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COST-EFFICIENT ENVIRONMENTALLY-FRIENDLY CONTROL OF MICRO-GRIDS USING INTELLIGENT DECISION-MAKING FOR STORAGE ENERGY MANAGEMENT

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ABSTRACT— A smart decision-making framework based on genetic algorithms (GA) and fuzzy logic is proposed for control and energy management of micro-grids. Objectives are to meet the demand profile, minimize electricity consumption cost, and to modify air pollution under a dynamic electricity pricing policy. The energy demand in the micro-grid network is provided by distributed renewable energy generation (coupling solar and wind), battery storage and balancing power from the electric utility. The fuzzy intelligent approach allows the calculation of the energy exchange rate of the micro-grid storage unit as a function of time. Such exchange rate (or decision-making capability) is based on (1) the electrical energy price per kilowatt-hour (kWh), (2) local demand (load), (3) electricity generation rate of renewable resources (supply), and (4) air pollution measure, all of which are sampled at predefined rates. Then, a cost function is defined as the net dollar amount corresponding to electricity flow between micro-grid and the utility grid. To define the cost function one must consider the cost incurred by the owner of the micro-grid associated to its distribution losses, in addition to its demand and supply costs, in such a way that a positive cost translates to owner losses and a negative cost is a gain. Six likely scenarios were defined to consider different micro-grid configurations accounting for the conditions seen in micro-grids today and also the conditions to be seen in the future. GA is implemented as a heuristic (DNA-based) search algorithm to determine the sub-optimal settings of the fuzzy controller. The aforementioned net cost (which includes pricing, demand and supply measures) and air pollution measures are then compared in every scenario with the objective to identify best-practices for energy control and management of micro-grids. Performance of the proposed GA-fuzzy intelligent approach is illustrated by numerical examples, and the capabilities and flexibility of the proposed framework as a tool for solving intermittent multi-objective function problems are presented in detail. Micro-grid owners looking into adopting a smart decision-making tool for energy storage management may see an ROI between 5 and 10.

Key Words: Micro-grid Network, Enhanced Fuzzy Decision-Making, Power Flow Analysis, Dynamic Electricity Pricing Policy, Genetic Algorithms, Environmental protection.

1. INTRODUCTION

A micro-grid is a combination of loads and generators designed locally as a small-scale electrical grid for the purpose of providing energy and distributing it between local consumers. In other words, a micro-grid 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 commercial buildings, industrial facilities, hospitals, schools, etc [1]. Typically, a micro-grid operates synchronously in parallel with the main grid. However, there are cases in which micro-grid operates in islanded mode, i.e. disconnected from the main grid [2]. Auction-based theory for pricing strategy in solar powered micro-grid is studied in [3]. In [1], the authors proposed a fuzzy logic-based decision-making approach to control power exchange with battery storage unit in micro-grid considering an ideal storage unit with both the limited-capacity and unlimited-capacity cases, and investigated the overall costs and profits the fuzzy approach could bring to the system. In [4] the concept of micro-grids and applications of intelligent systems theory have been applied to various problems and issues in these power systems. An overview of micro-grid systems control is given in [5].

In this article, the fuzzy logic-based decision-making framework will be enhanced by weighting factors determined based on the difference between current time and the predicted peak pollution time for the day ahead in order to elevate performance of the system by reducing micro-grid owner’s losses due to the electricity purchased from the main grid and increasing his gains or gains due to the electricity sold to the main grid while helping reduce the air pollution and modify the peak air pollution due to micro-grid operation. Genetic algorithms (GA) is the distributed search method used to enhance the fuzzy system and to determine the settings of fuzzy sets so that sub-optimal results for energy and pollution management could be achieved. When the micro-grid is connected to the main grid and is working synchronously with it, it is assumed that the flow of electricity can be two-way, i.e. either from the main grid to the micro-grid or vice-versa [1]. Whenever the flow of electric power is from micro-grid towards the main grid, the micro-grid, or in general the customer, is making profit by selling energy to the main grid. Otherwise, the consumer must pay for the amount of electrical energy purchased from the main grid. Without loss of generality, for each time instant, it is assumed that the electricity cost for bidding and selling energy is the same. Demand-side load management is not considered since the micro-grid is supposed to fully provide the local load with the demanded energy and to meet the load profile. Therefore, modification of the load profile using a demand-response algorithm for objectives such as peak shaving or achieving minimum variance generation profile is not the purpose of this article. In Section 2, the generic micro-grid model used for this study will be introduced. The cost function and control policy will be determined in Section III. Real-time intelligent fuzzy decision-making both with and without any restrictions on air pollution will be discussed in section IV. The weighted fuzzy approach will also be explained in the same section. Section V presents simulation results and discussions on pros and cons of using intelligent fuzzy energy management for micro-grids. In section VI discussions on the overall results and conclusions will be given.

2. SYSTEM MODEL

The generic model used for simulation of the micro-grid network can essentially be regarded as a three-bus power network, integrating every bus on the power network as three different types. The methods presented in this article are applicable and easily transferable to micro-grids of any size, therefore the three-bus system was chosen for illustrative purposes only. One of the buses in the distributed generation model is assumed to serve the renewable generators including 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 between main grid, i.e. utility, and the local micro-grid through which two-way power flow is available. The excess energy demanded by local load, which renewable electricity generation system cannot afford to supply, is drawn from the main grid through this bus. The excess energy existing at the micro-grid side can also be delivered to the main grid from the same bus. The third bus will be the integration of all local loads. This load can be anything from a common building or a smart house, to a group of factories, or any combination of all. Figure 1 shows schematic of generic micro-grid including renewable electricity generators and storage unit, utility, and local load.

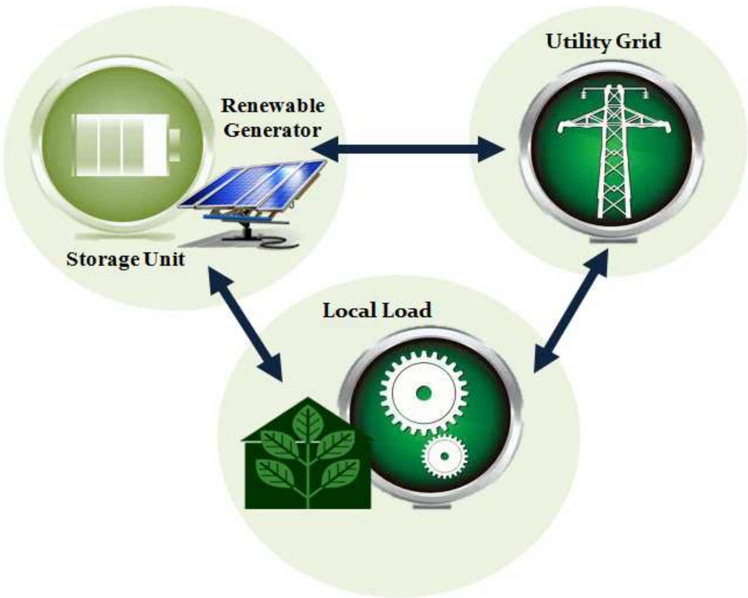

Figure 1 Schematic of a Generic Micro-grid Network

2.1 Simulation Scenarios

Six simulation scenarios are considered for the power network in this article. Specifications of these scenarios are given in Table I in the following including the elements of the power network model, the fuzzy inputs to the energy controller, and fuzzy output from the energy controller for each and every scenario:

Table I. I/O Configuration of Simulation Scenarios

	Power Network Model Elements	Fuzzy Inputs	Fuzzy Output
Scenario 1	Main grid (Utilities) Local Load	---	---
Scenario 2	Main grid (Utilities) Local Load Renewables	---	---
Scenario 3	Main grid (Utilities) Local Load Renewables Battery Storage	---	---
Scenario 4	Main grid (Utilities) Local Load Renewables Battery Storage Fuzzy Control	$\mathrm{Pr(t)}$ $P_R(t)$ $P_L(t)$	$P_B(t)$
Scenario 5	Main grid (Utilities) Local Load Renewables Battery Storage Enhanced Control	$\mathrm{Pr(t)}$ $P_R(t)$ $P_L(t)$ $\mathrm{C(t)}$	$P_B(t)$
Scenario 6	Main grid (Utilities) Local Load Renewables Battery Storage Pollution Control	$\mathrm{Pr(t)}$ $P_R(t)$ $P_L(t)$ $\mathrm{C(t)}$	$P_B(t)$

In Table I, $\mathrm{Pr(t)}$ represents price per kWh of electrical energy in Cents at time t, $P_R(t)$ is the electricity generation rate of renewable resources, which may include any combination of net production from either solar arrays or wind turbines, in kW at time instant t, $P_L(t)$ represents the local load, or the so called energy demand rate, in kW at time t, $C(t)$ represents the pollution measure which shows the micro-grid's contribution in the amount of CO_2 in the atmosphere, and $P_B(t)$ is the energy exchange rate of storage unit at time instant t.

It must be noted that in this study, the environmental-friendly aspect of the micro-grid control considers the effect that each and every scenario has on the air pollution, specifically speaking the amount of CO_2 added to the air due to micro-grid energy demand. Hence, instead of using detailed mathematical representations of the fluid dynamics for propagation of CO_2, the net amount of CO_2 emitted from conventional sources of energy due to micro-grid's excess energy demand and/or the amount of CO_2 eliminated from the atmosphere due to well-supervised storage and use of utility grid's power and renewable resources is studied. The pollution measure, $C(t)$, represents the average CO_2 concentration in the whole region of interest. The region of interest is referred to the city in which the micro-grid is located, and is not limited to the area around the micro-grid network or the area close to conventional power plants of the main grid. Assuming other sources of pollution keep a recurring profile of pollutant emission, which is a fair assumption for the simulation period of one week considered in this article, it will be possible to study how much micro-grid will incorporate to air pollution.

2.2 Micro-grid Structure in Simulation Scenarios

The micro-grid system model is simplified down to a three-node model, with three branches connecting every two nodes to each other, where the renewable generators are supposed to be located all together with the storage unit at a single node, the utility grid connections to the micro-grid network are summarized as the second node, and the consumers or the so called local load is considered as the third node. It is assumed that the renewable generators do not have any capability to provide the micro-grid with reactive power which means that the renewable resources bus should be considered as a PQ bus since at each instance of time both active and reactive power present at this bus are known for power flow calculations. The active power is known due to renewable generation available and the energy exchange with the storage unit, and the reactive power is also known to be zero all the time since it was the assumption that there's no reactive power capacity available at this bus. Utility bus is the standard choice for a slack bus since it is assumed that the voltage magnitude and angle are constant at this bus regardless of the amount of active and/or reactive power exchange through it. Load bus, therefore, needs to be the PV bus in order for power flow calculations to be done properly. In order to make this possible, there's this assumption that the load bus is associated with a synchronous compensator which helps keep the voltage magnitude constant at 1 p.u. regardless of the active or reactive power demand at the load side. Furthermore, the active power demand of the load is also known at each time instance, which together with the synchronous compensator make the necessary and sufficient conditions for a PV type bus to be there. In the following, characteristics of the three buses in the micro-grid model are mentioned for each simulation scenario:

2.2.1 Characteristics of Micro-grid Buses in Scenario 1

The network only consists of two buses as follows:

- First bus is of type slack (reference) and is used as the utility (main grid) connection node.
- Second bus is of type PV; used as the local load bus with a synchronous compensator.

Renewable energy generators and storage units are not considered in this scenario. Hence, the local loads, i.e. the consumers, are only supplied by the main grid which was the typical case prior to introduction of the definition of micro-grid, renewable resources and storage unit to the industry. This scenario is predominant in majority of cases around the globe in order to provide electricity from utility companies to the consumers.

For scenarios 2 to 6 refer to figure 1.

2.2.2 Characteristics of Micro-grid Buses in Scenario 2

Renewable resources are deployed in the micro-grid without any storage units available. Characteristics of the three buses in the micro-grid network model 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 is the slack (reference) bus and is used as the utility (main grid) connection node.
- Bus 3 is of type PV and is used as the local load bus with a synchronous compensator.

2.2.3 Characteristics of Micro-grid Buses in Scenario 3

In this scenario, the storage unit is also added to the model. Characteristics of the three buses in the micro-grid 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 storage unit.
- Bus 2 is the slack (reference) bus and is considered as the utility (main grid) connection node.
- Bus 3 is of type PV and serves as the local load bus with a synchronous compensator.

This must be noted that no intelligent control approach is employed in this scenario.

2.2.4 Characteristics of Micro-grid Buses in Scenario 4

Micro-grid structure in this scenario is the same as that of scenario 3. However, the intelligent decision-making approach, i.e. fuzzy control, is used as the energy control and management engine to provide the system with reduced costs and increased benefits. Buses have following characteristics:

- Bus 1 is a PQ bus and is used as the bus for renewable generation unit and storage unit.
- Bus 2 is the slack (reference) bus and is considered as the utility (main grid) connection node.
- Bus 3 is of type PV and serves as the local load bus with a synchronous compensator.

Three input variables to the intelligent control system include electricity price, local load demand, and renewable electricity generation rate. Output of the fuzzy control system will be the energy exchange rate between the storage unit and other elements of the micro-grid at each time instance

2.2.5 Characteristics of Micro-grid Buses in Scenario 5

This scenario is essentially similar to scenario 4 with another input variable added to the fuzzy controller called the air pollution index. Rules of the fuzzy inference engine are also modified in such a way to take into account environmental constraints besides providing the micro-grid with reduced costs and increased benefits. However, the main constraint is to still provide local load with the required energy demand. Making gain for micro-grid owner and reducing micro-grid’s negative impact on 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 modifying 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 storage unit.
- Bus 2 will be the slack (reference) bus and is used as the utility (grid) connection node.
- Bus 3 is of type PV and is used as the local load bus with a synchronous compensator.

2.2.6 Characteristics of Micro-grid Buses in Scenario 6

This scenario is almost a duplicate of the scenario five with only difference being the fuzzy decision-making engine is enhanced so that the control commands can be emphasized relative to the sensitivity of each condition. There will be a weighting factor which is determined based on the difference between current time and the estimated peak pollution time. Rules of the fuzzy inference engine are the same as those in scenario 5. However, the membership value of the fuzzy input variable air pollution index is weighted in such a way that whenever the current time-slot is close to the estimated peak pollution time, the emphasis on the membership value of high air pollution fuzzy set will increase and simultaneously the emphasis on the membership value of low air pollution fuzzy set will decrease, and vice-versa. The main constraint is to still provide the local load with the demand profile. Making gain for micro-grid owner and reducing micro-grid's negative impact on the air pollution compared to the first scenario are both of second priority and a compromise needs 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 storage unit.
- Bus 2 will be the slack (reference) bus and is used as the utility (grid) connection node.
- Bus 3 is of type PV and is used as the local load bus with a synchronous compensator.

The energy capacity of the storage unit is assumed to be limited and normalized. The state-of-charge (SOC) of battery unit will be computed at the end of each 15-minute period using the constant energy exchange rate for the same time interval determined by intelligent energy management approach. It is assumed that the stored energy curve is sufficiently linear within the 10% to 90% SOC range. The storage unit is assumed to be capable of supplying the micro-grid's local load for up to 10 hours at full demand when fully charged. This means that, for instance, a micro-grid with full demand of 1 MW at the load side should be associated with a storage unit that is capable of storing 10 MWh energy.

3. PROBLEM STATEMENT

Dynamic pricing policy for electricity purchase means the bid price is not constant during the day. 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 consumed during different time-intervals might be different. Therefore, a function is introduced to take into account the difference between amount of power given to the utility from the micro-grid, and the amount of power taken from the utility by the micro-grid. This function gives us a cumulative sum of the money that consumer must pay to the utility or, in some circumstances, the consumer gets from the utility companies by selling the electricity to the them due to proper purchase, storage, consumption, and sale policy. Eq. 1 represents this cost function:

$$Cost = \int_0^T \Pr(t)\, P_U(t) dt \tag{1}$$

Where the electricity price $\mathrm{Pr(t)}$ is the sell and bid value per kilowatt-hour of electrical energy. $\mathrm{P_U(t)}$ is the active power exchanged between micro-grid and the utility grid. If energy is received from the utility companies $\mathrm{P_U(t)}$ is assumed to be positive, and if power is delivered to the utilities $\mathrm{P_U(t)}$ will appear with a negative sign. The update duration of the electricity cost is assumed to be 15 minutes. Therefore, during the 24-hour day period, there will be a total of $\frac{24(\mathrm{h})}{\Delta \mathrm{T}} = \frac{24(\mathrm{h})}{15(\mathrm{min})} = \frac{24(\mathrm{h})}{0.25(\mathrm{h})} = 96$ time intervals for each of which the electricity cost will be determined by the utility companies and remains the same.

Eq. 2 represents the standard measure used for computing air pollution called air quality index introduced by the environmental protection agency (EPA) for major air pollutants [6]:

$$I = \frac{Pollutant\ Concentration}{Pollutant\ Standard\ Level} \times 100 \tag{2}$$

In this study, Carbon Dioxide (CO_2) is considered as the emission factor contributing to air pollution and global warming. A 1000 megawatt (MW) coal-fired power plant produces approximately the same amount of global warming as 1.2 million cars [7]. According to EPA reports the coal-fired power plants emit 2249 pounds of CO_2 per 1 megawatt-hour (MWh) of electricity generated while the power plants which use natural gas as the fuel to generate electricity produce around 1135 pounds of CO_2 for the same amount of energy generated. EPA has released a new rule to regulate CO_2 emissions from power plants. The new rule requires power plants to meet an output-based standard of 1,000 pounds or less of carbon emission per MegaWatt-hour (MWh) of electricity generated [8]. Constraining relationship between the energy taken from the main grid and the CO_2 added to the air is shown in Eq. 3:

$$p = \psi E \tag{3}$$

Where p represents how much CO_2 in units pound is added to the air, $E = \int \mathrm{P(t)dt}$ is the energy generated by the power plant during a specific time period where $\mathrm{P(t)}$ stands for the function representing output electrical power of the plant in megawatts (MW), and ψ is the restricting coefficient which is assumed to be $1000\left(\frac{\mathrm{lb}}{\mathrm{MWh}}\right)$.

Figure 2 in the following represents the three-bus model used for simulation of the micro-grid in different scenarios, as discussed earlier in Section II, along with the branch impedances and types of the buses.

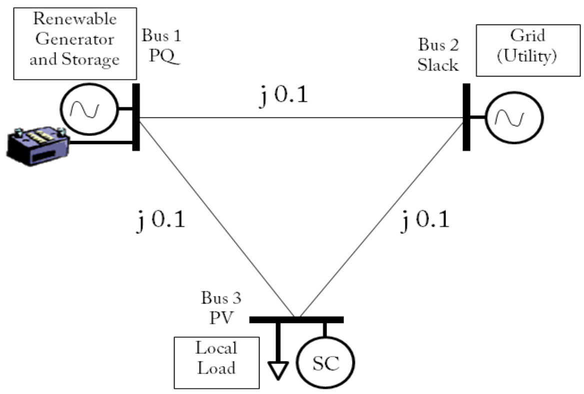

Figure 2 Three Bus Micro-grid Model

Mathematical representation of the active power exchange between the micro-grid and the main grid is given in Eq. 4:

$$P_U(t) = P_L(t) + P_{loss}(t) - P_B(t) - P_R(t) \tag{4}$$

$$s.t. \begin{cases} if\ P_B(t) < 0 & energy\ is\ being\ stored\ in\ battery, i.e. storage\ can\ be\ regarded\ as\ a\ load \\ if\ P_B(t) > 0 & energy\ is\ being\ drawn\ from\ battery, i.e. storage\ acts\ like\ a\ generator \end{cases}$$

Where $P_U(t)$ stands for the power purchased from the main grid, $P_U(t) > 0$, or sold to the main grid, $P_U(t)$<0, at time instant t. $P_L(t)$ is the demand of the local load at time instant t. $P_{loss}(t)$ shows the distribution loss due to branch impedances at time instant t. Considering $P_{loss}(t)$ makes it possible for the cost function to take into account the distribution losses over the branches of the power network in very large-scale micro-grids. However, for small-scale micro-grids the distribution loss, i.e. $P_{loss}(t)$, is small enough to be neglected. $P_B(t)$ 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, neglecting factors such as the reverse saturation current of solar farm, is assumed to be either equal to or greater than zero.

The value $P_B(t)$ will be determined by a management scheme for each 15 minute interval at the beginning of the interval based on samples of the input variables including electricity cost, renewable electricity generation rate, local load demand, and, only for scenarios five and six, air pollution or CO_2 concentration.

Hence, using the value of $P_B(t)$ calculated by the energy management scheme for each 15-minute interval, plus the continuously sampled values of $P_L(t)$ and $P_R(t)$, the 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. For the sake of generality, as represented in figure 2, the branches of the network are assumed to be alike with the same impedances.

There are a number of methods for calculation of power flow in the distributed generation network [9]. Four different types of buses are generally considered in a distributed generation network, the characteristics of which will be used for calculation in power flow algorithms. These four types include PQ, PV, slack, and isolated [10, 11]. For the simulation purposes of this paper, Gauss-Seidel iterative algorithm is implemented to do the power flow calculation [11].

4. INTELLIGENT DECISION-MAKING

A framework based on fuzzy logic [12] is used for energy management in the micro-grid network by control of the power exchange with battery storage unit in order to improve the cost function introduced in Eq. 1. Slightly different versions of the fuzzy controller are applied in the three scenarios four, five, and six. The three input variables to the fuzzy inference engine for scenario four include electricity cost per kWh or $\Pr(t)$, renewable electricity generation rate or $P_R(t)$, and local load demand or $P_L(t)$. The fuzzy inference engine serves as the controller which determines the rate at which electrical energy must be exchanged with 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 five, 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 different scenarios. $C(t)$ is the average amount of CO_2 on entire region of interest, neither only at specific points around the polluting power plants nor only around micro-grid local loads. Discrete-time mathematical representation for air pollution update is represented in Eq. 5 and Eq. 6:

$$C(k+1) = C(k) + \Delta C \tag{5}$$

$$\Delta C = \Delta p(k) - \Delta r(k) \tag{6}$$

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. The term $\Delta p(k) = p(k+1) - p(k) = \psi \int_{k\Delta t}^{(k+1)\Delta t} (\sqrt{P_U^2(t) + Q_U^2(t)})dt$ represents 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. Finally, the term $\Delta r(k)$ represents the removal portion of pollution associated with chemical reactions and pollution's dispersion in the atmosphere during k^{th} time interval. It is assumed that the pollution removal obeys the law of exponential decay. The coefficient for pollution removal is stochastically drawn out from a normal random distribution for each time interval.

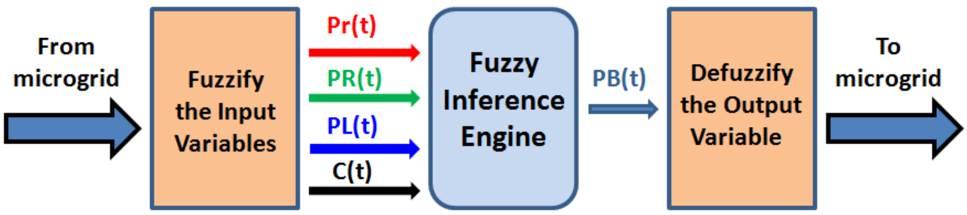

Figure 3 Structure of the real-time intelligent fuzzy decision-making approach; four input variables and one output variable

Figure 3 represents structure of the intelligent decision-making approach proposed in this article. Quantitative sensory data are gathered from different locations of the micro-grid network and also from the utility. These data include electricity price, Pr(t), renewable electricity generation rate, $P_R(t)$, local load, $P_L(t)$, and measure of CO_2 present in the air. These four variables undergo a fuzzification process in order to transform into linguistic terms which can be used for fuzzy decision-making in the rule-base of the inference engine. The output which results from the decision-making process, i.e. $P_B(t)$, is still in linguistic form however. Hence, a defuzzification process must be done in order to transform the output from linguistic or qualitative term into quantitative term so that it can be used for control and management actions in practical micro-grid network.

Original fuzzy sets for the four input variables and the only output variable of the fuzzy inference engine (see figure 3) are shown in figure 4.

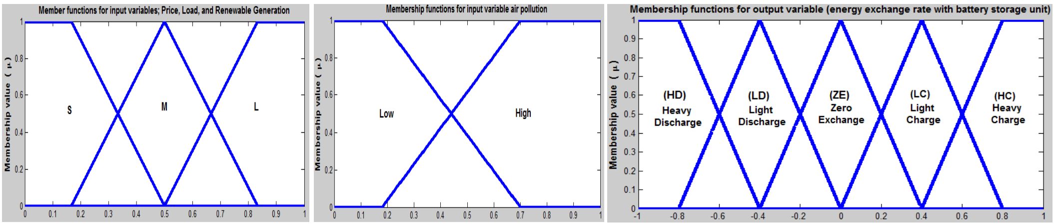

Figure 4 Fuzzy Membership functions for input and output variables of the Fuzzy Controller; (a) price, load and generation (b) air pollution (c) output

According to figures 3 and 4, the numerical values for the three input variables price, load, and generation are normalized to the zero to one interval, and then are fuzzified using three fuzzy sets defined as Low (L), Medium (M), and High (H) as represented in figure 4a. Air pollution has two membership functions defined as Low (L) and High (H) shown in figure 4b. 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 rate at which energy must be exchanged with the battery during the next 15-minute interval. As represented in figure 4c, output variable fuzzy set has five membership functions called Discharge Heavily (DH), Discharge Lightly (DL), Zero Exchange (ZE), Charge Lightly (CL), and Charge Heavily (CH). 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 [13]. Table 2 represents the fuzzy rule-base for scenario four where Pr represents the variable electricity price, P_R is the electricity generation rate by renewable resources including solar farm and wind farm, and P_L stands for the value of local load while P_B is the symbol of power exchange between storage unit and the rest of the nodes in micro-grid network.

The rules mentioned in Table II are determined based on human reasoning via expert knowledge. These rules or, in other words, the value of P_B, can also be regarded as the decisions made by an expert operator of such system based on combinations of different values for input variables. This means that the fuzzy inference engine can replace an experienced system expert and makes appropriate control actions based on current situation of the system. According to Table 2 there are 27 rules for the fuzzy system as expected, i.e. $(\text{Input variables})^{\text{Membership functions}} = 3^3 = 27$.

Table II Rule-base for Scenario 4

#		Pr		P_R		P_L		P_B
1	IF	**L**	AND	**L**	AND	**L**	THEN	**CH**
2	IF	**L**	AND	**L**	AND	**M**	THEN	**CH**
3	IF	**L**	AND	**L**	AND	**H**	THEN	**CH**
4	IF	**L**	AND	**M**	AND	**L**	THEN	**CH**
5	IF	**L**	AND	**M**	AND	**M**	THEN	**CH**
6	IF	**L**	AND	**M**	AND	**H**	THEN	**CH**
7	IF	**L**	AND	**H**	AND	**L**	THEN	**CH**
8	IF	**L**	AND	**H**	AND	**M**	THEN	**CH**
9	IF	**L**	AND	**H**	AND	**H**	THEN	**CH**
10	IF	**M**	AND	**L**	AND	**L**	THEN	**CL**
11	IF	**M**	AND	**L**	AND	**M**	THEN	**CL**
12	IF	**M**	AND	**L**	AND	**H**	THEN	**CL**
13	IF	**M**	AND	**M**	AND	**L**	THEN	**CH**
14	IF	**M**	AND	**M**	AND	**M**	THEN	**CL**
15	IF	**L**	AND	**H**	AND	**L**	THEN	**CL**
16	IF	**M**	AND	**H**	AND	**L**	THEN	**CH**
17	IF	**M**	AND	**H**	AND	**M**	THEN	**CH**
18	IF	**M**	AND	**H**	AND	**H**	THEN	**CL**
19	IF	**H**	AND	**L**	AND	**L**	THEN	**DH**
20	IF	**H**	AND	**L**	AND	**M**	THEN	**DH**
21	IF	**H**	AND	**L**	AND	**H**	THEN	**DH**
22	IF	**H**	AND	**M**	AND	**L**	THEN	**DL**
23	IF	**H**	AND	**M**	AND	**M**	THEN	**DH**
24	IF	**H**	AND	**M**	AND	**H**	THEN	**DH**
25	IF	**H**	AND	**H**	AND	**L**	THEN	**ZE**
26	IF	**H**	AND	**H**	AND	**M**	THEN	**ZE**
27	IF	**H**	AND	**H**	AND	**H**	THEN	**DH**

The role of fuzzy inference engine is critically important for obtaining satisfactory results. For instance, an example of Mamdani-based inference rule for scenario four is as follows:

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

The same modified rule, where membership value of the air pollution antecedent is weighted based on the difference between current time and estimated peak pollution time in scenario five for enhanced control is represented in the following:

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

Same rule, modified to be strictly environmentally-friendly based on air pollution constraints in scenario six, reads as follows:

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***.

Modified membership value of air pollution measure in scenario five, $\mu_M^{C(t)}$ is obtained as represented in equations 7 to 9 during a 24-hour period:

$$\mu_{L\_M}^{C(t)} = \xi \mu_L^{C(t)} \tag{7}$$

$$\mu_{H\_M}^{C(t)} = (1-\xi)\mu_H^{C(t)} \tag{8}$$

$$\xi = max\ (b_L, min\ (\left(1 - \frac{|t-t_p|}{max(t_p, 24-t_p)}\right), b_H)) \tag{9}$$

where ξ is the weighting factor. Parameter t is current time, and t_p represents the estimated peak pollution time, based on look-ahead prediction approach [14], for current day. b_L and b_H are two constant factors used as lower and upper boundaries for ξ to avoid some of the membership values and consequently some rules to be neglected at the transit time instants between consecutive days or when the estimated peak pollution time arrives. In our simulations, we chose $b_L = 0.0001$, $b_H = 0.9999$. This way, the importance of air pollution will be emphasized as the predicted peak pollution time approaches and will be at maximum and will be moderated as time goes further away from the predicted peak pollution time.

The primary objective in these simulations is for the micro-grid to meet the local load profile at all times. Under low-price electricity conditions, the action decided by the rules might even sometimes require the micro-grid network to purchase energy from grid and store it in the battery unit regarding the fact 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. Also, the proposed approach may sometimes bring some profit to the micro-grid rather than making it pay to the utility companies.

5. SIMULATION RESULTS

5.1. Intelligent Fuzzy Decision-Making

Simulation is done on the three bus system shown in figure 2 for the duration of one week. The Gauss-Seidel algorithm is implemented using MatLab® for power flow calculation [15]. Sample profiles are generated for electricity price rate, load demand profile, renewable electricity generation rate, and air pollution. The profiles for local load and the renewable electricity generation were generated based on available data for daily consumption of the University of Texas at San Antonio (UTSA) and also based on the daily generation of the solar panels installed on campus at UTSA respectively. Air pollution is updated using Eq. 5 and Eq. 6 mentioned in section IV. For scenarios 2 to 6, resulting air pollution is compared to that of scenario 1 and the difference is represented as a measure called air pollution change. i.e. *Pol*. In the same fashion, peak pollution change, i.e. *Peak*, refers to the difference between the peak values of pollution during the one week period of simulation for scenarios 2 to 6 with that of scenario 1. Final diagrams represent unit-less measures of the cost function (including distribution losses, demand and supply), pollution change, and peak pollution change.

Normalized profiles of the four input variables, all or some of which are fed to the fuzzy controller in different scenarios, are shown in figure 5 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 for the entire region of interest of the main grid occurs around 7:30 PM where the electricity price reaches its highest value.

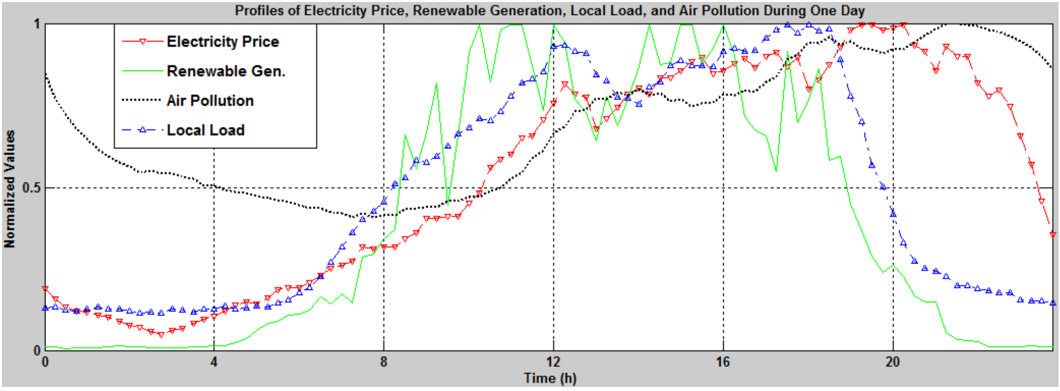

Figure 5 Profiles of Price, Renewables, Load, and Pollution; First day

Simulation results for six scenarios introduced in section II are represented in figures 6 to 10. In the simulations, nominal power generation capacity of the renewable electricity plant is assumed to be equal to the local demand's peak value. Figure 6 represents normalized values of the four variables electricity price, electricity generation rate by renewable generators, local energy demand, and the air pollution measure for one week. In figure 7, active power exchange between the micro-grid and the utility at bus number 2 - which is the connection point between the micro-grid and the utility or main grid - is shown for six scenarios for the duration of the first day. In figure 7, when each curve is positive, it means the electrical energy is being delivered to the micro-grid from the utility at the rate represented and the micro-grid owner must pay to the utility companies for purchase of energy. However, whenever each curve is negative it means that energy is being delivered to the main grid from micro-grid's side for that scenario at that time instant which results in some gain for the micro-grid owner.

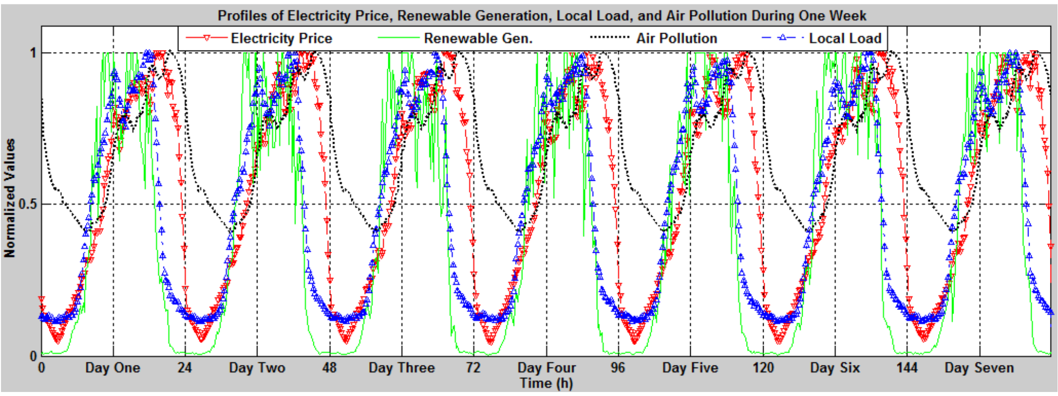

Figure 6 Profiles of Electricity Price, Renewable Generation, Local Load, and Air Pollution; One Week

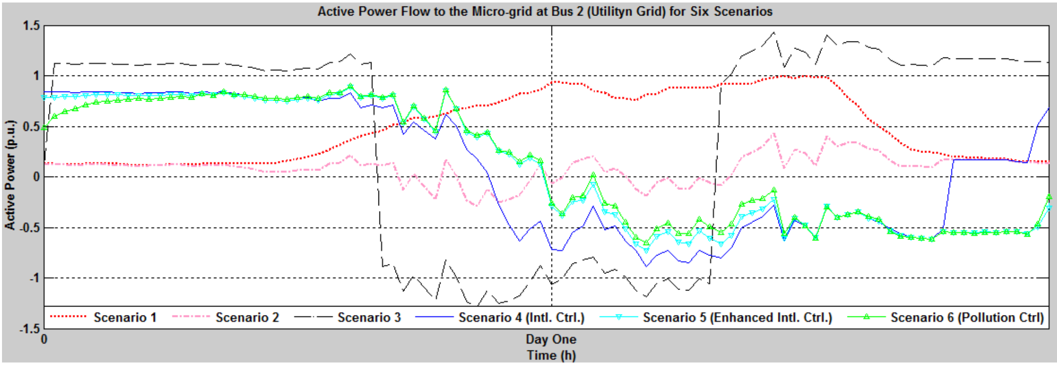

Figure 7 Power Exchange with the Main Grid in p.u. value; First Day; Six Scenarios

In figure 7, it can be seen that under scenario 3 where the micro-grid 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 with high probability will be undesired for the system. This happens because of the fact that there is no smart decision-making or control approach is used for the storage unit, i.e. the battery unit is pre-adjusted to start from an initial condition and get charged to its full capacity before it starts discharging the stored energy into the rest of the system. Hence, this can be concluded that applying an efficient control method to micro-grid is of utmost importance when storage unit is present in the network.

Factors of randomness and intermittency are associated with electricity price, local load, and renewable electricity generation rate in order to provide realistic situations for the simulation. Air pollution is updated after each time interval using Eq. 5 and Eq. 6. Air pollution does not see boundaries and its concentration needs to be estimated downstream of the sources based on factors such as wind blow and the pollution production rate, etc. [14]. The air pollution measure considered in this study is the average amount of CO_2 present in the air in the entire area of interest which includes surrounding space of the micro-grid plus the regions being supplied by the main grid.

Figure 8 represents the normalized curves indicating how much CO_2 is added to the environment for different scenarios during a one week period. It should be mentioned that curves depicted in this figure only represent the effect of the micro-grid on air pollution through considering the power exchange between the main grid and the micro-grid itself, without taking into account any effects of the pollution removal terms such as $\Delta r(k)$ as mentioned in Eq. 6. The results are also normalized in order to provide a relative view of the environmental effects of those six scenarios. As expected, 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 micro-grid, has the best results in this regard. In scenario 1 there is only the local load present in the micro-grid, and whatever the local load demands must be provided by the main grid. Therefore, there will never be any flow of energy from micro-grid towards main grid which results in the amount of CO_2 in the air to be always increasing gradually. However, in scenario 2, there are renewable generators besides load in the micro-grid network. In this scenario, whatever amount of energy generated by the renewable generators must either be consumed by the local load or must be delivered to the main grid since there is no storage unit available in the system. This will result in less amount of CO_2 added to the environment compared to the other scenarios since the huge amount of renewable energy added to utility grid utterly reduces utilities' dependence on fossil fuel for electricity generation.

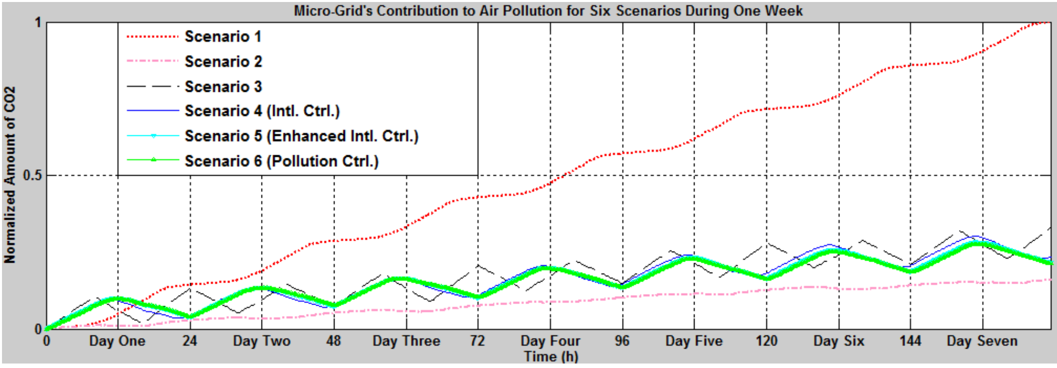

Figure 8 Normalized Micro-grid Contribution to Air Pollution; One Week; Six Scenarios

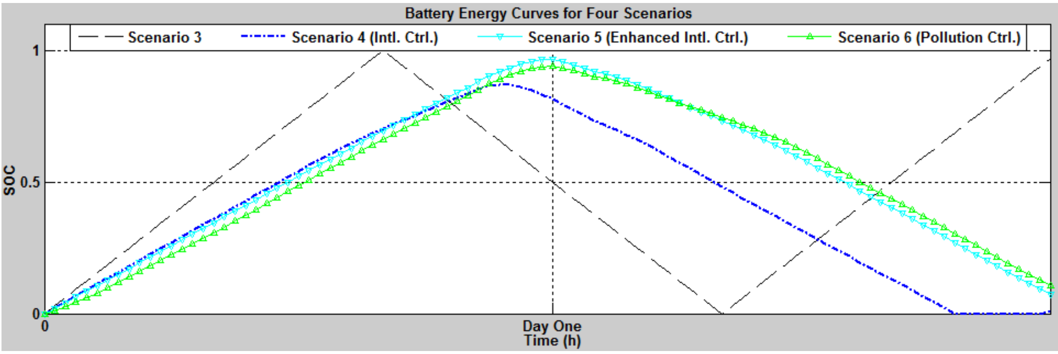

Figure 9 Normalized Battery Unit's Stored Energy; First Day; Four Scenarios

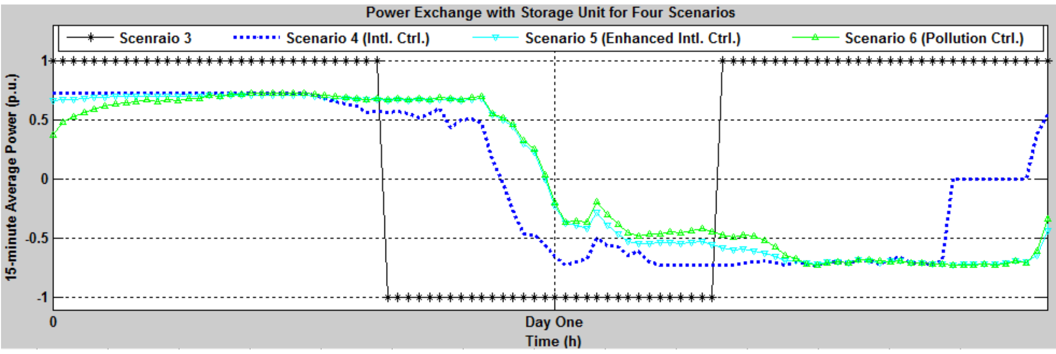

Figure 10 Normalized Battery Power Flow; First Day; Four Scenarios

However, scenario 2 does not bring as much environmental profit to the micro-grid owner as the last three scenarios, i.e. 4, 5, and 6, do. Scenario 6, which employs the air pollution control in fuzzy inference engine, on the other hand, stands right after scenario 2 on reducing CO_2 emission.

In scenario 6 there are lots of profit for the micro-grid owner and the consumers, though, which is not the case for scenario 2.

Normalized energy stored in battery unit is depicted in figure 9 for the period of the first day under four scenarios 3, 4, 5 and 6 in which the storage unit is utilized. Scenario 3, which does not employ any smart control on storage unit, uses the battery capacity to the full extent according to the predefined simple charge/discharge policy. Scenario 4 in which fuzzy intelligent control with no environmental constraints is deployed utilizes the battery capacity more than the other last two scenarios, since the highest priority objective in this scenario is to provide as much profit for the micro-grid as possible. Scenarios 6 in which air pollution reduction is considered as the high priority target alongside cost reduction, represents relatively less usage of battery storage capacity. The scenario 5 - which does dynamic weighted compromise between the air pollution reduction and the cost reduction - uses the battery capacity relatively more than the scenario 6 does. Figure 10 represents the power flow to the storage unit for one typical day under four scenarios in which storage unit was employed. Whenever the value of each curve is positive it means that the flow of energy was towards storage unit, i.e. electrical energy was being stored and vice versa. The red curve shows the power exchange with battery in scenario 3 when no control method was used. As it can be seen from the diagram, there are only two states in which the battery is being either charged or discharged and they follow each other in a periodic manner which is the most basic control approach implemented on storage unit and is not desirable. The green curve shows the power flow to/from battery unit in scenario 6 where pollution control is done. As expected, this curve represents the least variance compared to the other three curves since the modification of fuzzy rule-base in order to reduce the air pollution growth rate results in less storage of energy in the battery unit in order to reduce the amount of energy drawn from main grid.

Eq. 10 represents the relationship between balance, distribution loss and the overall cost of the network.

$$Balance = Cost - Loss \tag{10}$$

Where "Loss" stands for the overall sum of multiplication of the electricity price and dissipated energy on distribution branches, i.e. $S_L(t)$, for all 15-minute periods. Loss will always be greater than or equal to zero and is given by:

$$Loss = \int_0^T \Pr(t)\,.\,P_{loss}(t)dt \tag{11}$$

and "Cost" is calculated using Eq. 1 and represents the amount that the micro-grid owner has to pay to the main grid, if Cost > 0, or will get from the main grid, if Cost < 0. "Balance" will then be the measure of the money that micro-grid owner had to pay to the main grid,i.e. Balance > 0, or the profit that micro-grid owner will get from the main grid, i.e. Balance < 0, in case the power network were lossless or the network losses could be neglected.

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 as represented in Eq. 12

$$y_{crisp}(k) = \frac{\sum_{i=1}^{n}(max_{\mathrm{j}}\ (\mu_{kij}) \times y_{ki})}{\sum_{i=1}^{n} max_{\mathrm{j}}\ (\mu_{kij})} \tag{12}$$

Where $y_{crisp}(k)$ represents the energy exchange rate with the storage unit determined at the beginning of k^{th} time interval, *i* refers to the number of discrete points in the universe of discourse of output variable, which is between 1 and *n*. The factor *j* changes between 1 and the overall number of rules which in this case is $3 \times 3 \times 3 = 27$ for scenario 4, and $2 \times 3^3 = 54$ for scenarios 5 and 6, and represents the number of rule curves for each of which we consider the membership value of i^{th} point in the universe of discourse of the output variable. In other words, μ_{kij} represents the membership value of i^{th} point of output variable's universe of discourse in the j^{th} fuzzy rule for k^{th} time interval.

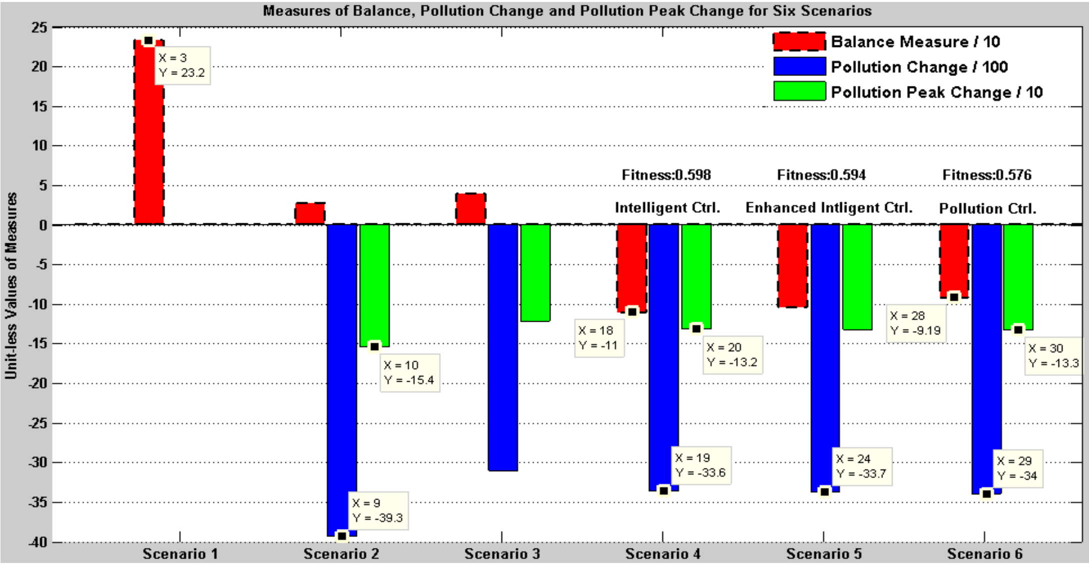

Figure 11 Measures of Balance, Pollution, Peak Pollution; Six Scenarios using Fuzzy Approach

Figure 11 represents the three final measures of balance, pollution change, and peak pollution change for all six scenarios obtained for the simulation of one week operation of the micro-grid. Scenario 1 is considered as the reference to which the pollution changes and peak pollution changes of all other scenarios will be compared. Therefore, the amount of pollution change and peak pollution change for the first scenario are assumed to be zero as the base of comparison, as represented in the diagram of figure 9. The pollution measures represent how much other scenarios contribute in increasing or decreasing the CO_2 emissions compared to scenario 1.

The fitness values represented in figure 11 for the Scenarios four, five and six represent the measure of their fitness to the whole strategy based on fitness function in Eq. 13. This will be explained in details in Section 5.2.

As it can be seen in figure 11, in the first Scenario the network cost is at its maximum level which is expectable since there is only local load and the main grid. Therefore, the consumer must only pay to the main grid in order to purchase the electrical energy required to provide the demand. Scenario 4 where real-time intelligent fuzzy decision-making approach is used with no environmental constraint brings the most profit to the micro-grid owner. This profit will be higher as the value of balance measure drops more and more below zero, i.e. as the Balance value becomes negative. Literally, negative balance can be interpreted as credit which is the definition the authors have used in the diagrams of cost and balance measures in this article. On the other hand, Scenario 6 - where the fuzzy decision-making method with environmental considerations is incorporated - results in better modification of air pollution compared to the Scenario 4, at the cost of losing some small portion of profit. This means that in Scenario 6, better results for air pollution control will be achieved while the cost reduction will be relatively degraded compared to Scenario 4. However, Scenario 5 in which enhanced fuzzy approach, i.e. the weighted fuzzy based on pollution peak instance estimation, is deployed with environmental constraints gives satisfactory results which may be regarded as a compromise between the two Scenarios four and six. In Scenario 5, the air pollution control is very close to Scenario 6 result and the profit value is also very close to the profit measure of Scenario 4.

5.2. Intelligent GA-Fuzzy Decision-Making

With the facts explained about figure 11, the need to have a merit function in order to get a uniform measure of each scenario's performance lead to the idea of using genetic algorithms as a DNA-based evolution method [16, 17] in combination with fuzzy decision-making framework in order to enhance performance of the proposed approach and get sub-optimal settings for fuzzy sets of the input variables. Hence, cost reduction and pollution modification could be achieved simultaneously without losing any of the objective functions due to over-emphasis on some other portions.

Figure 12 represents the overall structure of the combined GA-fuzzy approach for decision-making based energy management and control in the micro-grid networks. The flowchart of the genetic algorithms is also given in figure 12.

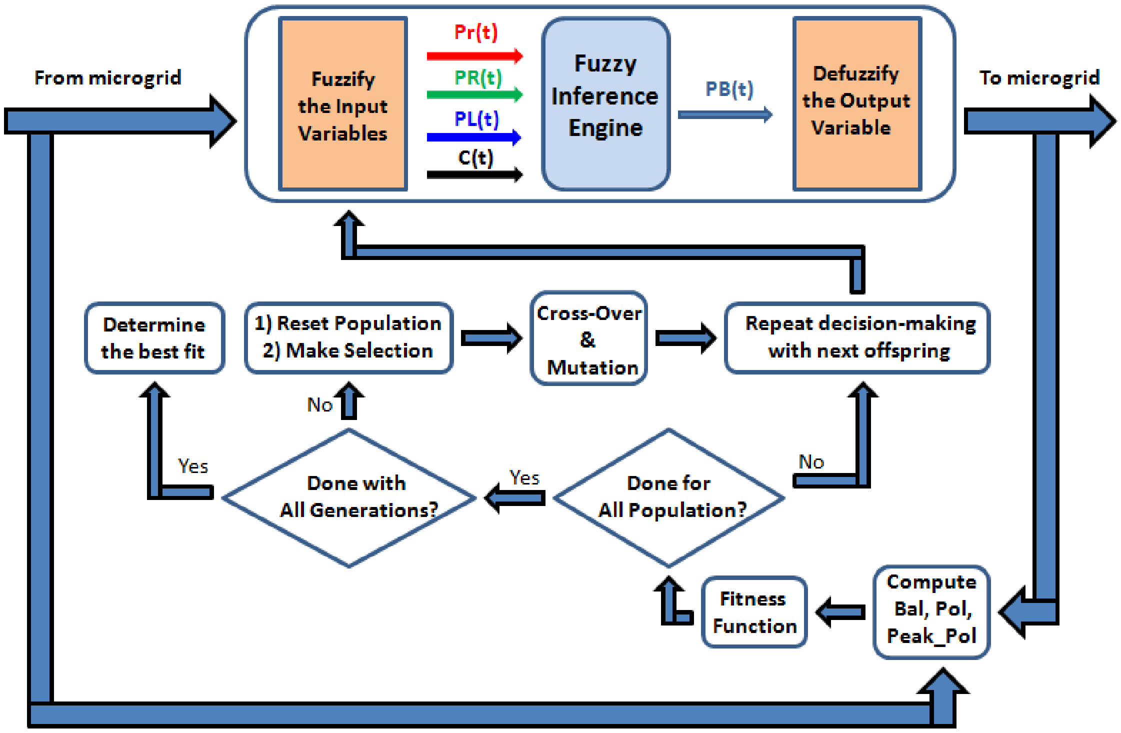

Figure 12 Structure and Flow-Chart of Combined GA-Fuzzy Approach

The first generation will be produced based on some random process. The next generations will be produced based on some evaluation and selection process, according to which the best fits or the strongest creatures will be present in consecutive generations, plus some genetic evolution which includes two major processes of cross-over and mutation. After a generation is formed, for each offspring, the fitness values for three last scenarios are computed and compared to each other for the highest fitness to be determined.

Then, among all population of a generation, the highest fitness values of different off-springs will be compared and the off-springs will be sorted in a descending order based on the value of their fitness. A selection process will take place based on the fitness values. The best ones will be transferred to the next generation plus some of the medium members and very few of the population with lower fitness values. After the selection process which determines a portion of the population for the next generation, some new off-springs will be generated based on cross-over and mutation processes applied to the members of current generation. These new off-springs will complement the preselected members in order to form the next generation. After the last generation is evaluated, the best off-spring will be chosen as the sub-optimal solution. In this study, the genetic algorithms were used for creating different combinations of fuzzy sets for the input variables of the fuzzy controller.

Eq. 13 represents the fitness function used for the genetic algorithms approach which can be regarded as the merit function of the whole system in order to evaluate performance of each different scenario:

$$F_{m_s}^{g} = \frac{(max_g(max_m(max\,(_s\,Bal))) - Bal_{m_s}^{g})}{|max_g(max_m(max_s(Bal)))|} - \alpha \frac{|min_g(min_m(min_s(Pol))) - Pol_{m_s}^{g}|}{|min_g(min_m(min_s(Pol)))|} - \beta \frac{|min_g(min_m(min_s(Peak))) - Peak_{m_s}^{g}|}{|min_g(min_m(min_s(Peak)))|} \quad (13)$$

Whre $F_{m_s}^{g}$ is the fitness value for scenario "*s*" of off-spring "*m*" in the generation "*g*". The variable s varies between 4 and 6, where s=4 refers to scenario four, s=5 implies scenario five and s=6 stands for the last scenario, i.e. scenario six. The generation number, g, changes between 1 and G where G is the total number of generations considered in the genetic algorithms. The off-spring number, m, changes between 1 and M where M is the number of population, i.e. off-springs, per generation. The term $\max_g(\max_m(\max_s(Bal)))$ refers to the maximum value of Balance measure for every scenario of all populations in the entire generations. This maximum value occurs at scenario 1 where the only element in the network is the local load besides the main grid. The interesting point is that regardless of the off-spring or the generation, this maximum value is always the same since similar price and load profiles are used for homogeneous and uniform evaluation of various fuzzy system set-ups and fuzzy sets' characteristics. Hence, the maximum Balance value was already at hand and consistent and was equal to 232. Term $Bal_{m_s}^{g}$ represents the Balance measure for scenario "*s*" of off-spring "*m*" in generation "*g*". The terms $\min_g(\min_m(\min_s(Pol)))$ and $\min_g(\min_m(\min_s(Peak)))$ represent the minimum value of the pollution measure and the minimum value of the peak pollution measure respectively among all different scenarios for every off-spring of the entire generations. Fortunately, these values were also already at hand and consistently occurred at scenario 2, where the only two elements of the micro-grid are local load and renewable generators alongside the utility grid, and were equal to -3930 and -154 respectively. We chose the values of α and β to be 2 and 4, respectively, so that more weight was given to the peak pollution reduction which is in most cases more important than the overall pollution reduction. Also, the air pollution is itself more critical and relatively more difficult than the cost to reduce, hence using the factors α and β will compensate effort.

The genetic algorithms was implemented using 20 generations, i.e. G=20, with population of 10 per generation, i.e. M=10, with each off-spring having 4 chromosomes corresponding to the fuzzy system's four input variables mentioned in section 2. The chromosomes included appropriate number of cells in order to determine the edges and centers of the fuzzy sets for the relevant variable. Each chromosome for fuzzy sets of the variables price, renewable generation rate, and local load, included 9 cells to cover the edges and centers of its three membership functions. Air pollution index which has two membership functions - as represented in figure 4 - requires six cells per chromosome.

The best measures of Balance, Overall Pollution Change, and Peak Pollution Change obtained by the combined GA-fuzzy approach are represented in figure 13. Fitness value of the last scenario, i.e. scenario 6 which focuses on pollution control and cost reduction simultaneously and equally, is the best of all based on Eq. 13.

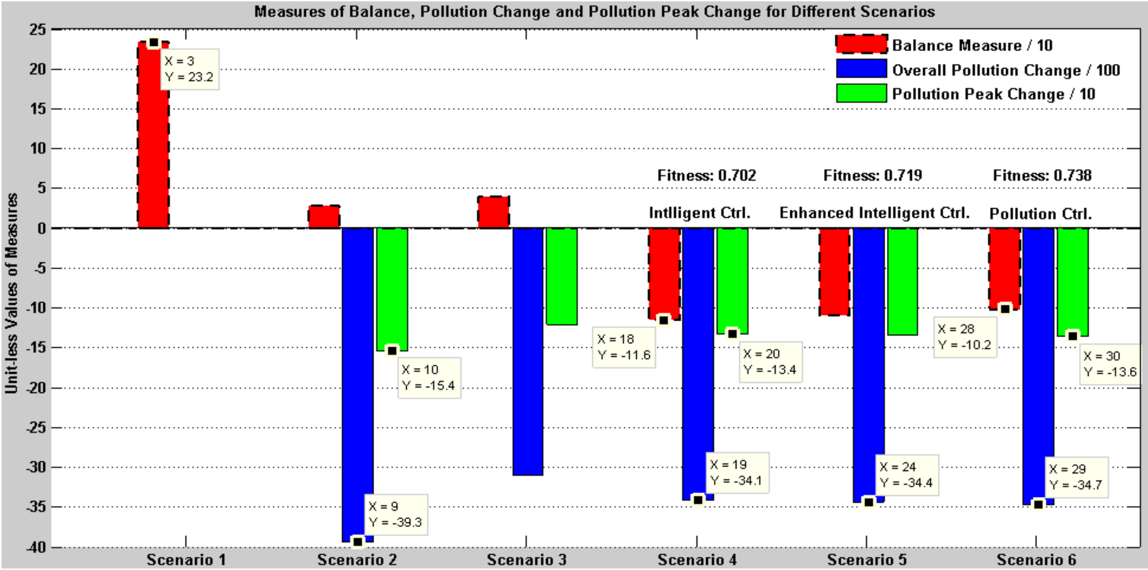

Figure 13 Measures of Balance, Pollution, and Peak Pollution; Six Scenarios using GA-Fuzzy Approach

Figure 13 also confirms the fact that maximum Balance always occurs at scenario 1 and is of the same amount, i.e. 232. This figure also shows that the minimum, i.e. best, amount of air pollution change and also peak pollution change happens when scenario 2 is employed. The minimum values of unit-less measures for pollution change and peak pollution change are -3930 and -154 respectively.

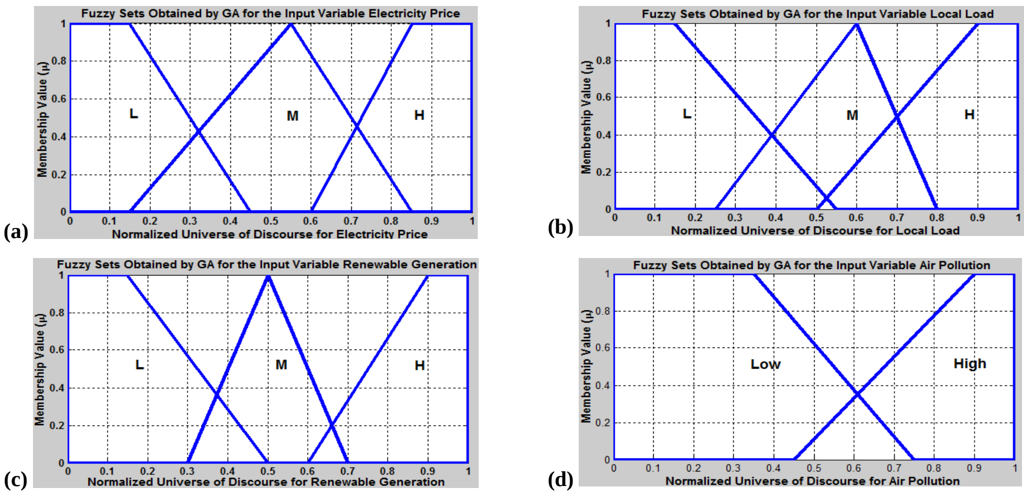

Figure 14 Sub-Optimal Best Fit Fuzzy Sets for Input Variables to the Fuzzy Controller obtained by GA-Fuzzy; (a) Electricity Price, (b) Local Load, (c) Renewable Generation, (d) Air Pollution

Figure 14 represents the fuzzy sets of the four input variables for the best off-spring obtained by combined GA-fuzzy approach. It can be seen that there are different fuzzy sets for each of the three variables price, renewable and local load. If we compare the three diagrams of figure 12-a,b,c with the diagram of figure 4-a where the three mentioned variables had similar fuzzy sets, the difference will be clearly revealed. The diagrams represented in figure 14 show the edges and centers of the fuzzy setes for the best fit off-spring of the GA-fuzzy combined method. This means that the control and energy management scheme will give the best results at hand for these settings of input variable fuzzy sets based on the fitness function defined by Eq. 13.

5.3. Numerical Examples

For any practical system of the same structure as mentioned for the micro-grid in this article, the actual numeric results can be obtained after replacing the variables in this study by the actual values of the practical system itself. As an example, if the peak load and the nominal power rating of the renewable electricity generation plant both are assumed to be 1 MW, i.e. $P_L^{max}(t) = 1\,(MW)$ and $P_R^{max}(t) = 1\,(MW)$, and the maximum electricity price is presumably 50 cents per kWh energy, i.e. $Pr^{max}(t) = 0.5\,(\frac{\$}{kWh})$, the resulting Balance values would be as represented in Table III.

Table III Balance Values of Six Scenarios for the Numerical Example

	Scn. 1	Scn. 2	Scn. 3	Scn. 4	Scn. 5	Scn. 6
Bal.	$ 29043	$ 3466	$ 4917	$ -13761	$ -11264	$ -12204

The balance values represented in table III are the monetary values that micro-grid owner has to pay to the utility companies or will receive from them. Positive values refer to a payment, and negative numbers represent the gain for the micro-grid owner. The result balance values are based on a one-week simulation time. This means, assuming identical gains for a total of 52 weeks of the year, scenario 4 will bring a $716,000 gain to the micro-grid using the smart decision-making approach for energy control. On the other hand, in scenario 3 which has the same structure as in scenario 4, without any smart control algorithms applied to the storage, the owner has to pay $256,000 to the electric utility every year comparatively. Comparing annual approximate results of scenarios 3 and 4 leads to the fact that using the smart decision-making framework proposed in this article yields an annual benefit of around $970,000 for the micro-grid owner. Approximating the cost of implementing such a decision making tool around $100,000 for the size of micro-grid described here, this brings a Return-on-Investment (ROI) of 10. It would be conservative to say that a utility or micro-grid owners looking into adopting a smart decision-making tool for energy storage management may see an ROI between 5 and 10.

6. CONCLUSION

An intelligent fuzzy logic-based framework for decision-making and energy flow control in micro-grids through adjusting energy exchange rate of storage unit is introduced and simulated for cases with and without environmental considerations. Six micro-grid structure and operation scenarios were considered. If an appropriate smart decision-making approach, such as the one presented in this article, is employed to manage energy storage, then adopting measures of cost and pollution will help reduce the net electricity consumption costs and increase the monetary gains for micro-grid owners. Scenario 6 reveals the fact that considering air pollution control policy within the fuzzy inference engine and modifying the fuzzy rules accordingly will result in less pollution compared to all other intelligent control scenarios addressed in this study. While scenario 6 helps reduce air pollution most significantly, the net cost of this scenario will be larger in comparison to scenario 4 which brings the most financial benefits to the micro-grid owner. The enhanced weighted fuzzy approach, i.e. scenario 5, turned out to be a compromise between the two cases of intelligent control, scenario 4, and pollution control, scenario 6. This means enhancing the fuzzy system by weighting regime based on the predicted peak pollution time for the current day, the controller will be capable of representing a compromised behaviour of both intelligent control and pollution control. Hence, both objectives of cost reduction and air pollution modification could be achieved by modifying the rules and enhancing the system by weighting factors. This means the intelligent fuzzy framework can be used as a tool for solving multi-objective function problems where more than one optimization target are of interest.

The use of genetic algorithms as a DNA-based search tool in order to improve the capabilities of intelligent fuzzy approach can also be considered for further expanding the solutions to multi-objective function problems.

The GA fuzzy intelligent decision-making framework seems to be capable of cost-efficient energy management in micro-grid under constraints such as meeting the demand profile, battery SOC, renewable electricity generation rate, and environmentally-friendly considerations. Micro-grid owners looking into adopting a smart decision-making tool for energy storage management may see an ROI between 5 and 10.

Topics of further research related to this work include considering demand-side load management, enhancing the proposed framework by solar energy and load profile forecast in order to prepare the system in advance for upcoming changes in both the climate and the network conditions.

7. ACKNOWLEDGEMENT

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