An Optimal Framework for Dynamic Energy Management in Microgrids

Noopura S. P.*, Sasidharan Sreedharan, Jayan M. V., and Tulika Bhatacharjee

Abstract— *This paper aims at optimizing the operation of a microgrid system through effective dynamic energy management simulation studies. An attempt is made to investigate the problems associated with real time power balancing in a microgrid. A joint optimization scenario is considered among different units, (i.e) demand side, supply side, DG side and the renewable side incorporating the inherent randomness associated with such a system. Randomness associated with load, wind, solar and grid pricing are modeled using a 5 minute prediction interval. A Particle Swarm based optimization technique is proposed where each of the particles correspond to the various possible scheduling scenarios of the battery storage system. Accordingly, a centralized controller is proposed that monitors the scheduled power flow from ESS and central grid at intervals of 5 minutes according to the fluctuations from the demand and forecasting modules to minimize the total operational costs per day. The results of the proposed controller are compared against a greedy algorithm to prove the effectiveness in cost curtailment.*

Keywords— **Controller, micro grid, particle swarm optimisation, time domain simulations.**

1. INTRODUCTION

A Microgrid can be defined as a small-scale, self-supporting network driven by an on-site generation source with the ability to separate from an external grid for sustainability [**1**]. Growing concerns about environmental issues and deregulation of the power industry has led to a phenomena of increase in installation of DG's and energy storage systems(ESS) worldwide [**2**]. Smart microgrids can help in managing the ever-growing demand without overloading the already existing infrastructure and can help in cutting costs involved in expansion. Cost minimization, improving renewable contribution, improving reliability and security are some of the numerous benefits of effective energy management in microgrids. The inclusion of Energy storage systems can help in minimizing the impact of intermittency of renewables in the microgrid [**3**] [**4**].The available local resources in a microgrid are mainly scheduled to satisfy load demand in a minimum cost manner. BSS can be effectively utilized by charging at low market price and discharging when grid price is high. This can in turn effectively lower the operational cost of microgrid which includes battery operating cost, cost of operating DG's and cost of import/export from grid. As reported in the literature, proper control and scheduling of battery systems can lower microgrid operational costs [**5**] [**6**]. Cost studies on microgrid would be incomplete without considering operational cost of BSS , because it is necessary to justify the reduction in operational cost of microgrid over the increase in capital investment of Storage system.

An analytical method to determine the ratings of a Vanadium Redox battery through optimal scheduling analysis has been proposed in [**7**]. The optimal scheduling problem is solved through dynamic programming and the ideal ratings of VRB for both grid connected and isolated modes of a microgrid has been determined. A Robust energy management technique accounting for the worst-case amount of renewable generation and load so as to maximize social benefits and minimize exchange cost was discussed in [**8**]. Taguchi's orthogonal array testing method is used to provide for the testing cases that represent the uncertainty of RG and load. Farzin et al. [**9**] have proposed a multi-objective optimization scenario using NSGA-II wherein operational cost minimization in grid connected mode and lowering levels of expected energy curtailment in case of unscheduled islanding events are the contradicting objectives. Also, a fuzzy decision making approach is used to represent the microgrid operator preferences for a compromise between the two objectives.

Mix mode energy management strategy using linear programming and mixed integer linear programming techniques have been investigated in [**10**] for lowering the operational cost of the microgrid. An optimal battery sizing technique has also been investigated for various levels of SOC. Tran et al. [**11**] has proposed an energy manager to improve the energy efficiency and lifetime of ESS using a smart local prediction and local scheduling algorithm. Battery lifetime model based on battery workload using Peukert Lifetime Energy throughput was also studied. A two-stage stochastic energy scheduling model for an interconnected microgrid which accommodates the inherent intermittency and variability of wind and solar models has been formulated in [**12**]. The scenarios used to model wind and solar are variable

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and the optimization achieves minimum power loss.

An economic scheduling model of microgrid in grid connected mode has been established in [**13**] considering battery lifetime. Comparative studies have been carried out corresponding to the cases without BESS depreciation cost, Wh throughput method and Weighted Wh throughput method. A Smart energy management system based on matrix real coded- Genetic Algorithm that predicts the hourly power generation according to inputs from a weather forecaster has been developed by Chen et al. [**14**]. Methods have been devised to improve upon the reliability and security of microgrids in [**15**] [**16**]. Methods based on computational intelligence and artificial intelligence for EMS has been widely reported in [**17**] [**18**] [**19**] [**20**].

The work considered in this study involves development of a robust controller which considers the dynamic nature of main grid and microgrid to dispatch necessary outputs from local resources of the microgrid at regular intervals of 5 minutes to propose a cost-effective scheduling algorithm. Most of the EMS problems in literature are formulated as offline optimization problems with a priori knowledge of hour-ahead data. The increasing penetration from Renewables and random nature of loads such as Electric Vehicles has contributed to voltage and frequency stability issues in microgrid. This can be solved by accurate generation – demand scheduling. Traditional hour ahead scheduling may fail in such a scenario due to smaller network size and random nature of loads which is an inevitable part of future Smart grids. Thus traditional EMS have to be modified to handle the increased complexity due to large amount of data arriving in shorter intervals.

To this need, we have proposed a dynamic controller based on Particle Swarm Optimization where-in the dynamics of renewables are captured appropriately and a suitable control strategy has been formulated. The algorithm uses 5 minute- ahead data of solar, wind, load and market data to arrive at a suitable control strategy. The charging/discharging schedule of the battery storage system is optimized using PSO and the final outcome is a series of commands corresponding to the current state of the microgrid. The challenge in dealing with the complex scheduling strategy with measurements from DG's, battery, renewable and the main grid in intervals of 5 minutes was analyzed efficiently using our controller. Time domain simulations were carried out to calculate the outputs from various sources and were optimized using PSO to reduce the overall operational costs.

The main contributions of this paper are listed below:

1) Develop a time –domain based control strategy which can mimic real-time solar, wind power and load variability to schedule dispatch levels of battery, main grid and controllable sources in a span of 5 minutes to minimize cost and emission levels.

2) Comparing the proposed controller with that of a greedy algorithm to prove the effectiveness in cost minimization.

Remainder of this paper is organized as follows. Section II explains the mathematical modeling of the components involved in the microgrid followed by the minimized objective function details. The proposed energy management strategy has been formulated in Section III along with explanation of different case studies that have been tested. Section IV highlights the results of implementation of the proposed scheme on a test microgrid and its capabilities in cost curtailment over the greedy algorithm. Robustness of the proposed controller has been explored through comparative studies and finally, concluding remarks are framed in Section V.

2. MATHEMATICAL MODELING

Fig 1 highlights the test case adopted along with the structure. Various components involved are modeled as described below. Synchronous generators are modeled as IEEE type 6, Turbine Governor as IEEE type1 and AVR's are modeled as IEEE type 2.

2.1 Modelling of battery

*Battery storage system is modelled as follows [**21**].*

If the BSS is charging,

$$SOC(t+1) = SOC(t) + P_b(t)\Delta t\, \eta^{ch} \tag{1}$$

If the BSS is discharging,

$$SOC(t+1) = SOC(t) - \frac{P_b(t)\Delta t}{\eta^{dch}} \tag{2}$$

where *E(t)* is the current capacity of BSS. For periodic use of BSS, the capacity at the last time period should be equal to the initial capacity which is represented as

$$SOC(0) \simeq SOC(T) \tag{3}$$

where T is the last time period which is 24 hours. This constraint ensures that the Battery is available in the same state of charge while considering for planning studies for the next subsequent time interval.

$$SOC_{min} \le SOC(T) \le SOC_{max} \tag{4}$$

Equation (4) ensures that battery is not charged/discharged beyond the specified limits.

Table 1. BSS parameters

Parameter	Value
Charging efficiency	90 %
Discharging efficiency	90 %
SOC_{min}	10 %
SOC_{max}	100 %

2.2 Modelling of Wind Energy Conversion System (WECS)

The turbine generator used for wind modeling is DFIG whose stator is directly connected and its rotor is connected through slip rings and lossless power electronic converter. [**22**].

2.3 Modelling of Solar PV cell

For describing the solar cell electrical circuit equations in [**23**] are used. This dynamic PV model is suitable for DG applications in microgrid. Operational costs of solar and wind is assumed as negligible.

2.4 Modelling of controllable sources

Fuel cell and Micro turbine are considered as the controllable sources. Since the output of renewables cannot be predicted, the controllable sources are adjusted to meet the power balance according to dispatchable source control as illustrated in fig 2 .For MT or fuel cell, the fuel cost can be viewed as a linear function .

$$C_c(t) = a + bP_c(t) \tag{5}$$

2.5 Cost Modelling

2.5.1 Battery cost modeling

BSS capital cost is defined as a function of two parts, one is related to the Energy rating and the other part depends on the power rating.

$$C_{capital} = C_P P_{max} + C_E E_{max} + C_0 \tag{6}$$

The Total cost per day can be evaluated as

$$C_1 = \frac{1}{365}\frac{r(1+r)^n}{(1+r)^n - 1}.C_{capital} \tag{7}$$

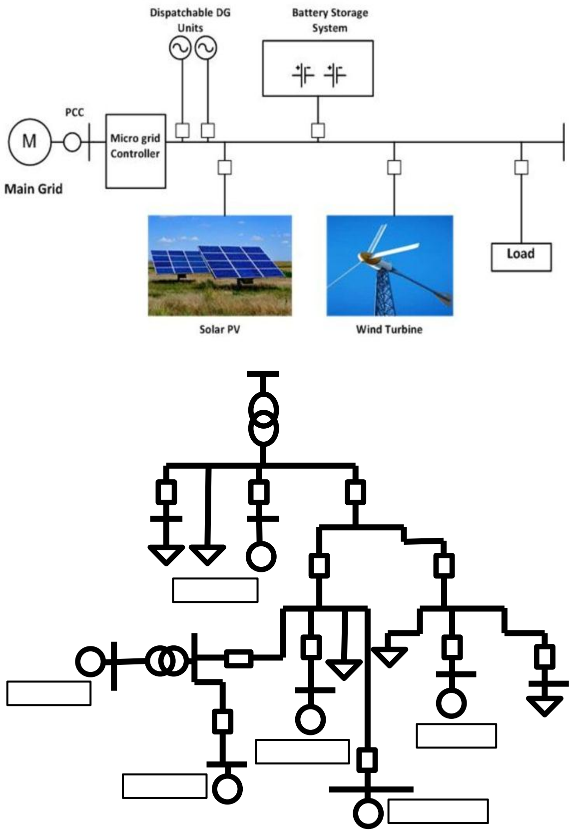

Fig.1.(a) Microgrid structure (b) Test Case.

Battery operation and maintenance cost is a fixed cost proportional to the power rating. The operation and maintenance cost per day can be modeled as follows.

$$C_2 = \frac{1}{365} C_{om}.P_{max} \tag{8}$$

Hence the total cost per day for the battery can be evaluated as

$$C_b = C_1 + C_2 \tag{9}$$

Assumed Battery parameters are tabulated in Table I.

2.6 Objective function

The EMS aims to minimize microgrid operational cost by maximizing the use of local production. The following objective function is minimized using PSO.

$$obj = Minimize\left[\sum_{t=1}^{T} C_c(t)\left(P_{fc}(t) + P_{mt}(t)\right) + C_b(t)P_b(t) - C_g(t)P_g(t)\right] \tag{10}$$

subject to the following constraints:

Power balance within the microgrid has to be checked at every time interval. The following power balance constraint has to be satisfied.

$$P_w(t) + P_{pv}(t) + P_c(t) + P_b(t) = P_L(t) + P_g(t) \tag{11}$$

$P_g(t)$ is negative when power is exported to the main grid from microgrid and $P_g(t)$ is positive when power is imported from the main grid to meet the deficiency.

$$0 \le P_g(t) \le \bar{P}_{gmax}(t) \tag{12}$$

Equation (12) ensures that power bought from the grid/sold to the grid is within the specified limits.

$$0 \le P_{dg}(t) \le \bar{P}_{dgmax}(t) \tag{13}$$

Equation (13) imposes power balance constraints on diesel generator and fuel cell. Apart from the above constraints, constraints from (1),(2) and (4) is checked in every time interval and (3) is checked at the last instant.

3. PROPOSED ENERGY MANAGEMENT STRATEGY USING PARTICLE SWARM OPTIMIZATION

Controller decides upon the ideal charge -discharge schedules from the battery such that the total operational cost per day is minimized. Energy dispatches from the battery and grid are governed by the following algorithm. The controller is designed to handle the complex data sets and determine the ideal dispatch levels of the battery. The fitness function is modeled as below and subject to all the constraints mentioned above. The violated constraints are penalized using a penalty factor.

$$Minimise\ F(c) = \left[\sum_{t=1}^{288} C_c(t)\left(P_{fc}(t) + P_{mt}(t)\right) + C_b(t)P_b(t) - C_g(t)P_g(t) + \sum_{n=1}^{N_v} P_f * V_c\right] \quad (14)$$

where,

$$Control\ variable = P_b(t) \text{ for t=1,2,3..288} \quad (15)$$

$F(c)$- Fitness function

N_v – Number of violated constraints

V_c - Violated Constraint

P_f- Penalty factor associated with violated constraint V_c

Figure 2 describes the methodology involved and fig.4 depicts the control strategy. The control variables chosen are the charge/discharge power output from the battery storage system for the chosen scheduling interval. The studies are carried out for a single chosen day-24 hours and Δt was taken as 5 minutes. This resulted in a total of 288 scheduling intervals. The PSO outputs the charge/discharge pattern and the remaining power output from various controllable sources are calculated to meet the power balance constraint. Since the randomness associated with grid pricing is also included, PSO tries to find the optimal set of charge/discharge pattern from the battery such that grid import occurs during low price intervals. Thus the final output corresponds to a series of power output vectors such that the cost of purchase from main grid is minimized, thus minimizing the overall costs incurred.

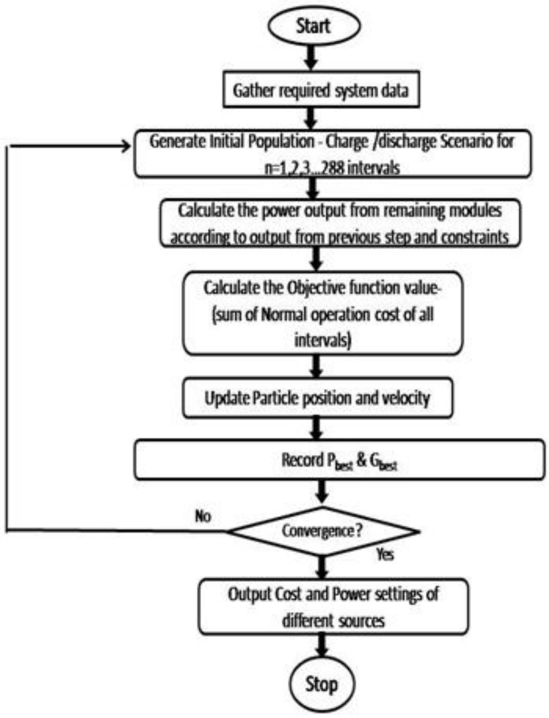

Table 2. PSO Settings

PSO is a population based method which effectively gets the knowledge from competition and co-operation among the particles in a swarm. PSO has been identified as robust in solving complex optimization problems with high degree of non-linearity and dimensionality and is thus used for our problem at hand [25]. The PSO settings used for our study are tabulated in Table II. The centralized controller is based on Particle Swarm optimization to determine the ideal periods for charge/discharge. According to outputs from forecasting modules, controller optimizes flow of energy among generation, demand and storage units so as to meet the network constraints while optimizing the objective function. A set of vectors of recommended energy flows from source to destination at intervals of every 5 minutes is output from the controller. PSO compares the various possible charging/discharging scenarios and outputs the best particle corresponding to minimum cost. The advantage of using available storage to offset anticipatory grid price hike has been effectively used in the design strategy as explained below.

1) The outputs from various units are input to the controller in span of 5 minutes.
2) The PSO based controller determines the dispatch set points of DG's and battery in such a way that the total cost function can be minimized.
3) The set points are determined for a particular day according to the renewable generation and demand prediction. Accordingly, the controller is designed to handle the complex data sets and determine the ideal dispatch levels of the battery. The developed algorithm is compared against a greedy algorithm.

Table 2. PSO Settings

Parameter	Settings
Type of PSO	Common
Maximum no of iterations	200
Population size	200
Acceleration constant 1	2
Acceleration constant 2	2
Initial inertia weight	0.9
Final Inertia weight	0.4

4. GREEDY ALGORITHM

The results of the proposed controller are validated against a greedy algorithm.

Schedule $P_b(t)$ such that,

$$F(c) = \left[\sum_{t=1}^{288} C_c(t)\left(P_{fc}(t) + P_{mt}(t)\right) + C_b(t)P_b(t) - C_g(t)P_g(t) + \sum_{n=1}^{N_v} P_f * V_c\right] \quad (16)$$

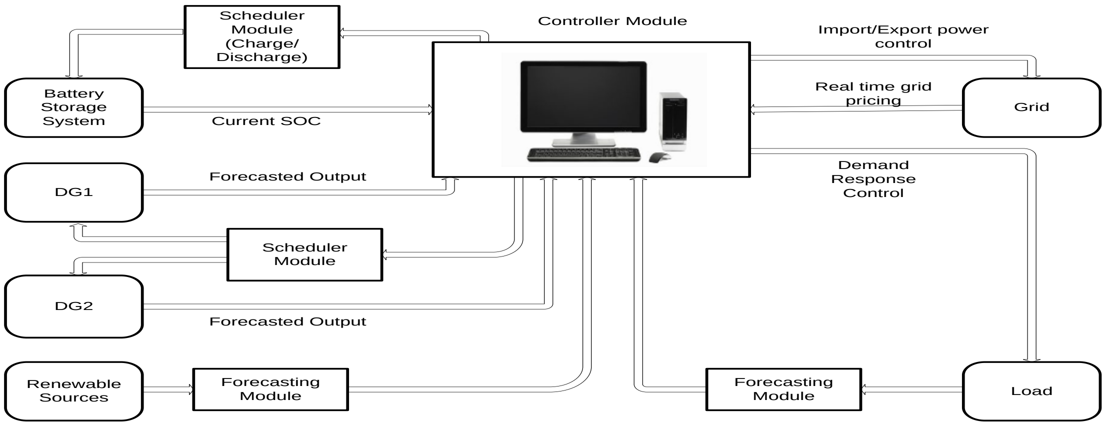

Fig.3. Microgrid control strategy.

subject to constraints (1)-(4) and (11)-(13).

The greedy algorithm is the base case without the presence of a controller. Thus the charge/discharge schedules are obtained in order to satisfy (11) without considering the future grid price variations. The outputs from the greedy algorithm are shortsighted as it minimizes the cost at each time without considering the possible future variations into account.

5. RESULTS AND DISCUSSION

To assess the validity of the proposed control strategy, case studies were carried out. Sample microgrid considered in this paper consists of 2 MW solar PV generation, 2.5 MW wind generation, 5 MWh battery energy storage system [26], 2.5 MW fuel cell and 2.5 MW micro turbine. Main grid considered is the IEEE 14 bus test case. A microgrid was connected to the main grid across the point of common coupling and the exchange power limit was set.

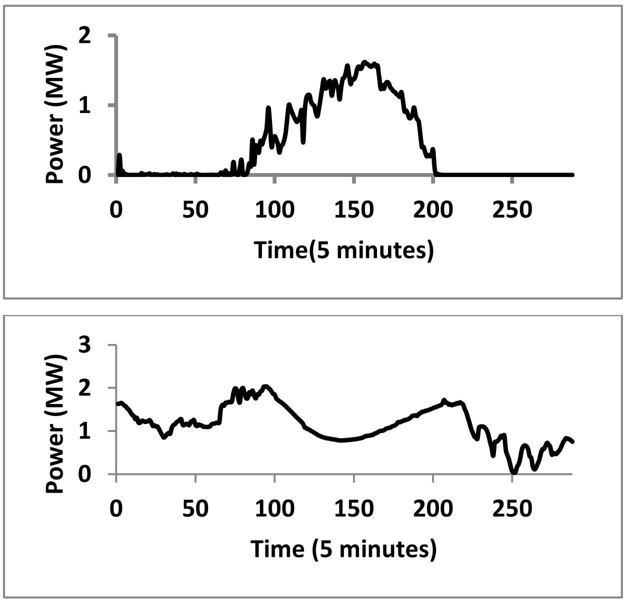

Fig 4. Renewable generation output (a) Solar (b) Wind.

Figure 4 shows the generation output from PV and wind modules. As can be seen, the variations are captured for intervals of 5 minutes. The PV output is obtained for a particular day from [27] and wind output is also captured for the same day [28]. Figure 5 plots the net load demand and the 5-minute real time pricing obtained from [29].

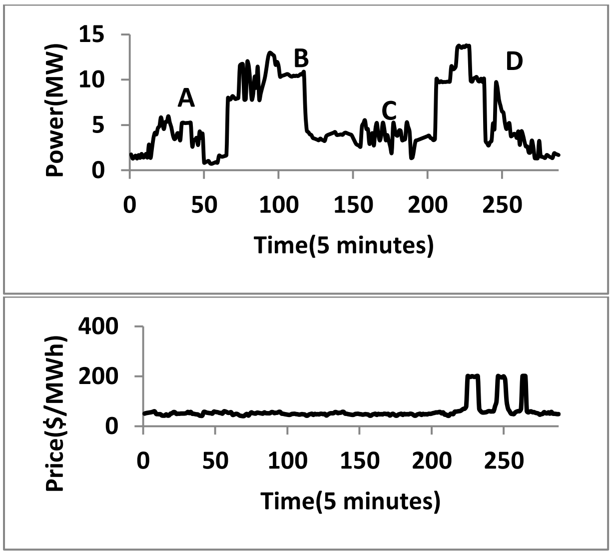

Fig 5. (a) Load (b) Real time pricing

Fig.6 (a) plots the results obtained from the PSO based controller and 6 (b) plots the results of greedy algorithm. The plots are shown for duration of 24 hours resulting in a total of 288 scheduling intervals of 5 minutes each. Thus a complex optimisation strategy involving a total of 2016 measurements involving measurements from Wind, Solar, Microturbine, fuel cell, battery , Grid and Load were handled efficiently using the proposed controller. It is worthwhile to note that the proposed controller took an average time of 0.52 seconds per interval, according to the parameters given in Table II to solve the complex optimisation scenario thus making it possible to extend in real time.

Points A, B, C and D correspond to the various load scenarios in Fig.5 (a). The corresponding scheduling results can be observed from Fig. 6(a). As observed from the figure, at point A the battery charges due to lightly loaded conditions which are typical in real time. It can be seen that the battery effectively manages the fluctuations in load as well as renewables. At point B, there is an increase in load demand, which is managed by the controller by importing from the main grid according to the real time pricing strategy. Also, the battery gets discharged for a short interval which results in subsequent charging in the next intervals. Point C corresponds to lightly loaded condition, resulting in power export to the main grid with exchange taking place according to real time pricing. At point D, when the load fluctuation is beyond the capacity of microgrid, power is again imported from the main grid, but only after the battery discharges to its maximum capacity.

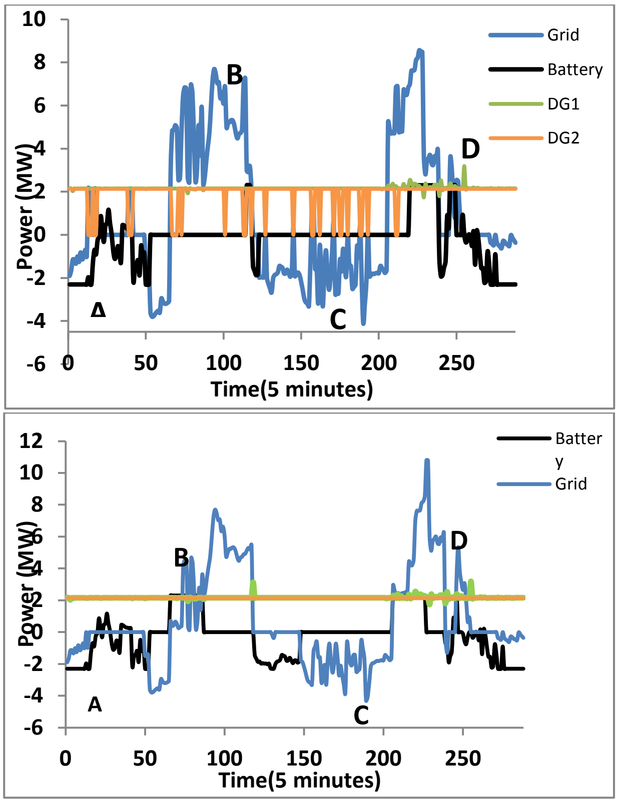

Fig.6. (a) PSO based scheduling of DERs in the microgrid (b) Greedy algorithm scheduling results.

Emission control is also implemented for the fuel cell thus optimising the litres of fuel consumed and minimising the grid emission factor. This is evident from the on-off control which is implemented for DG2.

The results are compared against a greedy algorithm whose scheduling results are discussed in Fig.6(b). The greedy algorithm is short sighted (i.e) optimization is considered only for that particular period without considering the possible future variations. At point A, battery is charged due to lightly loaded conditions followed by complete battery discharge at point B. On the other hand, scheduling using PSO prevents complete drainage of battery charge, thus enabling power export during instances of peak-pricing as observed at point C Thus the power imported/exported can be effectively optimised through ideal charge/discharge scheduling. At point D, battery is completely drained and the remaining required power is imported from the main grid. It can be observed that effective scheduling results in import of around 10 MW during peak interval, whereas greedy algorithm results in import of around 12 MW. Moreover DG2 scheduling is also not optimised resulting in higher micro grid emission factor.

Fig.6 plots the comparison results. As shown, the PSO algorithm outplays the greedy algorithm at all the intervals except in the middle part. This can be attributed to the short sightedness of the greedy algorithm, whereas the PSO algorithm reduces the net cost incurred for the MGO, even though the cost is compromised initially. Table III compares the cost obtained among the two algorithms. As shown total savings of 411.7$ were obtained for a single day using the PSO based controller.

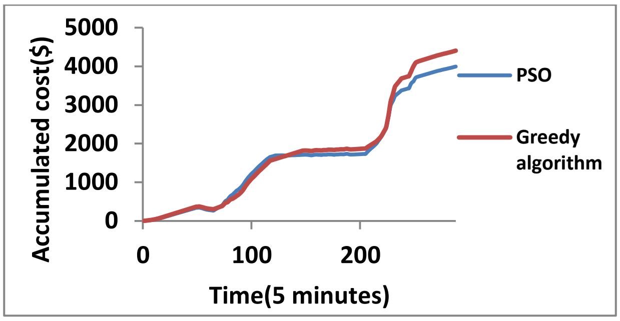

Fig 7. Time accumulated cost comparison

Table 3. Cost comparison

Method	Total Cost($)	Time average cost($)
Greedy Algorithm	4405.7	15.3
PSO Controller	3994	13.86

6. CONCLUSION

This paper presents a framework for optimal scheduling of DG's and ESS's in a microgrid in the context of cost optimization. The work is an attempt to model the future smart grid/microgrid framework where the variations in load and renewable might be highly uncertain thus resulting in the need to consider shorter time frames for optimization.

The major conclusions are discussed as follows:

1) Dynamic grid model coupled with micro grid has been developed and a cost effective control strategy has been investigated based on real time grid pricing and forecasted renewable outputs and load.

2) The charging/discharging schedule of ESS's and set point calculation of DG's is considered in a complex optimization framework mainly because of the reduced scale of optimization interval (i.e) 5 minutes.

3) A dynamic controller based on Particle Swarm optimization has been designed to deal with the optimization problem to develop an ideal scheduling strategy for the considered period of 24 hours.

4) The obtained results highlight the performance of the proposed controller. The time required for solving the scheduling problem is around 0.52 seconds per interval. Thus the proposed controller can effectively handle real time data and propose a control stategy .

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NOMENCLATURE

The main notations used in this paper are listed below for quick reference.

BSS	Battery storage system
MG	Microgrid
EMS	Energy Management System
PSO	Particle Swarm Optimization
P_b(t)	Battery output at time t
P_{max}	Power rating of BSS
E_{max}	Energy rating of BSS
Δt	Time interval of operation
η^{ch}	Charging efficiency of BSS
η^{dch}	Discharging efficiency of BSS
$SOC(t)$	Current State of charge of BSS
SOC_{min}	Minimum SOC value
SOC_{max}	Maximum SOC value
$SOC(0)$	Initial SOC value
$SOC(T)$	Final SOC value
C_c	Generation cost of controllabe sources
a,b	Cost coefficients of controllabe sources
$P_c(t)$	Power output of controllable sources at time t
$C_{capital}$	Capital cost of BSS
C_p, C_E, C_0	Cost coefficients of BSS
C_{OM}	Operation and Maintenance cost of BSS
r	Interest rate for financing BSS
n	Lifetime of BSS
C_b	Total cost of operation of BSS
$P_{fc}(t)$	Power output of fuel cell at time t
$P_{mt}(t)$	Power output of micro turbine at time t
$C_g(t)$	Cost of purchase from grid/ Revenue obtained by selling to grid at time t.
$P_g(t)$	Power output of main grid at time t
$P_w(t)$	Power output of wind at time t
$P_{pv}(t)$	Power output of solar PV panel at time *t*
$P_L(t)$	Total Demand of microgrid at time t.
$\overline{P}_{gmax}(t)$	Maximum power that can be imported from grid/exported to grid.