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Modeling and Simulation of Microgrid

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Abstract

Complex computer systems and electric power grids share many properties of how they behave and how they are structured. A microgrid is a smaller electric grid that contains several homes, energy storage units, and distributed generators. The main idea behind microgrids is the ability to work even if the main grid is not supplying power. That is, the energy storage unit and distributed generation will supply power in that case, and if there is excess in power production from renewable energy sources, it will go to the energy storage unit. Therefore, the electric grid becomes decentralized in terms of control and production. To deal with this change, one needs to interpret the electrical grid as a system of systems (SoS) and build new models that capture the dynamic behavior of the microgrid. In this paper, different models of electric components in a microgrid are presented. These models use complex system modeling techniques such as agent-based methods and system dynamics, or a combination of different methods to represent various electric elements. Examples show the simulation of the solar microgrid is presented to show the emergent properties of the interconnected system. Results and waveforms are discussed.

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Keywords: Microgrid; SoSs; Wind; Solar; Energy storage; neural networks; modeling; simulation; intelligence

1. Introduction

The current electric power grid suffers aging in both the developing and the developed world. The results of aging grid and old infrastructures become more pronounced as the number of power outages increases. Old equipment is prone to failures, and old engineering planning and operation methods are ineffective in tackling current challenges. To better deal with current challenges, a paradigm shift is needed. Recently, concepts from system engineering have been adapted to upgrade the electric power. That is, the electric grid can be treated as a complex system. A complex system is a large collection of interacting elements that act together to perform an

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overall nonlinear activity or task. A complex system is not centralized but distributed and self-organized. This paper investigates various models of microgrid components and treats them as a complex system.

2. System of Systems (SoSs) Definition

A system of systems is a relatively new concept in system engineering and is becoming a hot topic for researchers in different fields. Despite the fact that this concept is in its early stages, this concept has achieved widespread use, such as real-time systems and hardware-in-loop simulations [1]. It was restricted to two main domains: defense and information technology. Nowadays, it has entered a wide variety of different domains. Although there are different definitions of SoSs, the most general one That a *SoSs* are large-scale integrated systems that are diverse and autonomous, but are working together to achieve a common goal [2]. The main reason for initiating this concept is to improve either economy or performance. SoSs consist of employable heterogeneous subsystems. The subsystems can work independently and each one has no power over the other. However, subsystems are connected to communicate and transmit tasks and achieve an overall mission. Some characteristics distinguish SoSs from a complex monolithic system, and they are listed in table 1.

Table 1: Characteristics of SoSs

Characteristic	Definition
Operational independence	All subsystems work independently and have no interference with other subsystems
Evolutionary development	The overall system is not monolithic. Instead, it is flexible to adding new subsystems
Emergent behavior	All subsystems work as collective unit to accomplish a big task
Geographic distribution	The subsystems are sequentially distributed to facilitate the flow of information
Managerial independence	The subsystems are in control for their own operation

3. Microgrid as SoSs

Figure 1 shows an example of a microgrid contains renewable energy sources. The renewable energy sources are integrated to a dc bus through power electronic interfaces [3-6].One the most important goals of a microgrid is to be able to work with various types of renewable sources and meet the load demand in case of outages. The subsystems can communicate with each other to achieve the desired goal [7].

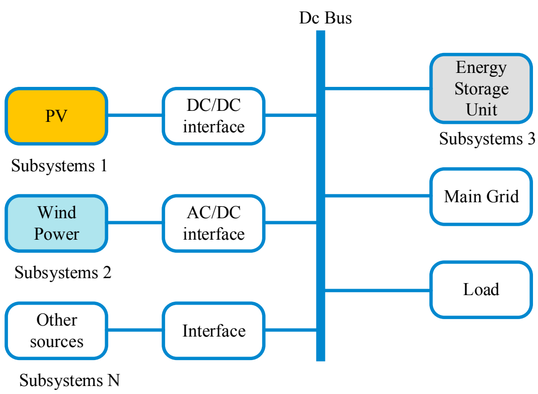

Fig.1. Example of a microgrid

4. Microgrid System Modeling

A complex system can be any system that contains a large number of elements that has distinguishing features such as a large number of interacting agents, self-organizing collective behavior, decentralization, openness, and nonlinearity between input and output. The central properties of complex systems are elements and their number, interactions and their strength, time scale of operations, variability, environment and its demand, and activities and their objectives. Attributes of complex systems are interdependent, independent, distributed, cooperative, competitive, and adaptive. Many examples of large-scale systems are built from components, such as internet networks, global satellite networks, enterprise information systems, and the electric power grid. There are many similarities between electric grids and complex computer systems so that microgrids can be treated as SoSs

4.1. Battery System modeling

A storage system is a vital element in the microgrid. It operates in the case of an electricity blackout, and it mitigates the variability of renewable energy sources. Therefore, it is usually placed between the renewable sources and the load to help the generation match the load demand at any moment, and by doing that, the stability of the system is assured. The size of battery storage is important, and detailed calculations should be made to meet the demand when the power from the electric grid is not available. The required battery capacity is given by

$$B_{size} = \frac{E_{load} \times Days_{off}}{DoD_{max} \times \eta_{temp}} \tag{1}$$

where E_{load} is the load that needs to be supplied during unavailability of power in ampere hour, $Days_{off}$ is the storage days (the days that power from the electric grid is unavailable), DoD_{max} is the maximum depth of discharge of the battery, and η_{temp} is the temperature corrector factor. At high penetration rate, fluctuating sources such as wind generation can cause a problem with balancing the system. These sources cannot be dispatchable and cannot be seen as a negative consumer. The control in this case might become very challenging. Knowing the charge quantity and setting it as a control input can mitigate the challenges associated with renewable energy integration. The charge quantity of the storage system is given by

$$E_B(t) = E_B(t-1)\cdot(1-\zeta) + (E_{GA}(t) - E_L(t)/\eta_{inv})\cdot\eta_{Batt} \tag{2}$$

where ζ, η_{inv} and η_{batt} are the hourly self-discharge factor, efficiency of inverter, and efficiency of the battery, respectively; $E_B(t)$ and $E_B(t\text{-}1)$ are the charge quantity of storage system at time t and $t\text{-}1$, correspondingly; and E_{GA} and E_L are the renewable energy power and load demand, respectively. The charge quantity is constrained by maximum and minimum charge quantities E_{Bmax} and E_{Bmin} [8], respectively.

4.2. Load Modeling

Modeling electric load is a very challenging task. The behavior of electric load depends on energy consumption of various devices that are turned on and off either automatically like air conditioning devices or manually like hair dryer. Often, electric load is modeled using a constant electric impedance for the sake of simplicity. However, the load can be modeled using machine learning algorithms or artificial neural networks if more accuracy is required. There are usually some demand peaks at various times of the day. The peaks are sharp during weekdays, because of air-conditioning and other high-power devices. Modeling load demand can be simplified as active and reactive power. The values of apparent power components P and Q are usually pre-set for the sake of simplicity. In this paper, the load was modeled and considered stochastic. Therefore, load profiles were generated using a feedforward neural network, as explained in section 5.

4.3. Modeling of Photovoltaic System

The physical model of solar irradiance on an inclined surface is given by

$$I_T = I_b R_b + I_d R_d + (I_b + I_d) R_r \tag{3}$$

where I_b is normal solar irradiance and I_d is diffused solar irradiance. Parameters R_d and R_r are the tilt factors for the diffused and reflected part of the solar irradiance. The sun position in the sky is the main factor that total solar irradiance depends on [9]. There are many models for hourly output PV power, which is given by

$$P_{sj} = \eta_r \eta_{pc} \gamma A_{PV} I_{Tj} \left(1 - \kappa \left(\left(T_a + \frac{I_{T,NOCT}}{(NOCT - T_{a,NOCT}} I_T \right) - T_r \right) \right) \tag{4}$$

where η_r is the reference efficiency of the module, η_{pc} is the efficiency of smoothing and conditioning power, γ is the factor of density of a cell in module (also called packing factor), κ is the temperature coefficient of the array, A_{PV} is the photovoltaic area, T_a is the instantaneous ambient temperature, T_r is the reference temperature, T_c is the monthly temperature, and *NOCT* is the normal operating cell temperature, which $T_{a,NOCT}$ is 20°*C* and irradiance is 800W/m^2 for a wind speed of 1 *m/s*. The equivalent circuit of the solar panel is shown in Fig. 2. The solar irradiance can be forecasted by statistical methods such as autoregressive moving average, or machine learning algorithms such as support vector machine. In this paper, solar irradiance was modeled using feedforward neural network.

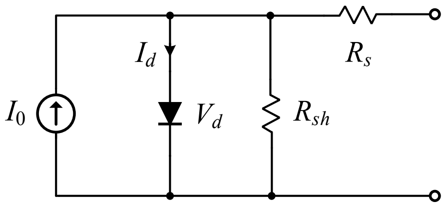

Fig. 2. PV equivalent electric circuit

4.4. Modeling of Wind Energy system

Wind speed is a renewable source of energy. Using aerodynamic techniques, one can design a rotor that converts wind speed into electric power. Although wind speed has some advantages like energy density and an excellent return on investment, it has some disadvantages like required periodic maintenance, the difficulty of installation, and intermittency. That is, it has a significantly variable output that is difficult to predict and might cause instability of the grid operation. To model such a source, we need to model the electric behavior of the wind turbine generator, as well as characterize of wind speed to capture the fluctuation.

a- Wind turbine model

Ref [4] gives the model of power energy of wind turbine. The height and speed characterization of the wind turbine are the main factors of the output power. The relationships are given by the power-law equation:

$$V_z = V_i \left[\frac{Z}{Z_i} \right]^x \tag{5}$$

where V_z, V_i, Z, and Z_i, are the wind speed at the hub, wind speed at reference, hub height, and reference height, respectively. The output power of the turbine generator is given by

$$P_W = \begin{cases} 0 & V < V_{ci} \\ \left(\frac{P_r}{V_r^3 - V_{ci}} \right) V^3 - \left(\frac{V_{ci}^3}{V_r^3 - V_{ci}} \right) P_r & V_{ci} < V < V_r \\ P_r & V_r < V < V_{co} \\ 0 & V > V_{co} \end{cases} \tag{6}$$

where V_r is the rated speed at which the wind turbine generates maximum power, V_{ci} is the cut-in speed at which the wind turbine generates minimum power, V_{co} is cut-out speed, and P_r is the rated power. Fig. 3 shows the wind turbine characterization.

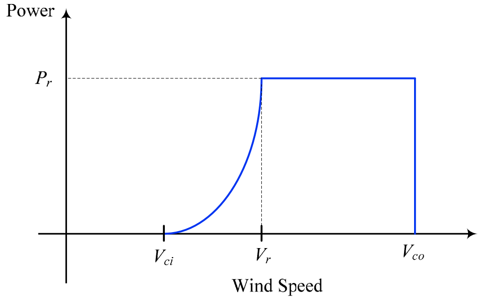

Fig. 3. Wind Power vs Speed modeling

The actual output power of wind turbine after considering the loss and the total swept area is given by

$$P = P_w A_w \eta \tag{7}$$

where η is the efficiency of the wind turbine and A_w is the total swept area [10].

b- Wind speed model

There are many wind speed modeling tools, such as autoregressive moving average (ARMA), hidden Markov models (HMM), and support vector machine (SVM), and many more. In this paper, a feedforward neural network is used to model the wind speed. More details about implementation can be found in section 5

5. General Modelling Using Neural Networks

Figure 4 shows the overall system modeled using time series neural networks. Each neural network was trained with labeled data before plugging it into the system. All networks are feedforward networks trained using the back-propagation algorithm. The solar power was trained using a feedforward neural network with 12 input neurons, 21 hidden neurons, and 1 output, which corresponds to the solar power. The input variables are the solar irradiance, the corresponding time, the humidity, and the temperature. The previous values of solar irradiance were taken into account. Choosing the best window size was based on trial and error. The best window size is three. The model was trained using the Levenberg-Marquardt backpropagation algorithm to update the weight vector. The wind power was trained using a similar neural network with 15 input neurons, 18 hidden neurons, and 1 output neuron, which is the wind power. The input to this network is the wind speed and direction, and the corresponding time. Previous values of wind speed and direction were taken into account to predict the next value of wind power. The wind power model was trained using the Levenberg-Marquardt backpropagation algorithm, as in solar power modeling. Modeling the load demand was the most difficult task because load demand contains human behavior of turning on and off devices which is highly unpredictable, and feature extraction can be a tedious task. However, a feedforward neural network with more neurons can represent the data. The inputs of the neural networks are power demand, weather, and corresponding time. The network architecture has 15 input neuron, 25 hidden neurons, and one output neuron, which is load demand. The best window size is also 3. The storage elements were modeled using a neural network with 6 input neurons, 12 hidden neurons, and an output neuron, which is the state of charge of the storage element. The best window size is 2. All of the previous models were trained using labeled data that were preprocessed and cleaned. Then, this data was divided as follows: 70% of the dataset is for training, 30% for test, and 15% was for validation. All of the hidden neurons are a hyper tangent activation function, which has a value between -1 and 1. This is helpful because some variables have two directions such as the battery current, where the negative current means the battery is charging and positive means the battery is discharging. The activation function of the output layer is linear function. The training was stopped early to prevent overfitting, and to make the model have a better generalization. Simulating the microgrid with neural network can make it treated as an SoS, where each source is an independent and the system is capable of adding extra sources. All sources perform the big task which is power balance between generation and load demand. Other tasks such as increasing the economic benefits can also be achieved by controlling these renewable sources.

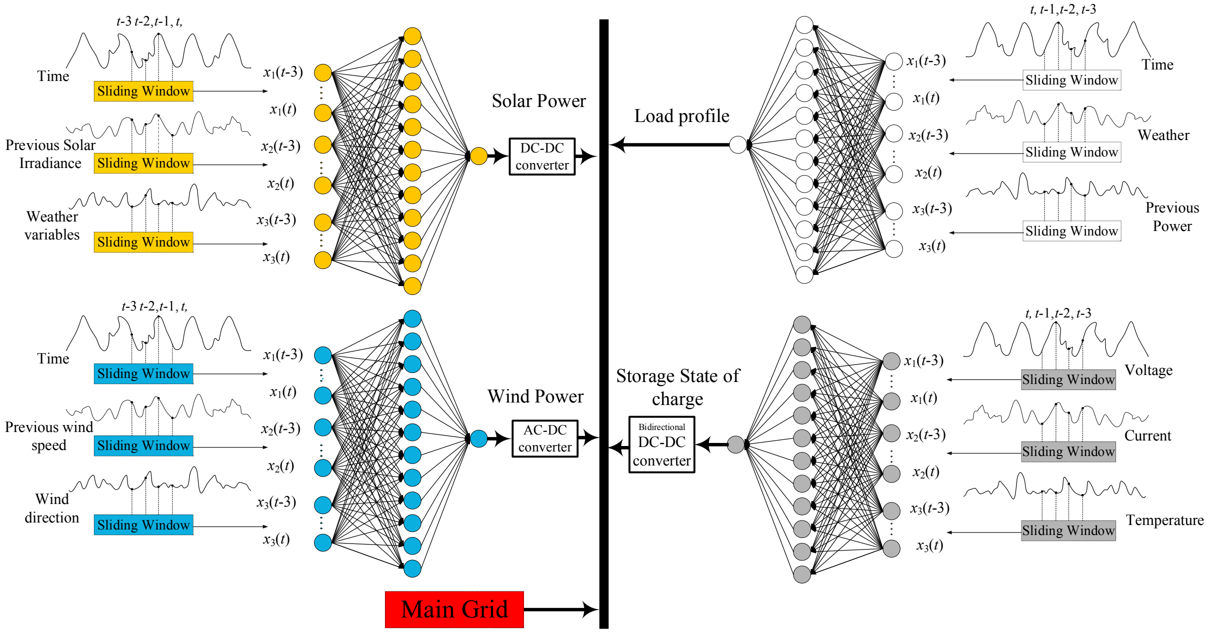

Figure 4: Microgrid modeling and simulation using neural networks

6. Control

Several different types of controllers can be found in literature, as shown in Fig. 5. These control techniques are suitable for working in SoSs. Hierarchical control uses different layers to control the grid. Typically, it consists of three layers: the primary layer, secondary layer, and tertiary layer. The primary layer is responsible for load sharing where droop control is used. Also, it is in charge of stabilizing the voltage and frequency. The secondary is in charge of checking the primary control errors. The tertiary layer monitors the flow from utility to the grid and vice versa [7]. In this paper, a primary control was implemented to balance the power between generation and load demand.

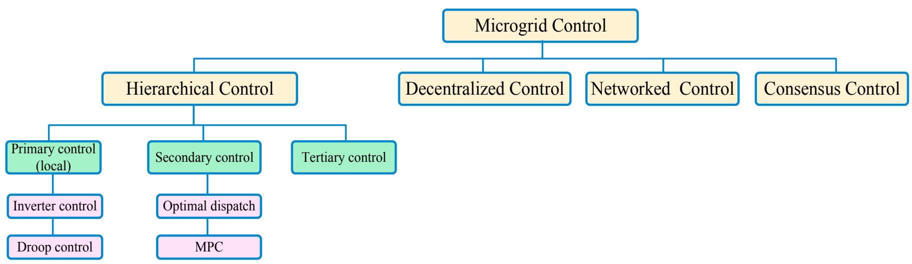

Fig.5. Control methodologies of microgrid

7. Case Study

This section illustrates a practical example of a microgrid. Missouri S&T solar village is a small-scale microgrid which is consisted of four solar homes tied to the grid. These homes are also backed up by a storage system of two 960 V batteries and a fuel cell. The main aim of this project is to better utilize the energy locally rather than sending it to the main grid. The overall microgrid is a possession of Missouri S&T and the energy supplier is Rolla Municipal Utilities (RMU). Currently, Missouri S&T is responsible for the payment the electricity usage, and the village is occupied by tenants. More information about the smart grid components is listed in Table 2 [11-12]. These components include a natural gas fuel cell, solar generation, lithium ion battery, and automated smart switchgear [13]. Figure 6 shows the picture of the microgrid, and Fig. 7 shows the simulation diagram. The solar village is simulated using Simulink with the same parameters listed in Table 2. Different PV data sources were obtained from [14-16]. The RMU was considered an ideal source with 13.8 kV and 60 Hz. The transmission line was simulated using PI section line with non-ideal components. The rest of the system was considered a constant load with active and reactive power equal to 1 MW and 1 kVAR, respectively. The solar village is connected to the transmission line using a distribution transformer. The distribution transformer is connected to phase A of the transmission line, and it is rated for 50 kVA power. The secondary side of the transformer is center tapped, which there are two phases at the secondary side with the 120V magnitude and opposite polarity. The load profile is the output of a neural network that was trained using data from [17]. The time resolution of the load profile is one minute.

Table 2: Parameters of the S&T microgrid

Load	Rating
Battery storage	60kWh
Bidirectional Inverter	50kW
Fuel cell	5kW
Photovoltaic Panels	2.4kW

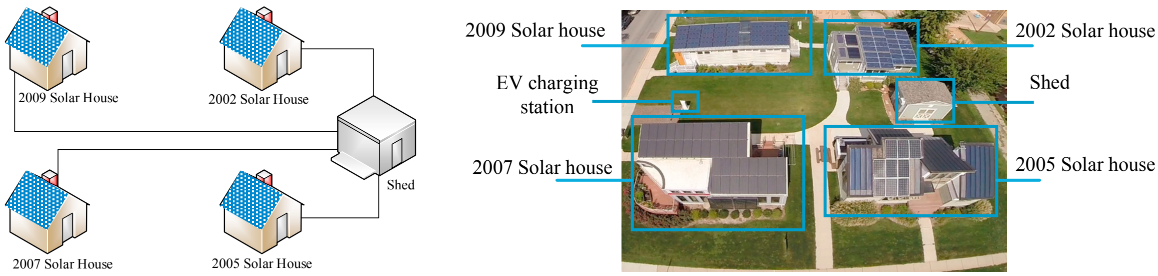

Fig. 6. Missouri S&T microgrid

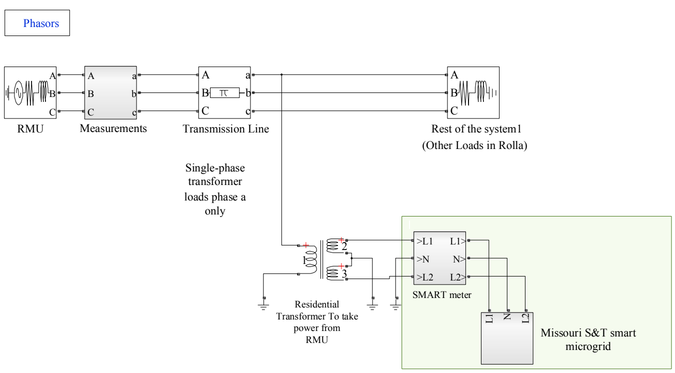

Fig. 7. Simulink model for S&T microgrid

7. Simulation Results

This section presents Missouri S&T microgrid simulation. Figure 8 shows the power consumption of each house, solar power, and generation from RMU. The usual goal is to control the battery and maximize the performance of the system. However, the battery in this simulation was eliminated so that the system is grid connected without battery storage. The goal, then, is to reduce the consumption from power grid by using available power from the solar panels as follows:

$$P_{utility} = P_{load} - P_{PV} \tag{8}$$

The simulation setup in the previous section was run for 24 hours. The output waveforms after completion are shown in Fig. 9. The voltage of phase A and phase B is 120 V, equal in magnitude and opposite in polarity. It also shows the current passing through the distribution transformer, where I_A, I_B, and I_N are the phase A current, phase B current , and neutral current, respectively. The power consumption seen by the grid at each house is also shown in Fig. 9., as well as the power loss in the transformer $P_{transformer}$. From the waveforms, one can see that the system is balanced, and each house utilizes the renewable energy effectively. The voltages are constant and steady, and the currents are within transformer limits.

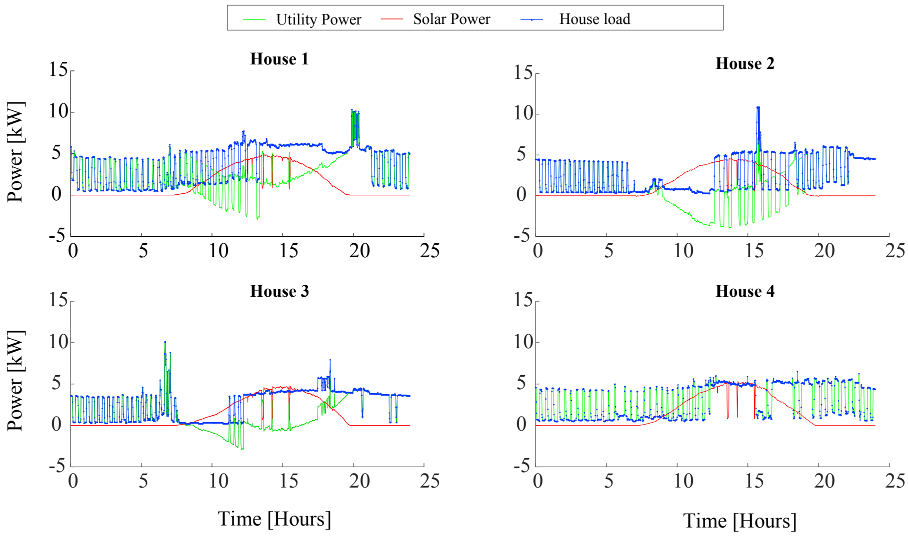

Fig. 8. Power at each house: Utility power (green), solar power (red), and house consumption (blue)

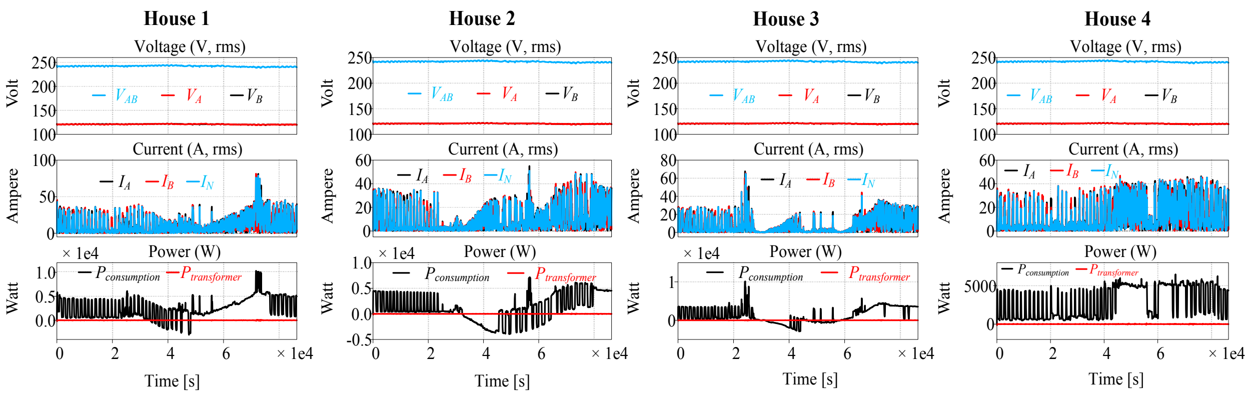

Fig. 9. Voltage and current balance at each house

Conclusion

This paper presented modeling and simulation of microgrid. This microgrid was treated as an SoSs and controlled to be able to utilize different energy sources. A practical example from Missouri S&T was implemented and simulated. The results were presented and to see that it utilized the renewable energy coming from the solar panels and optimally distributed it between homes. The neural networks were used to model the output power of microgrid components. Each component was treated as an autonomous system. These autonomous components were collaborating to achieve the overall goal, which is supplying the electric load. Simulink model and results are discussed for grid tied microgrid with no storage element. Future work includes simulating Missouri S&T with the battery storage elements and implementing battery control algorithm.

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