An Energy Acquisition Model for DISCOMs with High Renewable Energy Integration

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***Abstract*— In the existing power system, the penetration of renewable energy sources (RES) is very low. In future, RES is expected to play a key role in meeting the vast power demand. This will result in a risk to stability and reliability of the power system, owing to the intermittent nature of RES. They introduce significant errors in forecasting, depending on which Distribution Company's (DISCOMs) will purchase energy to meet the demand. Any difference between the real time demand and forecasted demand is to be met by the DISCOMs in the real time market (RTM) at extra prices, thus exposing them to the risk of price volatility. In this paper, an optimal operation strategy using battery energy storage system (BESS) is proposed, along with which optimization of placement and sizing of BESS is done using a novel optimization technique called teacher learning based optimization (TLBO) algorithm. The results show that this optimal operation strategy is able to yield significant savings for the DISCOMs and TLBO performs better than other heuristic algorithms. The entire work is carried out on an IEEE modified 15 bus radial distribution system, in both regulating and locational marginal price (LMP) markets.**

Keywords- Renewable energy integration, optimal operation strategy, battery energy storage system, teacher learning based optimization, distribution company, locational marginal price, real time market

I. INTRODUCTION

As on March 31, 2016, the contribution of renewable energy sources (RES) to the total installed power capacity in India is only 13%, while that of thermal power plants is 70.1% [1]. In future, there will be high integration of RES due to several reasons like pollution by conventional power plants, transmission corridor constraints, availability of abundant RES, etc. But this integration poses a serious risk to the stability and reliability of the system, due to the fact that they are highly intermittent, which leads to power quality issues. In such a case, the system operation should be tackled such that it remains intact. Apart from this, economic issues also arise in a deregulated power system. There are many works which address the issues faced by Generation Companies (GENCOs) [2].

In a vertically integrated power system, the main aim of the DISCOMs is to ensure reliability and stability of the system, and to maximize their profit. With high renewable integration, there may be significant errors in forecasting of demand, according to which it makes energy purchase decisions, which exposes DISCOMs to the risk of price volatility. Thus, there is a need for the DISCOMs to adopt an operation strategy which yields them savings as well as help them maintain the system reliability and stability.

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One potential solution is the use of energy storage systems (ESS). The aim of the present work is to form an energy acquisition model for the DISCOMs using ESS, such that the forecasted demand curve is traced, thus reducing the interaction of DISCOMs with the real time market (RTM). Meanwhile, optimization of placement and size of ESS is done and a cost-benefit analysis is performed to evaluate the economy of ESS.

ESS has been used for a number of applications like electric energy time-shift, load following, voltage support, etc [3]. There are many types of ESS like batteries, super capacitors, flywheel, etc. A comparison of their characteristics is given in [4]. However, due to space constraints, low cost, and being a mature technology, battery energy storage systems (BESS) are used in this work. Many works have addressed optimal placement and sizing of BESS. In [5], the loss payment of DISCOM is minimized by optimal scheduling of RES and ESS. But the author has not considered the economics of ESS. In [6], optimal placement and sizing of BESS is done using a loss sensitivity based algorithm, It takes into account only the loss minimization, ignoring the cost of BESS and the deregulated structure of power system. In [7], a bi-level optimization model is used to determine the optimal installation site and size of BESS. However, it does not consider the benefits of DISCOMs. [8] deals with the voltage fluctuation problems arising from high penetration of RES by using customer side ESS.

As the sizing and placement of BESS has a significant effect on the system losses, energy purchase decisions and economy of the system, it is a non-linear optimization problem subjected to many constraints like voltage limits, battery charge limits etc. This requires efficient optimization algorithms. In [9], optimal sizing of super magnetic energy storage system (SMES) is carried out using simplex method which is an unconstrained optimization technique and a local search technique. Many works have used genetic algorithm (GA), particle swarm optimization (PSO) to address the same problem [7], [10]. However, these algorithms require optimization of the parameters, otherwise they lead to local minima or maxima. In order to improve the performance of PSO, parameters like weight factor, social and cognitive factors are optimized using fuzzy logic controller, thus leading to an algorithm called Fuzzy particle swarm optimization (FPSO) [11]. It is expected to give better performance than PSO and GA.

In [12], a novel algorithm called Teacher learning based optimization (TLBO) is used for distributed generator (DG) placement with the aim of loss minimization. It is an algorithm free of parameters and thus expected to give better results than other heuristic algorithms. In [13], TLBO is used for DG placement for minimization of loss, capacity release of transmission lines, and voltage profile improvement. Neither of them focuses on the troubles faced by DISCOMs in the deregulated power system in the presence of RES.

In this paper, an optimal operation strategy using battery energy storage system is proposed, along with which optimization of placement and sizing of BESS is done using a novel optimization technique called teacher learning based optimization (TLBO).

II. OPERATION OF DISCOM

The assumptions [11] made in this work are:

- DISCOM is the sole system operator and electricity retailer.
- DG units are owned and operated by the DISCOMs and they are dispatchable both in the day ahead and real time operation.
- The day ahead procurement energy is set according to the forecasted net demand.

When there are RESs in the system, the net demand is forecasted as,

$$P_{Netfore}(t,day) = P_{Pred}(t,day) - P_{RES}(t,day) \quad (1)$$

where $P_{Netfore}$ is the forecasted net demand, in MW
P_{Pred} is the forecasted consumer demand, in MW
P_{RES} is the forecasted power from RES, in MW
day is the specific day in a year
t denotes specific time in a day
The equation (1) shows that RES introduced more uncertainty into the forecasted demand. The cost spent in purchasing the day ahead power [11] is,

$$\pi_{DA}(t,day) = \lambda_{DA}(t,day) P_{Netfore}(t,day)\Delta t \quad (2)$$

where $\lambda_{DA}(t,day)$ is the purchasing cost in day ahead market (DAM), in \$/MWh
Because of errors in forecasting, the real time net demand will be different from the forecasted value and this difference is met by the DISCOMs at real time price called regulating price [14] or penalty [15]. In this paper, both markets are analyzed. In regulating price mechanism, the cost of energy required in RTM is,

$$\pi_{RT}(t,day) = \lambda_{RT}^{RP} \mid (P_{Netreal}(t,day) - P_{Netfore}(t,day)) \mid \quad (3)$$

where λ_{RT}^{RP} is the penalty price, in \$/MWh
$P_{Netreal}$ is the real time net demand, in MW

For LMP mechanism,

$$\pi_{RT}(t,day) = \lambda_{RT}^{RP} \mid (P_{Netreal}(t,day) - P_{Netfore}(t,day)) \mid + \lambda_{Cong}^{LMP} \mid (P_{Netreal}(t,day) - P_{Netfore}(t,day)) \mid \quad (4)$$

where λ_{Cong}^{LMP} is the congestion price in LMP market, in \$/MWh Now, the total energy purchasing cost [11] is given by,

$$\pi_{total}(t,day) = \sum_{t=1}^{24} (\pi_{DA}(t,day) + \pi_{RT}(t,day)) \quad (5)$$

III. BESS OPERATION STRATEGY

In this work, BESS is operated in such a way that the system losses are minimized, DISCOMs profits are maximized and the ESS is better utilized. The BESS operation strategy is the same in both types of markets being dealt in this work. The BESS is triggered by the demand gap as shown below.

$$P_{ESS}(t,day) = P_{Netfore}(t,day) - P_{Netreal}(t,day) \quad (6)$$

The entire BESS operation strategy is reflected in Fig 1.The real time demand is greater than the forecasted demand from hours 12 to 16. During this period, there is a shortage of power as the DISCOM has already purchased $P_{Netfore}(t,day)$ from DAM, and hence, the DISCOM should obtain that power from any source. There are two ways that the DISCOM can resort to: Energy can be bought from the RTM or the BESS can be discharged. But when there is more demand, the price in RTM will be more than the day ahead price, thus there is a price risk. So, it is advisable for the DISCOM to derive the required power by discharging the BESS. Before giving a discharge signal, the capacity available with the BESS has to be known. The state of charge (SOC) of the BESS at node i [11] is calculated as,

$$SOC_i(t,day) = \frac{E_i(t,day)}{E_{r,i}} \quad (7)$$

The remaining energy available with the BESS for discharging [11] is calculated as,

$$E_{rest,i}^{Dis}(t,day) = (SOC_i(t,day) - SOC^{min})E_{r,i} \quad (8)$$

where *i* denotes the bus number
$E_{r,i}$ is the energy rating of the battery at bus i, in MWh
E_i is the energy stored in the battery at bus i, in MWh
There can be more than a single BESS. Each of them have to be discharged according to the discharging energy available with them. Thus, the amount of power for each battery [11] is allocated as,

$$P_i^{Dis}(t,day) = \frac{P_{ESS}(t,day) E_{rest,i}^{Dis}(t,day)}{\sum_{i=1}^{n} E_{rest,i}^{Dis}(t,day)} \quad (9)$$

If the available BESS are not able to supply the required power, the remaining power has to be bought from the RTM. If the real time demand is less than the forecasted demand as during hours 17 to 20, there is excess power available with the DISCOM, which can be sold in the RTM or can be used to charge the BESS. But when the demand is less, the real time price will be lesser than the day ahead price. Therefore, it is advisable for the DISCOM to use the excess energy to charge the BESS. Before doing so, the charging capacity available with the BESS [11] should be calculated. It is given by,

$$E_{rest,i}^{Chr}(t,day) = (SOC^{max} - SOC_i(t,day))E_{r,i} \tag{10}$$

The amount of power for each BESS [11] is allocated as,

$$P_i^{Chr}(t,day) = \frac{P_{ESS}(t,day)E_{rest,i}^{Chr}(t,day)}{\sum_{i=1}^{n} E_{rest,i}^{Chr}(t,day)} \tag{11}$$

where *n* denotes the number of buses.

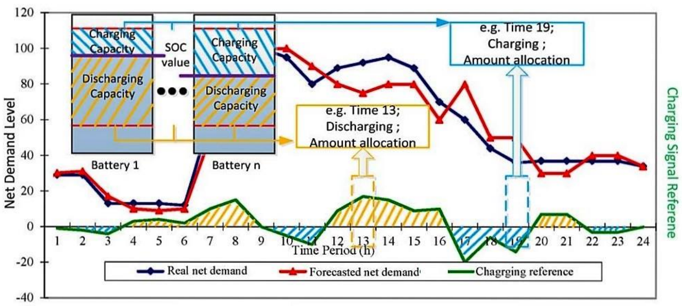

Figure 1. BESS operation strategy [11]

If the excess energy available is more than the capacity of BESS, the remaining energy is sold in the RTM.

Now that BESS is available, the DISCOM need not buy the entire forecasted demand from the DAM. The DISCOM has the electricity price forecasted. When this price is lower than a predetermined threshold, the DISCOM should buy more energy from the DAM. If the price is higher than a predetermined threshold, less energy should be procured from DAM. This amount is calculated according to the capacity of BESS. The change in the amount of energy purchased in DAM is given by [11] ,

$$Let\ a = \frac{\lambda_{DA}(t,day) - k_{up}\lambda_{DA}^{mean}}{\sum_{\lambda_{DA}(t,day)>k_{up}\lambda_{DA}^{mean}}(\lambda_{DA}(t,day) - k_{up}\lambda_{DA}^{mean})}$$

$$Let\ b = \frac{-(\lambda_{DA}(t,day) - k_{down}\lambda_{DA}^{mean})}{\sum_{\lambda_{DA}(t,day)<k_{down}\lambda_{DA}^{mean}}(\lambda_{DA}(t,day) - k_{down}\lambda_{DA}^{mean})}$$

$$\Delta P_{pred}(t,day) = a * \sum_{i=1}^{n} E_{r,i}\Delta SOC \quad if\ \lambda_{DA} > k_{up}\lambda_{DA}^{mean}$$

$$\Delta P_{pred}(t,day) = 0$$

$$if\ k_{down}\lambda_{DA}^{mean} < \lambda_{DA} < k_{up}\lambda_{DA}^{mean}$$

else

$$\Delta P_{pred}(t,day) = b * \sum_{i=1}^{n} E_{r,i}\Delta SOC$$

where
λ_{DA}^{mean} is the average electricity price in DAM, in \$/MWh
k_{up} is the upper price threshold
k_{down} is the lower price threshold.

IV. MATHEMATICAL FORMULATION

The operation of BESS, its placement and sizing should be carried out such that the system losses, the total procurement cost of the DISCOM and the BESS cost are minimized. The objective function is given as [11],

$$J = \sum_{day=1}^{365} \Pi_{total}(day) + \sum_{day=1}^{365}\sum_{t=1}^{24}\sum_{ij\in L}(I_{ij}(t,day))^2 r_{ij}\lambda_s + \sum_{i=1}^{n} C_{BESS,i} \tag{12}$$

where $C_{BESS,i}$ is the cost function of the battery at node i, which includes investment cost, maintenance cost, operation cost and residual value.

$$C_{BESS} = CI + CO + CM - CD$$

The objective function is subject to various operating constraints as mentioned below.

- Power balance constraint

$$P_{solar}(t,day) + P_{wind}(t,day) + P_{ESS}(t,day) + P_{powermarket}(t,day) = P_{load}(t,day) \tag{13}$$

  where $P_{powermarket}$ indicates the net amount of power bought or sold in the power market.
- Voltage constraint

$$V^{min} \leq V_i(t,day) \leq V^{max} \tag{14}$$

- Current constraint

$$I_{ij}(t,day) \leq I_{ij}^{max} \tag{15}$$

  This is to ensure thermal stability of the system.
- SOC limits

$$SOC_{Min} \leq SOC_i(t,day) \leq SOC_{Max} \tag{16}$$

- BESS charging-discharging power limits

$$P_{ESS,i}^{Dis/Chr,Min} \leq P_i^{Dis/Chr}(t,day) \leq P_{ESS,i}^{Dis/Chr,Max} \tag{17}$$

- DG operation limit constraints

$$P_{i,RE}^{Min} \leq P_i^{RE}(t,day) \leq P_{i,RE}^{Max} \tag{18}$$

It is clear that the above problem is a highly non-linear optimization problem, which cannot be solved by traditional optimization methods. Hence, heuristic methods are used. In this paper, TLBO is used and the results are compared against FPSO, GA, and PSO.

V. TEACHER LEARNING BASED OPTIMIZATION

This method is based on the learning process of students in a class, who are mimicked as learners in TLBO. They are analogous to population in other heuristic algorithms. Firstly, the students learn from the teacher, which constitutes teacher phase and then, they learn from their peers, forming learner phase in TLBO.

A. Teacher phase

The extent to which the students learn depends upon the knowledge of the teacher. And the knowledge of the teacher is evaluated by the performance of the class, i.e. the mean of their marks. Thus, the teacher tries to impart his/her knowledge to the students, bringing their knowledge on par with the teacher. This can be mathematically represented [16] as,

$$X_{new} = X_i + r(X_{teacher} - T_F.X_{mean}) \tag{19}$$

where X_i is the learner
$X_{teacher}$ is the best performer in the class
T_F is the teaching factor taken as either 1 or 2
X_{mean} is the mean of all learners
r is a random number between 0 and 1.
The best performer in the initial population is taken as the teacher. The new individuals thus formed are retained only if they are better than the previous learners.

B. Learner phase

The learning process of the students does not stop with the teacher. They further learn from their peers. So, each learner chooses another student randomly. If learner X_{ii} has chosen learner X_i, X_i may have more knowledge or less knowledge than X_{ii}. If X_i has more knowledge, then X_i learns from X_{ii} and thus moves close to X_{ii} [16].

$$X_{new} = X_i + r * (X_{ii} - X_i) \tag{20}$$

else, Xi is moved away from Xii

$$X_{new} = X_i - r * (X_{ii} - X_i) \tag{21}$$

The algorithm for TLBO is given in Fig 2.

VI. RESULTS AND DISCUSSION

The whole method discussed above is implemented on an IEEE modified 15 bus radial distribution system [11] whose data is drawn from [17] and the power factor is taken as 0.7. The power factor for the wind units is taken as 0.93. The load data, wind power data, solar power data, price data, both forecasted and real time, for a period of 1 year are taken from PJM website pertaining to PJM RTO [18]. The electricity price (λ_s) is taken as 0.2 \$/kWh and the discount rate for BESS is taken as 5%. k_{up} is taken as 1.2 and k_{down} is taken as 0.5 [11]. The rule base required for FPSO is taken from [11]. The parameters for the various algorithms are taken as, GA: crossover probability=0.8, mutation probability=0.01. In PSO and FPSO, weight factor=0.796 and social and cognitive parameters are 2 each. The fitness function is taken as 1/(1+objective function) . The population size is taken as 20 for all the algorithms and convergence criteria is fitness error of 0.0001. As lead acid and lithium ion BESS are well matured, they are used for the analysis. The parameters of BESS are shown in Table I. Minimum SOC for the BESS is taken as 0.2 and maximum SOC is taken as 0.8.

For the given system, without BESS, the penalty cost is obtained as 65,786 \$ for the considered year and the cost of

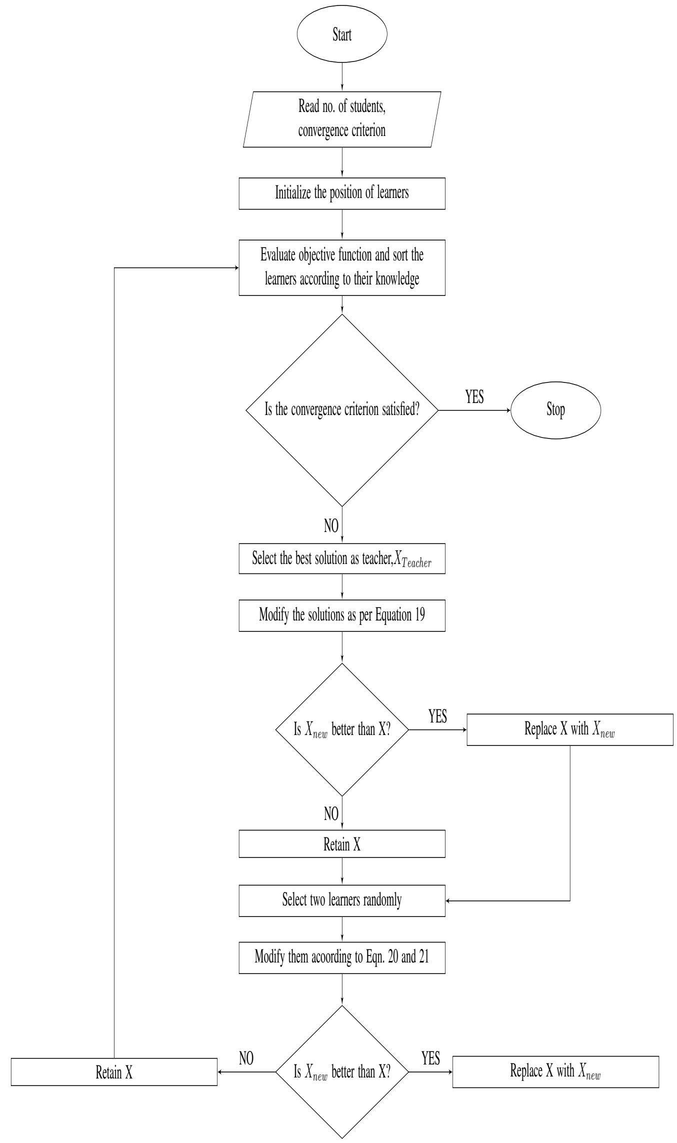

Figure 2. Flowchart for TLBO

Table I
PARAMETERS REQUIRED FOR BESS

Entry	Lithium ion BESS	Lead acid BESS
Lifecycle	1500 times	1000 times
Investment cost	$300E_r$	$80E_r$
Operation cost	$10E_r$	$10E_r$
Maintenance cost	$5E_r$	$10E_r$
Energy efficiency	85%	80%
Self discharge	2% per month	3% per month

energy loss is obtained as 65,704 \$. The optimization result with BESS is shown in the subsequent tables. The savings in each case are calculated as the difference of the cost incurred before placement of BESS and the cost incurred after placement of BESS. The losses are calculated by performing load flow on the test system as described in [19]. From Table

II, it can be observed that the Lithium ion BESS is not able to fetch any savings for DISCOM because of its high cost. From Table III, it is clear that, lead acid BESS is able to fetch significant savings for the DISCOM. So, further analysis is carried out only with lead acid BESS. Under LMP market, It can be observed from Table IV that the capacity of BESS required is only 0.72 MWh with TLBO, 0.83 MWh with FPSO, 0.85 MWh with PSO and 0.89 MWh with GA. Thus, TLBO performs better than the other algorithms. This is due to the fact that each iteration involves checking of optimality with three different solutions, which means the search space is better covered compared to the other algorithms. Moreover, TLBO is devoid of the parameters to be optimized, where other algorithms may involve errors due to use of sub-optimum parameters.

Table II
BESS OPTIMIZATION RESULT FOR LITHIUM ION BESS UNDER REGULATING MARKET

Entry	GA	PSO	Fuzzy PSO	TLBO
Location	5,6,12	1, 9, 12	4, 6,10	4,6,9
Capacity (MWh)	0.22,0.42,0.54	0.28,0.37,0.52	0.21,0.38,0.55	0.34,0.32,0.48
Total capacity required (MWh)	1.188	1.173	1.159	1.154
Loss cost($)	65,588	65,008	65,207	65,122
Penalty($)	21,822	21,325	20,868	20,792
BESS cost($)	3,56,400	3,21,000	3,17,880	3,46,200
Residual value($)	2,15,986	2,17,825	2,16,140	2,16,124
Savings($)	-	-	-	-
Time(sec)	3864	1987	1286	4912

Table III
BESS OPTIMIZATION RESULT FOR LEAD ACID BESS UNDER REGULATING MARKET

Entry	GA	PSO	Fuzzy PSO	TLBO
Location	3,5,9	1 ,9,11	4 ,6 ,9	3, 6, 9
Capacity (MWh)	0.52,0.98,0.97	0.39,1.03,0.88	0.73,0.79,0.68	0.44,0.98,0.61
Total capacity required (MWh)	2.47	2.3	2.2	2.03
Loss cost($)	65,868	65,318	65,162	64,903
Penalty($)	2206.6	1998.3	1983.15	1825.58
BESS cost($)	1,81,360	1,83,680	1,76,960	1,62,080
Residual value($)	1,20,938	1,20,950	1,21,320	1,27,350
Savings($)	9,242.4	15,402.7	17,503.85	19,659
Time(sec)	4166	1564	1252	5576

Table IV
BESS OPTIMIZATION RESULT UNDER LMP MARKET

Entry	GA	PSO	Fuzzy PSO	TLBO
Location	3, 4, 9	4, 9, 11	4, 6, 9	4, 6, 11
Capacity (MWh)	0.25,0.36,0.28	0.38,0.12,0.35	0.19,0.41,0.23	0.24,0.38,0.1
Total capacity required (MWh)	0.89	0.85	0.83	0.72
Loss cost($)	65,486	65,422	65,387	64,964
Penalty($)	10,846	9998.3	8910.25	7841.20
BESS cost($)	71,840	68,480	66,400	58,080
Residual value($)	38,562	38,684	38,526	38,498
Savings($)	34,068	39,179.7	41,866	54,731
Time(sec))	4834	1452	986	5982

To illustrate that the given operation strategy is successful in tracing the forecasted demand and reducing the interaction of DISCOM with RTM, the demand gap is shown with and without BESS in Fig 3 for a period of 1 week, in the regulating market. To illustrate that this method results in significant loss

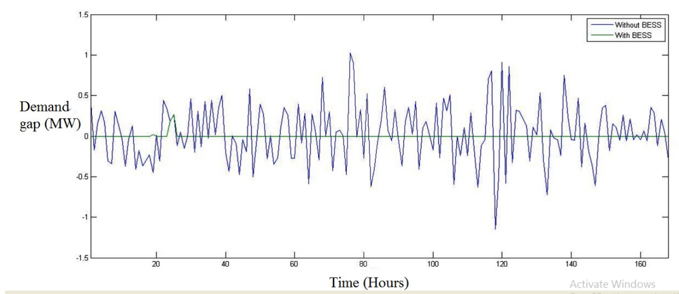

Figure 3. Demand gap graph with BESS and without BESS

reduction, power losses for a period of 1 week is shown in Fig 4.

It is clear that demand gap is zero for most of the time

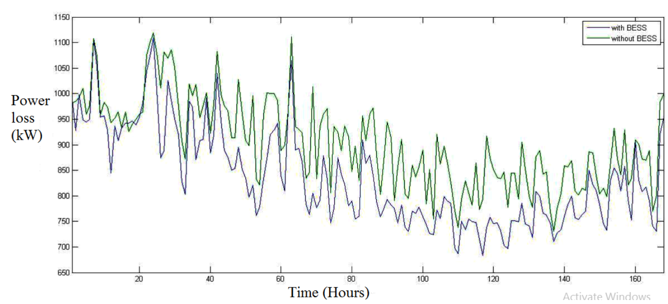

Figure 4. Losses comparison with and without BESS

under the considered period, with BESS. And the use of BESS also improved the voltage profile of the system. The minimum voltage without using BESS is 0.9529 p.u., whereas that with using BESS is 1.0225 p.u. To illustrate the advantage of this method over other methods in literature, let us place BESS at the DG locations i.e. 6, 9, 11. Now the total capacity of BESS required is obtained as 2.86 MWh, which is obtained as 0.72 MWh with this method in LMP mechanism, which is less than 30% of the rated renewable energy.

VII. Conclusion

In this work, an optimal BESS operation strategy is presented for the reduction of risk of DISCOMs with high renewable integration. Thus, an optimization problem is formed to optimally size and place the BESS. And the method is implemented on both regulating and LMP markets, with both lead acid and lithium ion BESS. From the studies, the operating strategy is robust and it can help the DISCOMs to reduce the risk of price volatility. Further, this method yielded savings for the DISCOMs with lead acid BESS in both the markets. With the development of technology, lithium ion BESS may become cost effective in future and may be used by the DISCOMs to make more savings, owing to its high energy density. Also, this method lead to reduced capacity requirement of BESS, reduced system losses and improved voltage profile. Four different optimization algorithms are used to optimally place and size the BESS. GA, PSO, Fuzzy PSO need some parameters to be optimized. On the contrary, TLBO is an algorithm specific parameter less algorithm and thus performed better than the other algorithms in terms of results, but the convergence rate is low which may lead to much better algorithms in future. Moreover, the lifetime of BESS is taken as a function of only depth of discharge and energy usage, independent of atmospheric conditions like temperature which can be included in future work.

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