Modelling the effects of low-cost large-scale energy storage in the UK electricity network

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***Abstract*— In this paper we present a framework for modelling the impacts of large-scale electricity storage in the Great Britain (GB) electricity network. Our framework consists of two principle components; firstly, a data-driven model of the GB powerplant dispatch, and secondly, an energy storage module. The storage module takes the powerplant dispatch and modifies it considering the specified energy storage characteristics (capacity, charging/discharging power and efficiency) in order to minimize an objective function. In particular, we consider two objective functions, minimizing the system running cost and minimizing the system emissions. We demonstrate our approach using data from the GB electricity system in 2015. Our model is primarily built in python and is entirely open-source in nature.**

Keywords—UK electricity system, optimization, MILP, non-linear optimization, energy storage, carbon emissions

I. Introduction

Globally, there is a huge need for a large-scale low-cost method of energy storage. If available, this type of technology could facilitate enormous deployments of renewable electricity generation and may ultimately represent the key missing technology to enable future sustainable energy systems. Offshore energy storage technologies represent promising methods of achieving this aim, with the primary advantage of many offshore energy storage proposals being potential cost effectiveness at large-scale rather than high efficiency. However, while facilitating renewable generation is the primary motivation for bulk energy storage development, actual energy storage operation in the power system is costs-driven, and therefore may or may not align with the goal of emissions reduction. In fact, some recent studies have suggested that costs-driven storage may introduce non-trivial increases in the level of system emissions [1, 2]. Therefore, there is a need for models to understand the effects of any new storage deployments. Marginal emissions factors represent the best way of estimating the impact of storage, essentially representing the emissions of the electricity generation unit that storage may either increase or decrease [3]. These can be satisfactorily estimated using statistical models based on historical data. A timeseries of marginal emissions factors then allows parties interested in storage to estimate the impact of storage by examining emissions at the times of charge and discharge. However, when considering bulk energy storage, it is likely that the storage operation itself may change the marginal emissions by changing the marginal plant on the system. In this case, dispatch models are required in order to understand how the storage changes the powerplant fleet operation.

In this work, we develop a dispatch model based on historical data. We then couple this with an energy storage module, which schedules storage operation, considering storage in the context of the entire electricity system. We consider storage operation in the GB electricity system, explicitly operating under two different operational strategies – (1) minimizing the operational fuel cost of the system and (2) minimizing the system wide emissions. We find that these strategies suggest conflicting energy storage operation, with minimizing fuel costs predominantly implying storage charging using coal generation and displacing CCGT which is unfavourable from an emissions perspective. However, considering a simple high wind scenario (wherein the wind generation from 2015 is tripled), these operation strategies start to overlap, with both using storage to avoid wind curtailment. Importantly, our model is developed with reproducibility in mind. It is developed in the python – one of the most popular open source programming languages – and is entirely open source in nature.

II. Methodology

To understand the operation of energy storage within the GB power network and its effects on the existing generation fleet, we first must approximate the dispatch of the power network. The merit order stack approach is the most common approach to understand how powerplants are scheduled within a system [4]. This involves 'stacking' the generation units within the system, starting with the lowest marginal cost units at the bottom of the stack and ordering the units by their marginal operational costs. The resulting dispatch then schedules generators to produce power when the demand is higher than the sum of the capacity of the generation units below them in the merit order stack. Therefore, a generation unit with a lower marginal cost will always be scheduled to produce at maximum capacity before a generation unit with a higher marginal cost is scheduled. This simple approach leads to discrepancies with observed plant dispatch, as powerplants are often dispatched out-of-merit in real systems [5]. Furthermore, renewable energy generators like wind and solar generators do not fit neatly within the merit order stack, since their output cannot easily be scheduled. The marginal fuel costs of these generation units are close to zero (since their fuel is free) and their output is often subsidized to promote clean energy development (allowing them to sell energy below zero price and still generate income, provided the sell price is greater than minus the subsidy). Therefore, when renewables are considered, the approach is typically to enter them at the base of the merit order, displacing the most expensive plants on the system when they are available [6]. Demand is then essentially considered net-of-renewables, and in the instance that demand is less than the total renewable generation, there are no plants generating and some renewable generation must be curtailed. This is of course an

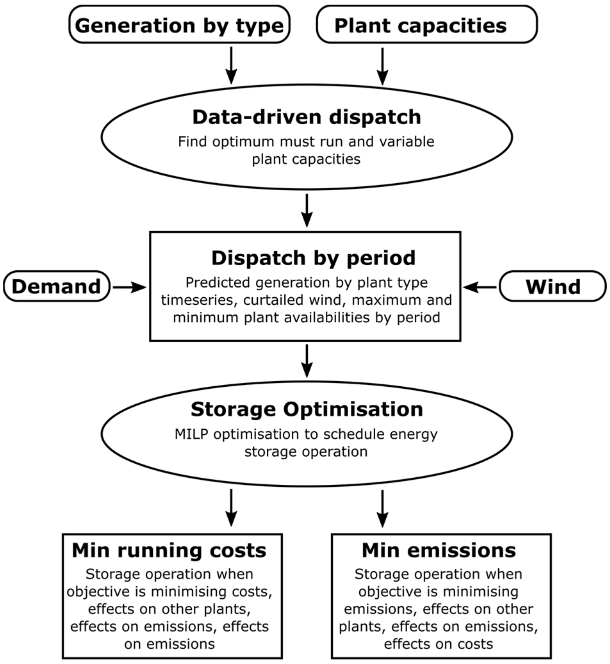

Figure 1: Schematic diagram of the model framework

oversimplification, but the qualitative effect has been observed in real electricity systems in many countries [6,7]. In real systems intermittent renewable energy is curtailed significantly before all the other plants in the system have reduced their output to zero, since some plant must be available to cope with sudden and unforeseen changes in the output of renewable generators.

Interconnectors are also difficult to account for within any dispatch model, since their operation depends on interactions between different electricity markets and therefore dispatch in multiple countries must be considered. In the case of the UK, there is interconnection with France (4GW), the Netherlands (2GW) and Ireland (1GW). In this paper we disregard the influence of interconnectors. Since the capacity of the GB interconnectors is significantly smaller than the installed plant capacity, in the GB context neglecting interconnectors is a reasonable first approximation, with recent research into the emissions associated with European electricity showing that GB has very similar consumption and production emissions intensities [8]. This can be contrasted with countries such as Austria, which has a low production intensity because of the high capacity of hydro power, but a higher consumption intensity because power is imported from nearby countries, such as Germany and the Czech Republic, with higher levels of generation from coal and gas.

A. *Data*

We use data from the GB system in 2015 to develop our model framework. The data is in the form of half-hourly generation by type obtained from the Elexon portal [9]. The included generator types are CCGT, coal, INTEW (East-West interconnector), INTFR (French interconnector), INTIRL (Moyle interconnector), INTNED (Dutch interconnector), NPSHYD (non pumped storage hydro), nuclear, OCGT, oil, other, pumped storage and wind.

Since we are interested in the effect of storage on these plants, we consider the total 'demand' at each time period that must be met by these powerplants is the sum of the output of all the plant types, neglecting interconnectors and Pumped Hydroelectric Storage (PHS). This essentially assumes that negative PHS output (i.e. pumping) and negative interconnector output (i.e. transferring energy out of the UK) are demand that must be met by the rest of the powerplant fleet and neglects the demand which is met by positive interconnector output or PHS discharging.

B. *An extended data driven merit order stack*

The above points lead us first to construct the simple merit order stack as shown in Figure 2A, based on the plant capacities as shown in Table 1. A naïve merit order stack, this model dispatches plants with low marginal operation costs at full capacity before any other plants with higher marginal costs are dispatched. We denote the generation from a particular plant type G_i, where G is the generation value and the subscript i indexes the different generator types (*i.e.* nuclear, coal, *etc.*). Considering the demand-net-of-wind that must be met by the major generation components at each time period indexed by subscript t, $D_t - W_t$, the merit order stack approach outlined yields a timeseries of the generation from each generation type, G_{it} . The total annual generation, G_i^{annual}, from each type i is given by summing the generation at each period, as shown in Equation 1.

$$G_i^{annual} = \sum_t G_{it} \qquad (1)$$

The simple merit order stack leads to the annual production values as shown in Figure 2B. This can be compared to the annual dispatch from the real data as shown in Figure 2H. We see that that the simple dispatch model grossly overestimates the share of energy generated by baseload generators, in particular nuclear and hydro, and underestimates the generation from more flexible generators, like CCGT.

TABLE I. MAJOR GENERATION COMPONENTS IN THE UK AS WELL AS THEIR ESTIMATED MARGINAL COSTS AND EMISSION RATES. CAPACITIES ARE APPROXIMATED FROM PAGE 153 OF [10]. MARGINAL COSTS ARE ESTIMATED USING FUEL COSTS FROM [11].

Fuel Type	**Capacity (GW)**	**Marginal Cost (£/MWh)**	**Carbon Intensity** (gCO_2/kWh)
Coal	15	26	937
CCGT	29	40	394
OCGT	1	60	651
Hydro	1.4	3	0
Nuclear	9.5	10	0
Other	2	70	300
Wind	4.9[1]	0	0

In general, we find that there is significant out-of-merit behaviour which leads to large discrepancies between the

[1] Wind has been de-rated by a capacity factor of 0.43

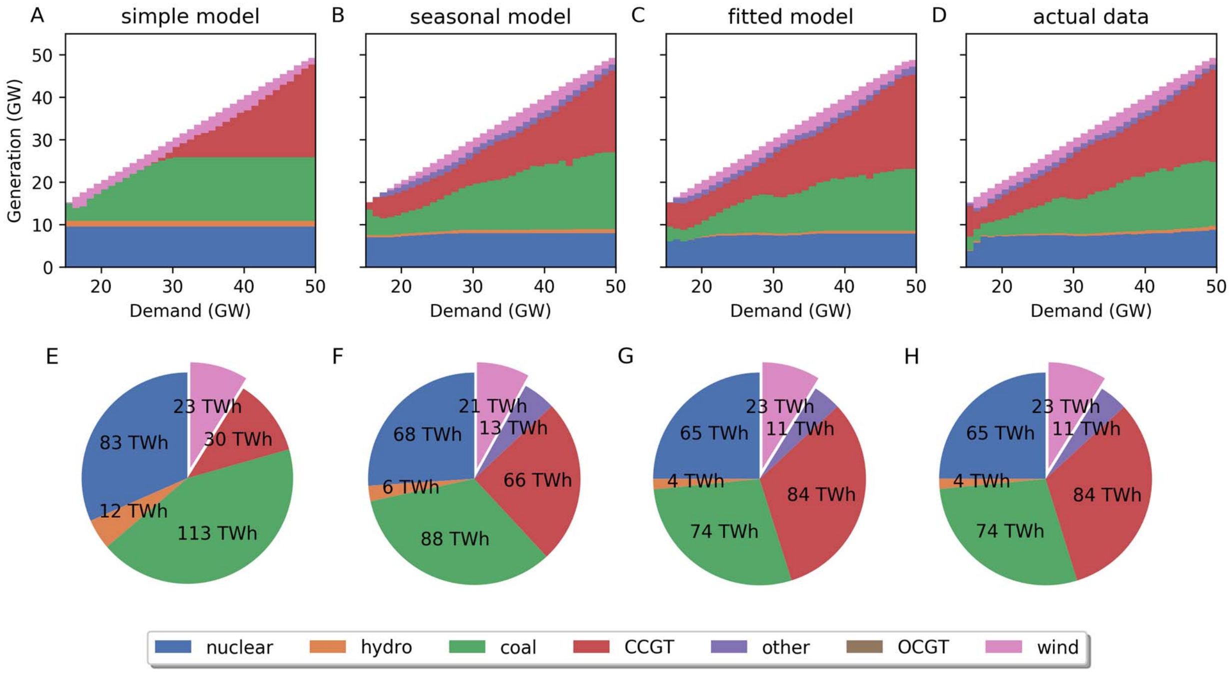

Figure 2: Merit order stack models for the UK vs. the actual dispatch. (A) Dispatch by demand of the different plant types in the simple model. (B) Dispatch by demand for the seasonal must-run model. (C) Dispatch by demand for the optimised model. (D) Dispatch by demand using real data. (E) Predicted annual generation by plant type in the simple model. (F) Predicted annual generation by plant type in the seasonal must-run model. (G) Predicted annual generation for the optimised model. (D) Actual annual generation values.

simple model dispatch and the data (compare Figures 2A and 2E with Figures 2D and 2H). We postulate that these effects predominantly arise from two situations. Firstly, the demand in the GB system changes significantly from season to season, with the maximum demand net of wind and interconnectors in the 2015 winter months being 49 GW (for the months of January-March) compared to the maximum demand in the summer months (July, August and September) of 36 GW. Therefore, it is likely that certain plants may shutdown entirely for low-demand seasons, since operating during these seasons would significantly increase their running costs for very few hours of operation. Furthermore, different generators have different degrees of flexibility and only certain plants have the ability to suddenly change their output. Therefore, the system operator requires that at all times there needs to be a certain level of flexible plant on the system. Typically, in the GB system the flexibility is provided by CCGT plants, and therefore we postulate there needs to be a minimum level of CCGT generation running all the time.

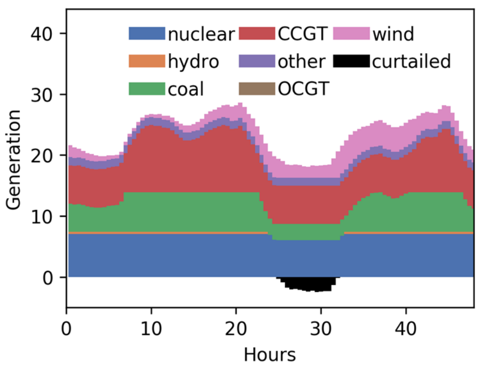

Figure 3: Illustrating the must run constraint. When demand-net-of-wind is reduced below the level of the must-run generation, wind is preferentially curtailed rather than reducing must-run generation.

To include these two effects, we specify a unique stack in each season (winter, spring, summer and autumn) and split the stack in each season into two components – a dispatchable component and a must-run component. The must-run component in particular adds an additional degree of complexity, since a situation can arise in which the demand is less than the must run component, particularly when wind is included. Therefore, we stipulate that when wind would otherwise reduce the demand below the value of the must-run generation, wind power is preferably curtailed before the must-run generation is reduced. Hence, the dispatch model including must-run and dispatchable components takes the timeseries inputs of demand, D_t, and wind, W_t, and returns the estimated generation of each plant type, G_{it}, and the wind generation curtailed, W_t^{cur}, for each time period. A similar approach is taken in [5] to avoid nuclear curtailment in their model. The must-run components for each plant type run at all times when the demand is greater than the sum of the must run components and the dispatchable component of the merit order is used to meet the demand above this level. This situation with curtailed wind and must-ruin components is illustrated in Figure 3.

In order to specify the exact levels of plant availability for the merit order stack in each season, we use a data-driven approach. Firstly, we plot the average daily plant dispatch and the average dispatch by demand in each season, as shown in Figure 4. Inspecting these plots, we estimate the system must-run and dispatchable components based on the minimum and maximum observed generation values for each of the different generation types, as described in Table 2. Where there is insufficient generation to cover the maximum demand in each season we modify the estimates accordingly until all demand

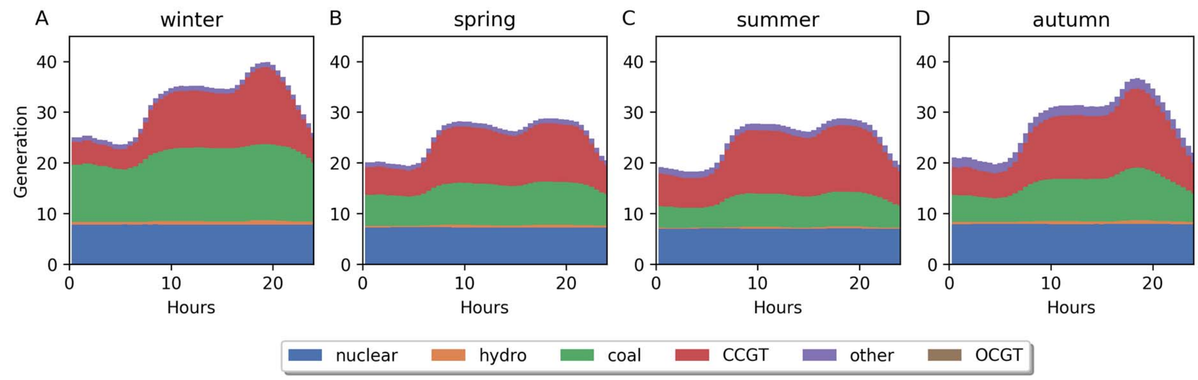

Figure 4: Average daily plant dispatch by season. (A) Winter. (B) Spring. (C) Summer. (D) Autumn.

TABLE II. PARAMETERS FOR THE THREE DISPATCH MODELS; SIMPLE MODEL, SEASONAL MUST-RUN MODEL AND OPTIMISED MODEL.

	Must-run components (GW)						Dispatchable components (GW)					
Model	**Nuclear**	**Hydro**	**Coal**	**CCGT**	**Other**	**OCGT**	**Nuclear**	**Hydro**	**Coal**	**CCGT**	**Other**	**OCGT**
Naive	-	-	-	-	-	-	8.0	1.0	16.0	29.0	2.0	1.0
Seasonal (winter)	7.0	0.5	8.0	5.0	1.	0.0	1.0	0.5	10.0	20	1.0	0.0
Seasonal (spring)	7.0	0.5	6.0	5.0	1.0	0.0	1.0	0.3	6.0	20	1.0	0.0
Seasonal (summer)	7.0	0.5	4.0	5.0	1.0	0.0	1.0	0.1	6.0	20	1.0	0.0
Seasonal (autumn)	7.0	0.5	5.0	7.0	1.0	0.0	1.0	0.1	6.0	20	1.0	0.0
Opt. (winter)	6.7	0.3	7.4	4.0	0.9	0.0	1.2	0.3	7.3	18.1	1.6	0.0
Opt. (spring)	6.1	0.0	3.5	5.6	1.0	0.0	1.2	0.5	5.0	20.0	1.0	0.0
Opt. (summer)	6.1	0.0	2.6	6.3	1.3	0.0	1.0	0.3	3.9	20.0	0.5	0.0
Opt. (autumn)	7.1	0.0	2.4	5.7	1.9	0.0	0.9	0.6	6.7	20.0	1.0	0.0

can be met throughout the year, including the effects of wind. We denote this model 'seasonal must-run model'. Figures 2B and 2F illustrate the average annual plant dispatch by demand and the total annual generation by plant type implied by the extended merit order stack approach specified. We can see that the model is a significant improvement on the simple merit order stack.

C. *Refining the extended merit order stack*

Finally, realising that our choice of plant availability levels may not be optimal, we refine the merit order stack by setting the rules for the must-run and dispatchable components via an optimisation process. In order to do this, we specify an error term which is the sum of squares of the difference between the modelled generation at each period and the actual generation, as shown in Equation 2.

$$Err^{\text{gen}} = \sum_i \sum_t \left(G_{it} - G_{it}^{\text{data}}\right)^2 \qquad (2)$$

The optimisation is constrained so that the maximum generation of each type that can be assigned to the merit order is the maximum installed capacity. Interestingly, we find that this in itself leads to unsatisfactory results as it selects plant availabilities that are insufficient to cover all the demand at several winter time periods. We also note that since wind is curtailed in our dispatch model when it would otherwise reduce the output level of some plant types below their specified the must-run values, the optimisation can naively lead to significant wind curtailment (compare Figure 2F with Figure 2H). However, the wind generation data used for 2015 represents the post curtailment generation. Therefore, we augment the error term with two additions; firstly, we add an error which penalises the model when demand is higher than available generation and secondly, we add a term which penalises the model for wind curtailment. Hence the total error specified for the model dispatch is given by Equation 3.

$$Err^{\text{tot}} =$$

$$Err^{\text{gen}} + \alpha^{\text{dem}} \sum_t \left(D_t - \sum_i G_{i,t}\right) + \alpha^{\text{cur}} \sum_t W_t \qquad (3)$$

Minimising this error is a non-linear optimisation problem, for which we use the SLSQP solver from the scipy version 1.1.0 [12]. The final weight parameters ($\alpha^{\text{dem}} = 10^2$ and $\alpha^{\text{cur}} = 2$) are selected based on trial and error. The optimisation returns the values for the must-run and dispatchable components of the merit order stack in each season as shown in Table 2. We denote this model 'optimised model'. Figures 2C and 2G illustrate the results of the optimisation. The model dispatch now looks quite satisfactory from an annual generation-by-type perspective, and while there are some differences in the typical dispatch by demand, we consider this sufficient to proceed with our energy storage model.

D. Modelling storage

Energy storage technologies move demand and generation from one period to another, essentially increasing the generation of one or more plant types at some earlier period, before reducing the generation of one or more components at some later period as the storage is used to cover some of the net system demand. We consider that storage may charge from only the variable components of the dispatch, essentially preserving the must run requirements of the plants, which, although estimated in a data-driven fashion in our model to approximate the UK network data, has real origins due to minimum plant running requirements and for grid flexibility.

Since any energy storage device is a net consumer of energy, the motivation for using storage resides in the ability to exploit different costs associated with different time periods. In a liberalised electricity market where the storage acts as an independent participant in the market, the operation will most likely be driven with the purpose of maximising the profit of the storage operator. Hence, the operator will consider the prices and risks associated with different strategies, and schedule their services accordingly. From a system planner perspective, the energy storage may also be used explicitly to reduce the system operational cost. This is representative of the storage action taken as part of a vertically integrated utility, wherein both generation and storage are included (and could include other components such as transmission and distribution). It is interesting to note that the vast majority of large-scale energy storage in existence today was first commissioned under this operational paradigm [13].

In this work, we consider two storage operational objectives from a system planner perspective. First, we use storage to minimize the running costs of the system, which we define as the sum of powerplant costs over the year. Second, we use storage to minimize the system emissions, which we define as minimizing the sum of the annual operational emissions.

For these objectives, we define two costs for each generation type (as specified in Table 1). Firstly, π_i in \$/MWh, intended to broadly represent the marginal cost of generation (based primarily of fuel costs), and secondly, γ_i in tonnes of CO2 per GWh, the marginal emissions (cost solely in terms of emissions) of each generation type. Emissions and costs associated with building and decommissioning are neglected in this model. We specify the storage operational characteristics, including maximum energy capacity, maximum charging power, maximum discharging power and charging and discharging efficiency.

The operation of the energy storage device is then determined with Mixed Integer Linear Programming (MILP), using the Pyomo package [14], an open-source tool for optimization applications in the Python programming language. Pyomo a is fully open-source python-based environment allowing for similar functionality to many algebraic modelling languages like AIMS or GAMS. Pyomo is compatible with many different solvers, and we utilize the CPLEX solver for linear programming [15], which is also freely available for academic use.

The objective functions are specified in Equations 4 and 5 for the running costs and emissions minimisations respectively.

$$\min \sum_i \sum_t \pi_i G_{it}^{st} \tag{4}$$

$$\min \sum_i \sum_t \gamma_i G_{it}^{st} \tag{5}$$

In Equations 4 and 5, G_{it}^{st} is the operation of the powerplants which has been modified by the introduction of storage. These are subject to the following inequality constraints in Equations 6–14. Equation 6 ensures that the stored energy, SOC_t, cannot be higher than the storage physical capacity, SOC^{MAX} and Equations 7 and 8 keep the charging energy, ΔSOC_t^+, and discharging energy per time period, ΔSOC_t^-, within their specified limits. The maximum charging energy is $\Delta SOC^{+\mathrm{MAX}}$ and the minimum discharging energy is $\Delta SOC^{-\mathrm{MIN}}$.

$$0 \leq SOC_t \leq SOC^{MAX} \tag{6}$$

$$0 \leq \Delta SOC_t^+ \leq \Delta SOC^{+MAX} \tag{7}$$

$$\Delta SOC^{-MIN} \leq \Delta SOC_t^- \leq 0 \tag{8}$$

Equation 9 stipulates the relationship between the change in the stored energy and the energy transfer to/from the storage device.

$$SOC_t = \begin{cases} SOC_{t-1} + \Delta SOC_t^+ + \Delta SOC_t^- & \forall t \geq 1 \\ 0 + \Delta SOC_t^+ & t = 0 \end{cases} \tag{9}$$

Equation 10 stipulates the charging efficiency, η^{chg}, and the charging sources (storage may charge from the different generation types and curtailed wind). The charging from a particular generation type i at time t is denoted by T_{it}^+ and charging from curtailed wind is T_t^{cur}.

$$\Delta SOC_t^+ = \frac{\sum_i T_{it}^+ + T_t^{\mathrm{cur}}}{\eta^{chg}} \tag{10}$$

Equation 11 stipulates the discharging efficiency, η^{dischg}, and which generation types storage may displace (storage can displace all the plant types but not curtailed wind). The discharging which replaces a particular generation type i at time t is denoted by T_{it}^-.

$$\Delta SOC_t^- = \sum_i T_{it}^- / \eta^{\mathrm{dischg}} \tag{11}$$

Equation 12 ensures that storage can only store wind up to the curtailed amount in each period.

$$W_t^{\mathrm{cur}} - T_t^{\mathrm{cur}} \geq 0 \tag{12}$$

Equation 13 adjusts each generation type according to the storage action.

$$G_{it}^{st} = G_{it} + T_{it}^+ + T_{it}^- \tag{13}$$

Equation 14 ensures that all generation types must stay within their specified limits.

$$G_i^{\mathrm{must-run}} \leq G_{it}^{st} \leq G_i^{\mathrm{must-run}} + G_i^{\mathrm{dispatch}} \tag{14}$$

Finally, to restrict the model so that storage cannot be scheduled to charge and discharge at the same time, we specify the inequality constraints Equations 15–19 using the big M method.

$$\Delta SOC_t^+ \geq -M\Psi_{\mathrm{t}} \tag{15}$$

$$\Delta SOC_t^+ \leq M(1 - \mathrm{X}_{\mathrm{t}}) \tag{16}$$

$$\Delta SOC_t^- \leq M\mathrm{X}_{\mathrm{t}} \tag{17}$$

$$\Delta SOC_t^- \geq -M(1 - \Psi_{\mathrm{t}}) \tag{18}$$

$$\Psi_{\mathrm{t}} + \mathrm{X}_t \leq 1 \tag{19}$$

In these Equations M is some large integer and Ψ_t and X_t are boolean variables. $\Psi_t = 1$ if the storage is charging and X_t=1 if the storage is discharging. The relationship between the boolean variables and the storage charging and discharging, ΔSOC_t^+ and ΔSOC_t^- , is explicitly specified through Equations 15–18.

E. Storage characteristics

Since this analysis is concerned with large-scale energy storage systems and PHS represents the current benchmark for any large-scale electricity storage system, we consider storage systems with characteristics broadly based on PHS. The exact characteristics are described in Table 3. The UK currently has approximately 2.7 GW of installed PHS capacity, and the largest facility, Dinorwig PHS, has approximately 8 hours of storage [13]. We arbitrarily consider the effects that an extra 2.5 GW of PHS with 8 hours of storage may have in the UK electricity system (essentially doubling the current PHS capacity).

TABLE III. MODELLED STORAGE CHARACTERISTICS

Parameter	**Value**
Capacity	20 GWh
Charge power	2.5 GW
Discharge power	2.5 GW
Charging efficiency	86.6%
Discharging Efficiency	86.6%

F. Renewable scenarios

We consider two renewable energy scenarios, one where the installed wind level is the same as the 2015 level and another (a high wind scenario) wherein the wind capacity is tripled. For the purposes of this analysis, we simply triple the wind timeseries from 2015. Of course, this a gross simplification as it assumes that any new capacity would be installed in exactly the same proportions and at exactly the same locations as existing wind installations, and furthermore it assumes these new plants would have the same performance characteristics. Future work will improve the model in this regard.

III. RESULTS

A. Storage Model Validation

Figure 5 shows four days of the model output in both the system running costs minimisation and the emissions minimisation (as compared to the original dispatch). It is clear that when storage is used to minimise the system fuel cost, the model acts to increase the generation from less expensive plants, as seen by the increases in nuclear, hydro and coal generation. Figure 5B shows that the storage operation results in valley filling, increasing the generation from nuclear and hydro when it is below its dispatchable limit and then increasing the coal production. CCGT is displaced during the day when the CCGT level is above the must-run value. When storage is used to minimise the system emissions, the storage still charges during the valleys from nuclear and hydro when available. However, it charges with CCGT generation rather

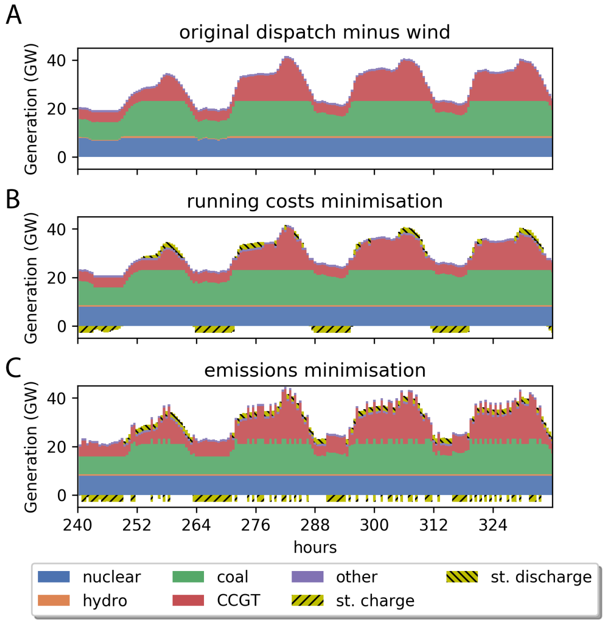

Figure 5: Illustrating the results of the storage scheduling model for four example days. (A) shows the original dispatch to meet the demand-net-of -wind. (B) illustrates the running costs minimisation. (C) shows the emissions minimisation.

than coal, since coal has much higher marginal emissions. Interestingly, the 'optimal' storage operation yields a jagged net demand profile. This is because it is always beneficial from an emissions perspective to replace coal with CCGT, so the minimum system emissions alternates between charging with CCGT and then reducing coal in the consecutive period if there is any spare capacity. In real systems, this type of operation is suboptimal since frequently changing the output levels of thermal plants will increase their operational costs. Therefore, in future work we will investigate the addition of costs associated with changing plant outputs in the objective function.

B. 2015 Wind generation

The annual results for the 2015 wind scenario are shown in Figure 6. Figure 6A illustrates the distributions of the generation outputs by period from each different generation type. It can be seen that the when storage is used to minimise running costs, the mean nuclear and hydro generation are increased slightly, the mean coal generation is increased significantly and the average CCGT generation is decreased. The effect on the coal and CCGT generators is largest, since nuclear and hydro typically operate near full capacity during most periods under the model dispatch without storage. Figures 6A and 6B show that the costs minimisation increases the annual coal production by 5 TWh (from 74 TWh to 79 TWh) and decreases CCGT by 4 TWh. The round-trip storage efficiency of 75% explains the relatively smaller reduction in CCGT generation as compared to the increase in coal generation and nuclear. When storage is used to minimise the system emissions, it significantly reduces the mean coal generation and increases the mean level of CCGT generation.

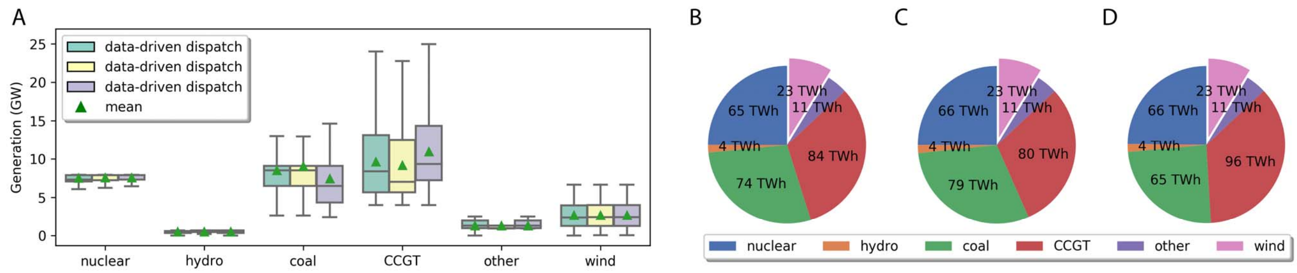

Figure 6: Annual results of the energy storage simulations comparted to the original model dispatch in the 2015 wind scenario. (A) Boxplots illustrating the distribution of generation levels for each generation type. (B) Total annual generation by type for the model dispatch with no storage. (C) Total annual generation by type with storage minimising fuel costs. (D) Total annual generation by type with storage minimising emissions.

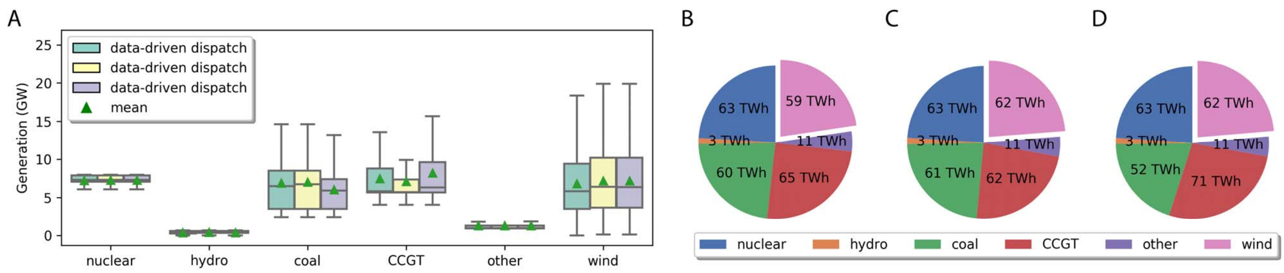

Figure 7: Annual results of the energy storage simulations comparted to the original model dispatch in the high wind scenario. (A) Boxplots illustrating the distribution of generation levels for each generation type. (B) Total annual generation by type for the model dispatch with no storage. (C) Total annual generation by type with storage minimising fuel costs. (D) Total annual generation by type with storage minimising emissions.

On an annual basis this corresponds to an increase in coal generation of 9 TWh and an increase in CCGT of 12 TWh. In both storage operation scenarios, wind is increased very slightly, however since wind curtailment in the original dispatch was approximately 0.3%, this corresponds to a very small increase.

C. High wind generation

In the high wind scenario, the significant amount of wind curtailment makes a large difference to the results. With three times the wind generation and the rest of the system components unchanged, our dispatch model suggests that as much as 15% of wind output may be curtailed. This means that in both the running costs and emissions minimisations, storage can charge with wind energy that would have otherwise been curtailed. We therefore see in Figure 7A that the distribution of wind generation is shifted upwards. Furthermore, we find that when storage is used to minimise fuel costs, both the increase in the mean coal generation and the decrease in the mean CCGT generation are significantly less severe. In annual terms as shown by Figure 7B and 7C, the 2.5 GW of additional storage increases the amount of wind generation by 3 TWh, increases coal generation by 1 TWh and decreases CCGT generation by 3 TWh. For the emissions minimisation, the mean coal generation is decreased by around 1GW and the mean CCGT generation is correspondingly increased. In annual terms, comparing Figures 7B and 7D we find that the coal generation is decreased from 60 TWh in the dispatch without storage to 52 TWh when storage is minimising emissions. Annual CCGT is increased from 65 TWh to 71 TWh.

IV. Discussion and Conclusions

This paper has developed a data-driven dispatch model of the GB electricity network and coupled it with an energy storage module. The data-driven dispatch model uses historical data from the year 2015 and enhances the simple merit order stack approach by specifying seasonal must-run and dispatchable components based on generation by plant-type data. Compared to the simple merit order stack, the data-driven dispatch function much better approximates the actual system dispatch for GB in 2015.

TABLE IV. MEAN ELECTRICITY COST AND EMISSIONS INTENSITY

	Mean cost of electricty (£/MWh)	**Mean Carbon Intensity** (gCO_2/kWh)
(2015 wind) no storage	25.7	433.1
(2015 wind) fuel cost minimisation	25.4	438.9
(2015 wind) emission minimisation	26.3	418.9
(high wind) no storage	21.3	353.1
(high wind) fuel cost minimisation	20.8	348.6
(high wind) emission minimisation	21.4	336.7

The storage module allows bulk electricity storage to be simulated, considering its impact on the rest of the plants in the system. Two different objective functions have been specified for the energy storage module – minimising system running costs and minimising system emissions. The storage module finds the optimum operation of the storage device that minimises the respective objective function, accounting for the associated output changes for the other plants in the system.

We find that when storage is introduced into the system, the effect on the existing plants depends strongly on the operational objective. In general, when storage is operated with the goal of minimising the system running costs this increases coal and decreases CCGT generation (see Table 4). The opposite occurs when the storage is used to minimise system emissions. However, when there is a large excess of wind generation, our model predicts that these two operational strategies – minimum system costs and minimum system emissions – start to overlap (see Table 4), as both encourage the use of wind that would otherwise be curtailed due to the must-run requirements of the plants on the system.

Of course, our model is a simplification and the dispatch function based on the 2015 GB data may perform poorly when used out of sample – which could be the case in the high wind scenario. Furthermore, some of the storage schedule results are practically implausible due to their requirements for other plants in the system to rapidly change outputs. However, we believe our model to be a useful step in the right direction. Future work will continue to refine the dispatch function to better approximate the real system and produce better out-of-sample prediction when the plant mix is different. Therefore, the next steps will be to improve the performance of the dispatch model (*i.e.* by introducing smaller generator tranches [5]) and to study the out-of-sample prediction by considering subsequent years of data. We also hope that by developing a framework that is entirely open source and in python, our model can be used and refined by other parties.

V. CODE AVAILABILITY

The model developed in this paper will shortly be made available at https://github.com/EdwardBarbour/OSES2019

VI. REFERENCES

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