Dynamic Charge Scheduling of Solar PV-Storage Hybrid Resources Based on Solar-Load Correlation

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***Abstract*—Solar PV-storage hybrid resources are an attractive way of reducing grid dependency for project developers when collectively serving small communities. A well-structured charging schedule of the battery storage can improve the effectiveness of the hybrid system by reducing the grid dependency at the peak demand hours and improving the utilization of the battery. Studying the correlation between load and solar curves helps to identify periods at which short-term charging or discharging of the battery can aid to those benefits. In this paper, a dynamic charging schedule is proposed, where a nominal schedule is created based on full day forecasting of load and solar output, and further adjustments are made to the schedule based on the hourly expected correlation between load and solar curves. The proposed method is then tested on a test system based on actual data for a period of one year. The results show that the proposed approach can reduce the maximum power import from the grid, overall cost of imports and improve the battery utilization.**

***Index Terms*—hybrid resource, battery storage, charge scheduling, solar load correlation, solar forecasting**

I. Introduction

Hybrid Resources that combine solar PV and battery storage are becoming increasingly popular among those who seek to reduce dependency on the grid while consuming green energy [1]. Owing to the high cost involved with battery storage, hybrid resources are typically set up at larger scale involving a community of solar customers [2]. Solar power purchase agreements (PPA) designed for such communities allow customers to buy power from third party project developers at a lower rate than from the utility, by hosting the hybrid resource at their premises without taking ownership of the system [3]. In rural areas where solar potential is high, local government entities or aggregator entities can deploy a large-scale hybrid system by installing rooftop solar PV panels at the homes of the customers with a centralized storage system, prompting the adoption of hybrid resources and letting the customers indulge the benefits of PPA [4].

The charging schedule of the battery storage can influence how well a hybrid system can contribute to reducing the dependency on the grid and reducing the cost of electricity. Battery storages are typically charged during the day when there is excess solar production, so that the hybrid resource can continue to partially supply the demand after sunset. Most prevalent methods of charging schedule is to use day-ahead load and solar forecasts, and optimize battery charging decisions for increased self-consumption [5] or peak load shifting [6]. This way of charging can be ineffective on days when the solar or load curves deviate significantly from their forecasts. A dynamically changing charging schedule is needed to address this uncertainty and utilize both resources effectively. YanQi et al. proposed a method to make dynamic changes to the day-ahead schedule based on the real time solar output and storage availability [7]. All of these methods do not take into account the inherent synchrony between solar and load which can influence changes to forecasted load curve [8]. Yang et al. proposed a method to make charging decisions based on the correlation between historical load and solar [9]. However, their method creates a fixed repeatable schedule and does not account for changes in correlation that might occur in the immediate future.

In this paper, a two-step method to develop battery storage charging schedule is proposed. Solar and load behavior for the immediate future is forecasted, based on which nominal start times for charging and discharging are decided at the start of every day. This schedule is then further improved by calculating correlation between solar output and load at every hour from the forecast as well as historical data, and making appropriate charging decisions. The proposed method is presented in detail in Section II. It is then implemented on a test system and its efficiency in fully utilizing the benefits of hybrid systems is compared against multiple fixed charging methods in the sections that follow.

II. Methodology

The proposed method to make the battery storage charging and discharging decisions based on the correlation between load and solar output is illustrated in Fig. 1. In this method, at the start of every day, expected load and solar output behavior for the whole day is forecasted based on the recent historical data. From these forecasts, expected correlations are predicted, and a nominal charging schedule is created with a single charging start time and a single discharging start time. Then,

This work was sponsored partially by Sunflower Electric Power Corporation Grant and partially by US NSF EPSCOR RII Track 1 #2148878.

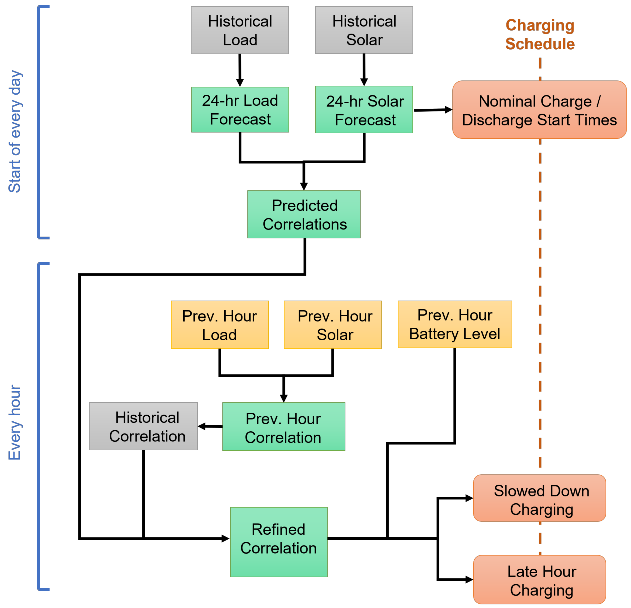


Fig. 1: Correlation based dynamic charge scheduling method

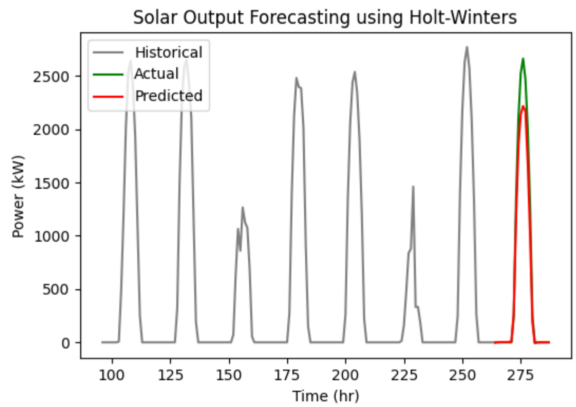


Fig. 2: Solar output forecasting of a sample day using triple exponential smoothing

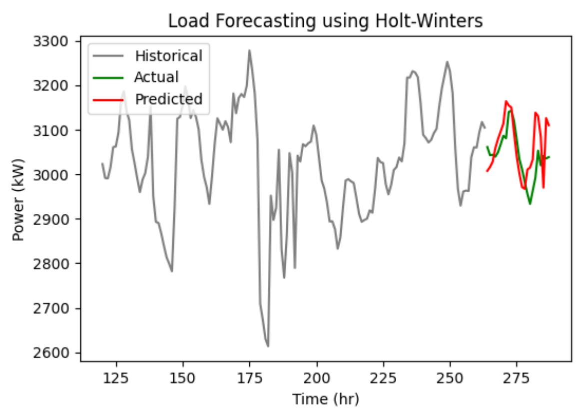


Fig. 3: Load forecasting of a sample day using modified triple exponential smoothing

at an hourly basis, predicted correlation values are refined using historical correlation values, which is then used to make further adjustments to the nominal charging schedule.

A. Solar and Load Forecasting

Expected load and solar output for a 24-hour period are forecasted using the triple exponential smoothing technique also known as the Holt-Winters method. This method is a widely adapted statistical forecasting technique used in many domains, including power systems where it has been used for short-term load forecasting and solar PV power forecasting [10]. It estimates the future data points based on their expected level, trend, and periodicity. A simple, additive type of triple exponential smoothing is given in a recursive format in (1)

$$\hat{y}_{t+n} = a_t + nb_t + c_{t-p+1+p(n-1)} \tag{1}$$

$\hat{y}_{t+n}$ is the estimated point n time-steps away from the current known point which is at t^{th} time-step. p refers to the number of time-steps between each repeating cycle (period). The level component a_t, trend component b_t, and periodicity component c_t are obtained as in (2)-(4). From the recursive format of these equations, it can be seen that the influence of the preceding historical data points decays as it moves further from the current point. Best values for coefficients α, β, and γ are determined by training on actual known values of the selected time series.

$$a_t = \alpha(y_t - c_{t-p}) + (1-\alpha)(a_{t-1} + b_{t-1}) \tag{2}$$

$$b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1} \tag{3}$$

$$c_t = \gamma(y_t - a_t) + (1-\gamma)c_{t-p} \tag{4}$$

Solar irradiance follows a 24 hour cyclic pattern, and therefore the periodicity of solar output can be captured by making $p = 24$ for the equations in (1)-(4). It is assumed that 7 days of historical data would be enough to capture any short-term trend that is present in the solar output. The triple exponential smoothing method was tested on solar output data obtained from a microgrid setup at Wichita State University, scaled to represent a combined output of 1000 solar panels [11]. Fig. 2 shows the prediction for solar output on Jan 5, 2021 based on a week-long historical data preceding it, and the actual solar output seen on that day. It can be seen that the predicted output is slightly smaller than the actual output because of the low-solar output days that have occurred in the preceding week.

Load forecasting is done slightly different from solar output forecasting, as load behavior is likely to be more similar to the data obtained during similar days of the week in previous weeks. It is necessary to capture a weekly cyclic pattern in addition to the daily cyclic pattern. To achieve this, triple exponential smoothing is applied only to six preceding days, and the resulting forecast is averaged with the actual load seen seven days earlier, which would be from the same day of the week. The prediciton for load on Jan 5, 2021 is given in Fig. 3.

B. Nominal charging schedule

Once the forecasting is done, a simple charging schedule is created where a charging period and discharging period are allocated. This schedule is nominal and does not take into account the similarity in behavior between solar and load yet. The charging start time is taken to be the second successive hour of non-zero solar output and the discharging start time is taken to be 3 hours from the maximum solar output. Nominal charging and discharging are assumed to happen at the manufacturer specified rates of the battery storage subject to solar availability and demand constraints.

C. Correlation of the forecasts

The similarity in behavior between both 24-hr load forecast and 24-hr solar output forecast can be obtained by calculating Pearson's correlation coefficient (ρ) as given in (5) where $\overline{L_i}$ and $\overline{S_i}$ correspond to the mean values of load and solar output data respectively.

$$\rho = \frac{\sum(L_i - \overline{L_i})(S_i - \overline{S_i})}{\sqrt{\sum(L_i - \overline{L_i})^2 \sum(S_i - \overline{S_i})^2}} \tag{5}$$

To track the change in correlation between both over time, Pearson's coefficient is calculated at every hour by considering a a 3-hour window of forecasts centered around the current hour.

D. Refinement of correlation

The correlation predicted using the method in II-C can be very different from the actual correlation as it compounds the errors from both individual forecasts. Therefore, a method to adjust the correlation values is developed using historical correlation values that get recorded hourly. This method is only used to adjust the correlation value of the current hour if the previous hour's predicted correlation and actual correlation deviates by more than 20%. If such deviation is found, the change in correlation from the previous hour's actual value is given as a series of weighted changes during that hour period in the last six days as given in (6).

$$\tilde{\rho_i} = \rho_{i-1} + \sum_{d=1}^{6}(0.5^d \times (\rho_{i-1-24d} - \rho_{i-24d})) \tag{6}$$

Fig. 4 shows the correlation predicted from the solar and load forecasts of January 5, 2021, and the following adjustment to the correlation made by the proposed method. The refinement method had picked up the error in prediction for 12:00 and kept on adjusting the correlation until 18:00, resulting in a graph that is closer to the actual correlation values compared to the original prediction.

E. Adjustments to charging schedule

Based on the refined correlation values the following adjustments are made to the nominal charging schedule to improve the utilization of the hybrid resource.

- During the nominal charging period, if the correlation between solar and load is found to be negative, and the battery level is above 50%, charging rate is slowed down. The solar output is shared between the battery (P_B) and the houses (P_H) as in (7).

$$\frac{P_B}{P_H} = \frac{1 - |\tilde{\rho}|}{|\tilde{\rho}|} \tag{7}$$

- During the nominal discharging period, if the correlation between solar and load is found to be positive, and the battery level is below 50%, the battery is allowed to recharge rapidly, while still allowing for the solar output to be shared with the houses as in (8).

$$\frac{P_B}{P_H} = \frac{\tilde{\rho}}{1 - \tilde{\rho}} \tag{8}$$

To prevent the battery storage from physical deterioration due to high frequency of switching, the number of charge-discharge cycles allowed per week is limited to 12.

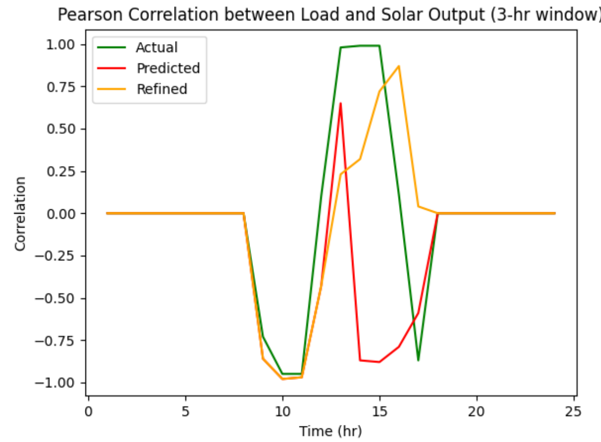


Fig. 4: Predicted correlations and refined correlations for a sample day

III. Test System and Implementation

For testing the proposed methodology, a rural town in Kansas state was modeled to have a large-scale hybrid system to supply a large portion of its load requirement[1]. It was assumed that 1000 homes in this town is installed with solar PV panels each of 3.8kW rating and facing south. The system is assumed to be connected to a battery storage of 10MWh capacity. The load and solar data corresponding to a one-year period between December 2021 to November 2022 was used for the study.

In order to compare the effectiveness of the proposed methodology, two additional cases of battery charge scheduling were implemented and tested. The cases and their assumptions are explained in sections III-A and III-B.

[1]The test system was built based on proprietary data that was obtained through a Non-Disclosure Agreement.

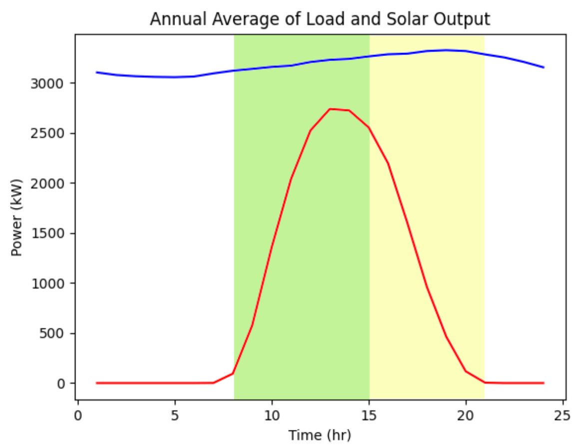


Fig. 5: Annual Average Load and Solar output for 24 hours

A. Annual Fixed Charging

In this method, the battery charging schedule is decided annually and is kept fixed throughout the year. Fig. 5 depicts the average values of the loads and solar outputs encountered at each hour of the day for the entire year. Based off these values, the best times to start charging and discharging can be decided by iterating through all possible combinations and selecting the period that results in best correlation between both curves during charging. The best combination of charging and discharging periods for this case is given in Table I with their corresponding Pearson correlation values. The discharge period is only specified to calculate the correlation during non-zero solar output period, but the battery is allowed to discharge even past this period until it is completely drained.

TABLE I: Charging and Discharging periods for Annual Fixed Charging case

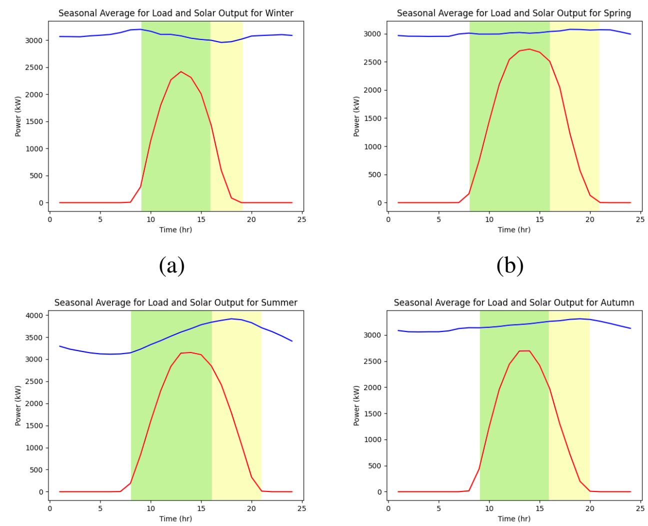
	Time Period	Correlation
Charging	08:00 - 15:00	0.936
Discharging	15:00 - 21:00	0.146

B. Seasonal Fixed Charging

In this method the battery charging schedule is changed at the start of every season to account for the seasonal variance in weather which might affect the customer load patterns and the available daylight hours. Fig. 6 depicts the average values of the loads and solar outputs encountered at each hour of the day for the entire year. Similar to the previous case, the best times to start charging and discharging are decided as the best possible combination with respect to the correlation between both curves and are given in Table II with their corresponding Pearson correlation values.

C. Correlation based Dynamic Charging

The methodology proposed in II is applied to the selected test system. Fig. 7 shows the distribution of recorded charging



(a) (b) (c) (d)

Fig. 6: Seasonal Average Load and solar output for 24 hours during a) Winter b) Spring c) Summer and d) Autumn

TABLE II: Charging and Discharging periods for Seasonal Fixed Charging case

Season	Time Period	Correlation
Winter	09:00 - 16:00	-0.56
	16:00 - 19:00	-0.778
Spring	08:00 - 16:00	0.864
	16:00 - 21:00	-0.028
Summer	08:00 - 16:00	0.945
	16:00 - 21:00	0.922
Autumn	09:00 - 16:00	0.497
	16:00 - 20:00	-0.729

and discharging start times in this case. It is evident from the figure that the late hour charging scenario has happened a considerable number of times, which in turn has resulted in instances where battery had been discharging well into the night.

IV. Results

The three cases of battery storage charging schedules are compared with each other using three different criteria.

A. Maximum rate of Import

At each hour the load demand that is in excess of the solar output allocated for houses and the discharge from battery storage has to be imported from the grid. . This is illustrated in (9) where P_G refers to power imported from the grid, and P_L refers to the load. Reducing the maximum rate of import from the grid reduces the likelihood of stressing the transmission line used for importing.

$$P_{G,t} = P_{L,t} - (P_{H,t} + P_{B,t}) \tag{9}$$

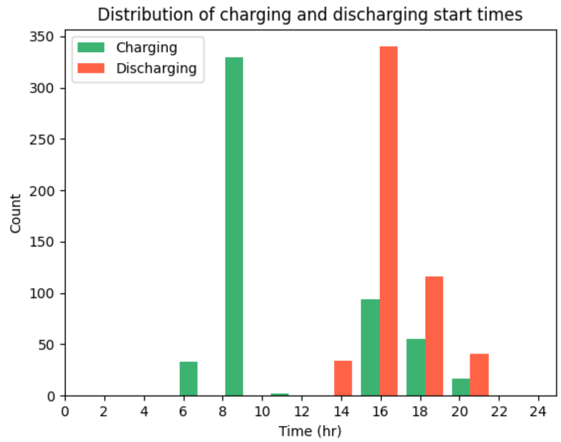


Fig. 7: Charging and Discharging start times for correlation based dynamic charging schedule

B. Total Cost

Overall expense that is incurred by the customers can be found by multiplying the imported power by the locational marginal pricing (LMP) at the corresponding transmission node as in (10). In instances where the combined production from the hybrid resource exceeds the load, the surplus is exported back to the grid at the same LMP value.

$$E = \sum_{t=1}^{T}(P_{G,t} \times LMP_t) \tag{10}$$

C. Battery Utilization Ratio

Battery Utilization Ratio (BUR) measures how much of the battery storage's available capacity was utilized to store energy during the entire period of study. It can be given as in (11) where $SOC_{B,t}$ refers to the state of charge in the battery at time t and C_B refers to the installed capacity of the battery storage. It is assumed that the battery does not undergo degradation during the period of study and charge retention does not vary with time.

$$BUR = \frac{\sum_{t=1}^{T} SOC_{B,t}}{T \times C_B} \tag{11}$$

The results of the three charging schedules when they are subject to the three metrics are presented in Table III

TABLE III: Comparison of the battery charging cases under different performance metrics

	Max Rate of Import (kW)	Total Cost (USD)	Battery Utilization Ratio (%)
Annual Fixed	4556.13	743,686.0	0.0217
Seasonal Fixed	4556.13	742,020.9	0.0208
Correlation Based	4501.64	734,484.7	0.0228

From the results, it can be noted that the correlation based dynamic charging schedule outperforms the other two fixed charging schedules in all three metrics. It brought down the overall expense for the year by 1% while reducing the maximum rate of import and improving the battery utilization ratio.

V. Conclusion

A solar PV-storage hybrid system has merits in improving flexibility of adjusting intermittent generation. In this paper, a method to charge the battery storage of the hybrid system dynamically by taking the correlation between solar and load is proposed. The method creates a nominal charging schedule based on a full day forecast, and then makes changes to the schedule based on the actual recorded correlation at every hour. The efficiency of the proposed method was tested against two fixed charging schedules in a rural town test system for-one year period by using three performance metrics. The results show that considering solar-load correlation for battery storage can reduce the maximum power imported from the grid, reduce the overall cost of import and improve the battery utilization.

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