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Efficient Energy Management System for Smart Grid Using Bacterial Foraging Optimization Technique

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Abstract: ***Distributed devices in smart grid systems are decentralized and connected to the power grid. The connection made through different types of equipment transmits. This produces the numerous energy losses, when power flows from one bus to another bus. The most efficient approaches to reduce energy losses is to integrate the renewable energy resources in Distributed Generation's (DG's). The uncertainty of DG may cause instability issues. The major issue includes congestion in the power grid due to the sudden power consumption by the customers, which affects the efficient energy delivery. Energy management with DG regulation is one of the most efficient solutions to solve these instability issues. In the considered power system with DG's and consumers, the Locational Marginal Pricing (LMP) based unified Energy Management System (uEMS) model is considered. This model increases the profit benefits for DG's and increases the stability of Distributed Energy System (DES). In this paper, the Bacterial Foraging Optimization (BFO) is employed to reduce losses i.e. based on Loss Reduction Allocation (LRA) method. Using LRA method the energy loss reduction is calculated and this model accurately rewards DG contribution and offers a good competitive market. Moreover, the entire DG's profit is increase by the BFO technique. The IEEE 37 bus feeder system is to be considered to validate the proposed uEMS model to increase the DG system stability. Furthermore, this implementation gives the idea of formulating efficient energy management system of future Indian scenario.***

Keywords: Distributed Generation, ***Locational Marginal Pricing, Bacterial Foraging Optimization, unified Energy Management System, Distributed Energy System, Loss Reduction Allocation, IEEE 37 bus feeder system.***

1. Introduction

The overall efficiency of the power system is improved using Energy management system with DG units. DG devices is to be strategically placed in power systems for reducing power losses on-peak operating costs, improving voltage profiles, reliability, and efficiency. The uncertainty of DG may cause instability issues. The similar consumption habits of customers, the peak load period of power consumption may cause congestion in the power grid and affect the energy delivery.

Energy management with DG regulation is considered to be one of the most efficient solutions for solving the instability issues. With growing load demand in the distribution network, it provides potential scope for research in terms of analyzing the distribution network to meet the demand with the present infrastructure. DG is small-scale power generation that is usually embedded in the distribution system. DG units are mainly energized by wind, solar and fuel cell. The main feeder originates from substation and passes through different consumer loads. Most of the distribution system suffers with high power losses because of transmitting power from one bus to another bus. Installing DG units at non-optimal places may result in an increase in system losses, implying an increase in costs. Moreover, if multiple DG units are installed, optimal approach for placement of DGs in order to maintain the stability and reliability of the system become more crucial. The Smart Grid is a modern electric power grid infrastructure for improved efficiency, reliability and safety, with smooth integration of renewable and alternative energy sources, through automated control and modern communications technologies [1].

Renewable energy generators seem as a promising technology to reduce fuel consumption and greenhouse gas emissions. Importantly, smart grid enabling new network management strategies provide their effective grid integration in DG for Demand Side Management and energy storage for DG load balancing, etc. [2]. Renewable energy sources (RESs) [3] are widely used for reducing system losses and increasing the reliability, efficiency and security of electricity supply to customers are some of the advances that smart grid system will increase. In the smart grid, reliable and real-time information becomes key factor for reliable delivery of power from the generating units to the end-users. The sensory information includes the use of a distribution class Locational Marginal Price (LMP) to drive energy management related controls, and a distribution class state estimation procedure has been described based on a non-iterative algorithm that uses synchronized voltage and current measurements. In order to realize such an ambitious energy plan, RESs such as Wind Power (WP), Solar Power (SP) and Distributed Energy Resources (DERs), such as Electric Vehicles (EVs) and Heat Pumps (HPs), will be extensively used and will play an important role in the future power system [4,5].

In particular, congestion problems that might occur in distribution networks due to the high penetration of DER have already drawn attention from Distribution System Operators (DSOs), manufacturers and researchers. DSO [6,7] has the main responsibility for resolving the congestion in distribution networks, can choose to reinforce the network through long term planning or employ market methods so as to incentivize the DERs to respect the system capacity limits. Compared to direct control methods for congestion management [8,9], market-based methods maximizes the social welfare, cause least discomfort to customers and encourage more participation in the energy planning. By extending LMP [10] from transmission networks to distribution networks, [11,12] have developed the Distribution LMP (DLMP) concept and applied it to handle the congestion issues in distribution networks with DG's. In DLMP, the local DGs will be properly subsidized if they produce more power and reduce the energy requirement at the local bus from remote areas during congestion periods.

Smart Grid goals to allow increased energy sources, more power to demand and to support market driven by consumers. Enhanced efficiency and reliability are also key goals of Smart Grid. Nodal pricing is one of the most effective mechanism in a Distribution Power System (DPS) [11] to reduce losses and regulate DG generation and the LMP is the most developed method to detect nodal prices [13,14].

The Bio inspired Optimization Algorithm such as Ant Colony Optimization (ACO) [15], Biogeography Based Optimization (BBO) [16,17], Bat Motivated Optimization (BMO) [18], etc., Eventhough ACO is proposed to solve the DG resources, it is struck in local optima. BBO is solved for scheduling problem took much time in finding the fitness value. BMO has complex steps involved to solve the DG problems.

In this paper, the BFO algorithm is proposed to formulate the efficient energy management system. Bacterial Foraging Optimization technique [19,20,21] is a new evolutionary computation technique based on the foraging behavior of Escherichia coli (E.coli) bacteria in human intestine. BFO is better than the Particle Swarm Optimization (PSO) in terms of convergence, robustness and precision. The design, implementation and testing of BFO were compared with those of Genetic Algorithm (GA) illustrated that a faster settling time, less or no overshoot. In this paper the energy losses in distribution system is reduced by using Energy Management System with Smart Grid maintaining the system with high efficiency. BFO technique is the best optimal solution to find the high efficiency and reducing the energy losses.

2. Problem Formulation

The main objective to increase the efficiency in the power system and to reduce energy loss using Energy management system for Smart grid with DG regulation.

5.3 Loss Reduction Allocation [LRA] Method

LRA method to increase the total DG benefit by clearly calculating energy loss reduction. LRA method was proposed for Distributed Power Supply (DPS) connected with DGs, which shows that the contribution of DG resource is significantly reduces energy losses and increase efficiency.

Distributed losses for each bus using LRA method is defined as follows,

$$d_t = u_t\left(1 + u_t \frac{\partial loss_t}{\partial P_t}\right) \tag{1}$$

Where u represents the price at reference bus, d is the price at non reference buses, Loss denotes the energy loss , P represents the active power

LRA problem due to its good performance and simplicity of implementation.

$$\Psi_i(\upsilon) = \sum_{i\in s} W(|s|)*[\upsilon(s) - \upsilon(s-i)] \tag{2}$$

$$W(|s|) = \left(\frac{n-|s|!*(|s|-1)!}{n!}\right) \tag{3}$$

Where i represents the DG taking part in reduced amount of losses, |s| is the number of DG within each coalition, n is the total number of DG's, $\nu(s-i)$ is the reduced amount of losses related to coalition s when one DG i does not participate, W(|s|) is the Weighting factor of the Shapley value.

DPS without any connected DGs is defined as a base system, so that the reduced system losses is being calculated, as more DGs are connected to it.

$$\upsilon(s) = Loss_{base} - Loss(s) \tag{4}$$

$$\upsilon(s-k) = Loss_{base} - Loss(s \cap \bar{k}) \tag{5}$$

Where s is a set of different DGs, v(s) is the loss reduction of s, $s \cap \bar{k}$ is the set of s without Gk

Each DG may influence system total losses, optimal DG will minimize system total losses.

LRA is obtained by

$$LRA_k(\upsilon) = \sum_{k\in s} W(|s|)*[\upsilon(s) - \upsilon(s-k)] \tag{6}$$

$$W(|s|) = \frac{(K-|s|)\times(|s|-1)!}{K!} \tag{7}$$

Where LRA_k denotes the reduced loss belonging to Gk due to its participation, n is the number of DG, and |s| is the number of DG in set s. Then, the DLMP deviation Δd of the k^{th} DG to calculate its next iteration DLMP obtaining by,

$$(\Delta d)^i_{t,k} = \frac{LRA^i_{t,k} \times u_t}{P^i_{t,k}} \tag{8}$$

5.4 Iterative Method For LRA Calculation

In Energy Management System, both the DG and customer is needed, DLMP, loss, benefit of DG, consumption and DLMP of customer. An iterative method is introduced to obtain status information of DG and customer in uEMS.

The initial time-slot is set as t = 0 and calculate status information of each time-slot by iteration. In LRA, the cost $C_{t,k}$ of each DG G_k in time-slot t is obtained by

$$C_{t,k} = a_k P^2_{t,k} + b_k P_{t,k} + c_k \tag{9}$$

Where $P_{t,k}$ is the generation of G_k, a_k, b_k and c_k are the coefficients of Gk. Initially, all DLMP $d_{t,k}$ of DG and customer equal to the uniform price u_o of wholesale market, the generation $P_{0,k}$ of each G_k is set to a fixed value that meets $C_{0,k} = u_o$.

DG and DLMP of each bus at all time-slots is calculating by,

$$P^{i+1}_{t,k} = \frac{d^i_{t,k} - b_k}{2a_k} \tag{10}$$

$$d^{i+1}_{t,k} = u_t + (\Delta d)^i_{t,k} + B \times^{feedback}_{t,k} \tag{11}$$

Where i denotes the i^{th} iteration, $d_{t,k}$ is the DLMP of k^{th}

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DG in t time-slot, Δd is the deviation of DLMP in the i^{th} iteration, B indicates the gain of load feedback DLMP signal. Equations (9) and (11) is used to calculate the optimal DG and DLMP.

The iterative method for LRA of uEMS converges to given terminates criterion ε that satisfies the following condition:

$$\max\{P^{i+1}_{DG,t,k} - P^{i}_{DG,t,k}\} \le \varepsilon. \quad (12)$$

LRA operates until the maximum of deviation of each DG is less than a given terminal criterion ε. The new generation of each DG is calculating by LMP and the maximum is used as a terminal criterion. The benefit of the base system is represented as follows:

$$benefit_{t,base} = u_t Demand_t - d_t(Demand_t + Loss_{t,total}) \quad (13)$$

Where $Demand_t$ denotes the total demand of all customers in time-slot t, $Loss_{t,total}$ represents the total loss of all buses for DPS without any DG.

The benefit of DPS with DLMP at DG-connected busses is given by

$$benefit_{t,dps} = u_t Demand_t - d_t(Demand_t + Loss'_{t,total}) - \sum_{k=1}^{K} P_{t,k}(d_{t,k} - u_t) \quad (14)$$

The benefit is calculated by subtracting by (13) and (14) equations:

$$\Delta benefit_t = d_t(Loss_{t,total} - Loss'_{t,total}) - \sum_{k=1}^{K} P_{t,k}(d_{t,k} - u_t) \quad (15)$$

Where K is the number of DGs, $Loss_{t,total}$ – is the reduced loss due to the contribution of connected DGs.

3. Bacterial Foraging Optimization Algorithm

Bacterial Foraging Optimization Algorithm (BFOA) is proposed by Kevin Passino in the year 2002. Application of group foraging strategy of swarm of E.coli bacteria in multi-optimal function optimization is the key idea of this new algorithm. Bacteria search for nutrients is a manner to maximize energy obtained per unit time. Individual bacterium also communicates with others by sending signals. Bacterium takes foraging decisions after considering two previous factors. The process by which a bacterium moves by taking small steps while searching for nutrients is called chemotaxis.

The key idea of BFOA is mimicking chemotactic movement of virtual bacteria in the problem search space.

P : Dimension of the search space

S : Total number of bacteria in the population,

N_c : The number of chemotactic steps,

N_s : The swimming length.

N_{re} : The number of reproduction steps,

N_{ed} : The number of elimination-dispersal events,

N_{ed} : Elimination-dispersal probability,

$C(i)$: Size of step taken in the random direction specified by the tumble.

BFO algorithm is explained by following steps

3.1 Chemotaxis

This step chemotaxis represents the movement of bacteria in search for a nutrient gradient.

3.2 Swarming

Generally, the E.coli bacteria always form groups to search for the food particles. The intelligent technique in this BFO is swarming (grouping behaviour) step.

3.3 Reproduction

In this reproduction step, the least healthy bacteria die and replaces by healthier bacteria i.e. the bacterial population is split into two based on their fitness evolution, the least healthy bacteria replaces by the best ones. This keeps the swarm size constant.

3.4 Elimination and Dispersal

This step keeps the bacterial population constant. In the reproduction step, the least healthy bacteria is eliminated and moves to a random location.

3.5 Steps Involved In Bacterial Foraging Optimization Algorithm

Step 1: Initialize the parameters

$p, S, N_c, N_s, N_{re}, N_{ed}, P_{ed}, C(i)(i = 1,2\ldots S), \theta^i$

Choose the initial value for the $\theta^i, i = 1,2\ldots S$ θ^i. These must be done in areas where an optimum value is likely to exist. They are randomly distributed across the domain of the optimization space. After computation is completed, the value of p (position of each member in the population of the S bacteria) is updated automatically and termination test is done for maximum number of specified iterations.

Step 2: Elimination-Dispersal loop: $l = l + 1$

Step 3: Reproduction loop: *k= k+1*

Step 4: Chemo taxis loop: *j= j+1*

(i) For *i*= 1, 2,….,*S* take a chemo tactic step for bacterium '*i*' as follows:

(ii) Compute cost $J(i, j, k, l)$.

(iii) Let $J(i, j, k, l) = J(i, j, k, l) + J_{cc}(\theta^i(j.k.l), P(j, k, l))$

(iv) Let J_{last} = $J(i, j, k, l)$ to save this value since find better cost via a run.

(v) Tumble: Generate a random vector $\Delta(i) \in \Re^p$ with each element , $\Delta_m(i)$, *m= 1,* 2,….,*p* a random number on $[-1,\ 1]$ and $\Re$ is a real number.

(vi) Move let

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \quad (16)$$

This results in step of size *C(i)* in a direction of tumble for bacterium *i*

(vii) Compute $J(i, j+1, k, l)$

If the loss is minimum, then next step is to be carried out else go to step (iii)

(viii) Swim.

(a) Let *m=0* (counter for swim length)

(b) While *m<Ns*
Let m=m+1
If $J(i,j+1,k,l) < J_{last}$ (if there is improvement), let
$J_{last} = J(i,j+1,k,l)$
Let

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{17}$$

use this $(j+1,k,l)$ to compute the new $J(i,j+1,k,l)$.
Else, let *m=Ns.* End of while statement
(ix) Go to next bacterium *(i+1)* if $i \neq S$
Step 5: If *j<Nc* go to step 4.
Continue chemo taxis, since the life of the bacteria is not over.
Step 6: Reproduction
a) For the given *k* and *l*, and for each *i=1,2,….,S,*

$$\text{let } J^i_{health} = \sum_{j=1}^{N_c+1} J(i,j,k,l) \tag{18}$$

be the health of bacterium *i*.
Sort bacteria, chemo tactic parameter *C(i)* in order of ascending cost J_{health}.

(b) The S_r bacterium with the highest J_{health} values die and other S_r bacteria with the best values split.
Step 7: If $k < N_{re}$, go to step 2.
In case, the method has not reached number of *s* specified reproduction steps.

Step 8: Elimination-Dispersal
For $i = 1,2\ldots S$ with probability P_{ed}, eliminate and disperse each bacterium.
Eliminate bacterium and disperse one to a random location on the optimization domain. If $l < N_{ed}$, then go to step 1, otherwise end.

4. Implementation of Bacterial Foraging Algorithm

BFO Technique, which determines the DLMP of each DG, customer in a DPS, calculates the generation and involved distribution loss of each DG. To achieve a competitive electricity market environment, Bacterial Foraging Optimization Algorithm to calculate system total losses and distributes them to each DG fairly. Although system losses are inevitable in a DPS, regulating DG reduces the amount of system total losses. Specifically, the benefit from the reduced amount of system losses is allocated to each DG as a reward, which will encourage DGs to supply a more effective power system. This method is much better than allocating system losses directly to DG in proportion, because individual DGs regulate their own generation by obtaining rewards or punishments in loss allocation. A DPS without any connected DGs is defined as a base system, so that the reduced system loss is calculated, as more DGs are connected to it.
Equations are defined by system loss *volt(s)*

$$volt(s) = Loss_{base} - Loss(s) \tag{19}$$

$$volt(s-k) = Loss_{base} - Loss(s \cap \overline{k}) \tag{20}$$

Where s is a set of different DGs, volt(s) is the loss reduction of $s, s \cap \overline{k}$ s, is the set of s without G_k. Bacterial Foraging Algorithm problem is solved by the Shapley value method is obtained by

$$BFO_k = \sum_{k \in s} WF(|s|) * [volt(s) - volt(s-k)] \tag{21}$$

$$WF(|s|) = \frac{(K - |s|) * (|s| - 1)!}{K!} \tag{22}$$

BFO_k denotes the reduced loss belonging to Gk due to its participation, n is the number of DG, and |s| is the number of DG in set s. Then DLMP deviation Δd of the k^{th} DG to calculate its next iteration DLMP is obtained by

$$\Delta d^i_{t,k} = \frac{BFO^i_{t,k} * u_t}{P^i_{t,k}} \tag{23}$$

In unified Energy Management System, the status of both the DG and customer is needed, including the generation, DLMP, loss, and benefit of DG, as well as consumption and DLMP of customer. However, because of the private agents in a DPS, the status information in each time-slot is unknown for Distribution Utility Companies (DUCs). To set an initial time-slot t = 0 and calculate status information of each time-slot by iteration method. In BFO, the cost $C_{t,k}$ of each DG G_k in time-slot t is obtained by

$$C_{t,k} = a_k P^2_{t,k} + b_k P_{t,k} + c_k \tag{24}$$

Where $P_{t,k}$ is the generation of G_k, a_k, b_k, and c_k are the coefficients of G_k.

Initially, all DLMP $d_{t,k}$ of DG and customer equal to the uniform price u0 of wholesale market and the generation P0,k of each Gk is set to a fixed value that meets $C_{0,k} = u_o$.

DG and DLMP of each bus at all time-slots is calculated by

$$P^{i+1}_{t,k} = \frac{d^i_{t,k} - b_k}{2a_k} \tag{25}$$

$$d^{i+1}_{t,k} = u_t + (\Delta d)^i_{t,k} + B *^{feedback}_{t,k} \tag{26}$$

Where i denotes the ith iteration, $d_{t,k}$ is the DLMP of k^{th} DG in t time-slot, Δd is the deviation of DLMP in the ith iteration.
B indicates the gain of load feedback DLMP signal [e.g., B = 0.033, which could be obtained by performance evolution as the similar process as in [14], where the optimal value of B is accessed by integral square error (ISE)], d feedback indicates the feedback of DLMP signal.

This method used to be calculate the optimal DG and DLMP. However, because of the interaction of DG, DLMP, and shared reduced loss, it is difficult to calculate the accurate value of each other by some equations directly. Hence, an iterative method for BFO calculation is proposed to deal with this challenge.

4.1 Implementation of LRA using BFO

Inputs: *u*0, *Load* (energy consumption load of consumers)
Outputs: *BFO, d, P*

BFO {
$d = u0$ // Initialize DLMP of each bus to wholesale market price $u0$
P // compute DG generation
$P^{previous} = P$ //initialize previous generation to calculate deviation
$\Delta P = P$ //initialize generation deviation
While (max $\Delta P < \varepsilon$) Do
{
//terminal criterion
For $s \in S$
Do{
Loss // calculate loss with DG coalition
}
ENDFOR
BFO // calculate shapley value using *Loss* by its given equations
ΔLMP // calculate *LMP* deviation using *BFO*
$d = d + \Delta LMP$
$\Delta d^{feedback}$ // run *BFO* with *d*, *Load*
$d = d + \Delta d^{feedback}$
$P^{previous} = P$
P //compute DG generation
$\Delta P = P - P^{previous}$
}
ENDWHILE
}
ENDBFO

The iterative method of BFO converges to a given terminate criterion ε that satisfies the following condition:

$$\max\left\{P_{DG,t,k}^{i+1} - P_{DG,t,k}^{i}\right\} \le \varepsilon \tag{27}$$

BFO operates until the maximum of deviation of each DG is less than a given terminal criterion ε. In each loop cycle, BFO first calculates the generation P of each DG by each DG's DLMP d, then the optimal coalition s and the reduced loss of DG due to the coalition are detected. This reduced loss of each DG is considered as the benefit to remunerate DG and allocated to its nodal price, which is indicated by the deviation of LMP (ΔLMP). Considering that DG is modeled as a constant power factor that is regulated by nodal price according to its cost function, the increment of nodal price for DG bus will affect its generation in return. Therefore, then new generation of each DG is calculated by ΔLMP, and the maximum is used as a terminal criterion.

The benefit of the DUC for a base system is represented as follows:

$$benefit_{t,base} = u_t Demand_t - d_t\left(Demand_t + Loss_{t,total}\right) \tag{28}$$

Where $Demand_t$ denotes the total demand of all customers in time-slot t and $Loss_{t,total}$ represents the total loss of all buses for Distribution Power Supply without any DG. The benefit of DUC for a DPS with DLMP at DG-connected busses is to be calculated by the given equation:

$$benefit_{t,dps} = u_t Demand_t - d_t\left(Demand_t + Loss^{'}_{t,total}\right) - \sum_{k=1}^{K} P_{t,k}\left(d_{t,k} - u_t\right) \tag{29}$$

Where $Loss^{'}_{t,total}$ represents the total losses of all buses in DPS with DGs connected. The deviation of DUC's benefit is calculated by subtracting the equations 29 and 30,

$$\Delta benefit_t = d_t\left(Loss_{t,total} - Loss^{'}_{t,total}\right) - \sum_{k=1}^{K} P_{t,k}\left(d_{t,k} - u_t\right) \tag{30}$$

Where K is the number of DGs, and the term $Loss_{t,total} - Loss^{'}_{t,total}$ is the reduced loss due to the contribution of connected DGs.

5. Results and Discussions

5.1 Simulation Settings

The BFO model is simulated and analyzed in modified IEEE 37-bus feeder system with DGs connected to buses 6, 9, and 15, which are mostly the center of the test system, as shown in below Figure 1. The coefficients (a and b) of DG's cost function are shown in Table I from Proposition 1. It should be mentioned that coefficient c is related to fixed costs. Therefore, this parameter does not have influence on output.

Table 1: Coefficients of DG's Cost Function

DG System	*a* $(\$/MW^2)$	*b* $(\$/MW)$	*c* $(\$)$	*Maximum Generation* (MWh)
DG 1	0.043	20	0	20
DG 2	0.25	30	0	20
DG 3	0.1	35	0	20

Proposition 1*:* Coefficients of DG is calculated by two given marginal price ($d1$, $d2$) and marginal product $P_{DG,1}, P_{DG,2}$ of DG by the following equations:

$$.\, a = \frac{d_1 - d_2}{2\left(P_{DG,1} - P_{DG,2}\right)} \tag{31}$$

$$b = d_1 - P_{DG,1}\frac{d_1 - d_2}{P_{DG,1} - P_{DG,2}} \tag{32}$$

Proof: For a given DLMP d_t of DG at time-slot t

$$Benefit\left(P_{DG,t}\right) = d_t . P_{DG,t} - \left(aP_{DG,t}^2 + bP_{DG,t} + c\right) \tag{33}$$

To maximize the DG's benefit, the above-mentioned equation is solved as follows:

$$P_{DG,t} = \frac{d_t - b}{2a} \tag{34}$$

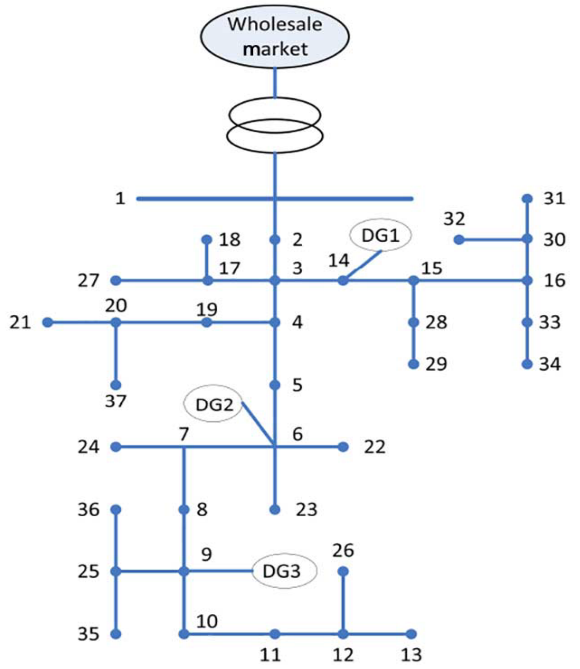

Figure 1: IEEE 37-Bus Feeder System

Given two set of marginal price (d_1, d_2) and marginal product

$$P_{DG,1} = \frac{d_1 - b}{2a} \tag{35}$$

$$P_{DG,2} = \frac{d_2 - b}{2a} \tag{36}$$

To analyze the performance from the viewpoint of loss reduction, DG, DG benefit, and load stability for an actual DPS, the uncertainty in spot price, and demand scenarios must be modeled. To describe their stochastic features, the processes of spot price and demand scenarios need to be statistically analyzed making the spot price and load approach real DPS. To this end, load and wholesale market price in ISO New England are used to generate the wholesale market price and system total load in every 5 min for 24 h, with an active power demand peak of 124 MW. The performance of the BFO algorithm is analyzed and compared to the existing LMP method (LMP) in loss reduction, DG's benefit, and DG's DLMP price.

To find out how to regulate DG and how DG combinations infect the DPS, three different DGs combination scenarios are employed to analyze the system model.

(i) Case (BASE) is an IEEE 37-bus feeder power system without any connected DGs.

(ii) Single DG case (SD) is the base case with a DG connected at bus 6, 9, or 15: SD#1 stands for DG#1 connected at bus 6, SD#2 stands for DG#2 connected at bus 9, and SD#3 stands for DG#3 connected at bus 15.

(iii) Multiple DG case (MD) is the base case with all three DGs connected to their respective buses, as shown in Figure 1. The system losses for a 24-h time-slot of the SD and the MD scenarios. The improvement in system loss reduction is due to BFO, which regulates each DG to the optimal level. In LMP method, a global optimal solution is hard to obtain, because of the complex co affection between DGs, which causes total system losses to increase. The system losses of BASE are significantly larger than that of SD and MD, which illustrate that integrating DG in a Distributed Power Supply, is effectively reduce system losses. Clearly, uEMS with BFO reduces the energy supply of wholesale market in peak load period. When customer load increases, a positive DLMP will generated to increase the nodal price of customer buses, which stimulates DGs in the DPS to make generation. To fair allocate distributed loss to each DG, an iterative method is used to calculate the deviation of distributed losses. In this part, the convergence process of iterative BFO is analyzed. It should note that the minimum value is the optimal status for loss reduction, where DG has optimal generation and system loss is minimum. When the wholesale market price is 34.5 ($/kWh) obtained in an iterative time-slot, the convergence process of BFO is considered, where $P^i_{DG,k}$ indicates the system loss with generation for the kth DG in the ith iteration. In this iterative method, each DG initially sets its DLMP to wholesale market price and its generation.

As a result, BFO achieves maximum benefit of DG and reduces system loss. Additionally, the speed of convergence for the proposed iterative method is also recorded within the per-5-min simulation of 24-h (total 288 times). 98.1% simulations converged after only one or two loops. Specifically, 87.4% of the simulations converged after one loop, 10.7% after two loops, and only 1.9% after more than two loops. It is shown that this iterative method in BFO has a high speed of convergence.

6. Conclusion

In this paper, the uEMS model is proposed to realize loss reduction and maintain stability for Power System in the Smart Grid. The BFO algorithm is employed to allocate the DG participation and loss reduction. In addition, it is used to approximate the optimal generation scheme for DGs to obtain maximum benefits. Furthermore, a demand response mechanism is used to generate a DLMP signal as feedback to regulate the DLMP price for each bus. LRA is integrated using a DLMP signal for the DERs. The proposed results based on a modified IEEE 37-bus system shows that uEMS leads more fair competitive environment for DGs. The considered uEMS model increases the DG benefits in terms of reduced system losses and increase in stability. The future scope includes potential cooperative incentives and communication means is to be incorporated in the unified Energy Management System.

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