [21], [22]. As the main feature, due to its inherent massive parallelism, RNN 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 [23].

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 a RNN with fixed convergence is used [24]. The RNN structure is based on the Karush-Kuhn-Tucker (KKT) optimality conditions [25], [26], and the KKT multipliers are considered as control inputs to be implemented with fixed time stabilizing terms [27], [28]. In contrast to the publications which use recurrent neural networks for microgrid optimization [29]–[31], the proposed approach provides fixed convergence time to the solution; which is independent of the initial conditions. Real-time results validate the feasibility of the proposed algorithm.

In the following, Section II and III presents the microgrid laboratory prototype connection and control structure respectively. Section IV explains the problem of optimal power amount to be supplied by each energy source in a microgrid prototype. Section V shows the proposed RNN. The real-time results are presented in section VI. Finally, in Section VII the conclusions are slated.

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This work was supported by the National Council of Science and Technology (CONACYT), Mexico, under Grant 129591

II. Electrical Microgrid Prototype

The microgrid laboratory prototype contains a DC voltage bus as a common interjection point for a batteries bank, which stores surplus power, a photovoltaic cell bank and a load test bench. From the operational point of view, the micro-sources must be equipped with power electronic interfaces and control to provide the required flexibility for ensuring its operation as a single aggregated system, and to maintain the specified power quality and energy output. This flexibility would allow the microgrid to present itself to the main utility power system as a single controlled unit, which meets local energy needs for reliability and security.

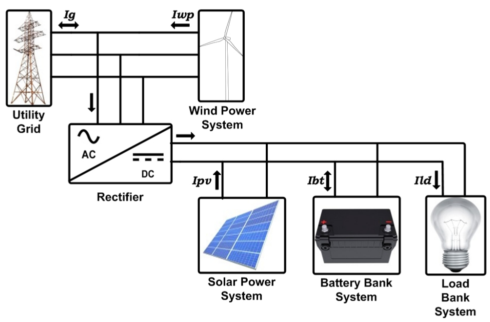

Fig. 1. Microgrid prototype connection scheme.

The microgrid prototype connection scheme can be seen in Fig.1, and a properly picture is displayed in Fig.2. All these devices are developed by Lab-Volt[1]. .

Fig. 2. Microgrid prototype.

III. Prototype control structure

Divide and conquer are the basis of a multi-agent system. In this kind of system, there are special agents (SA) which verify the related inputs and outputs signals for an specific task, i.e. wind power energy production. A central module (CM) serves as a link point for communications between agents. SA has autonomy over easily to solve problems, i.e. short circuits. CM takes decision over important issues detected by SA, i.e. bus fail, or the interconnection of the microgrid, i.e. changing to island mode, as [32] explains. Many microgrids have applied MAS to reduce runtime for an interconnected system, whose agents are connected to it, as presented in [33].

The microgrid laboratory prototype control structure is based under a MAS design (Fig.3); this kind of scheme allows us to add other energy sources in the future. By now, only two agents have been developed and the CM tasks are executed by a common PC using serial and USB communication (Fig.4).

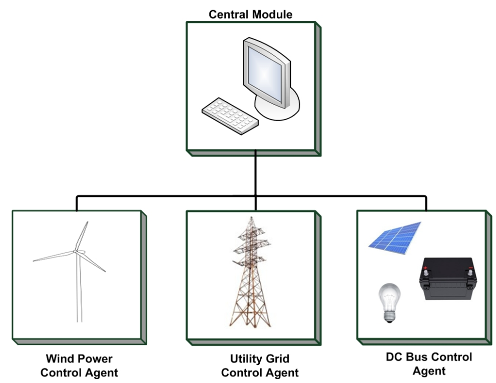

Fig. 3. Microgrid prototype control scheme.

Fig. 4. Microgrid agents.

A. Wind Power Control Agent

The Wind Power Control Agent (WPCA) extracts the maximum power available from the wind, as presented for isolated wind control unit in [34]. Using a data acquisition and control module (Fig.5), we can get different voltages, current and angular speed data from WPS.

[1] Lab-Volt,675, rue du Carbon G2N 2K7 Quebec, Quebec Canada.

Fig. 6. DC bus control agent.

Fig. 5. Data acquisition and control module.

For the generator speed control, the WPCA has an internal controller which allows speed tracking. By means of a PI controller, the generator speed reference ω_r^{ref} is forced to track a wind generator power reference P_w^{ref}. The controller description is:

$$\omega_r^{ref} = K_p e_P + K_i \int_t e_P d\tau \tag{1}$$

where e_P is the error power tracking defined as:

$$e_P = P_w - P_w^{ref} \tag{2}$$

P_w is the wind generator power, K_p is proportional constant and K_i is the integral constant.

B. DC Bus Control Agent

In order to verify, at any moment, voltage magnitude and quality in the DC bus, a DC bus control agent (DCBCA) has been developed according to the microgrid laboratory prototype requirements (Fig.6). In order to obtain an efficient energy distribution, the DCBCA monitors the voltages present in the utility grid and the output current values. This agent also has the authority to disconnect any load in short circuit. A user interface is connected to the DC bus acquisition and control module in order to display the most important signal values for pertinent analysis. This module serves as a link between the different types of energy sources.

C. Utility Grid Control Agent

Utility Grid Control Agent (UGCA) has the task to measure power and voltage delivered by utility grid. These values are send to CM to ensure microgrid functionality.

IV. Optimization Statement

A. Wind Power System (WPS)

This system includes a three phase induction motor with a dynamometer to emulate the wind power impacting in the propellers. The wind generated power P_W is:

$$P_W = \begin{cases} 0 & V_t \leq V_{W_{min}} \\ 0 & V_t \geq V_{W_{max}} \\ P_m & V_{W_{min}} \leq V_t \leq V_{W_{max}} \end{cases} \tag{3}$$

$t = 1, 2, ..., T$

where:

V_t Generator speed at time t
$V_{W_{min}}$ Generator minimum allowed speed
$V_{W_{max}}$ Generator maximum allowed speed
P_m Calculated WPS power.

$V_{W_{min}}$ is $1840 rpm$ because at this speed the motor begins to act as a generator and $V_{W_{max}}$ is $2000 rpm$ for safe dynamometer functionality. With this speed values, the wind generator $P_{W_{min}}$ is equal to 0 and $P_{W_{max}}$ is 240 Watts.

B. Solar Power System

Solar power systems (SPS) is implemented by means of a two cells photovoltaic work bench. SPS power contribution P_S is restricted as

$$0 \leq P_{S_t} \leq P_{S_{max}} \tag{4}$$

$t = 1, 2, ..., T$

where:

P_{S_t} SPS power at time t
$P_{S_{max}}$ SPS maximum power

SPS maximum power $P_{S_{max}}$ for the microgrid laboratory is 1.2 Watts.

C. Battery Bank System

Microgrid power surplus is stored on a Battery Bank System (BBS), which includes two lead-acid batteries. Battery power P_B has to satisfy the next constraint .

$$P_{B_{min}} \leq P_{B_t} \leq P_{B_{max}} \tag{5}$$

$t = 1, 2, ..., T$

where:

P_{B_t} BBS power at time t
$P_{B_{min}}$ BBS minimum allowed power
$P_{B_{max}}$ BBS maximum allowed power

BBS maximum and minimum power are fixed to increase the batteries lifespan as long as possible. For this purpose $P_{B_{min}}$ is established as a 40 percent of its charge and $P_{B_{max}}$ as 70%. Therefore if the batteries has a power rate of 0.6 watts $P_{B_{min}}$ is taken as 0.24 watts and $P_{B_{max}}$ as 0.42 watts.

D. Utility Grid System

The microgrid has a junction point with the utility grid system all the time as can be seen in Fig.1.

The power from this system P_G is formulated as:

$$0 \leq P_{G_t} \leq P_{G_{max}} \tag{6}$$

$t = 1, 2, ..., T$

where:

P_{G_t} Utility power at time t

$P_{G_{max}}$ Utility maximum allowed power

Utility power can be considered has an infinite source; however for this microgrid $P_{G_{max}}$ bound is set to 250 watts.

The main goal is to optimize the power of the microgid based on the available energy sources and the required output power for the load P_L, which can be expressed as :

$$\begin{cases} \text{Minimize} & P_G - P_W - P_S - P_B \\ \text{s.t} & P_G + P_W + P_S + P_B = P_L \\ & 0 \leq P_{G_t} \leq P_{G_{max}} \\ & P_{W_{min}} \leq P_{W_t} \leq P_{W_{max}} \\ & 0 \leq P_{S_t} \leq P_{S_{max}} \\ & P_{B_{min}} \leq P_{B_t} \leq P_{B_{max}} \end{cases} \tag{7}$$

Microgrid constraints according the equations (3) to (6) are based on the prototype inherent features.

The linear programming formulation (7) can be written as

$$\begin{cases} \min_x & \mathbf{c}^T x \\ \text{s.t} & \mathbf{A}x = \mathbf{b} \\ & l \leq x \leq h \end{cases} \tag{8}$$

where the utility grid power and maximizing WPS, SPS and BBS power are defined as: $\mathbf{c}^T = \begin{bmatrix} 1 & -1 & -1 & -1 \end{bmatrix}$, $x = \begin{bmatrix} P_G & P_W & P_S & P_B \end{bmatrix}^T$, $\mathbf{A} = \begin{bmatrix} 1 & 1 & 1 & 1 \end{bmatrix}$, $\mathbf{b} = [P_L]$, $l = \begin{bmatrix} 0 & P_{W_{min}} & 0 & P_{B_{min}} \end{bmatrix}^T$ and, $h = \begin{bmatrix} P_{G_{max}} & P_{W_{max}} & P_{S_{max}} & P_{B_{max}} \end{bmatrix}^T$.

V. RNN Optimizer

Let the linear programming problem (8), where $x = \begin{bmatrix} x_1 & \dots & x_n \end{bmatrix}^T \in \mathbb{R}^n$ are the decision variables, $\mathbf{c} \in \mathbb{R}^n$ is a cost vector, $\mathbf{A}$ is an $m \times n$ matrix such that $\text{rank}(\mathbf{A}) = m$ and $m \leq n$; $\mathbf{b}$ is a vector in $\mathbb{R}^m$ and, $l = \begin{bmatrix} l_1 & \dots & l_n \end{bmatrix}$, $h = \begin{bmatrix} h_1 & \dots & h_n \end{bmatrix} \in \mathbb{R}^n$.

Let $y = \begin{bmatrix} y_1 & \dots & y_m \end{bmatrix}^T \in \mathbb{R}^m$ and $z = \begin{bmatrix} z_1 & \dots & z_n \end{bmatrix}^T \in \mathbb{R}^n$. Hence, the Lagrangian of (8) is

$$L(x, y, z) = \mathbf{c}^T x + z^T x + y^T (\mathbf{A}x - \mathbf{b}). \tag{9}$$

The KKT conditions establishes that x^* is a solution for (8) if and only if x^*, y and z in (8)-(9) are such that

$$\nabla_x L(x^*, y, z) = \mathbf{c} + z + \mathbf{A}^T y = 0 \tag{10}$$

$$\mathbf{A}x^* - \mathbf{b} = 0 \tag{11}$$

$$z_i x_i^* = 0 \text{ if } l_i < x_i^* < h_i,\ \forall i = 1, \dots, n. \tag{12}$$

Following the KKT approach, here a recurrent neural network which solves the problem (8) in fixed time is proposed. For this purpose, let

$$\Omega_e = \{x \in \mathbb{R}^n : \mathbf{A}x - \mathbf{b} = 0\}$$
$$\Omega_d = \{x \in \mathbb{R}^n : l \leq x \leq h\}.$$

According to (8), $x^* \in \Omega$ where $\Omega = \text{int}(\Omega_d \cap \Omega_e)$.

From (10), let

$$\dot{x} = -\mathbf{c} + z + \mathbf{A}^T y. \tag{13}$$

Then, y and z will be designed such that Ω is a fixed time attractive set, fulfilling conditions (10)-(12).

In addition to condition (12), z is considered such that

$$\begin{cases} z_i \geq 0 & \text{if } x_i \geq h_i \\ z_i \leq 0 & \text{if } x_i \leq l_i \end{cases}. \tag{14}$$

Thus, defining

$$\sigma = \mathbf{A}x - \mathbf{b} \tag{15}$$

a suitable choice for y and z is proposed as

$$y = \mathcal{SL}(\sigma) \tag{16}$$

$$z = \mathcal{FS}(x, \Omega_d). \tag{17}$$

With the stabilizing terms (16)-(17), the dynamics of the system (13)-(15) become

$$\dot{\sigma} = -\mathbf{A}\mathbf{c} + \mathbf{A}\mathcal{FS}(x, \Omega_d) + \mathbf{A}\mathbf{A}^T \mathcal{SL}(\sigma) \tag{18}$$

$$\dot{x} = -\mathbf{c} + \mathcal{FS}(x, \Omega_d) + \mathbf{A}^T \mathcal{SL}(\sigma) \tag{19}$$

As a conceptual approach to the stabilization of (18)-(19), it can be considered from the definition of $\mathcal{FS}(x, \Omega_d)$ in (19), that x reaches the set Ω_d in a fixed time t_d. For $t > t_d$ the operator $\mathcal{FS}(x, \Omega_d) = 0$, then from (18) it follows

$$\dot{\sigma} = -\mathbf{A}\mathbf{c} + \mathbf{A}\mathbf{A}^T \mathcal{SL}(\sigma). \tag{20}$$

from the definition of $\mathcal{SL}(\sigma)$, the solutions of (20) reach $\sigma = 0$ in a fixed time $t_e > t_d$.

At this point, it is clear that the conditions (11) and (12) are satisfied. Now, by using the *equivalent control method* [35] as solution of $\dot{x} = 0$ in (13) for $t > t_e$, it follows that $z = \mathcal{FS}(x, \Omega_d)_{eq} = 0$ and $\mathbf{c} + \mathbf{A}^T \mathcal{SL}(\sigma)_{eq} = 0$, satisfying condition (10).

Usual recurrent neural networks approaches to solve (8) are based on the idea of define a dynamical system with structural features from the KKT. Then, an important step is the design of activation function which fulfills (12). A class of activation functions which satisfy the KKT conditions, providing fixed time stabilization to the set Ω_d, $z = \mathcal{FS}(x, \Omega_d)$ is proposed as

$$\mathcal{FS}(x, \Omega_d) = \begin{bmatrix} \mathcal{FS}_1(x_1, [h_1, l_1]) & \dots & \mathcal{FS}_n(x_n, [h_n, l_n]) \end{bmatrix}^T$$

where $\mathcal{FS}_i(\cdot)$ is defined as

$$\mathcal{FS}_i(x_i, [l_i, h_i]) = \begin{cases} f_s(x_i - l_i) & \text{if } x_i \leq l_i \\ 0 & \text{if } l_i < x_i < h_i \\ f_s(x_i - h_i) & \text{if } x_i \geq h_i \end{cases} \tag{21}$$

with $f_s(\cdot) = -k_{i1}\text{sign}(\cdot) - k_{i2}(\cdot) - k_{i3}(\cdot)^3$.

For this case, $y = \mathcal{SL}(\sigma)$ is selected as

$$\mathcal{SL}(\cdot) = -k_{i4}\text{sign}(\cdot) - k_{i5}(\cdot) - k_{i6}(\cdot)^3. \tag{22}$$

With this stabilizers selection, the stability and convergence of the proposed neural network is given in [24].

VI. Real-Time Results

Real time test are done based on microgrid constraints defined in section IV.

DCBCA and WPCA measured values are send to CM. The RNN uses the load power calculated as the vector $\mathbf{b}$ of the equation (8), and set the power references for the system agents.

RNN obtained reference for DCBCA are a continuous value; however this agent can only turn on or turn off the batteries and the solar cells from the microgrid; for this reason a high limit for activation and a low limit for deactivation is established.i.e. if BBS high limit is overcome then this module is connected to the microgrid; on the other hand if the reference power is lower than the low limit, the module is disconnected. This same logic is applied to SPS control.

WPCA PI controller use the RNN power WPS reference to change the dynamometer speed and accomplish the power set for this module.

To test RNN on the microgrid laboratory prototype, at the beggining we let the microgrid to stabilize the power according to the reference provided by RNN. At 10s a 145Ω resistive load is connected to the DC Bus; then at 18.5s and 30s a same value resistor is plug in; then a fourth 19Ω load is connected at 41s; this last one represent a high disturbance to the system. The loads are disconnected at the same order to show the transient behavior of the microgrid, as Fig.7 displays.

On Fig.8 the utility grid behavior is shown, it can be seen that the power is close to the $P_{G_{min}}$ which is set as 0 watts.

On Fig.9 the WPS power and power reference is displayed. It can be seen that this module reaches the reference power all the time and is bounded within the fixed limits.

Fig.10 shows how SPS reaches their power references except in the time between 41s and 53s, since a related controller for this module has not been developed yet.

BBS tracking error is higher than the other modules because a related controller for this module is not yet developed too, Fig. 11.

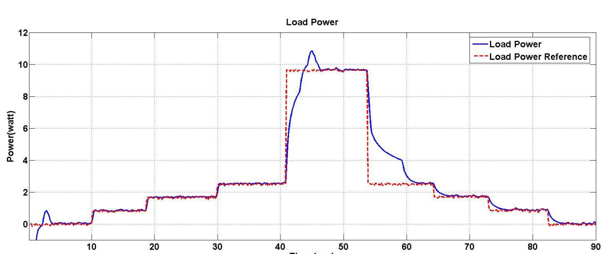

Fig. 7. Load power and RNN references sum.

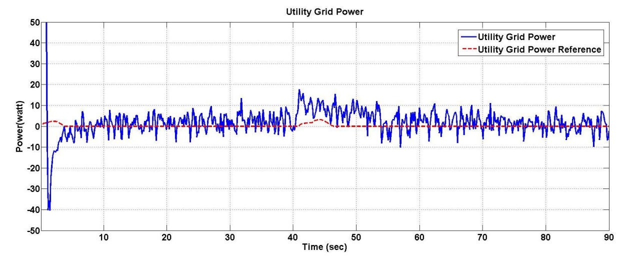

Fig. 8. Utility grid power and RNN utility grid power reference.

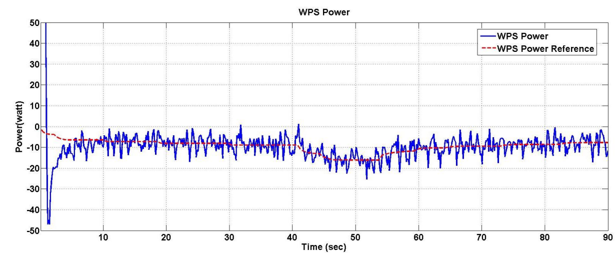

Fig. 9. Wind power and RNN wind power reference.

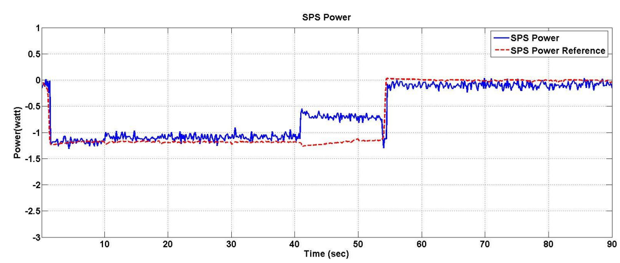

Fig. 10. Solar power and RNN solar power reference.

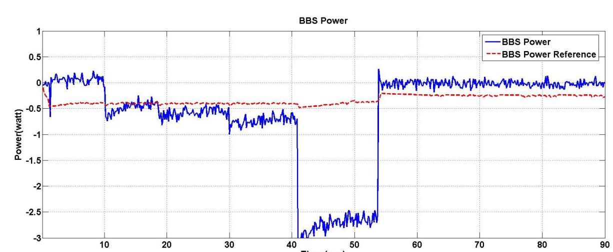

Fig. 11. Battery power and RNN battery power reference.

VII. Conclusion

In this paper a novel optimization algorithm is applied in real-time. A recurrent neural network is used to obtain the optimal solution to a microgrid laboratory prototype source assignment problem. 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 alternative power sources connected to it. Real time results validates that the proposed optimization algorithm can be implemented for control an small power microgrid.

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