Intelligent Decision Making for Energy Management in Microgrids with Air Pollution Reduction Policy[1]

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Abstract— **Fuzzy Logic-based decision-making framework is implemented for energy management in microgrid systems in order to meet targets such as providing local consumers with required energy demand and making good revenue for the microgrid owner under a time-varying electricity cost policy while helping reduce negative environmental effects due to air polluting sources of electrical energy such as coal fire plants which operate in the main grid in order to provide local microgrid loads. Typically, a microgrid system has two modes of operation. It either works synchronously with the main grid or operates independently from the utility grid in an isolated mode. Distributed renewable energy generators including solar, wind in association with batteries and main grid supply power to the consumer in the microgrid network. One day period is divided to a finite number of time slots. The Fuzzy intelligent approach implemented in this article determines the rate at which power has to be delivered to/taken from the storage unit during the next time slot depending on the electricity price per kWh of energy, local load demand, electricity generation rate through renewable resources, and air pollution factor which are sampled at predetermined rates. Cost function is defined as the sum of balance/revenue due to electricity trade between microgrid and the main grid, which includes the power provided to local load and distribution losses. Five different scenarios are considered for local load and microgrid assembly operation. Measures of balance/revenue will be extracted to represent benefits of using Fuzzy logic for energy management in microgrids with air pollution reduction policy.**

Keywords- Microgrid Network, Intelligent Fuzzy Decision-Making, Power Flow Analysis, Time-Varying Electricity cost.

I. INTRODUCTION

Microgrid is a small-scale electrical grid that is designed to provide energy and distribute it between local loads. A microgrid is an aggregation of multiple distributed generators (DGs) such as renewable energy sources, conventional generators, in association with energy storage units which work together as a power supply network in order to provide both electric power and thermal energy for small communities which may vary from one common building to a smart house or even a set of complicated loads consisting of a mixture of different structures such as buildings, factories, etc [3]. Typically, a microgrid operates synchronously in parallel with the main grid. However, there are cases in which a microgrid operates in islanded mode, or in a disconnected state from the main grid [1]. Auction-based theory for pricing strategy in solar powered microgrid is studied in [2]. In [3], Authors considered Fuzzy decision-making to control battery storage unit in microgrid considering an ideal storage unit both with no maximum limit for the amount of energy stored in the battery and with maximum limit, and investigated the overall costs and profits the Fuzzy approach could bring to the system.

In this article, when the microgrid is connected to the main grid and is working synchronously with it, we assume the flow of electrical power can be either from the main grid to the microgrid or vice-versa [3]. Whenever the flow of electric power is from microgrid towards the main grid, the microgrid, or in general the customer, is making profit by selling energy to the main grid. Without loss of generality, we have assumed that for each time instant the electricity cost rate for buying energy from the main grid is equal to that of the electrical energy sold to the main grid. Demand side management is not implemented since it is assumed that the main restriction is to always provide local load with whatever amount of energy it requires. In section II, model of the microgrid for this study will be introduced. The cost function and control policy will be determined in Section III. Intelligent decision-making both with and without policies on air pollution reduction will be discussed in section IV. Section V includes simulation results and discussions on pros and cons of using intelligent Fuzzy energy management for microgrids.

II. SYSTEM MODEL

The model used for simulation of the microgrid network can generally be assumed as a three-bus power network which summarizes all the busses on the network as three different types. One of the busses in the distributed generation model is assumed to serve the renewable generators which include either solar farm, wind farm, or any other renewable generation units either in association with battery storage unit or without any storage. Another bus is assumed to be there as the representative for connection of the main grid (utility) to the local microgrid which will provide the complement part of the power demanded by the local load that renewable

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electricity generation system cannot afford or will deliver the excess power from microgrid's side to the main grid. The third bus will be the summary of all busses for local loads to which the demanded power is to be provided. This load can be anything from a common building or a smart house, to a group of factories, or a mixture of all mentioned. Figure 1 shows an overall microgrid schematic including renewable electricity generators and storage unit, utility, and local load.

Figure 1 Microgrid Network General Schematic

There are five simulation scenarios in this article, specifications of which are given in Table 1. The parameters mentioned in table 1 will be introduced and used in the next sections:

Table 1. Characteristics of Five Simulation Scenarios

	Microgrid Model Elements	Fuzzy Inputs	Fuzzy Output
Scenario 1	Main grid Local Load	---	---
Scenario 2	Main grid Local Load Renewables	---	---
Scenario 3	Main grid Local Load Renewables Battery Storage	---	---
Scenario 4	Main grid Local Load Renewables Battery Storage Fuzzy Control	Pr(t) $P_R(t)$ $P_L(t)$	$P_B(t)$
Scenario 5	Main grid Local Load Renewables Battery Storage Fuzzy + Pollution Control	Pr(t) $P_R(t)$ $P_L(t)$ C(t)	$P_B(t)$

In the following, characteristics of the three buses (see Figure 2) in network model are mentioned for each scenario:

A. Characteristics of Buses in Scenario No 1

For scenario number one we only assume our network to be consisted of two busses as follows:

- First bus is of type Slack (reference) and is used as the Utility (grid) bus.
- Second bus is of type PV used as the Local Load bus.

Hence, we assume there is not renewable generation units installed and no battery storages are available and the local load, i.e. the plant only is supplied by the main grid which was the typical case prior to introduction of renewable resources and storage units to the industry. This is also the current case where no microgrids are available.

B. Characteristics of Buses in Scenario No 2

We assume there are renewable resources employed on the microgrid without any storage units available. The characteristics of the three buses in the microgrid Network model simulated in this article are as follows in the second scenario:

- Bus 1 is a PQ bus and is used as the bus for renewable generation unit.
- Bus 2 will be the Slack (reference) bus and is used as the Utility (grid) bus.
- Bus 3 is of type PV and is used as the Local Load bus.

C. Characteristics of Buses in Scenario No 3

The storage unit is also assumed to be at hand in addition to the renewable resources. Bus characteristics of the three buses in the microgrid Network model simulated in this scenario are as follows:

- Bus 1 is a PQ bus and is used as the bus for renewable generation unit and finite-capacity battery storage unit.
- Bus 2 will be the Slack (reference) bus and is used as the Utility (grid) bus.
- Bus 3 is of type PV and is used as the Local Load bus.

This must be considered that no intelligent control approach is employed yet.

D. Characteristics of Buses in Scenario No 4

In this scenario almost everything is the same as scenario three except for the fact that the intelligent decision-making approach, i.e. Fuzzy control, is also employed to provide the system with reduced costs and increased benefits. Therefore, buses will have following characteristics:

- Bus 1 is a PQ bus and is used as the bus for renewable generation unit and finite-capacity battery storage unit.
- Bus 2 will be the Slack (reference) bus and is used as the Utility (grid) bus.
- Bus 3 is of type PV and is used as the Local Load bus.

In this scenario, there are three input variables to the intelligent control system which including electricity price, local load demand, and renewable electricity generation rate.

E. Characteristics of Buses in Scenario No 5

This scenario is similar to the previous one with another input variable added to the Fuzzy controller called the air pollution index. The rules of the Fuzzy inference engine are also modified in such a way to take into account environmental concern besides providing the microgrid with reduced costs and increased benefits. The main objective in this scenario is still to provide local load with the required power demand. Making revenue for microgrid owner and reducing the air pollution compared to the first scenario are both of second priority and a compromise has to be made for these two secondary goals when generating the Fuzzy rule-base. Characteristics of buses in this scenario are:

- Bus 1 is a PQ bus and is used as the bus for renewable generation unit and finite-capacity battery storage unit.
- Bus 2 will be the Slack (reference) bus and is used as the Utility (grid) bus.
- Bus 3 is of type PV and is used as the Local Load bus.

This must be noted that battery storage units are assumed to be ideal batteries, i.e. no dynamic transient conditions for changes in the amount of stored energy in batteries are assumed. However, the energy capacity of the storage unit is assumed to be limited, i.e. that is a finite energy capacity battery.

III. Problem Statement

Time-varying pricing policy for electricity purchase means the bid price is not constant during the day time. The update duration of electricity cost is assumed to be 15 minutes. This implies that the money consumers have to pay to the utility for the same amount of energy used during different time-intervals might be different. Therefore, a function is defined to take into account the difference between amount of power given to the utility from the microgrid, and the amount of power taken from the utility by the microgrid. This function give us a cumulative sum of the amount that consumer must pay to the utility or, in some circumstances, the consumer obtains by selling the electricity to the utility due to proper purchase, storage, consumption, and sale policy. Eq. 1 represents this cost function:

$$Cost = \sum_{k=1}^{T} (\Pr(k) \times \Delta t \times S_U(k)) \qquad \text{Eq. 1}$$

where the electricity price rate Pr(k) is the sell and bid price per kilowatt-hour of electrical energy. $S_U(k)$ is the amount of power transferred from/to microgrid to/from the main grid during k^{th} 15-minute period. If power is received from the Grid $S_U(k)$ will be positive, and if power is delivered to the grid $S_U(k)$ will appear with a negative sign. Δt is the duration of the time interval which here is assumed to be 15 minutes. Therefore, there will be $T = \frac{24(h)}{\Delta T} = \frac{24(h)}{15(min)} = \frac{24(h)}{0.25(h)} = 96$ time intervals for each of which the electricity cost will be determined during the 24 hour day period.

Air pollution is taken into account in this article as the factor of environmental health threat. Eq. 2 represents the standard measure used for computing air pollution called Air Quality Index (AQI) introduced by Environmental Protection Agency (EPA):

$$AQI_{pollution} = \frac{Pollutions\ Data\ Reading}{Standards} \times 100 \qquad \text{Eq. 2}$$

EPA calculates AQI for five major air pollutants, including ground-level ozone, particle pollution (also known as particulate matter), carbon monoxide, sulfur dioxide, and nitrogen dioxide, using the pollutant data reading updated every hour during the day. EPA has released a new rule to regulate CO2 emissions from power plants. The new rule requires power plants to meet an output-based standard of 1,000 pounds of CO2 per megawatt-hour (MWh) of electricity produced. Constraining relationship between the energy taken from the main grid and the CO2 added to the air is assumed is shown in Eq. 3:

$$p = \psi E \qquad \text{Eq. 3}$$

Where p represents how much CO2 in unit pound is added to the air, $E=\int P(t)dt$ is the energy generated by the power plant during a specific time when P(t) stands for the function representing output electrical power of the plant in Megawatts, and ψ is the restricting coefficient which is assumed to be equal to $1000\left(\frac{lb}{MW}\right)$.

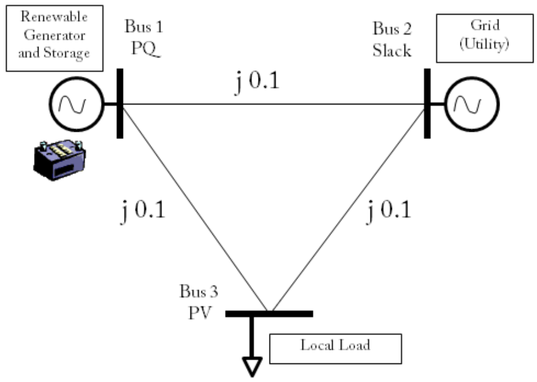


Figure 2 Three Bus Model of microgrid

Figure 2 represents the three-bus model used for simulation of the microgrid in different scenarios along with the branch impedances and types of the buses.

Mathematical representation of the active power sold to or purchased from the grid can be expressed as shown in Eq. 4:

$$P_U(t) = P_L(t) + P_{loss}(t) - P_B(t) - P_R(t) \qquad \text{Eq. 4}$$

$$s.t. \begin{cases} if\ P_B(t) < 0\ energy\ is\ being\ stored\ in\ battery \\ if\ P_B(t) > 0\ energy\ is\ being\ drawn\ from\ battery \end{cases}$$

Where $P_U(t)$ stands for the amount of power given to the microgrid, $P_U(t) > 0$, or taken out from it, $P_U(t)<0$, at time instant t. $P_L(t)$ is the demanded power of the local load at time instant t. $P_{loss}(t)$ shows the distribution loss due to branch impedances at time instant t. $P_B(t)$ is the rate at which energy is given to storage unit, i.e. $P_B(t) < 0$, or is taken from it, i.e. $P_B(t) > 0$, at time instant t. Accordingly, $P_R(t)$ represents the electrical power at the output of renewable generators at time instant t which is either equal to or greater than zero.

The value $P_B(t)$ will be determined by the fuzzy controller for each 15 minute interval at the beginning of the interval based on samples of the three, except for the scenario five which has four, input variables to the Fuzzy system including electricity cost, renewable electricity generation rate, local load demand, and, only for scenario number five, air pollution.

Hence, based on the value of $P_B(t)$ calculated by intelligent Fuzzy controller for each 15-minute interval, and the continuously sampled values of $P_L(t)$ and $P_R(t)$, values of $P_U(t)$ and also $P_{loss}(t)$ can be determined by a power flow calculation algorithm in power networks since the impedances of the branches are known.

Power flow calculation and analysis in the microgrid is the basic tool to simulate the whole system. There are a number of well-known methods for calculation of power flow in the distributed generation network [4]. Four different types of busses are generally considered in a distributed generation network, the characteristics of which will be calculated in power flow algorithms. These four types include PQ, PV, Slack, and isolated [5, 6]. For the simulation purposes of this paper, Gauss-Seidel iterative algorithm is implemented to do the power flow calculation. [6]

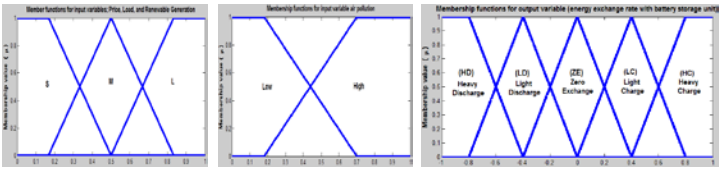
IV. INTELLIGENT DECISION-MAKING

Fuzzy logic [7] is used for control and energy management by determining the flow of power to/from the battery storage unit in order to improve the value of the cost function in Eq. 1. The three input variables to the Fuzzy inference engine for scenario 4 include electricity cost per kWh or Pr(t), renewable electricity generation rate or $P_R(t)$, local load demand or $P_L(t)$. The Fuzzy inference engine serves as the controller which determines a measure of power that must be sent to/taken from the battery unit during each 15 minute period, based on the samples of the three input variables at the beginning of that period.

In scenario 5, a fourth input variable will be fed to the Fuzzy inference engine called air pollution measure or C(t). For the purposes of this study, an exemplary pollution profile is generated for a typical 24 hour period in order to examine capabilities of the different scenarios. C(t) is assumed to be the average amount of CO_2 on global area, not only at specific points around the polluting power plants or only around microgrid local loads. Hence, a simplified discrete-time mathematical representation for air pollution update is represented in Eq. 5 and Eq. 6:

$$C(k+1) = C(k) + \Delta C \qquad \text{Eq. 5}$$
$$\Delta C = \Delta p(k) - \Delta r(k) \qquad \text{Eq. 6}$$

where $C(k)$ represents the measure of pollutant, here CO_2, concentration at the end of k^{th} 15-minute time interval. ΔC stands for the change in the CO_2 measure during the k^{th} time interval. $\Delta p(k) = p(k+1) - p(k) = \psi \int_{k\Delta t}^{(k+1)\Delta t} (\sqrt{P_U^2(t) + Q_U^2(t)})dt$ represents the measure of the amount of CO_2 added to the air during k^{th} time interval due to operation of the main grid's power plants when Δt represents the duration of each time interval, i.e. 15 minutes. $\Delta r(k)$ represents the removal term of pollution associated with chemical reactions and pollution's dispersion in the atmosphere during k^{th} time interval.



(a) (b) (c)

Figure 3 Fuzzy Membership functions for input and output variables of the Fuzzy Controller; (a) price, load and generation (b) air pollution (c) output

Fuzzy membership functions for the four input variables and the only output variable of the Fuzzy inference engine are shown in figure 3.

The numerical values for the three input variables price, load, and generation are normalized to the [0 1] interval, and then are Fuzzified using three Fuzzy sets defined as Low (L), Medium (M), and High (H) as can be seen in figure 3a. Air pollution has two membership functions defined as Low (L) and High (H) represented in figure 3b. After Fuzzification, the input variables will be fed to Fuzzy inference engine where the rule-base is applied to them and the Fuzzy output will be determined based on human reasoning. There is only one output variable for the Fuzzy controller which determines the amount of power to be exchanged with the battery during the next 15-minute interval. As represented in figure 3c, output variable Fuzzy set has five membership functions called Heavy Discharge (HD), Light Discharge (LD), Zero Exchange (ZE), Light Charge (LC), and Heavy Charge (HC). The power drawn from the batteries can be used to help the renewable electricity generation unit provide the local load with required demand, can be sold to the main grid, or can be partially used for both reasons [8]. The role of Fuzzy inference engine is critically important for obtaining satisfactory results. For example, some rules can be as follows in different scenarios:

IF the *Price* is ***Medium***, **AND** the *Renewable Generation Rate* is ***Low***, **AND** the *Load* is ***Medium***, **THEN** the *Battery* should be ***Lightly Discharged***.

IF the *Price* is ***Medium***, **AND** the *Renewable Generation Rate* is ***Low***, **AND** the *Load* is ***Medium***, **AND** the *Air Pollution* is ***High***, **THEN** the *Battery* should be ***Heavily Discharged***.

The primary objective in these simulations is to provide the local load with all the power it demands at any circumstances. Under low-price electricity conditions, the action decided by the rules might even sometimes require the microgrid network to purchase energy from grid and store it in the battery storage unit since the main point here is that the electricity price is low. This consequently results in more degree of freedom for the system to sell energy to the main grid during high-price periods, even under cases of high local load demand. Hence, having feasible rules predefined for the Fuzzy system helps improve the cost function drastically. The proposed approach may even sometimes result in so that the microgrid owner makes some revenue instead of paying to the utility, while provides the local load demand to the fullest extent.

V. SIMULATION RESULTS

The simulation is done on the three bus system shown in figure 2 for the duration of one week period. The Gauss-Seidel algorithm is implemented using Matlab for power flow calculation [9]. Some exemplary data are generated for electricity price rate, load demand profile, renewable electricity generation rate, and air pollution. Air pollution is updated after every time interval using Eq. 5 and Eq. 6 mentioned in section IV. For scenarios 2 to 5, resulting air pollution is compared to that of scenario 1 and the difference is represented in the simulation results as a measure called air pollution change. In the same fashion, peak pollution change refers to the difference between the peak values of pollution during the one week period of simulation for scenarios 2 to 5 with that of scenario 1. Final diagrams represent unit-less measures of balance/revenue, air pollution change, and peak pollution change so that we can compare outcomes of different scenarios for a single microgrid.

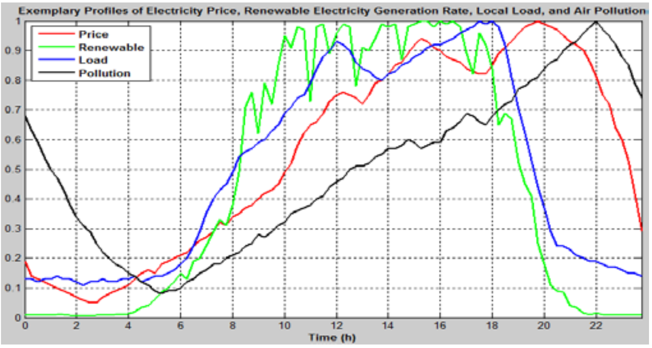


Figure 4 Profiles of Price, Renewables, Load, and Pollution

The normalized exemplary profiles for the four input variables, all or some of which are fed to the Fuzzy controller in different scenarios, are shown in figure 4 for a typical 24-hour period. These variables include electricity price, renewable electricity generation rate, local load demand, and air pollution. The data is generated arbitrarily for simulation purposes only considering similarity to the real world issues and with regard to the fact that the peak electricity consumption duration of the whole region of interest for the main grid occurs around 7:30 pm where the electricity price reaches its peak value.

Simulation results for five different scenarios are represented in figures 5 to 9. This must be noted that in this study, the renewable electricity generation plant is assumed to be able to fully provide microgrid's local load at its maximum generation rate conditions. Eq. 7 shows the relation between balance, distribution loss and the overall cost of electricity.

$$Balance = Cost - Loss \quad \text{Eq. 7}$$

$$Loss = \sum_{t=1}^{T}\left(\Pr(t).S_L(t)\right) \quad \text{Eq. 8}$$

Where Cost is calculated using Eq. 1 and represents the amount that the microgrid owner has to pay to the main grid, if Cost > 0, or will get from the main grid, if Cost < 0. Loss stands for the overall sum of multiplication of the electricity price and wasted power on distribution branches, i.e. $S_L(t)$, for all 15-minute periods. Loss will always be greater than or equal to zero. Balance will then be the measure of the amount than microgrid owner had to pay to the main grid,i.e. Balance>0, or the amount of revenue that microgrid owner will get from the main grid, i.e. Balance<0, in case the power network were lossless or could be assumed to be lossless.

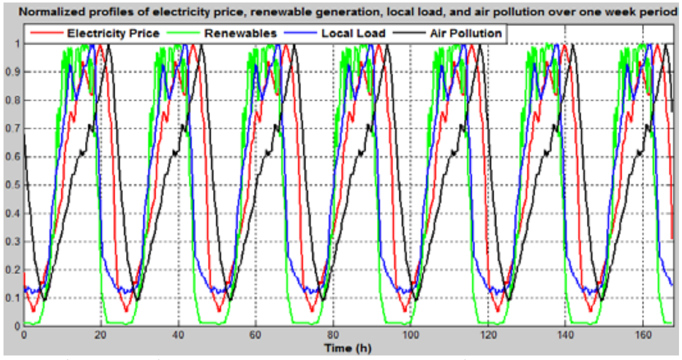


Figure 5 Price, Renewables, Load, and Pollution over one week

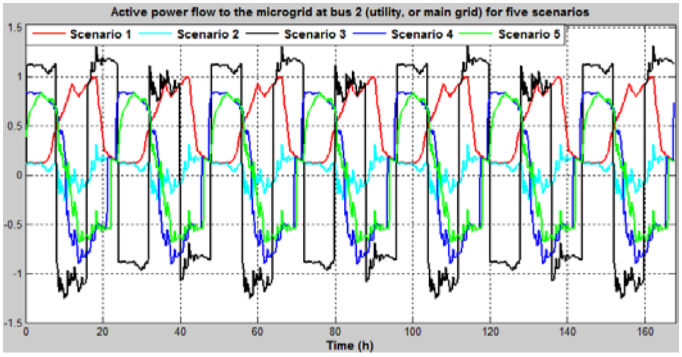


Figure 6 Power Exchange with the Utility or Main Grid; Five scenarios

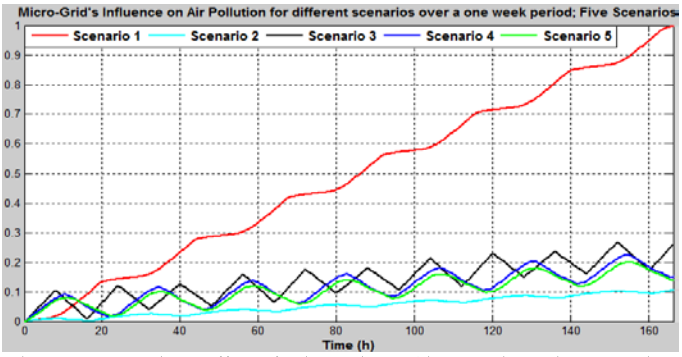


Figure 7 Normalized Effect of Microgrid on Air Pollution; Five scenarios

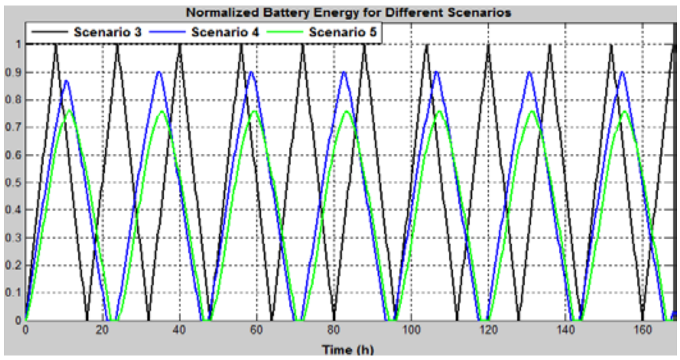


Figure 8 Normalized Battery Unit's Energy over a week; Five Scenarios

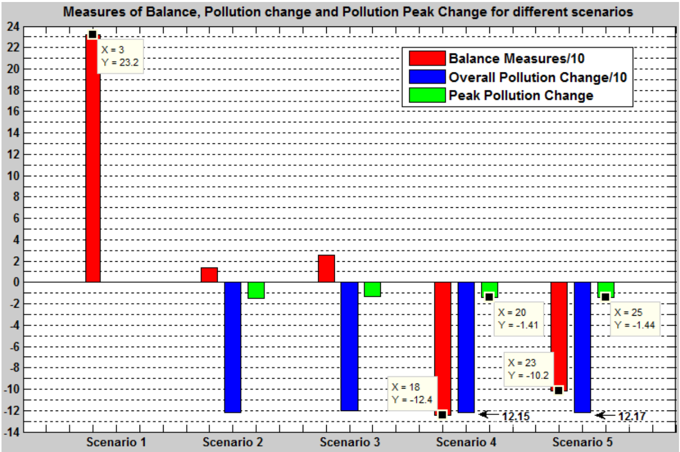


Figure 9 Final Measures of Balance, Pollution and Peak Pollution for

The center of gravity, i.e. centroid, defuzzification is used for computing crisp values of the output variable from union of the curves obtained by Fuzzy rules.

Figure 5 represents profiles of the four input variables of the Fuzzy system for the period of one week. Some factors of randomness and intermittency are associated with electricity price, local load, and renewable electricity generation rate in order to provide more realistic situations for the simulation. Air pollution is updated after each time interval using Eq. 5 and Eq. 6. In figure 6, power flow at bus number 2 which is the connection point between microgrid and the main grid is shown for five scenarios. It can be seen that in scenario 3 where the microgrid has renewable electricity generation unit and battery storage without any intelligent control system applied, there are cases when the power flow exceeds the value 1 p.u. which may be undesired for the system. This happens because of the fact that the storage unit is predefined to start from an initial condition and be charged to its full capacity before starting to discharge the stored energy to the microgrid. Hence, this can be concluded that applying an efficient control method to microgrid is of utmost priority when storage unit exists in the system. Figure 7 represents the normalized curves indicating amount of CO_2 added to the environment for different scenarios. Scenario 1 where no renewable generation system and no batteries are involved has the worst effects on environment, and scenario 2 which includes only the renewable generation unit without any storage units in the microgrid, has the best results in this regard. Also, scenario 5 which incorporates the air pollution control in Fuzzy inference engine stands right after scenario 2 on reducing CO_2 emission. The point is that in scenario 5 there are lots of profit for the microgrid owner and the consumers which is not the case for scenario 2. Normalized battery energy is depicted in figure 8 for three scenarios 3, 4, and 5. Figure 9 represents the three final measures of balance, pollution change, and peak pollution change for all five scenarios. The pollution measures represent how much other scenarios incorporate in increasing or decreasing the CO_2 emissions compared to scenario 1.

VI. Conclusion

The proposed Fuzzy logic-based approach is applied for energy management in a generic model of microgrid systems by controlling the flow of energy to/from storage unit. Five scenarios were considered for simulation. Measures of balance, pollution change, and peak pollution change represented that using efficient battery storage in association with renewable electricity generation units and intelligent decision-making approach can eliminate all the balances that the microgrid owner has to pay to the utility for electricity consumption and even bring revenue for the microgrid owner if the appropriate rule-base is defined for the inference engine. This must be noted that in this study, renewable electricity power plant life-cycle and costs, and also the costs associated with battery storage purchase, installation, and maintenance are not considered. Scenario 5 reveals the fact that applying the air pollution control policy to the Fuzzy inference engine rules will result in less pollution compared to all other scenarios, however, the balance measure will drop to some extent in comparison to scenario 4 which brings most financial benefits to the microgrid owner.

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