A vision of flexible dispatchable hybrid solar-wind-energy storage power plant

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Abstract
Dispatchable renewable generation is essential for 100% renewables power system. It is in the interest of both power system operators and customers since it reduces the need for flexibility and reserve. To this end, battery energy storage systems (BESS) are proposed for integration in the renewable power plant. This paper presents the optimal dispatch unit for a dispatchable hybrid solar-wind power plant with BESS framework. It achieves optimal dispatchable renewable generation (from dispatchable hybrid renewable (solar-wind) power plant with BESS, DHRB, operator perspective), subject to operational limits, by exploiting the synergy of wind and solar energy and combining it with storage capability of BESS using two different operation strategies, maximisation of revenues and maximisation of renewables harvesting. A continuous BESS degradation model is incorporated in the proposed rolling-algorithm-based-optimal dispatch unit to improve the accuracy of results. The applicability of the proposed methodology and the performance of the operation strategies are demonstrated using a case study and the operation strategies are compared. Further, the effect of BESS size on its degradation and dispatchable power in a hybrid solar-wind power plant with BESS are investigated through BESS lifetime. An indicative economic analysis is carried out to provide ground for the extra investment on and sizing of BESS for a dispatchable hybrid renewable power plant.

1 | INTRODUCTION
The share of renewables in global electricity generation is expected to rise to 30% by 2022 mainly due to growth in wind and solar generation capacity [1]. Realisation of high wind and solar penetration in moderately interconnected power systems entails addressing several aspects including, intermittency, reactive power scarcity, network capacity limitations and fault behaviour, among others [2, 3].

A dispatchable generation unit can change its output, within the announced operational limits, per the request of the system operator. Solar and wind power plants, can potentially vary their output between zero and the maximum available power [4]. However, due to the intermittency of the available power (i.e. variable wind speed and solar irradiance), they are inherently non-dispatchable; meaning that there is no guarantee that the expected amount of power will be available on demand, for a given length of time [5]. Accordingly, despite the power generated by solar and wind power plants replacing the power from conventional units (due to priority dispatch and/or low marginal cost [6, 7]), these renewable generation sources cannot commit for providing a certain amount of power. Provision of sufficient flexibility and reserve to overcome the non-dispatchability of solar and wind generation is a current challenge for the electricity market operator. This paper focuses on alleviating the non-dispatchability of renewables. Dispatchable renewable generation may reduce the need for reserve and flexibility and improve reliability [8].

Control of battery energy storage system (BESS) to achieve dispatchable power in solar and/or wind power plants has been investigated in the literature. Rule-based control is proposed in [9–11]. In [9], hourly dispatch of wind and solar generation is achieved using the average wind and solar power hourly forecast as set-points for wind and solar generation.
Any difference between the set-points and actual power generation is compensated by power injection/drawing with BESS. Employing 1 h average forecast as set-points requires large BESS capacity for practical operation. A shorter time period, i.e. 5-min is used by [10] for dispatching a utility-scale PV system. The authors define three operating modes (normal, deficit and excess power) for controlling a hybrid energy storage system (battery and super-capacitor). They show that the more forecast error, the larger spinning reserve is needed to overcome power deficit from the solar PV system. In [11] the lifetime cost of a standalone hybrid renewable system with fuel cell and battery, as well as an auxiliary AC generator, is minimised. Initially, genetic algorithm is used to find an appropriate configuration of power generation sources. For a given configuration, critical values of the rule-based control strategy are found using genetic algorithm. These values are used to produce set-points for a standalone hybrid system based on a number of predefined rules. However, rule-based techniques may result in instances in which set-points cannot be met, as shown by [9].

For smoothing the wind and solar power output, [12] proposed using a dynamic filtering controller or a dynamic rate limiter. Moreover, to prolong the lifetime of the BESS, power set-points are provided to each battery unit individually based on its state of charge. This strategy aims to keep an even state of charge for all battery units. A similar strategy is proposed by [13]. The authors separate the problem into two stages. In the first stage, scenario-based stochastic programming is used to optimise the expected wind power plant revenues over the generated scenarios with the day-ahead forecast of wind and electricity price. In the second stage, the BESS is controlled in real-time to meet the committed power of the wind power plant. To tackle the day-ahead forecast error, [14] considers three scenarios of wind power (pessimistic, normal and optimistic) based on the day-ahead forecast. During the trading day, the pessimistic power references is committed in the initial dispatch intervals. Real adjusting between pessimistic and optimistic power reference is allowed in the following dispatch intervals (when a more accurate forecast is available) to improve battery use and observe market requirements.

The energy arbitrage capability of batteries is targeted in [15, 16]. By integrating a wind power predictor with the control scheme, [15] proposed a fuzzy logic based decision-making system that maximised revenue while observing the electricity market and battery operational constraints. The 5-min re-bidding opportunity in the Australian electricity market is a key enabler of this work. In order to ensure cost-efficient use of the battery, the authors of [16] use cost coefficients to express the lifetime decrease of battery, violation of power fluctuation limits and wind power curtailment. Using model predictive control and genetic algorithm, their methodology finds the optimal set-points for wind turbine pitch angle and BESS power for a given time interval.

In [17], a distributed scheduling solution for customer sized renewables is proposed for load following at a 1-h resolution. In [18], the energy hub concept is used to fulfil electricity, heating and biogas demand, i.e. load following in a microgrid. A coupling matrix is developed to mimic the energy conversion within various means of conversion and storage facilities such as battery, gas tank, combined heat and power generator, gas furnace, electric boiler, biomass digester, photovoltaic thermal panels and wind turbines. Although a penalty factor is applied to energy transactions in the storage facilities to avoid their overuse, the effect of degradation on the capacity of the storage facilities through their lifetime is not discussed. The authors of [19] extend their previous work ([18]) by augmenting the coupling matrix for several microgrids to enable economic coordination of the available resources. Energy trading with the grid is considered with a constant feed-in-tariff. To enable distributed optimisation, the cost minimisation problem is decomposed to local problems using Lagrangian relaxation. The problem is solved iteratively, and the Lagrangian multipliers are updated in every iteration until the problem converges. The authors of [20] propose a distributed robust optimisation framework to tackle the multi-microgrid scheduling problem for load following. The electricity price is taken as the uncertain factor and the unilevel problem is formulated with the aid of the duality theorem. This is then converted to local problems for each microgrid through Lagrangian relaxation. The problem is solved in a two phase iterative approach in which the Lagrangian multipliers and the electricity price are updated. A sensitivity analysis is carried out to show the performance of the proposed framework in both risk-averse and deterministic (referred to as risk-seeking by the authors of [20]) modes. A major concern around such a robust optimisation algorithm is that the problem is solved against the worst possible condition which could be highly improbable and potentially result in unnecessary higher cost. The authors of [21] propose a solution for the scalability of the coordination of available resources, i.e. energy storage (without degradation) and distributed generation units in multiple microgrids to perform load following. A deep convolutional neural network is developed to estimate the cost of serving the aggregated load of the microgrids. The interaction among the microgrids and the grid is replicated using cooperative game theory in a distributed fashion.

In [22] the resources available in multiple microgrids are scheduled for the day-ahead hourly market. The aim is to primarily minimise the local cost function of each microgrid and then the global cost of serving the aggregated load. This paper mimics the flow between the microgrids by an iterative flow selection approach. The square of the battery power is penalised in the initial formulation and then this formulation is linearised by piece-wiseging the battery power. Hence, the degradation is effectively reduced. However, the impact of degradation on the actual capacity of energy storage units is neglected. An energy management system is proposed in [23] to manage renewables, energy storage units and diesel generators available to a commercial building in order to fulfil the electrical power and space heating and cooling demands. The electrical energy demand for space heating/cooling is determined based on a given thermal comfort range and with the aid of a simplified single heating zone, first order resistor-capacitor thermal model. The energy management system schedules the available resources in the day-ahead and 5 min ahead in order to minimise cost of demand. In this regard bi-directional non-dispatchable power exchange
with the grid is considered at times of insufficient and excess power generation. The operation of the energy storage units does not bear any degradation cost, nor the degradation impact is reflected on the capacity of these units. The authors of [24] propose a robust energy management system for renewable, energy storage units and combined heat and power generation units available in a greenhouse to meet the demand of the greenhouse in both grid-connected and islanded operation modes. In the islanded mode the maximum load that can be met is limited. Hence the proposed energy management system allows for violating control parameters which affect the plant growth in the greenhouse. However, to avoid such violations in consecutive time intervals, additional penalty factors are introduced for those parameters that were violated in the previous interval. The algorithm proposed also estimates precedence of parameters for allowing violation. The 1-h resolution renewable generation scheduled in this paper is not dispatchable. Moreover, not applying any penalty to the use of energy storage units can result in their fast degradation. In [25] a hierarchical control algorithm is proposed to achieve various modes of operation of the available renewables in a microgrid, including constant power (referred to as flat tie-line power) by using energy storage units to compensate for renewable power fluctuations within 15-min intervals. The reference power used in the algorithm is based on the average available renewable power. Similar to [9], such a non-optimised reference power results in instances in which set-points can’t be met. Although dispatchable renewable generation is not directly targeted in this paper, however, the proposed algorithm can potentially be employed for implementing the dispatchable renewable power concept.

This paper presents the optimal dispatch unit of a unified framework for dispatchable hybrid renewable (solar-wind) power plant with BESS (DHRB), which is optimal and also considers BESS degradation. Dispatchable renewable generation can facilitate high renewables penetration in power systems with limited interconnection by reducing the need for reserve and flexibility. Previous works mainly focus on developing controllers with set-points that may not be optimal (and/or even achievable), they often consider wind or solar energy separately, with BESS for a dispatchable renewable power plant, and they usually neglect battery degradation for this purpose (the latter results in inaccuracy in long term operation). This paper complements the previous works by exploiting the synergy of wind and solar energy and combining it with storage capability of BESS to achieve optimal dispatchable renewable generation subject to operational limits using two different operation strategies, maximisation of revenues and maximisation of renewables harvesting. It incorporates a continuous BESS degradation mechanism in the proposed rolling-algorithm-based-optimal dispatch unit (which is essential) to improve the accuracy of results. A case study is carried out to demonstrate the applicability of the sizing methodology and compare the effect of operation strategies. The effect of operating renewables in a hybrid fashion with various BESS sizes on the power plant dispatchable power and BESS degradation are investigated through BESS lifetime. An economic analysis is carried out to provide ground for the extra investment on and sizing of BESS for a DHRB. To summarise,

- The novel idea of identifying the configuration and presenting strategies which could potentially allow a 100% renewable energy based generation system to emulate the performance of traditional conventional power generation in several regards is presented.
- Our proposed sizing methodology helps in identifying the optimal size of a hybrid wind and PV power plant which respects the output power fluctuation constraints with minimum utilisation of battery energy storage systems.
- The proposed generation scheduling strategies guarantee to achieve the dispatch levels for the hybrid system. Although studies have been published for designing hybrid wind/PV systems which reduce the output power fluctuations, yet there still remains absence of methods which can guarantee dispatch levels for 100% renewable systems.
- In addition to the technical benefits, the financial analysis at the end of the manuscript highlight the economic viability of the proposed techniques for the generation owners.
- As a result of the proposed strategies, the renewable sources can be treated as dispatchable generation which would lead to substantial reduction in procurement of balancing reserves and hence, significant balancing cost savings for the utility.

Hence, this paper is a step towards achieving the goal of providing highly predictable and smooth power output from renewable sources, which the authors believe has not been addressed in literature.

The rest of the paper will be divided as follows: Section 2 presents the DHRB. It describes the framework, the dispatch time horizon, the rolling-algorithm-based-optimal dispatch unit employed in the DHRB framework, and the BESS degradation mechanism. Section 3 introduces the case study DHRB. Section 4 demonstrates the applicability of the proposed methodology with the case study and discusses the findings. Finally, Section 5 concludes this paper and suggests direction for future research.

## 2 Dispatchable Hybrid Power Plant

### 2.1 Framework

A hybrid renewable power plant consists of several renewable power generation sources. It is operated by an energy management system to inject the generated power to the grid. ESS may be employed in hybrid power plants to improve the efficacy of the power plant operation. Two types of ESS are envisaged, smoothing ESS and dispatch BESS. The former is a high-power-rating-low-capacity ESS such as super capacitor, super conducting magnetic energy storage, flywheel etc. exclusively available for treating the intermittency of renewables. The latter is a high capacity BESS with limited power rating, e.g. C or 2C for primarily handling renewables variability. Figure 1 illustrates...
a framework for DHRB. Four key components can be identified in this framework,

- **forecast unit**: carries out forecasting of parameters that affect solar and wind generation, e.g., humidity, temperature, wind speed and direction and solar irradiance, for a given time interval ahead. Depending on the forecast horizon, the forecasting unit must employ suitable techniques that are sufficiently accurate and fast. Machine learning models namely nonlinear auto-regressive with exogenous input and support vector machines, among others, exhibit good performance for near-time forecasting [26, 27]. Therefore, they are candidates for employment in the forecasting unit of the DHRB.

- **Aggregation unit**: using the forecast data, estimates the maximum power output of the wind power plant and solar PV system \( P_w \) based on the layout of the power plant, degradation and other characteristic of the equipment, at every given time step. It is emphasised that the output of the forecast and aggregation units should be the forecast power corresponding to the lower confidence limit at a sufficiently high confidence level to enable reliable dispatchable power from DHRB.

- **Optimal dispatch unit**: finds the optimum set-points for the wind power plant, solar PV system and BESS \( P^* \) based on the estimated available power from wind power plant, solar PV system and the state of the charge of the BESS such that the equipment (and grid code) constraints are respected; these shall be used to bid in the electricity market. The market decisions \( P^* \) are forwarded to the real-time control unit.

- **Real-time control unit**: controls the wind power plant, solar PV system, BESS and smoothing ESS such that the setpoints provided by the optimal dispatch unit (based on market decisions) and instructions by the system operator are met \( (P^*, Q^*) \).

This paper focuses on the optimal dispatch unit of the DHRB framework shown in Figure 1.

2.2 Dispatch time horizons

Electricity system operators, carry out economic dispatch studies ahead of the dispatch time interval (settlement period, \( d \)). To ensure optimal operation of the power system, the system operator considers various factors including available generation capacity, cost of generation, demand and the power system constraints. Therefore, system operators require power generation companies (GENCOs) to submit the volume of the electricity they can provide and the associated cost \( n_D \) settlement periods ahead of the dispatch (e.g., submission deadline in the UK electricity market is two settlement periods ahead of the dispatch [28]). Moreover, to meet technical constraints and grid code requirements, GENCOs may consider \( n_D \) periods after the target settlement period in their resource assessment. Thus, at every moment, four time horizons ahead may be defined from GENCOs’ (in this paper, DHRB operator) perspective for participation in the electricity market (as shown in Figure 2 for \( n_D = 2 \)),

- **Present operation** \( (d^* - n_D - 1) \) which corresponds to the real time operation of the DHRB, based on the committed power, and is dealt with the real-time control unit (Figure 1).

- **Past announced settlement periods** \( (d^* - n_D) \) to \( d^* - 1 \) for which the DHRB operator has already bid in the electricity market and should realise the committed power despite the changes that might have occurred in the available renewable generation forecast in order to avoid power shortage penalty.

- **Target settlement period** \( d^* \) which is the nearest (in time) settlement period for which the DHRB operator shall bid.

- **Future expected settlement periods** \( (d^* + 1) \) to \( d^* + n_D \) which provide an indication of the future renewable generation forecast for efficient resource management.

The last three time horizons are considered by the optimal dispatch unit (Figure 1) of the DHRB.

2.3 Optimisation problem definition

This paper deals with optimal dispatch of DHRB power for injecting to the grid from the perspective of the DHRB operator. Considering the past announced, target, and future expected settlement periods, an optimisation problem can be formulated to find the optimal set-points of a DHRB. The constraints of
the optimisation problem are given by (1)–(14).

\[ P_{\text{h},d} = \sum_{s=1}^{S} P_{\text{h},d} + \sum_{w=1}^{W} P_{\text{w},d} + \sum_{b=1}^{B} P_{\text{b},d} \quad \forall \text{ } t_d \in T_d \]  

(1)

\[ P_{\text{w},d} = \lambda_{\text{w},d} P_{\text{d},d}' \]  

(2)

\[ \omega_{\text{w},d} \lambda_{\text{w},d} \leq \lambda_{\text{w},d} \lambda_{\text{w},d}^\text{max} \]  

(3)

\[ P_{\text{b},d} = \lambda_{\text{b},d} P_{\text{d},d}' \]  

(4)

\[ \omega_{\text{b},d} \lambda_{\text{b},d} \leq \lambda_{\text{b},d} \lambda_{\text{b},d}^\text{max} \]  

(5)

\[ P_{\text{h},d} = \lambda_{\text{h},d} P_{\text{d},d}^{\text{max}} - \lambda_{\text{h},d} P_{\text{d},d}^{\text{max}} \delta_{\text{h},d} - \lambda_{\text{h},d} P_{\text{d},d}^{\text{max}} \delta_{\text{h},d}^{-1} \]  

(6)

\[ \omega_{\text{h},d} \lambda_{\text{h},d} \lambda_{\text{h},d}^\text{min} \leq \lambda_{\text{h},d} \lambda_{\text{h},d}^\text{max} \lambda_{\text{h},d}^\text{max} \]  

(7)

\[ \omega_{\text{h},d} \lambda_{\text{h},d} \lambda_{\text{h},d}^\text{min} \leq \lambda_{\text{h},d} \lambda_{\text{h},d}^\text{max} \lambda_{\text{h},d}^\text{max} \]  

(8)

\[ \omega_{\text{h},d} + \omega_{\text{h},d} \leq 1 \]  

(9)

\[ E_{\text{h},d} = N_{\text{h}} T_{\text{N}} T_{\text{h}} + \lambda_{\text{h},d} P_{\text{h},d}^{\text{max}} \delta_{\text{h},d}^{-1} \]  

(10)

\[ E_{\text{b}}^{\text{max}} \lambda_{\text{b},d} \lambda_{\text{b},d}^\text{min} \leq E_{\text{h},d} \leq E_{\text{b}}^{\text{max}} \lambda_{\text{b},d} \lambda_{\text{b},d}^\text{max} \]  

(11)

\[ \sum_{s=1}^{S} P_{\text{h},d} - \sum_{w=1}^{W} P_{\text{w},d} - \sum_{b=1}^{B} P_{\text{b},d} \leq \lambda_{\text{w},d} \lambda_{\text{w},d}^\text{min} \leq \lambda_{\text{w},d} \lambda_{\text{w},d}^\text{max} \]  

(12)

\[ \lambda_{\text{h},d} P_{\text{h},d}^{\text{max}} \leq \sum_{s=1}^{S} P_{\text{h},d} + \sum_{w=1}^{W} P_{\text{w},d} + \sum_{b=1}^{B} P_{\text{b},d} \]  

(13)

\[ \begin{cases} P_{\text{h},d} = P_{\text{h},d} - P_{\text{h},d} \quad d < d^* \\ P_{\text{h},d} = 0 \quad d \geq d^* \end{cases} \]  

(14)

Equation (1) requires the power output set-points of the wind power plant, solar PV system and BESS in every time step, \( t_d \), within the settlement period, \( d \), to be found such that the total power output of the DHRB remains constant during the settlement period. For every \( t_d \), Equation (2) defines the active power output set-point of the wind power plant as a fraction \( \lambda_{\text{w},d} \) of the forecast available wind power \( P_{\text{d},d}' \). It should be noted that \( \lambda_{\text{w},d} \) is a dependent variable of the optimisation problem. The capability of the wind power plant in altering its output may be narrower than the theoretical range, i.e. zero to the maximum available power; this constraint is imposed by Equation (3). The binary variable, \( \omega_{\text{w},d} \), enables turning off the wind power plant, i.e. \( P_{\text{w},d} = 0 \) in time steps that \( \lambda_{\text{w},d} \) is not feasible. In a similar fashion to the wind power plant, the active power output set-point of the solar PV system for every \( t_d \) is defined by Equation (4) and its utilisation factor is constrained by Equation (5). The power output of BESS at each \( t_d \) is given by Equation (6). The first term is the power injected due to discharging of BESS and the second term is the power drawn for charging it. BESS is discharging when \( P_{\text{b},d} > 0 \) and charging when \( P_{\text{b},d} < 0 \). As noted, the discharging and charging power are defined as fractions \( \lambda_{\text{b},d} \) of the maximum discharge and charge rate of BESS \( (P_{\text{b},d}^{\text{max}} \) and \( P_{\text{b},d}^{\text{max}} \) subject to its discharge and charge efficiency \( (\delta_{\text{h},d} \) and \( \delta_{\text{b},d} \)). Due to technical and physical limits, the feasible/recommended range for discharging and charging of BESS may be narrower than zero to the maximum rate. This constraint is included by Equations (7) and (8). The degradation factors, \( x_{\text{b},d}^{\text{max}} \), \( x_{\text{b},d}^{\text{min}} \), \( r_{\text{b},d}^{\text{max}} \) and \( x_{\text{b},d}^{\text{min}} \) reflect the power fading of BESS and their derivation is discussed in Section 2.4. The role of binary variables, \( \omega_{\text{w},d} \) and \( \omega_{\text{b},d} \) is similar to that explained for wind power plant and solar PV system. It is evident that simultaneous discharging and charging of BESS is not a viable and/or feasible solution, therefore, Equation (9) allows BESS to only discharge or charge at every \( t_d \) by requiring \( \omega_{\text{h},d} = 0 \) and/or \( \omega_{\text{b},d} = 0 \). The stored energy in the BESS at the end of every time step \( (E_{\text{h},d}) \) is dependent on the stored energy at the end of the previous time step \( (E_{\text{h},d-1}) \) as well as the power injected/drawn by the BESS during the current time step; this is given by Equation (10). The hourly self-discharge of BESS (at the rate of \( \delta_{\text{b},d} \)) is mimicked by the first term in Equation (10). To prolong the battery lifetime, the state of charge is maintained within \( [\lambda_{\text{b},d}^{\text{min}}, \lambda_{\text{b},d}^{\text{max}}] \) per Equation (11) in all time steps. The degradation factors, \( x_{\text{b},d}^{\text{max}} \) and \( x_{\text{b},d}^{\text{min}} \) reflect the capacity fading of BESS and their derivation is discussed in Section 2.4. There may be time steps at which the stored energy in BESS is at its minimum limit. If due to self-discharge, the stored energy in BESS further drops, there will be breaching of the BESS operation constraints. Hence, the combination of Equation (11) and the self-discharge component of BESS (i.e. \( \delta_{\text{b},d} \)) can make the problem infeasible. Accordingly, Equation (12) allows the DHRB output to become negative, i.e. consume relatively small power (e.g. in Li-ion batteries up to 0.0042 – 0.0125% per hour [29] of the minimum allowed energy level subject to charge efficiency). This enables cancelling BESS self-discharge component when enough renewable generation is not available. It is trivial that the frequency of such a power draw from grid can be reduced by increasing the forecast horizon, however, not guaranteed to be avoided. Further, Equation (13) limits the BESS charge power at every time step to the total renewable power output plus the least power required to cancel BESS self-discharge component. This constraint implies that BESS is only used for the provision of dispatchable renewable power and not energy arbitrage. However, if the DHRB operator decides otherwise, Equations (12) and (13) need to be amended accordingly. Equation (14) defines the power shortage as difference between the DHRB set point and the committed power for past announced settlement periods. This value is equal to 0 for the target and future expected settlement periods since the DHRB has not been committed for these settlement periods yet.
For the purpose of comparison, the constraints given by Equations (1)–(14) are used to define two separate optimisation problems, each corresponding to an operation strategy.

### 2.3.1 Maximisation of DHRB revenues

\[
\max \sum_{d=1}^{N_D} \left( \frac{P_{d,h} - \Theta_{d,h}^0 - \sum_{j=1}^{B} \sum_{t_j \in T_j} C_{d,h(t_j)}}{N_D} \right)
\]

subject to Equations (1)–(14).

In the objective function, Equation (15), the predicted electricity price at every \(d\) (\(C_{d,h}^0\)) is used to calculate the income of the DHRB subject to penalty on \(P_{d,h}^p\). Excessive use of BESS shortens its lifetime. To avoid exhausting BESS (to further harvest renewables), the latter term in Equation (15) applies a penalty to BESS energy transactions (\(\chi_{d,h,t}\)). The penalty factor is based on the BESS capital cost (\(C_{d}\)) and the BESS nominal energy transaction (\(\chi_{h,\text{total}}\)). BESS energy transaction, \(\chi_{d,h,t}\), is defined as the summation of all energy input and output to BESS due to its charging, discharging and self-discharge during the time step of interest, \(\ell_j\). Similarly, BESS nominal energy transaction, \(\chi_{h,\text{total}}\), is the total amount of energy that can charged to and discharged from BESS during its useful lifetime, i.e. before BESS’ capacity falls below a certain percentage (EOLs) of its rated capacity. Accordingly, \(\chi_{d,h,t}\) and \(\chi_{h,\text{total}}\) are given by Equations (16) and (17), respectively. It is worth mentioning that Equation (17) is the opened form of the similar equation given in [30].

\[
\chi_{d,h,t} = \frac{E_{h,\text{start}} - \delta_{h,\text{start}} + \lambda_{h,\text{start}} P_{d,h}^\text{max} + \lambda_{h,dc,\text{start}} P_{d,h}^{\text{max}}}{N_D N_T} (16)
\]

\[
\chi_{h,\text{total}} = \frac{\frac{Q_{d,h}^\text{max}}{h_{d,t}} - \lambda_{d,h} E_{d,h} F_{d,h}(EOL_{d,h})}{(N_d + 1)^{-1}} + 1 (17)
\]

### 2.3.2 Maximisation of renewable harvesting

\[
\max \sum_{d=1}^{N_D} \left( \frac{1}{N_D N_T} \left( \sum_{t_j \in T_j} P_{d,h(t_j)} + \sum_{a=1}^{W} P_{d,h(t_j)} - P_{d,h}^a M \right) \right)
\]

subject to Equations (1)–(14), where \(M\) is a large number to ensure \(P_{d,h}^a \geq 0\), if the problem doesn’t become infeasible.

The two defined mixed integer linear problems (MILPs) may be solved (separately) for a given number of past announced settlement periods and future expected settlement periods to find the power set-points for the wind power plant \((P_{d,w})\), solar PV system \((P_{d,s})\) and BESS \((P_{d,b})\) at every time step such that the respective objective is realised while the power output of the DHRB remains constant during each settlement period and the results shall be compared.

### 2.4 Battery degradation

Battery modules in a BESS degrade with time, utilisation, environmental and operating condition. To avoid overestimation of the available resources, it is essential to consider this factor for long-term BESS operation and sizing. Several degradation models have been proposed for various battery technologies [31]. For this paper the linear model presented by [30] was employed. Based on this model the battery degradation coefficients are defined.

\[
\chi_{h,dc,t}^\text{max} = \chi_{h,dc,t}^\text{min} = (19)
\]

\[
\chi_{h,dc,t}^\text{max} = \chi_{h,dc,t}^\text{min} = \chi_{h,dc,t}^\text{end} = 1 (21)
\]

It is emphasised that more sophisticated battery degradation models may also be incorporated [32–35].

Direct inclusion of the battery degradation model given by Equations (19)–(21), i.e. treating degradation coefficients as variables does not affect the MILP nature of the optimisation problems defined in Section 2.3. However, to enable the integration of more sophisticated degradation models, the battery degradation coefficients shall be calculated prior to solving the optimisation problem and treated as parameters. To this end, prior to solving the optimisation problem, the battery degradation coefficients are calculated for two time steps:

- Start of the first settlement period, which is the beginning of \(d = n_D\) (based on previous operating points) and is named \(\chi_{\text{start}}\).
- End of the last settlement period: which is the end of \(d = n_D\) (based on worst operating scenario, i.e. \(\omega_{h,dc} \lambda_{h,dc,t} = \omega_{h,dc} \lambda_{h,dc,t} = 1\)) and is named \(\chi_{\text{end}}\).

Provided that the time length of, \(d = n_D^+\) to \(d = n_D^-\), is sufficiently small, a linear approximation may be used to calculate the degradation coefficients at every time step, using \(\chi_{\text{start}}\) and \(\chi_{\text{end}}\):

\[
\chi_{d,t} = \frac{(\chi_{\text{end}} - \chi_{\text{start}})(d - d^+ + n_D^- + \text{frac}(\frac{d^+ - 1}{N_T}) \chi_{\text{start}} + \chi_{\text{end}}) + \chi_{\text{start}}}{n_D^+ + n_D^- + 1} (22)
\]

In Equation (22), the function, \(\text{frac}(\cdot)\), yields the fractional part (decimal part) of the input value. The degradation coefficients found with this approach are then passed to the optimisation problem as parameters (rather than variables).

It is worth mentioning that compared to BESS, the degradation of wind power plants and solar PV systems is a slower
CASE STUDY

Rolling algorithm

In this algorithm, the optimisation problem is solved for (e.g., forecast, battery degradation coefficients) in every run series. It facilitates continuous optimisation using updated data. Figure 3. Rolling is a technique for optimisation over a time period. For a given confidence level, e.g., 95%. However, for real-world operation, the renewables forecast is generated in real-time by the forecast and aggregation units (see Figure 1) based on the lower confidence limit with the desired confidence level for several time steps ahead. It was assumed that each settlement period is 30 min long and the electricity market operator requires power bids to be submitted 1 h ahead (these can be adjusted based on market requirements in each power system). For efficient management of BESS, two future expected settlement periods were used, however, more can be considered depending on the availability of forecast data and computational cost. It was assumed that the wind power plant and solar PV system can regulate their output between 0 and maximum available power at every time step. The DHRB injects power under a contract-for-difference (CFD) scheme [44] with £60/MWh strike price (2019 £) [45].

The short-term balancing and reliability cost increase due to the intermittency of renewables is assumed £5/MWh [46, 47]; since a DHRB guarantees the dispatch, the additional short-term balancing and reliability cost can be avoided and deemed as a potential income for the DHRB. Wind power plant and PV system parameters, BESS parameters and other parameters of the optimisation problem are summarised in Tables 1–3, respectively. It is acknowledged that in a market which exposes renewable generation to the market electricity prices, a time series of predicted $C_{\lambda,d}$ should be used instead. This requires prediction of $C_{\lambda,d}$ based on the historic values, loading and fuel prices, among others, which is out of the scope of this paper. Moreover, the committed/dispatched power depends on the market and

2.5 Rolling algorithm

To adapt the presented methodology for the continuous operation of the DHRB, rolling algorithm shall be employed per Figure 3. Rolling is a technique for optimisation over a time series. It facilitates continuous optimisation using updated data (e.g., forecast, battery degradation coefficients) in every run [38]. In this algorithm, the optimisation problem is solved for $d^n - n_D^n$ to $d^n + n_D^n$ time window and results are stored. The target settlement period is increased by 1, i.e., the time window slides ahead by 1 settlement period. Once forecast data is available for $d^n + n_D^n$ the optimisation problem is solved again to find set-points for $d^n + n_D^n$ and update set-points for the other settlement periods. As implied, the forecast for every $d_D$ can be updated (and perfected) $n_D^n + 1$ times before $d$ leaves the sliding time window. Employing the rolling algorithm enables readjustment of the solar-wind and BESS set-points according to the most recent forecast not only for the target but also the past announced settlement periods as long as the settlement period is still within $d^n - n_D^n$ to $d^n + n_D^n$ time window. In this paper, BESS sizing is considered. Therefore, the stop criteria is BESS end of life, however, any other stop criteria may be used by the DHRB operator.

It should be noted that the distribution of renewables forecast error depends on the forecast horizon. The nearer in time the forecast subject, the more concentrated the error around the mean value [39, 40]. The accuracy of forecast reduces with the increase in forecast horizon. For a given confidence level,

| Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|
| $\lambda_{w_{max}}$ | 1.0 | $\lambda_{w_{min}}$ | 0.0 |
| $\lambda_{w_{max}}$ | 1.0 | $\lambda_{w_{min}}$ | 0.0 |
| $\lambda_{w_{max}}$ | 1.0 | $\lambda_{w_{min}}$ | 0.0 |

FIGURE 3 Rolling algorithm for DHRB

TABLE 1 Wind power plant and PV system parameters
TABLE 2 Battery parameters

| Parameter     | Value | Parameter     | Value |
|---------------|-------|---------------|-------|
| $E_{b}^{max}$ | 5 MWh | $\lambda_{b,e}^{max}$ | 1.0   |
| $\delta_{b,e}$ | 0.005% | $\lambda_{b,e}^{min}$ | 0.0   |
| $\lambda_{b,c}^{max}$ | 1.0 | $\lambda_{b,c}^{min}$ | 0.0   |
| $\lambda_{b,d}^{max}$ | 10 MW | $\delta_{b,d,e}^{max}$ | 1.0   |
| $\lambda_{b,d}^{min}$ | 0.95 | $\delta_{b,d,e}^{min}$ | 0.0   |
| $E_{OLb}$ | 0.65 | $N_{b}$ | 4000   |
| $C_{b}$ | £261/kWh [48] | - | -     |

TABLE 3 Other parameters

| Parameter     | Value     | Parameter     | Value  |
|---------------|-----------|---------------|--------|
| $C_{h,d}$ | £65/MWh | $C_{h,d}^{e}$ | £2700/MWh |
| $\eta_{D}^{+}$ | 2 | $\eta_{D}^{+}$ | 2 |
| $\eta_{T}^{+}$ | 3 | $\eta_{T}^{+}$ | 2 |

4  | RESULTS AND DISCUSSION

4.1  | Operation strategy

The presented rolling algorithm was run to dispatch the DHRB for one year with two different strategies, maximisation of DHRB revenues (max revenue) and maximisation of renewable harvesting (max harvest). Power output set-points were optimised by the algorithm for the wind power plant, solar PV system and BESS. Figures 4–6 illustrate the power set-points for the wind power plant, solar PV systems and BESS, respectively, for a sample summer day. When considered individually, the power output of the wind power plant, solar PV system and BESS, fluctuate significantly within every settlement period (30 min). However, the net power produced by the DHRB stays constant for the duration of every settlement period; this is shown in Figure 7.

It is evident from these figures that the power set-points found by max revenue and max harvest strategies follow a similar trend, however, in some time steps they are not identical; this is more visible in the BESS set-point. This discrepancy is mainly due to the difference in charging/discharging BESS (and consequently charge state) in the studied strategies. Accordingly, the use of BESS is categorised:

- Inevitable use: since any uncommitted power ($P_{h,d}^{c}$) is heavily penalised in both strategies (by $C_{h,d}^{c}$ in max revenue and big M in max harvest), BESS is used to meet the committed power for $d^{+} - n_{D}^{+}$ and storing the results took on average 2 s for every iteration (every target settlement period).

- Optimum use: considering that a penalty is applied to the energy transactions of BESS (charge/discharge) in Equation (15), max revenue entails minimal use of BESS unless it’s essential (inevitable use) or it results in a higher revenue in the $d^{+}$ to $d^{+} + n_{D}^{+}$ interval. In contrary, the use of BESS is not penalised in Equation (18). Accordingly, the optimisation problem uses BESS as needed to avoid non-dispatchable power as much as possible, i.e. maximise harvesting of renewables. It should be noted that non-dispatchable power is the portion of power that is neither dispatchable nor stored in BESS.

The BESS state of charge for the sample summer day is shown in Figure 8. It is noted that the energy input and output...
for the max revenue strategy is smaller than that of the max harvest. A similar trend holds for the rest of the days of the year. Figure 9 illustrates the annual cumulative probability of BESS power set-point. The set-point is within 0.5 MW in 57% and 45% of the time steps for max revenue and max harvest, respectively.

As implied by Figure 7, part of the available renewable energy is non-dispatchable. Table 4 lists the annual dispatchable and non-dispatchable energy achieved in the studied strategies. Compared to max revenue, at the cost of higher energy transaction in BESS, the max harvest strategy yielded approximately 1 GWh more dispatchable energy by reducing the non-dispatchable energy. However, the excess usage of BESS in max harvest case raises concerns about BESS exhaustion. The degradation coefficient of BESS is shown in Figure 10 for 1 year of DHRB operation with max revenue and max harvest strategies. The larger BESS energy transaction manifests in faster degradation of BESS with max harvest strategy. Therefore, max harvest may not be an ideal operation strategy for a DHRB.

It is worth mentioning that indeed max revenue and max harvest can be combined as a multi-objective problem by applying weighting factors and summing up Equations (15) and (18). However, compared to max revenue, this means that by sacrificing revenue, renewables harvesting is increased with multi-objective problem. More harvesting of renewables than what results with max revenue, requires more use of BESS, hence its faster exhausting. As mentioned earlier, the problem is solved

| Strategy       | Dispatchable energy (GWh) | Non-dispatchable energy (GWh) |
|----------------|----------------------------|-------------------------------|
| Max revenue    | 257.75                     | 1.41                          |
| Max harvest    | 258.71                     | 0.38                          |
from the DHRB operator’s point of view. Hence, a lower income and shorter BESS lifetime is not acceptable.

4.2 BESS size and economy

To study the effect of BESS size, a multi-year analysis was carried out for BESS sizes ranging from 2.5 to 17.5 MWh, with 2.5 MWh increment (rated at 2C) using the max revenue strategy. For this purpose the 1-year wind and solar generation profile was duplicated for 10 years and used as an input to the presented algorithm. The total non-dispatchable energy in the first year of operation of DHRB is depicted in Figure 11. Initially, the annual non-dispatchable energy reduced with the increase in BESS size, however, after a certain size of BESS (i.e. 10 MWh) the improvement was marginal.

Figure 12 illustrates the degradation coefficient of BESS through its lifetime (note that EOL = 0.65). The increase in the BESS size prolonged its lifetime. This is due to the fact that the larger BESS size, the smaller the per-unit depth of charge and discharge will be.

The existing approach for wind and solar generation is to inject all the generated power to the grid in a non-dispatchable fashion (if wind curtailment is not mandated by the system operator). Provision of sufficient flexible reserve is a key to tackle the intermittency of the injected power. Hence additional balancing and reliability costs will be inflicted due to the integration of non-dispatchable renewable generation. In the case study, this cost is assumed £5/MWh [46, 47] for the renewable energy injected to the grid. Since a DHRB guarantees the dispatch, it does not inflict such an additional cost. Therefore, this amount is taken as the only additional reward/incentive provided to the DHRB compared to a wind power plant and/or solar PV system that are operated with the existing approach. However, the DHRB must bear two types of costs in order to avail of this reward/incentive,

- Capital: the capital cost of BESS (£261/MWh of BESS capacity), and
- Operational: the loss of income at the rate of £60/MWh (equivalent to the CFD strike price) for the portion of the available renewable power that is non-dispatchable and/or is used to charge BESS.

It is worth mentioning that the worst case has been assumed for the operational cost in the case study. In the best case, any non-dispatchable power from DHRB shall be injected to the grid and treated with the existing approach, hence, the income for this portion of the available power secured.

An economic analysis was carried out on the simulation results for the BESS sizes and DHRB operation strategy of interest, i.e. max revenue. The additional income/loss of the DHRB compared to a similar size wind power plant and solar PV system operated with the existing approach was calculated for each case. This was used to establish the average annual rate of return for the extra investment on BESS that the DHRB should incur. As seen in Figure 13, for all of the BESS sizes, the rate of return is a positive value meaning that despite the operational cost borne, because of the £5/MWh incentive/reward, the DHRB is able to produce higher revenue than a similar size wind power plant and solar PV system operated with the
existing approach. Moreover, it is evident from Figure 13 that the lower the BESS size the better the annual average rate of return will be. However, it should be considered that the lifetime of BESS will also be shorter. This means that the DHRB will have less time for making revenue before it needs to replace batteries. It is pointed that the non-linearity of the annual rate of return against the BESS capacity is due the fact that the total capital cost increases with BESS size, however, the average annual additional income of DHRB (compared to a similar size wind power plant and solar PV system operated with the existing approach) does not increase substantially after 10 MWh.

Figure 14 shows the cumulative additional cash flow of the DHRB when operated with max revenue strategy (compared to a similar size wind power plant and solar PV system operated with the existing approach) through the lifetime of BESS for various sizes of BESS. To provide further ground for comparison, the same analysis was also carried out for DHRB operated with max harvest strategy; the results are shown in Figure 15. It is noted that with both DHRB operation strategies, max revenue and max harvest, regardless of the BESS size, the slope of the cumulative cash flow trend is positive. This indicates that DHRB is able produce higher revenue compared to a similar size wind power plant and solar PV system operated with the existing approach. In all cases, it is seen that the DHRB is able to recover (cumulative cash flow becomes positive) its additional investment (on BESS) solely through the additional £5/MWh incentive/reward. Hence, DHRB is superior to existing approaches. Moreover, in general, compared to max harvest, the cumulative cash flow of DHRB at the end of life of BESS is higher when DHRB is operated with max revenue strategy. It is witnessed that the higher the size of BESS, the higher the cumulative cash at the end of life of BESS will be when max revenue strategy is used. Both phenomenons lie on the fact that the longer the BESS lifetime, the more dispatchable energy can be injected by the DHRB. This denotes the importance of the operation strategy and the right choice of BESS size.

5 CONCLUSION

This paper focused on alleviating the non-dispatchability of renewables by a DHRB, which is optimal and also considers BESS degradation. Dispatchable renewable generation can facilitate high renewables penetration in power systems with limited interconnection by reducing the need for reserve and flexibility. The DHRB framework consists of four main units: forecast, aggregation, optimal dispatch and real-time control. The focus of this paper was mainly devoted to the optimal dispatch unit employed in the DHRB framework. A continuous BESS degradation mechanism was incorporated in the proposed rolling-algorithm-based-optimal dispatch unit which optimises the dispatchable power of the DHRB. Two different operation strategies, i.e. maximisation of DHRB revenue and maximisation of renewable harvesting were considered for this purpose. The dispatchable power found by the presented algorithm can be used to participate in the interval-ahead (e.g. hour-ahead in the UK) electricity market. Simulation was carried out for 1 year period on an 80 MW DHRB. At every
time-step, set-points were found for the wind power plant, solar PV system and BESS such that the operational constraints of the equipment were respected. It was demonstrated that dispatchable renewable power is achievable with the presented algorithm. Comparing the results, it was concluded that max harvest yields more dispatchable energy compared to max revenue at the cost of faster exhaustion of BESS. Therefore, it might not be an ideal operation strategy. The effect of BESS size on its degradation and non-dispatchable energy with the presented algorithm was studied. It was shown that employing larger size of BESS reduces the annual non-dispatchable energy, however, the rate of improvement decays with the increase of BESS size. A larger BESS capacity results in a longer lifetime of BESS as well as higher total capital cost. An economic analysis was carried out by extending the simulation to the end of life of BESS. It was demonstrated that the average annual rate of return of extra investment on BESS (for a DHRB) decreases with the increase of BESS size when max revenue operation strategy is taken. However, it should be noted that because of the longer lifetime, the higher the BESS size, the higher the cumulative cash flow at the end of life of BESS will be. It is pointed out that due to the use of lower confidence limit of the forecast, it is highly probable (depending on the confidence level) for the actual DHRB available power to be higher than predicted. The surplus power can be injected as non-dispatchable. Moreover, part of the energy stored in the battery as well as any dispatchable power that is not committed, can be used to participate in the reserve market. However, there is the dilemma for the power plant operator to whether use the uncommitted power to participate in the reserve market or simply to also inject it as non-dispatchable generation. Participation in the reserve market depends on the minimum bid constraint and the yearly/hourly/sub-hourly reserve market price, among others. Furthermore, the availability of reserve capacity needs to be guaranteed which entails conservative market orders by DHRB. Future research may focus on addressing this question as well as the integration of demand response in a DHRB.

**NOMENCLATURE**

\[
P_{i,d}^0, P_{i,b}^0 \quad \text{Forecast available active power from solar and wind power plant at } t_d
\]

\[
\lambda_{i,d}^{\text{max}}, \lambda_{i,d}^{\text{min}} \quad \text{Utilisation factor bounds of solar PV system available active power}
\]

\[
\lambda_{w,d}^{\text{max}}, \lambda_{w,d}^{\text{min}} \quad \text{Utilisation factor bounds of wind power plant available active power}
\]

\[
E_{\text{OL}} \quad \text{Per unit capacity of battery energy storage system (relative to nominal capacity) at its end of life}
\]

\[
N_b \quad \text{Battery energy storage system nominal charge cycles}
\]

\[
C_b \quad \text{Battery energy storage system capital cost}
\]

\[
X_{\text{b,total}} \quad \text{Total available energy transaction of battery energy storage system through its lifetime}
\]

\[
\delta_{h,c} \quad \text{Hourly self-discharge percentage of battery energy storage system}
\]

\[
\delta_{h,c}, \delta_{b,c} \quad \text{Charge and discharge efficiency of battery energy storage system}
\]

\[
\rho_{b,d}^{\text{max}}, \rho_{b,d}^{\text{min}} \quad \text{Battery energy storage system charge power fading coefficients at } t_d
\]

\[
\lambda_{b,d}^{\text{max}}, \lambda_{b,d}^{\text{min}} \quad \text{Depth of charge and discharge bounds of battery energy storage system}
\]

\[
\rho_{b,d}^{\text{max}}, \rho_{b,d}^{\text{min}} \quad \text{Battery energy storage system discharge power fading coefficients at } t_d
\]

\[
\lambda_{b,c}^{\text{max}}, \lambda_{b,c}^{\text{min}} \quad \text{Utilisation factor bounds of battery energy storage system discharge active power rate}
\]

\[
P_{b,d} \quad \text{Active power output set-point for hybrid power plant at } d
\]

\[
P_{w,d}, P_{s,d}, P_{b,d} \quad \text{Active power output set-point for solar PV system, wind power plant and battery energy storage system at } t_d
\]

\[
E_{b,d} \quad \text{Stored energy in the battery energy storage system at } t_d
\]

\[
X_{b,d} \quad \text{Total battery energy storage system energy transaction through } t_d
\]

\[
\lambda_{b,c,d}, \lambda_{b,c,d} \quad \text{Utilisation factor of battery energy storage system available charge and discharge rate at } t_d
\]

\[
\lambda_{w,d}, \lambda_{w,d} \quad \text{Utilisation factor of available solar and wind power plant active power at } t_d
\]

\[
\omega_{s,d}, \omega_{w,d} \quad \text{Status of solar and wind power plant at } t_d \quad (\text{binary, on: } 1, \text{off: } 0)
\]

\[
\omega_{b,d}, \omega_{b,d} \quad \text{Status of charge and discharge of battery energy storage system at } t_d \quad (\text{binary, on: } 1, \text{off: } 0)
\]

\[
P_{s,d}^0, P_{w,d}^0, P_{b,d}^0 \quad \text{Actual active power output of the solar PV system, wind power plant and battery energy storage system}
\]
\[
\begin{align*}
\hat{n}_{D}^+ & \quad \text{Number of future expected settlement periods} \\
\hat{n}_{D}^- & \quad \text{Number of past announced settlement periods}
\end{align*}
\]

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