DP-Based Optimization of BESS to Substitute RICE Reserves for Improved Economic Benefits

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***Abstract*— In regions with a significant proportion of renewable energy sources, reciprocating internal combustion engines (RICE or IC) are frequently employed as grid reserve solutions. This study suggests a scheduling technique for battery energy storage systems (BESS) that utilizes dynamic programming (DP) to replace IC units, adding versatility to the total reserve capacity and resulting in higher BESS earnings compared to traditional scheduling approaches. The capacity sweeping approach to optimize BESS's revenue sometimes leads to operation which is counter intuitive to conventional battery sizing approaches.**

***Keywords*— Load scheduling, dynamic programming, BESS, renewable energy sources, energy arbitrage.**

I. Introduction

As renewable energy resources (RES) become more prevalent, greater reserve capacity is required for the grid compared to traditional generators. Reciprocating internal combustion (RICE or IC) generation units are commonly utilized for reserve requirements due to their fast start-up time and ability to reach full output capacity quickly [1]. However, their higher heat rate results in increased hourly power production costs when compared to load-following combined cycle (CC) generation units. This cost can be mitigated by substituting IC units with battery energy storage systems (BESS). The increasing adoption of BESS can be attributed to their ability to offer a range of valuable services to the grid [2],[3]. Nevertheless, optimizing the scheduling of BESS is crucial for maximizing economic benefits. Often, the BESS are scheduled for energy arbitrage and peak shaving applications using RB algorithms [3]-[5] and realized by grid connected power electronics technology [6]-[8].

However, the load scheduling of a BESS inclusive grid system can be optimized using superior algorithms based on dynamic programming (DP) [9]-[12], artificial neural networks (ANN) [13] and etc., particularly since more accurate (machine learning derived) load forecasts and PV Power forecasts are recently accessible. For example, DP based algorithms have been used to optimally schedule the controllable loads in the grid such as air conditioner load [9]. They also have been used to manage BESS in grid level [10] and residential level [11],[12]. However, prioritizing BESS over expensive reserves for economic benefit is less explored, especially with the inclusion of accurate cost models for turning on and turning off smaller IC generators, as is commonly practiced by generating authorities.

In summary, this paper presents the following research contributions:

- Using DP algorithm, the BESS is scheduled to effectively substitute the expensive IC units and reduce its total power generation. This reduces the total carbon emission of the electric energy sector and supports the carbon tax policies.
- Here, the DP algorithm implemented using time of use (TOU) tariff values, which were created from the time varying contribution of different power generation units with different heat rate values of typical smaller IC generators. The realistic model that includes the heat rates of the ICs makes it easy to adapt the approach to any grid or residence level application.
- The results are demonstrated on scaled real utility load data and realistic (real world) production situations. It is demonstrated that the improved models and DP approach for the BESS is adding more flexibility to managing total reserve capacity with economic benefit.
- The revenue trend of the BESS capacity size increment as an utility reserve is explored. This offers BESS sizing insights from the economic point of view, particularly when the BESS has small capacity.

II. Problem Statement

The RICE or IC units are often used for backup and reserve applications. Their output capacities are significantly smaller than the CC load following generators. However, during high demand periods, on many days of the year, multiple low

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efficient IC units must be used along with the load following CC unit to meet load demand. However, this increases the hourly power production cost and has increased CO2 emissions. Further, to operate the small IC units at their maximum efficiency, they are often producing full power output. For instance, even if only a small demand increase needs to be met, the entire available IC unit is normally brought online at full power, and the excess power generation is reduced from the high efficiency CC units.

However, if properly modeled and scheduled, a BESS can sometimes avoid the need to turn on IC units that normally are operated when RB algorithms are implemented. In this paper, the grid system is created using the data of the City of Tallahassee Electric & Gas Utility (TAL) which is obtained from [14] which is listed in Table Ⅰ. and the appropriately scaled annual demand data from TAL for their respective grid system. Fig. 1 shows the load scheduling and the hourly power production cost of the created grid system for a 24-hour period.

In the load scheduling shown in Fig. 1 before 11^{th} hour the load is matched by the highly efficient CC generation units; after 11^{th} hour the increase in the load requires the low efficient IC generation units to be online. This increases the hourly power generation cost.

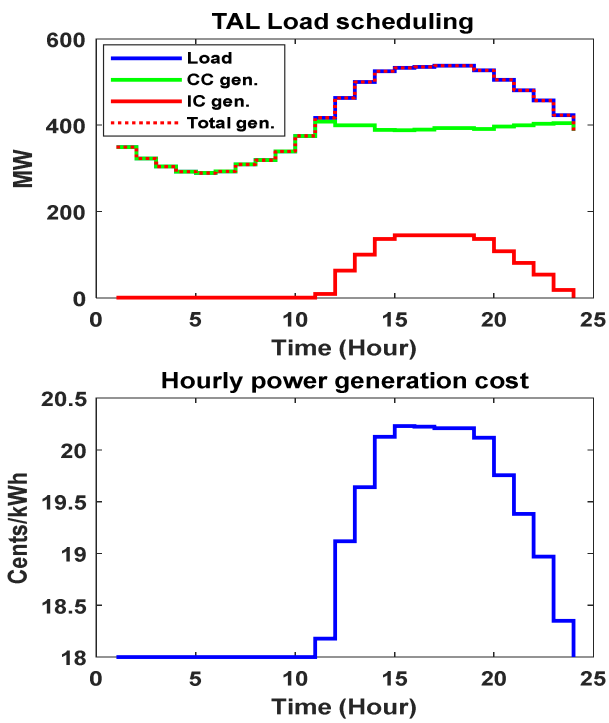


Figure 1: TAL load scheduling and generation cost/kWh

The load scheduling equation for the proposed grid system is given in (1)

$$D_n = \sum_{k=1}^{l} g_{CC_k}(n) + \sum_{k=1}^{m} g_{IC_k}(n) \quad (1)$$

where D_n is the total demand, $g_{CC_k}(n)$ and $g_{IC_k}(n)$ are the output power from a CC and IC units at the n^{th} hour, l and m are the number of CC and IC units online respectively and $n \in [1, N]$.

This research has created a software that also varies the storage capacity of the batteries while running the DP using the historical load and generation data from TAL. For different storage capacities, their annual revenue is calculated, which is essential for the economical insights of variable BESS capacities. The software guides the utility to determine the optimal sizes of BESS from an economic point of view as well as dynamically schedule its operation to maximize profits. The BESS is scheduled along with the other generation units using a DP algorithm and its advantages over the conventional RB algorithms that are often used to operate the BESS energy management scheduling. Since the DP algorithm uses the TOU tariff values created from the time varying contribution CC and IC units, it can be adapted to any grid or residential system by using the appropriate TOU values for the corresponding system.

III. RB & DP Based Battery Management System

Often, RB algorithms are used to manage the BESS's state of charge (SOC) [3-5]. Depending on the scale (domestic or utility) and application (peak shaving, demand side management, arbitrage, etc..) the RB algorithm may vary a little. But, in general RB algorithms charge the battery during low demand period and discharge it during high demand period.

Two typical RB algorithms for battery power scheduling are presented as baselines to compare with the proposed DP algorithm. In the RB algorithm 1, the battery is charged during the low production cost hours (hours 1-10 in Fig. 1). When it detects the inflation in the hourly production cost and a possibility of discharging the battery energy for profit, the RB-1 algorithm discharges the power from the battery.

One disadvantage of this method is during long duration of high demand hours the battery capacity is depleted before reaching the peak demand hours of the day. But, the contribution of low efficienct IC units are relatively high in the peak demand hours. Also, some utilities determine the power transmission cost based on the peak hour power consumption [3]. So RB 1 algorithm is not suitable for peak shaving applications. To overcome this problem, the RB-2 algorithm waits for the peak demand hour and discharges the battery only for a few hours around the maximum peak hour depend on the battery energy capcity. The generalized RB algorithm is shown in Fig. 2.

Since the battery is modelled as an active load, the load scheduling equation becomes as (2)

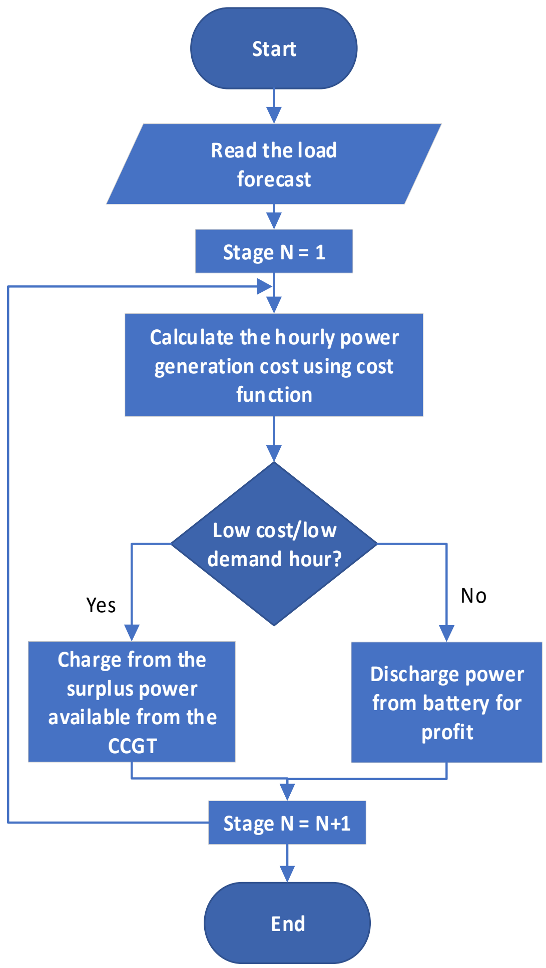
$$D_{(n,i)} = G_{CC}(n,i) + G_{IC}(n,i) + P_B(n,i) \quad (2)$$

where $P_B(n,i)$ is one of the battery's possible output power at the n^{th} hour and $i \in [P_{B\_min}, P_{B\_max}]$. G_{CC} and G_{IC} are the total power generated by all the CC and IC units respectively for the i^{th} output power of the battery at the n^{th} hour. By adding the cost function of each generation unit into (2), the total power production cost of the hour can be calculated as

$$Cost(n,i) = (C_{CC} * G_{CC}(n,i) + C_{IC} * G_{IC}(n,i) + C_B * P_B)\,\Delta T \quad (3)$$

TABLE I - PARAMETERS OF THE GENERATION UNITS OF THE PROPOSED GRID SYSTEM

Generation Unit's Output Power Capacity (MW)	Type	Role	Number of Units Available	Minimum Output Power (MW)	Average Heat Rate (Btu)
250	CC	Load following generator & spinning reserve	1	130	5783
225	CC	Load following generator & spinning reserve	1	125	5783
9	RICE or IC	Peak support & non-spinning reserve	2	-	8748
18	RICE or IC	Peak support & non-spinning reserve	5	-	8748
46	RICE or IC	Peak support & non-spinning reserve	2	-	8748



and $$\Delta T = \frac{T}{N} \quad (4)$$

where T is the optimization period, N is the number of stages and ΔT is time duration of each stage. *Cost(n,i)* is the total power production cost for the corresponding stage n and battery output power $P_B(i)$. C_{CC}, C_{IC} and C_B are the cost function coefficients of CC, IC and BESS respectively which provides the expenditure of each unit per kWh of energy produced. These cost function coefficients of CC and IC generation units are constructed based on the generation unit's heat rate and carbon tax policy [15-18]. The cost function coefficient values (cents/kWh) of CC and IC generation units are given in Table. II along with the carbon tax values.

The cost function coefficient of BESS (C_B) is calculated based on its capital investment expenditure and the battery life throughput [19],[20]. This battery life throughput value varies depend on the Depth of Discharge (DOD) as given in (5) and (6)

$$Battery\ life\ throuhput = C_E \times n_{cycles} \times DOD \quad (5)$$

$$Battery\ degradation\ cost = \frac{Battery\ price}{Battery\ life\ throughput} \quad (6)$$

Table III shows the nonlinear degradation cost for various DODs which is essential for optimized operation of DP algorithm. These values are calculated by considering the Li-ion battery price as 304 USD/kWh [20].

Using these cost function coefficients of different generation units and BESS, the hourly power generation cost for various load conditions is calculated. This parameter is used by the RB algorithms to decide the charging and discharging actions of the BESS.

In DP algorithm, all the possible combinations of battery charging and discharging actions are considered over the optimization period (T). A matrix like structure of SOCs with dimensions of N × P_{Bmax} is created. The SOC matrix created for the DP algorithm is shown in Fig. 3.

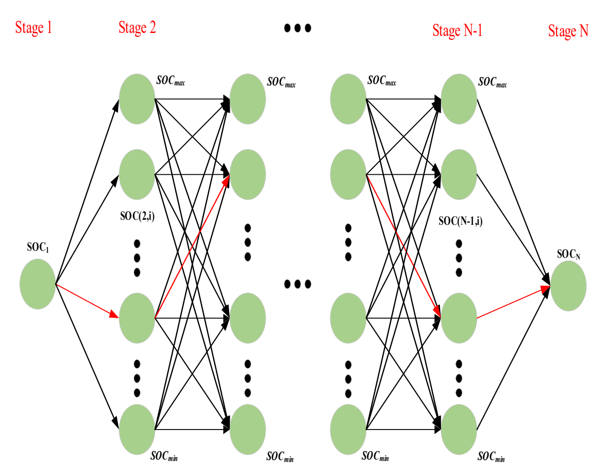


TABLE II - FUEL COST AND CARBON EMISSION TAX DETAILS OF DIFFERENT GENERATION UNITS

Generation Unit	Electrical conversion efficiency (%)	Heat rate calculated. (Btu/kWh)	Fuel consumption (CF/kWh)	Fuel cost @ (1CF of gas = 0.814 cents) (cents/kWh)	Carbon emission (Kg/kWh)	Carbon tax (Cents/kWh) (@ carbon tax value = 3cents/kg)	Cost function coefficient (Fuel cost + carbon tax Cents/kWh)
Large gas fired CCGT power plant	59%	5783	5.6146	4.57	0.3084	0.9252	5.49
IC engine generators	39%	8748	8.49	6.91	0.4666	1.3997	8.3137

TABLE III - Li iron battery degradation cost

DOD (%)	Li-ion battery degradation cost(cents/kWh)
20	0.84
40	2.30
60	5.06
80	7.92
100	10.13

From the SOC matrix total power production cost of each stage (ΔT) for every SOC state (i) is calculated. Now, using the shortest path algorithm, the lowest possible overall total power production cost over the optimization period is chosen, which is expressed as follows.

$$Total\ cost = min\left\{\sum_{n=1}^{24}\sum_{i=-P_{max}}^{P_{max}} Cost(n,i)\right\} \qquad (7)$$

Before implementing RB and DP algorithms, the following assumptions are made. Battery SOCs at the beginning and end optimization period (T) are assumed as 50%. Battery's lowest and maximum SOCs are assumed as 5% and 100% respectively. In real time, completely discharging the battery can be harmful for its life throughput. To realize that situation, the battery is not allowed to discharge below 5% SOC in the simulation.

The DP algorithm used in this paper shown in Fig. 4. The battery power scheduling is performed for every day of TAL's annual load forecast data for the period of one year using MATLAB. This load scheduling process is simulated for a wide range of battery energy capacities for both RB and DP algorithms. The revenue trend over the battery capacity sweep is shown and discussed in the next section.

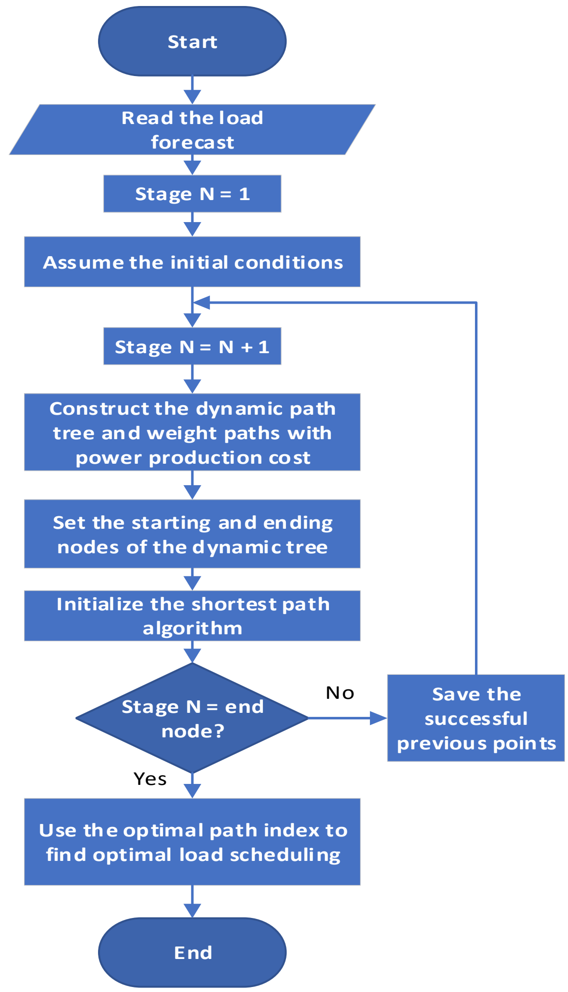


Figure 4: DP algorithm.

IV. RESULTS AND DISCUSSIONS

Even though, the load scheduling is done for a wide range of battery capacities, a 20 MW and 40 MWh BESS is chosen to compare the performances of RB and DP algorithms. The 24-hour load forecast shown in Fig. 1 is used to demonstrate the load scheduling process of each algorithm.

For the given load forecast, the load scheduling done by RB 1 algorithm is shown in Fig. 5. The figure also shows the battery output power and SOC status along with its effects on IC units power generation and hourly power production cost/kWh.

The RB 1 algorithm detects low demand hours from hour 1-10; and decides to charge the BESS. A completely depleted 20 MW, 40 MWh battery can be fully charged in 2 hours. However, rapid charging is not advised to improve the battery life throughput. So, the battery is charged with the lowest possible charging rate which is decided based on the length of the low demand period duration. During these low demand hours, the highly efficient load following CC units are operating below their full capacity. So, charging the battery during these hours does not require the service of IC units. This keeps the hourly power production cost per kWh uninflated.

The RB 1 algorithm [4] detects an inflation in the hourly power production cost after 10th hour due to high demand and IC units service to match the load. The RB 1 algorithm decides to discharge the battery during these hours to substitute the IC units partially or completely. Here, the output power of the battery is decided based on the DOD cost values listed in Table. III. The energy from the battery is only sold under profitable conditions which can be seen in from hour 11-16 in Fig. 5. After 16th hour, the demand is high enough to keep several IC units online. But there is not enough energy in the battery to replace the IC power generations, not even partially. So, the battery output power remains zero. Since, an assumption made that every day the battery's SOC starts at 50% and ends at 50%, right at the 24th hour the battery starts to replenish its energy back to 50%.

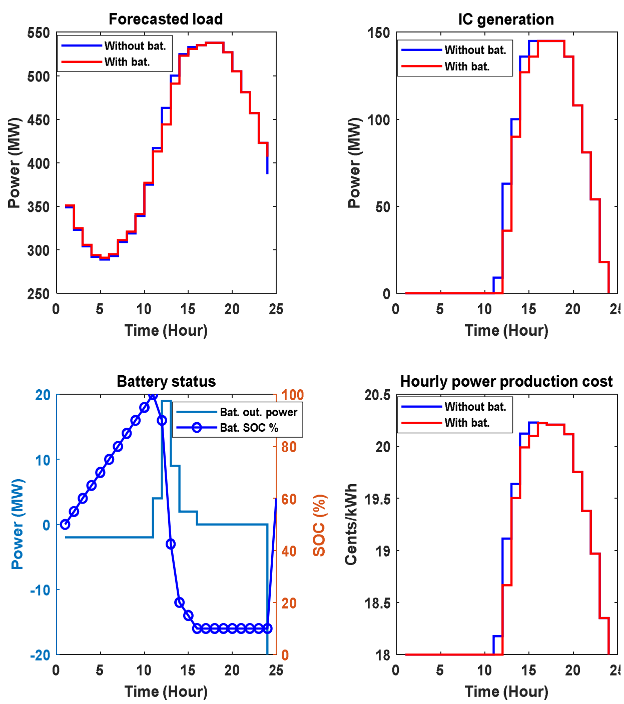


Figure 5: RB BMS algorithm 1

The Load scheduling done by RB 2 [3] algorithm is shown in Fig. 6. The battery charging process is the same as RB 1 algorithm. RB 2 algorithm differs in the discharging process from RB 1. In RB 1 algorithm, the battery energy is often completely discharged before the peak demand hours. For some utility level peak shaving applications, algorithms like RB 2 are used, where the battery energy is discharged during the peak demand hours. As shown in Fig. 6, the RB 2 algorithm waits for the peak demand hours (hour 15-17) and discharges its energy during that period. As a result, the contribution of IC generation units is highly reduced during those peak hours and the hourly power production cost per kWh is also significantly reduced in those hours relative to the RB 1 algorithm.

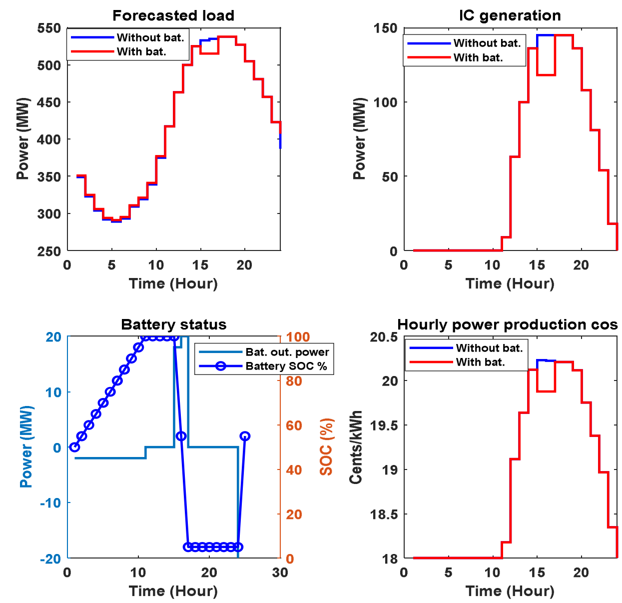


Figure 6: RB BMS algorithm 2

Fig. 7 shows the load scheduling by the DP algorithm. The DP algorithm chooses the most profitable hours to charge and discharge the battery over the given period of time. This optimized operation of DP algorithm is achieved by the TOU tariff values produced by the cost functions coefficients that assigns varying degrees of importance to different generation units.

Unlike RB algorithms, DP does not operate within a fixed set of conditions to reduce the power production cost. The DP algorithm considers all the charging and discharging combinations, which enables it to charge the battery even during high demand hours for a better selling opportunity. For example, in Fig. 7 at hour 17, the battery SOC is above 70% and load power is at its peak. But DP algorithm finds better selling periods for the energy between hours 19-24. Additionally, it finds that the CC units are operating below its generation capacity during hours 17-19 to compensate the extra power produced by the IC units by calculating the hourly power production cost using the TOU tariff values. So, during hours 17-19, the DP algorithm not only decides not to discharge the

BESS but also decides to charge the BESS to increase the power generation of CC units which helps to improve the heat rate of the CC units in real time. Since the BESS charged by the CC units during hour 17-19, there is no increase in the power generation of IC units in the corresponding period which is shown in Fig. 7. The charged BESS is discharged later during hours 19-24 for better profit by the DP algorithm.

By increasing the overall (IC + BESS) reserve capacity, the flexibility of the system is improved, resulting in a reduction in the total power generation of low-efficiency IC units. This is optimized using the DP algorithm, particularly with the battery capacities which can substitute the smallest IC unit for less than an hour i.e., 8MWh or less in this case. For instance, if an additional 8 MW demand occurs at the 13th hour, a 9 MW IC unit would be required to be online. Later in the day, during hours 19 and 20, there is an additional 4 MW demand per hour, which also requires the 9 MW IC unit to be online. While rule-based (RB) algorithms consider only profits achieved during peak demand hours or earlier periods, dynamic programming (DP) algorithms take into account the entire time frame. For example, RB algorithms deliver the 8 MW power required at the 13th hour, whereas the DP algorithm prefers to discharge the 8 MW power during hours 19 and 20, thereby eliminating a total of 18 MWh from low-efficiency IC units instead of discharging it earlier.

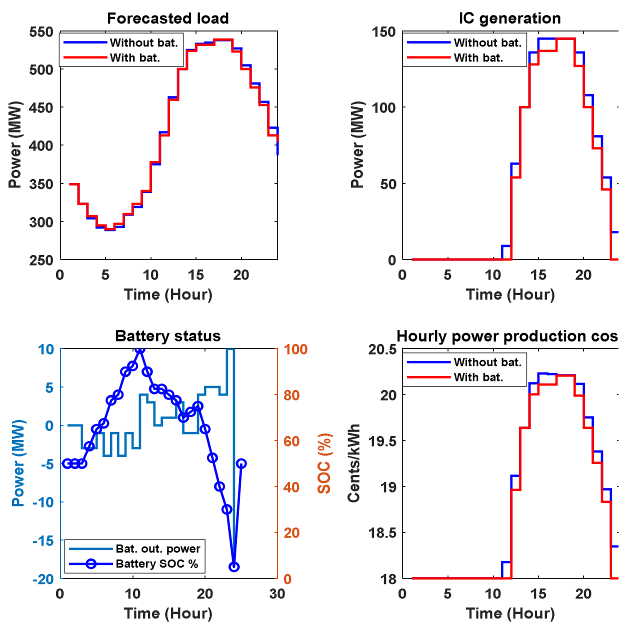


Figure 7: DP BMS algorithm

These RB and DP algorithms are simulated for each day of the annual load for various battery capacities. A battery energy capacity range from 2 MWh to 120 MWh is considered for the simulation. The annual revenue generated as a function of battery capacity size using the RB and DP algorithms is shown in Fig. 8. The DP algorithm generates more revenue than both RB algorithms for all the battery capacities. This increased revenue achieved by the DP algorithm reduces the payback period of the BESS.

The difference between the revenue generated by the RB and DP algorithm is relatively high for the batteries with the low energy capacity (2-40 MWh). This can be observed by calculating the battery annual revenue per MWh which is shown in Fig. 9.

In conventional battery sizing approach for the peak shaving or capacity firming application [2], the BESS is sized to deliver the generator power which needs to be substituted for 2-4 hours. i.e., a 9 MW IC unit requires an 18 – 36 MWh BESS. But this research produces a counter intuitive result.

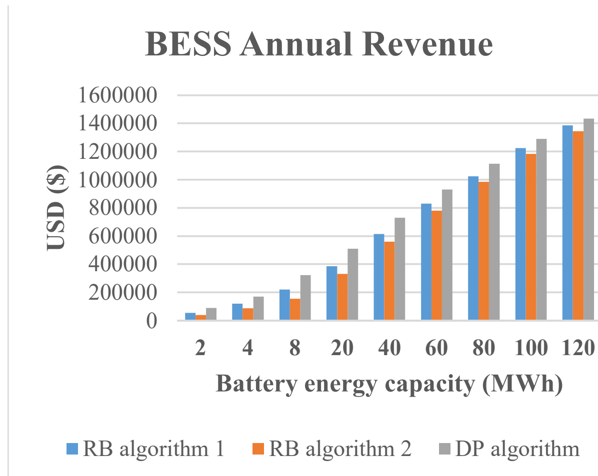


Figure 8: Battery annual revenue

From Fig. 9 for the City of Tallahassee example, the revenue/MWh is declining rapidly after 8 MWh and reaches the saturation after 40 MWh. It shows that a BESS with a capacity smaller than the smallest IC backup unit i.e., 9 MW, has more revenue/MWh rate than larger batteries. This result is counter-intuitive to the general guidelines of BESS sizing.

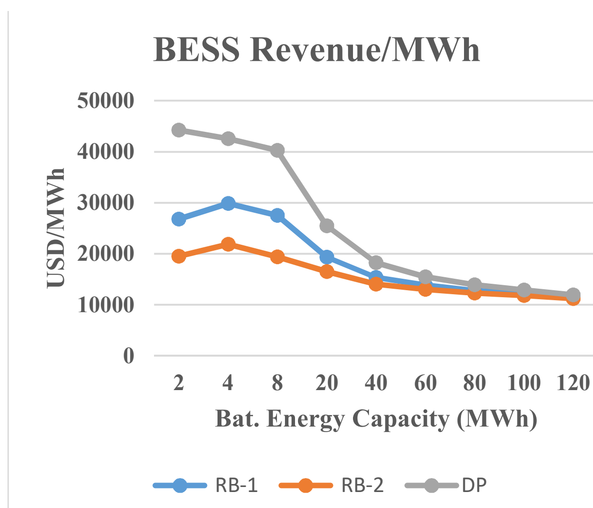


Figure 9: Annual revenue/MWh

V. Conclusion and Future Works

This research demonstrates that utilizing DP-based optimization of BESS to substitute low-efficiency IC units is more advantageous than traditional RB scheduling methods and yields economic benefits. Additionally, discharging the BESS during high demand hours for a longer duration is more profitable than a shorter duration during peak demand hours, as evidenced by the results. The DP algorithm not only reduces the power production of IC generation units but also increases the power produced by the CC generation units which improves the average heat rate of the operating CC units in real time.

The DP algorithm can be used by any grid or residential system to produce TOU tariff values. Furthermore, the DP algorithm can be prioritized to extend the BESS lifetime. The DP software was augmented with supplementary analysis features, enabling users to determine the optimal battery energy capacity for maximum economic gain. The DP software was combined with additional analysis features that can allow the users to size the battery energy capacity for optimal economic benefit.

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Abridged Legal Disclaimer

The views expressed herein do not necessarily represent the views of the U.S. Department of Energy or the United States Government.

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