Energy Delivery Networks

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***Abstract*—Energy storage technologies that are connected to medium- or low-voltage distribution systems are referred to as Distributed Energy Storage (DES). DES are becoming more common as the storage technologies are becoming cheaper. Energy stored on the distribution system, whether it is generated by Distributed Generation (DG) or central generation units, could provide crucial services (such as load leveling, automatic generation control, smoothing fluctuations in intermittent sources, etc) to electricity suppliers. The need of the hour is to effectively utilize these distributed storage devices so as to lower operating costs while offering aforementioned services.**

In contemporary literature, while DES have been considered, they could only be charged/discharged from/to the grid. The current work marks a significant departure with the goal of allowing storage devices to charge each other. Such battery-to-battery energy transfer is useful for instance in scenarios when generators cannot be run for certain reasons, or that it might cause too much load on the network, if the storage devices were to be charged directly from the power grid. Simulation results on a 30-bus IEEE benchmark system validate the benefits of inter-storage charge transfers.

I. Introduction

Energy storage technologies that are connected to medium- or low-voltage distribution systems are referred to as Distributed Energy Storage (DES). DES are becoming more common as the storage technologies are becoming cheaper. Energy stored on the distribution system, whether it is generated by Distributed Generation (DG) or central generation units, could provide crucial services (such as load leveling, automatic generation control, smoothing fluctuations in intermittent sources, etc) to electricity suppliers. If used effectively, the DES could lead to substantial reduction in electricity distribution costs by enabling critical services such as load leveling, load following and bulk energy management [1].

We identify an important unexplored opportunity for effective use of DES: *Energy Delivery Networks (EDNs) that allow storage devices to charge each other*. This is in sharp contrast to the existing approach of allowing charge transfers only between the grid and the storage devices. Given that the storage devices may be located at different positions of the network, our work also involves taking into account the right point of time to schedule charging transfers between various storage devices of the network taking into consideration the current load on the network.

The concept of battery-to-battery charge transfer is inspired by content delivery networks (CDN). CDN is a large distributed system of servers deployed in multiple data centers across the Internet [2]. The goal of a CDN is to serve content to end-users with high availability and high performance. CDNs also offload the traffic served directly from the content provider's origin infrastructure, resulting in cost savings for the content provider. Battery networks, like CDNs, can alleviate congestion in power networks and the load on generators during the peak hours. However, there are a few fundamental differences between the two types of delivery networks: first, unlike content, stored charge can't reused; second, while there is no loss associated with writing and reading content, storing and retrieving energy suffers from significant conversion and storage losses; third, while lifetime of CDN servers usually are not impacted by read and write operations, the batteries have a limited number of charge/discharge cycles and moreover, the number of charge discharge cycles reduces with the depth of discharge; fourth, the rate of reading and writing content has no impact on the amount of data recalled. On the other hand, available charge capacity in a battery is a function of charging and discharging rates as explained by Peukert's law.

One natural question that arises is: if that batteries are allowed to charge each other, would it cost-effective given the limited number of charge/discharge cycles of batteries? This work initiates a study in this direction and finds that there is a cost advantage in allowing batteries to charge each other.

Another issue that may be raised is that batteries supply DC power, while the grid supplies AC power. Thus, a typical power transfer between (say) the grid to the battery would involve a *single* conversion from AC to DC. However, a battery to battery transfer over the transmission network would involve *two* conversions: one from DC to AC (so that the power can be transmitted over the network) and then from AC to DC. Our framework incorporates these factors as extra penalties and despite such costs, our results indicate that battery to battery transfers are favorable.

A. Organization

We present the related work in Section I.A, and our main contributions in Section I.B. We proceed to elucidate our main idea by a toy example in Section II. In Section III, we formulate the main problem as a mathematical program and outline the various constraints. In Section IV, we present the battery model that we work with in order to translate the charging and discharging amounts into number of charging/discharging cycles. In Section V, we discuss the solution approach. Finally in Section VI, we elaborate on the simulation results, and discuss the comparative advantage of our approach. We conclude with some general comments in Section VII.

B. Related Work

The prominent progress and cost reduction of electronic power technology have made *battery energy storage* (hereafter, BES) one of the most promising devices. In the past decade, several centralized battery energy storage systems were installed worldwide for peak energy cost shaving, load smoothing, etc. However, in recent years, grid-scale distributed energy storage devices are becoming more popular mainly to handle intermittent renewable sources. Recently, Lux research predicted that annual global demand for grid-scale energy storage will reach an astounding 185.4 gigawatt-hours (GWh) by 2017 and there is a \$113.5 billion incremental revenue opportunity for an industry that currently generates sales of \$50 to \$60 billion a year.

The modeling, optimal location, capacity determination and economic benefits of BES have been studied extensively in literature. For example, Jung et al. [3] presented a method for determining installation sites of BES for load leveling. Lo et al. [4] proposed multi-pass dynamic programming (MPDP) algorithm for finding optimal BES power and energy capacities in a power system. Bingying et al. [5] proposed an optimization model to determine the sizing capacity of flow battery that can be charged/discharged very quickly. Xie et al. [6] proposed a multi-time-scale model of energy storage for analyzing the impact of energy storage on power system operations such as primary control, secondary frequency regulation, and economic dispatch. Daneshi et al. [7] studied the impact of BES on peak load reduction, system operating cost, transmission congestion, commitment and dispatch of the units in power system for different level of wind penetration. Walker et al. [8] evaluated the effect of BES on power system dispatch and showed batteries can be used for peak shaving and frequency regulation for a limited time period. Kottick et al. [9] studied the impact of a 30MW BES on frequency regulation in the Israeli power system. In this paper, authors also showed that large BES facilities can provide significant damping when a part of system got isolated during disturbances. Lee et al. [10] studied the effect of BES on industrial customers and proposed the optimal operation schedule of a BES for "time-of-use" rates of industrial customers. Reckrodt et al. [11] proposed an economic model for BES where the economic factors and their relationships are traceable through the so-called *influence* diagram. Denholm et al. [12] analyzed the role of energy storage in the electricity grid, focusing on the effects of large-scale deployment of variable renewable sources primarily wind and solar energy. Xiaoping et al. [13] proposed a dynamic economic dispatch method for micro-grids including battery energy storage. In this paper, authors explained how grid to battery (B-G) or battery to grid (B-G) energy transfer can reduce the operation costs of a micro-grid. Sortomme et al. [14] proposed an optimal dispatch scheme for micro-grids which can reduce costs by selling stored energy at high prices and shave peak loads of the larger system. A technical report from Sandia Labs [15] addressed the storage opportunity drivers, challenges, and notable developments affecting storage.

C. Our Contribution

In this work, we consider two aspects of distributed storage devices.

In contemporary literature, while storage devices have been considered, the devices can only be charged/discharged from the grid. Our *main* result marks a significant departure with a goal of enhanced optimization by *allowing storage devices to charge other*. This is useful for instance in scenarios when generators cannot be run for certain reasons, or that it might cause too much load on the network, if the storage devices were to be charged directly from the power grid.

II. Basic Idea

In current technology, the transfer of power happens between battery to the grid or the grid to the battery. In contrast, we are optimizing the total cost of operations including that of external storage, where *battery to battery charging is allowed*. We will be able to generate improved schedules for charging the various batteries, so that real-time demand may be fulfilled. We will illustrate this idea with a simple toy example.

Let us consider a power system with 2 nodes, N_1 and N_2. There is one transmission line connecting the two nodes. The line voltage will be assumed to be 66 KV. There are also 2 generators G_1 and G_2 (of capacities 10 MW and 6 MW, respectively) connected to the node N_1 and N_2, respectively. A single load is connected to the node N_2. There are two batteries B_1 and B_2 of capacities 4 MWh each, such that B_1 is connected to node N_1 and B_2 is connected to node N_2. See Figure 1.

Two scenarios are presented in the following. For both of the scenarios we assume that the B1 is fully charged (4MWh), whereas B2 is fully empty (0MWh).

In the first scenario only power transfers between battery and grid are allowed: thus, a battery to grid transfer is labelled as B-G while a grid to battery power transfer is labeled as G-B. In the second scenario, power transfers are not restricted to just the above, transfers between battery to battery (labelled B-B) are also allowed in this scenario.

In practice, generators typically have a reasonably high *ramp-up* time. This is the time it takes for a generator to be started up and be fully operational. For purposes of this example, we assume that the generator G_1 has a *low* ramp-up time, while the generator G_2 has a *high* ramp-up time. We effectively assume that during the off-peak period, only the generator G_1 may be running (perhaps because G_1 was already running, having been started at some earlier time), while during the peak period, both the generators are running.

A. Scenario without B-B power transfer

In power grid load varies a lot throughout the day and peak load can be 50% higher than the base load. Let say, for any system, base load is 15MW, off-peak load is 10MW and peak load is 20MW. During the off-peak period, since the generator G_1 is already running, it can supply the load of 10 MW. In this case network loss can be calculated as follows:

$$\text{Loss} \quad = \quad i^2 \cdot R = \left[\frac{P}{V}\right]^2 .R = \left[\frac{10MW}{66KV}\right]^2 .10\Omega = 0.2295\ MW$$

During peak, the load is supplied by *both* the generators G_1 (10MW) and G_2 (6MW) and battery $B2$ (4MW) providing a total supply of 20 MW, as shown in Figure 1. In this case, the total flow on the line becomes 20 MW. The transmission losses (i.e. the i^2R losses) during this period will be $\text{Loss} =$

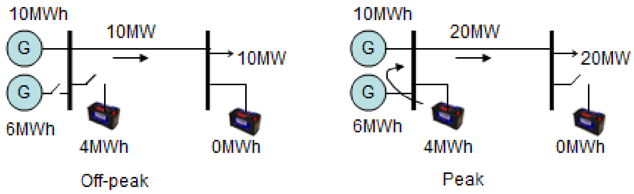

Fig. 1: Scenario without B-B energy transfer

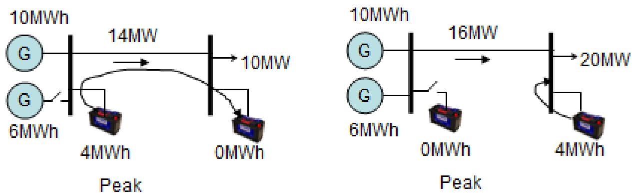

Fig. 2: Scenario with B-B energy transfer

0.9182 MW. Thus, for one hour peak period and one hour off-peak period, the *cumulative energy loss* (network+battery loss(10%)) can be calculated as:

$$\text{Cumulative Loss} = 1{*}(0.2295{+}0.9182){+}0.04{*}.1 = 1.1517 \text{ MWh} \tag{1}$$

B. With B-B transfer

In this scenario we will see how the transmission loss varies when B-B charge transfer is considered. As shown in Figure 2, during off-peak period 4 MWh energy stored in the battery at N_1 is transferred to the battery B_2 at N_2. Therefore, power flow through the network will be 14 MW (10 MW from generator and 4 MW from battery). The $i^2{\cdot}R$ loss can be computed as $\text{Loss} = 0.4499$ MW. During peak period, 20 MW load was supplied from both the generators (10MW from G1 and 6 MW from G2) and from the battery B_2 at node N_2. In this case flow on the line will be only 16 MW. Network loss in this scenario is $i^2{\cdot}R = \left[\frac{16MW}{66KV}\right]^2.10\Omega = 0.5877$ MW.

Thus, the cumulative energy loss is calculated to be $1 * (0.4499 + 1 + 0.5877) + 0.1(.04 + .04) = 1.0456$ MWh. It is instructive to see that, even though battery loss becomes double, B-B charge transfer has caused the total loss to reduce significantly, from 1.1517 MWh to 1.0456 MWh. This example clearly shows the potential of B-B charge transfer in smart grid.

III. Problem Statement

Given the above discussions, we define the main problem considered in this paper. We call this the Short-term Energy Management with distributed energy Storage problem (shortened as the SEMS problem).

The input to this problem consists of a number of generators (NG), and a number of batteries (nb). Each generator has various attributes. In this work, we will use the letter i to index generators or batteries. Thus a generator i has a generation cost curve. This cost curve is parametrized by the amount of power supplied s; it is the cost of generation of s units of power by the generator. In this work, we consider the generator cost curves to obey a *quadratic* law - this is in fact in accordance with real life scenarios. A generator also has a *running cost*, and *start-up* and *shut-down* costs: these are called *operation costs* of the generator.

Similarly, a battery has various attributes. A battery i has a *capacity* BCAP_i, as also *charging* and *discharging* costs; these costs are functions of the amounts charged or discharged.

The overall objective of the SEMS problem is to minimize the total cost of operation of the generators, along with attempting to minimize the total charging and discharging costs of the batteries, *while allowing charge transfers between batteries*. For an apt comparison, we also consider the scenario where B-B transfers are disallowed (the results are at the end of this section). Formally, the objective function to be *minimized* is as follows:

$$\sum_{t=1}^{T}\left[\sum_{i=1}^{NG}(F_i(P_{i,t}) + S_i(u_{i,t}) + H_i(u_{i,t})) + \sum_{i=1}^{nb}(F(C_{i,t}) + F(D_{i,t}))\right] \tag{2}$$

For conciseness, the notation utilized above is defined in the glossary below. The generator cost functions considered in this paper are assumed to be quadratic functions of the generator output: $F_i(P_{i,t}) = (a_i + b_i P_{i,t} + c_i P_{i,t}^2)$.

Glossary:

$F_i(.)$	generation cost function for generator i;
NG	number of generators;
nb	number of batteries;
$P_{i,t}$	power generated by i^{th} generator at time t;
a_i, b_i, c_i	cost coefficients of generator i ;
$u_{i,t}$	unit on/off status at time period t;
$S_i(\cdot), H_i(\cdot)$	are start-up cost and shut-down cost, respectively for generator i;
$C_{i,t}, D_{i,t}$	are charging and discharging costs, respectively for battery i at time period t.

Constraints: The SEMS problem is to optimize the above objective subject to certain natural constraints. Altogether there are 7 types of constraints present in the optimization framework: (1) Supply Demand Balance, (2) Generator Capacity Constraints, (3) Ramp Rates, (4) Start Up and Shut Down constraints, (5) Minimum Up and Down time, (6) Battery Charging/Discharging and (7) Network Constraints.

Constraints (1) and (7) concern the overall electrical network. Constraints (2), (3), (4) and (5) arise from considerations involving the generators in the network, while constraint (6) concerns the storage devices in the network. Owing to space constraints we will describe only the constraints that are novel in this paper. Thus, we will bypass the description of usual constraints like Supply Demand Balance, etc and proceed to describe the battery charging/discharging constraints.

Battery Charging/Discharging Constraints: There is a cost associated with charging or discharging a battery/storage device. A battery i has a certain lifetime that depends on how often it is charged and discharged, and also depending on the *state of charge* (SOC) state at different time points. The SOC of a battery i is thus parametrized by the index i and the timeslot t. The SOC constraints are as follows:

$$\text{SOC}_{i,t} = \text{SOC}_{i,t-1} + K_c{\cdot}C_{i,t}{\cdot}\Delta - K_d{\cdot}D_{i,t}{\cdot}\Delta \tag{3}$$

$$0 \leqslant \text{SOC}_{i,t} \leqslant \text{BCAP}_i \tag{4}$$

Here $\mathrm{SOC}_{i,t}$ is the state of charge of battery i at timeslot t and Δ is the time period in a fraction of an hour. Recall that BCAP_i denotes the *battery capacity* of battery i. Constraining the number of charging or discharging cycles is a highly non-linear constraint. We tried to work around this issue by designing proxies by relaxing this constraint, but some of the approaches led to acute non-convexity in the underlying mathematical program. Finally we incorporated a linear proxy for the charging/discharging cycles, and this corresponded to how the cycles are dealt with in practice.

IV. Battery model

Currently, many energy storage elements are available with different technologies, capabilities and applications. These storage elements include pumped-hydro storage, compressed air energy storage, regenerative fuel cells, battery energy storage (BES), superconducting magnetic energy storage, flywheels, super capacitors, thermal energy storage systems, and hydrogen energy storage. Being most promising, this paper concentrated on BES. However, any other storage could be used without loosing generality.

A BES has a certain lifetime that depends on how often it is charged and discharged, and also depending on the *state of charge* state at different time points. There are several standard method of estimating battery life based on it's usage. In this paper, battery life is estimated using the crack propagation model proposed in [16]. This choice of model results in a cycle life prediction of the battery with a few parameters. For completeness of the paper the model is discussed in brief as follows.

As batteries can be charged or discharged multiple times within a certain time interval, the effective number of throughput cycles N in that time interval can be calculated as follows:

$$N = \frac{\int_{time\ m} |I(t)|dt}{Q_{nom}/2} \tag{5}$$

where, $I(t)$ is the (absolute) value of battery current at time t, Q_{nom} is the *nominal* charge capacity of the battery. The factor of 2 arises because both charge and discharge currents are taken into account.

The damage over the life of the battery (L) for M time intervals is given by:

$$L = \sum_{m=1}^{M} life(m) = \sum_{m=1} fn.(soc_{avg}, soc_{dev}, T) \tag{6}$$

The variable L is a function of average state of charge soc_{avg}, standard deviation soc_{dev}, and battery temperature T as discussed in [16]. This variable L will change over the life of the battery from 0 (new) to 1 (no capacity left).

V. Problem solving

There are various potential approaches to the SEMS problem. Thus, for instance, one can use *heuristic approaches* such as Genetic Algorithms (GA) or Particle Swarm Optimization (PSO). However, our solution methodology is principally guided by three factors: (a) **Scalability**: The solution needs to be scalable to larger networks, (b) **Guarantee**:The solution needs to have a performance guarantee, in other words, guarantees that the solution obtained is close to being *optimal*, and (c) **Extendability**: Given the dynamic nature of networks and types of constraints, the solution framework should be easily extendable; i.e. it should be relatively easy to incorporate other classes of constraints into the solution framework.

Heuristic approaches like the ones listed above usually have the feature that they provide fast solutions; however they are not easily extendable, nor do they provide performance guarantees. This motivates us to use the framework of mathematical programming as our solution method. We use the OPL/CPLEX framework to solve our mathematical program, with OPL being the modeling language, and CPLEX being the solver. The principal point that enables us to utilize CPLEX successfully for our problem is that the various *costs* are *convex* (since, quadratic functions with positive coefficients for the squared terms are convex). Thus the generator costs as well as the network losses on a resistive element are convex quantities. These observations enable us to formulate the SEMS problem as a *mixed integer convex* program. In our work, we use CPLEX v12.3 with OPL as the modeling language.

VI. Simulation Results

In the following, we present our results on a benchmark, the IEEE 30-bus system [17]. IEEE benchmark 30-bus system consists of 30 substations, 6 generating units, 21 loads, 37 transmission lines, and 4 transformers. System parameters (such as topology, resistance, reactance of each link, etc.) of this system is available in [17]. Generator parameters such as bid curves, minimum and maximum generation limits, minimum up and down time, ramp up and ramp down rates, start up and shut down costs used in this simulation are presented in Table I. A typical daily load profile, as shown in Figure 3, is used in this simulation.

In order to evaluate the system performance with network of batteries, three lithium-ion batteries (of 5MWh each) were placed at bus 15, bus 19, and bus 24, respectively. Maximum charging and discharging current limits of each battery were assumed as C/2 and C/5, respectively. Batteries were assumed to operate for 30000 cycles for an average depth of discharge (DoD) of 30%[18]. Impact of these storages were evaluated from the perspective of day-ahead unit commitment, economic dispatch, and network loss minimization. Each of these aspects are discussed below.

We consider and compare three scenarios: (i) when batteries are not present, (ii) when batteries are present, but the only charge transfers allowed are between battery and grid, (iii) when batteries are present, and charge transfers are allowed between battery and grid, *and* between batteries.

A. Unit Commitment

The Unit Commitment (UC) problem plays a central role in planning and operational decisions in a smart grid. UC is a regular activity of independent system operators (ISOs), regional transmission organizations, and utility companies. The day-ahead market utilizes the unit commitment to identify a unit commitment schedule. UC is the problem of finding an optimal up and down schedule for a set of generators over a planning horizon so that total cost of generation and transmission is minimized, and a set of constraints, such as demand requirement, upper and lower limits of generation, minimum up/down time limits, ramp up/down constraints, transmission constraints, and so forth, are observed.

For all the three scenarios, optimal unit commitment schedules of all the generators were computed. To compensate the variable load, largest generators 1 (G1) and 2 (G2) were started and stopped while other generators were remained ON all the time. Unit commitment schedules for G1 and G2 are shown in Table II. Table II shows that, for scenario 1, $G1$ was shut down at time slot 3 and was restarted again at time slot 7, whereas, generator 2, was shut down at time slots 5 and 21 and was restarted again at time slots 7 and 23. In this case, generators were shut down for three times and also were started for three times. Therefore, total start up and shut down cost became $3*100+3*1000 = \$3300$. Similarly, for scenario 2, generators were shut down for 3 times and were started for two times. Hence, total start up and shut down cost became $2300. In this case, BES has helped to minimize one start up cost. Again in scenario 3, BES has further minimized one start up and one shut down cost hence start up and shut down cost got reduced to $1200. This shows that BES with B-B charge transfer could significantly improve the unit commitment schedules by minimizing start up and shut down cost of generators.

B. Economic dispatch

We also did economic dispatch for the scenarios mentioned above and dispatch costs related to each of these scenarios are presented in Figure 4. For the first scenario, dispatch cost is $86811/day, whereas, in the second scenario, it reduces to $85400/day and in third scenario, cost further reduces to $84659/day. For scenario 2, cost got reduced compared to scenario 1 because batteries were charged from available cheaper generators during off-peak period and discharged the energy during peak period which helps in purchasing power from costly generators. In scenario 3, cost got further reduced because inter-battery charge transfer within the battery network has reduced the network power loss and start-up shut-down cost of generators. In this case, charging and discharging patterns of all the batteries are presented in Figure 5. Figure 5 shows that in most of the time, batteries accumulation charges when cheaper sources are available and discharge the stored energy during peak period. It is also that in several instances, charge transfer happened within the network of batteries. For example, within battery 15 and 19 charge transfer happened in between 1-2, 6-7, 11-12 and 17-18 hours. Similarly, between batteries 15 and 24 charge transfer happened in between 5-6 and 7-8 hours. Between batteries 19 and 24 charge transfer happened only during 21-22 hour. In this scenario, effective loss of battery life cycles were estimated as 2.9 ($L = 3.26 \times 10^{-6}$) , 2.8 ($L = 3.13 \times 10^{-6}$), and 2.6 ($L = 3.05 \times 10^{-6}$) for battery 15, 19 and 24, respectively. This costs $691.39 corresponds to the cumulative loss of battery life. In spite of such loss, effective cost of dispatch got reduced by $2450. This leads to annual saving of $365 * 2450 = \$894,250$ for the chosen test system. This shows the potential of battery network in power grids.

C. Network Loss Minimization

Figure 6 compares the network loss with and without battery storage for the given system. It shows that network loss got significantly reduced specifically during 4-8 hours, 11-13 hours, and 17-21 hours. Cumulative power loss has reduced from 74MWh to 70 MWh which is almost 5% of the total loss. This means batteries could save 4000 units (KWh) of energy in every day. This is equivalent to saving of $4000unit * 0.1(\$/unit) * 365 = \$146,000$ *per year* for this small system. Profit is expected to increase with the increase in system size or battery network size. This shows the potential of deploying large scale energy storage network in smart grids.

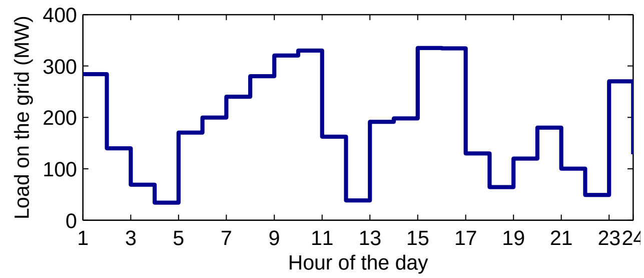

Fig. 3: Daily load profile of IEEE 30-bus system

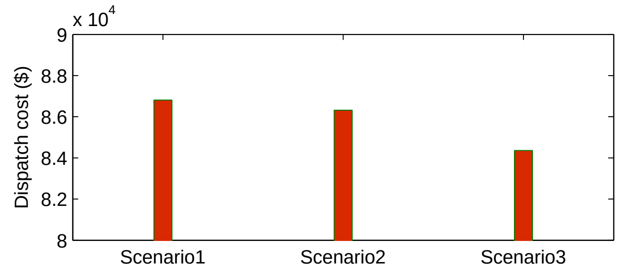

Fig. 4: Cost Comparison in the 3 scenarios

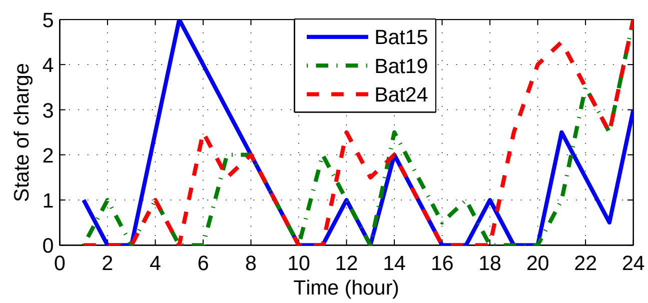

Fig. 5: State of charge of battteries

VII. Conclusions

This work evaluates the impact of distributed energy storage in smart grid in the context of unit commitment, economic dispatch, loss minimization, etc. This work marks a significant departure with a goal of enhanced optimization by allowing storage devices to charge other. The scheme is validated by

TABLE I: Generator parameters

Unit	Bus	a	b	c	P^g_{min}	P^g_{max}	Min up time	Min down time	R_i^{up}	R_i^{down}	S	H
		$	$/MWh	$\$/MWh^2$	MW	MW	h	h	MW	MW	$	$
G1	1	0	15.00	0.0200	15	80	2	2	25	25	1000	100
G2	2	0	14.75	0.0175	15	80	2	2	25	25	1000	100
G3	13	0	16.00	0.0250	10	50	3	3	15	15	1000	100
G4	22	0	14.00	0.0625	10	50	4	4	15	15	1000	100
G5	23	0	16.00	0.0250	5	30	3	3	10	10	1000	100
G6	27	0	15.25	0.0083	10	55	4	4	15	15	1000	100

TABLE II: Unit commitment schedules for IEEE 30 bus system

Scenario	Gen	Time Period																							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	G1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	G1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	G1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
1	G2	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1
2	G2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0
3	G2	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

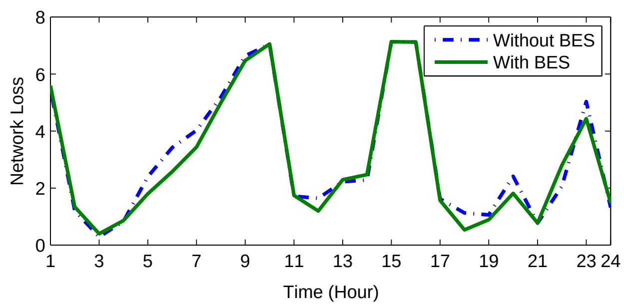

Fig. 6: Network loss for IEEE 30 bus system

simulation results. Simulation results have shown that the distributed energy storage system can store, deliver and properly distribute power among energy storage devices following the optimization of long-term requirements. Overall, our results thereby indicate that usage of energy storage systems can result in cost savings for both the utility companies and the end customers.

REFERENCES

[1] W. Jewell, P. Gomatom, L. Bam, and R. Kharel, "Evaluation of distributed electric energy storage and generation," 2004.

[2] E. Nygren, R. K. Sitaraman, and J. Sun, "The akamai network: a platform for high-performance internet applications," *SIGOPS Oper. Syst. Rev.*, vol. 44, no. 3, pp. 2–19, Aug. 2010.

[3] K. H. Jung, H. Kim, and D. Rho, "Determination of the installation site and optimal capacity of the battery energy storage systems for load leveling," in *IEEEPES Summer Meeting*, 1995, pp. 23–27.

[4] C. H. Lo and M. D. Anderson, "Economic dispatch and optimal sizing of battery energy storage systems in utility load-leveling operations," *IEEE Transactions on Energy Conversion*, vol. 14, no. 3, pp. 824–829, 1999.

[5] W. Bingying, Z. Buhan, M. Biao, and Z. Jiajun, "Optimal capacity of flow battery and economic dispatch used in peak load shifting," in *4th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT)*, 2011, pp. 1395–1400.

[6] L. Xie, A. A. Thatte, and Y. Gu, "Multi-time-scale modeling and analysis of energy storage in power system operations," in *IEEE EnergyTech*, 2011.

[7] H. Daneshi and A. K. Srivastava, "Impact of battery energy storage on power system with high wind penetration," in *IEEE PES Transmission and Distribution Conference and Exposition*, 2012, pp. 1–8.

[8] L. N. Walker and H. L. Graham, "Effects of battery storage devices on power system dispatch," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-100, no. 1, pp. 375–383, 1981.

[9] D. Kottick, M. Blau, and D. Edelstein, "Battery energy storage for frequency regulation in an island power system," *IEEE Transactions on Energy Conversion*, vol. 8, no. 3, pp. 455 – 459, 1993.

[10] T. Y. Lee and N. Chen, "Effect of the battery energy storage system on the time-of-use rates industrial customers," *IEE Proc. Gener. Transm. Distrib.*, vol. 141, no. 5, pp. 521–528, 1994.

[11] R. C. Reckrodt, M. D. Anderson, and R. M. Kluczny, "Economic models for battery energy storage: Improvements for existing methods," *IEEE Transactions on Energy Conversion*, vol. 5, no. 4, pp. 659–665, 1990.

[12] P. Denholm, E. Ela, B. Kirby, and M. Milligan, "The role of energy storage with renewable electricity generation," National Renewable Energy Laboratory, Tech. Rep. NREL/TP-6A2-47187, Jan 2010.

[13] L. Xiaoping, D. Ming, H. Jianghong, H. Pingping, and P. Yali, "Dynamic economic dispatch for microgrids including battery energy storage," in *2nd IEEE International Symposium on Power Electronics for Distributed Generation Systems*, 2010, pp. 914–917.

[14] E. Sortomme and M. A. El-Sharkawi, "Optimal power flow for a system of microgrids with controllable loads and battery storage," in *IEEE PES Power Systems Conference and Exposition*, 2009, pp. 1–5.

[15] J. Eyer and G. Corey, "Energy storage for the electricity grid: Benefits and market potential assessment guide," Sandia National Laboratories, Tech. Rep., 2010.

[16] A. Millner, "Modeling lithium ion battery degradation in electric vehicles," in *IEEE Conference on Innovative Technologies for an Efficient and Reliable Electricity Supply (CITRES)*, Sept 2010, pp. 349–356.

[17] http://www.ee.washington.edu/research/pstca/.

[18] http://exergonix.com/documents/CS1000-DESS.pdf.