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An Optimal Scheduling and Dispatch of Energy Storage System under Demand with Time Based Pricing

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Abstract - **An ESS acts as a buffer between a generator and its load. Renewable energy sources often generate power during off-peak periods or when demand for energy is low. ESSs enable better integration of renewable energy sources into an electrical grid by (time-shifting) the generated power and smoothing out spikes in demand. Therefore an optimal operation methods for battery storage systems to minimize the operation cost or maximize the profit of an electricity user is highly required. An optimal operation technology that can maximize the benefit from using multiple batteries storage is proposed.**

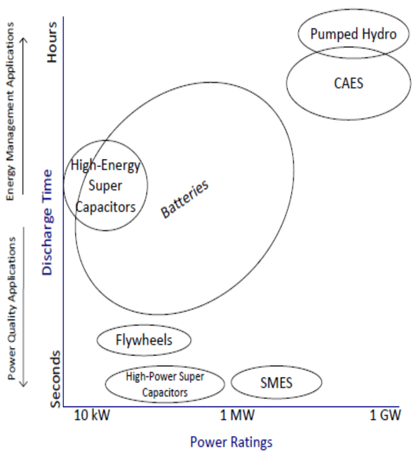
The two levels of operation framework are optimal scheduling and real-time dispatch. The optimal scheduling employs a model predictive control technique to take into account uncertainty in estimation of the SOC of each battery system. The scheduler generates a sequence of the battery schedule sets and states over the control horizon that minimizes electricity charge while satisfying operation constraints for stable battery use and peak regulation.

The real-time controller determines real-time operation mode that is either normal mode or peak-cut mode and dispatches the final set points. The time step of the real-time control is designed short enough to effectively handle the inter-scheduling uncertainty. The real time controller receives the scheduled outputs, and then calculates a hourly set of final commands that ensure to satisfy the operation constraints on real-time level.

INTRODUCTION

Traditional power grids were designed to supply energy produced by a few central generators connected to the high voltage (HV) network. Nowadays, this scenario is changing because of the remarkable growth of medium- to small-sized renewable energy source (RES) plants, such as hydroelectric, solar and wind, distributed on medium and low voltage (MV and LV) grids the contribution of RESs to the world's electricity generation in 2010 was about 19% of total global electricity consumption, a considerable increase with respect to previous years. In the European Union, for example, a total of about 58.8 GW of new power capacity was constructed in 2010, and the renewable share of new power installations was 40%. The widespread diffusion of RESs is motivated by the substantial socio-economic benefits obtainable with these sources: reduction of greenhouse gas emissions and air pollution, diversification of energy supply, diminished dependence on imported fuels, economic development and jobs in manufacturing, installation and management of RESs plants . Despite these obvious benefits to the environment, industry and consumers themselves, there are some barriers that can limit renewable sources' penetration. In fact, renewable generation is variable, uncertain and is just partially dispatch able. For this reason, the energy dispatching is much more challenging than in the past, and new instruments are required to ensure the real-time balancing between demand and supply. In addition to RESs penetration, traditional power grids face also other challenges that limit theirefficiency among which are the non-optimal dimensioning and usage of grid resources. In fact, in order to match customers' demand of electric energy, installed generation, transmission and distribution capacities must be able to meet the peak of demand. Moreover, sufficient additional capacity must be available to deal with the uncertainty in generation and consumption. As a consequence, grids resources are underutilized for most of the time. Smart grids (SGs) are the new generation of power grids, which have been introduced to address the main issues of traditional grids. Specifically, SGs can make grids more efficient and smarter by means of facilitating the deployment of renewable energy sources, decreasing oil consumption by reducing the need for inefficient generation during peak usage periods, optimizing resources utilization and construction of back-up (peak load) power plants and enabling the integration of plug-in electric vehicles (PEVs) and energy storage systems (ESSs). In order to properly design these new generation grids, a reference model has been defined, which consists of seven functional blocks, which are, namely, bulk generation, transmission, distribution, operation, market, service provider and customers. The bulk generation domain generates energy by using resources like oil, coal, nuclear fission and RESs and stores electricity to manage the variability of renewable resources. The energy produced is dispatched through the transmission and distribution sectors, which are controlled by the operation domain. The balance between supply and the demand is guaranteed by the market domain, which consists of suppliers of bulk electricity, retailers who supply electricity to users and traders who buy electricity from suppliers and sell it to retailers and aggregators of distributed small-scale power plants. The service provider manages services for utilities companies and end-users, like billing and consumers' account management. Finally, customers consume energy, but can also generate and store electricity locally. This domain includes residential, commercial and industrial customers, who can actively contribute to the efficiency of the grid.

2.1Battery Energy Storage system



Energy storage technologies for different applications

Energy storage systems provide a viable option in mitigating these problems. They help in meeting the load mismatch and facilitating integration of RES via storing the extra energy from RES when demand is low and discharging the stored energy during peak load hours. Energy storage systems can be installed to serve the power system in many other applications as reported. In general, energy storage applications can be divided into two broad areas: energy management applications and power quality applications. Several energy storage technologies are available for use; however, some technologies may excel over others in some applications because of the different inherent characteristics. Amongst the various energy storage technologies, Battery Energy Storage Systems (BESS) have received significant attention over the last decade because of their role in improvement in system operational aspects and reduction in cost. BESS are also suitable for microgids because of their capability to be used for both energy management and power quality improvement applications. This is because of their fast response, options for different energy to power ratios, and compactsize and mobility. The Therefore, appropriate BESS technology, the optimal size, and the optimal operation strategy including charging/discharging cycles need to be chosen carefully, so as to result in the maximum benefit to the microgrid. To increase the benefit from BESS, more than one application can be synthesized at the same time; however, optimal sizing of such systems is a challenging problem. In general, the larger the installed size of BESS, the greater is the improvement in microgrid operations, in addition to a reduction in thermal generation costs. However, high installation cost (which includes the equipment cost and some associated fixed costs) is the main barrier to the wider deployment of BESS. Therefore, the proper size of BESS need be determined in an operational-planning framework based on cost-benefit analysis to maximize the total microgrid operational benefits at the least possible BESS installation cost. operational strategies of BESS differ from one application to another.

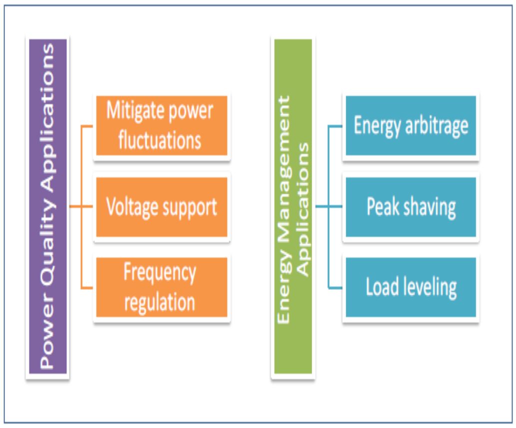
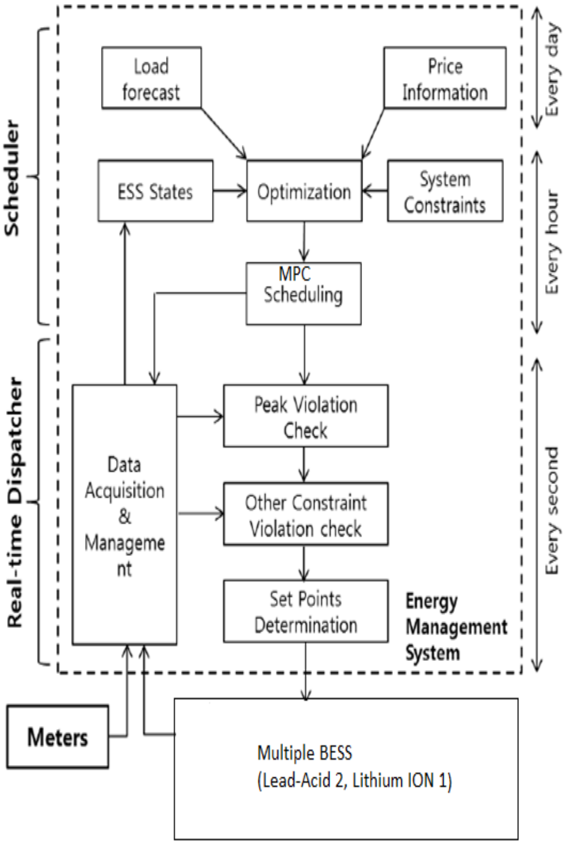


Figure 2.2: Energy storage applications with RES

2.2 Time Based Pricing

Dynamic pricing has been increasingly used by utilities as one of the means to reduce the discrepancy between power supply and demand. By providing economic incentives to consumers, utilities expect to shift power usage away from peak periods, thereby improving stability and lowering production costs in the long run. The success of dynamic pricing of course highly depends on the consumer's actual response to the time-varying prices. It is generally inconvenient and impractical for consumers to manually keep track of constantly changing prices and take action accordingly. To achieve the full economic benefit of dynamic pricing, it is imperative that power consuming devices be equipped with an automatic price-aware scheduling mechanism that requires minimal action from the consumers. The current work looks at the smart scheduling problem exclusively at the consumer's side, with the goal of maximizing individual economic advantage. This is sharply different from the scheduling problem in direct load control, which is performed by utilities. For example, with direct load control a utility may install smart switches that can turn off some of the users' appliances during a high-demand period. In such scenarios, the utility schedules the tasks requested by a number of consumers subject to a total load shedding constraint within a finite time horizon, On the contrary, in the decentralized scenario that we consider, the consumers do not give up the control of their appliances to the utility. Instead, the appliances are controlled by local agents, also referred to as schedulers that make individual decisions based on the current price and some partial information about future prices. Since the time-varying electricity price is largely determined by the constantly changing supply and demand, it is difficult to predict the exact future prices especially for long horizons. Thus the price information is causal and partially available when the scheduling takes place. For example utilities usually provide some estimated day-ahead prices as a guideline for the consumers. Different approaches to electric price prediction can be found. However, many random factors such as different consumers' reactions to real-time prices and the intermittency of renewable energy sources generally lead to prediction noise that should not be ignored. In fact, in the current work we point out that neglecting the prediction noise may lead to a significant economic loss to the consumers.

BLOCK DIAGRAM



SIMULATION OUTPUT

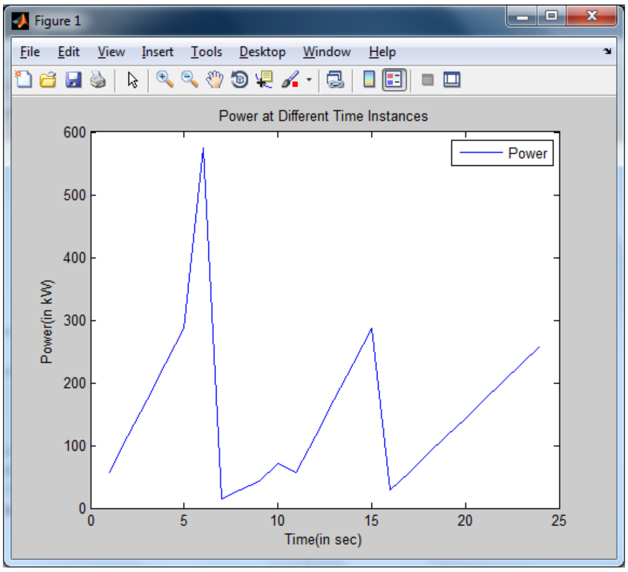


Fig1. Power dispatched at different time instances

The actual scheduled power through the Model Predictive control Algorithm at different time instances.

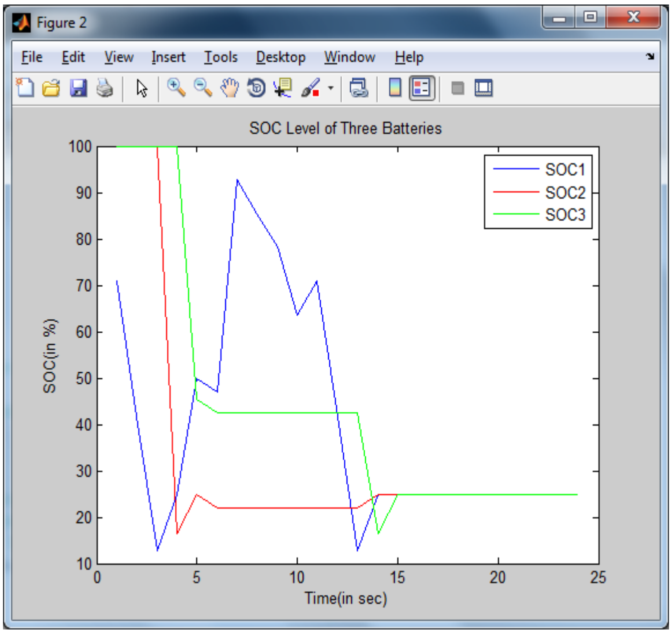


Fig2. SOC levels of three batteries at different time instances

This figure shows the SOC levels of two lead acid battery and lithium polymer battery at different time instances.

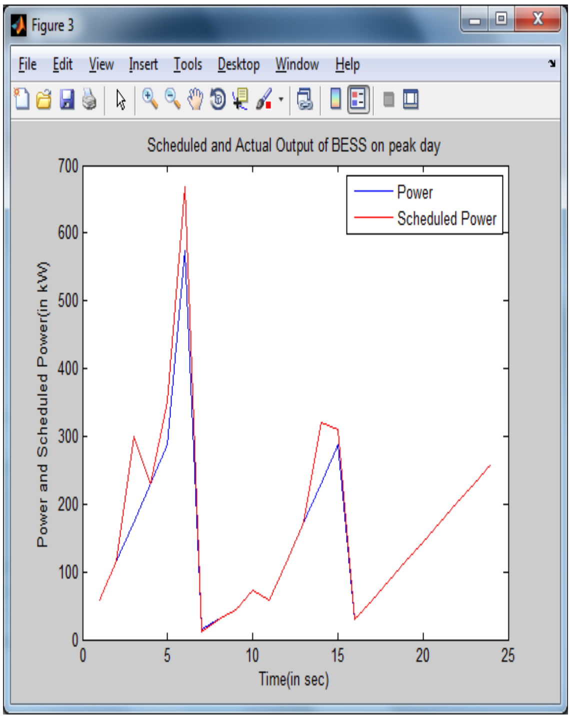


Fig3. Scheduled and Actual output of BESS on peak day

It shows the actual scheduled power and the managed power at real time dispatching at different time instances. The peak violation in the scheduled power is managed and regulated in the real time dispatching module to withstand the reliability of the battery

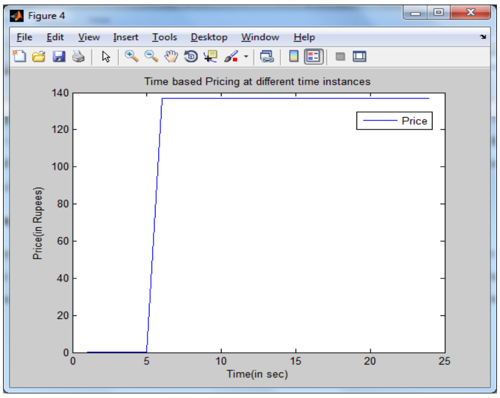


Fig4. Price Variation at Peak Cut Mode

It shows the abrupt increase in price at peak cut mode after five seconds duration

CONCLUSION

A novel framework for multi-functional BESS scheduling to minimize total operational cost of sustainable Battery System using Dynamic Pricing optimization. Multi-functioning of BESS includes Demand Response, peak shift and Time Of Use to get the most profit and guarantee the maximum peak constraint as well. Furthermore, from the trade-off between the operating cost and battery cost, the battery usage can be controlled by checking the SOC, and this results in prolonging battery lifetime by up to almost five times. Since this approach is general and thus applicable to other applications and load types as well, such as office buildings, large-scale residential complexes and factories, etc., where the electricity consumption pattern is periodic usually.

FUTURE WORK

- This work can be further extended by considering a battery model in terms of electrochemistry that focuses on temperature change in particular. Considering temperature can model more accurate battery wear-out since cell degradation is easily affected by temperature change.
- Back-up plans are necessary for emergencies such as temporary loss of communications from load meters or battery management systems. The scheduler can operate alone without communications, but higher accuracy in load forecast should be secured for reliable back-up operation.

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