INCORPORATING AGEING PARAMETERS INTO OPTIMAL ENERGY MANAGEMENT OF DISTRIBUTION CONNECTED ENERGY STORAGE

Adib ALLAHHAM
Newcastle University – UK
Adib.allahham@newcastle.ac.uk

David GREENWOOD
Newcastle University – UK
David.greenwood@newcastle.ac.uk

Charalampos PATSIOS
Newcastle University - UK
haris.patsios@newcastle.ac.uk

ABSTRACT

This paper presents an optimal management system for a Battery Energy Storage System (BESS) providing demand peak reduction to its local electricity distribution network. This optimal energy management system (EMS) is based on a Material properties Model (MPM) of the BESS, enabling the EMS to take advantage of continuously updated information describing the BESS's parameters. The EMS schedules the charging/discharging of the BESS in such a way that it minimizes the battery degradation and the operational cost, and maximizes the BESS's efficiency. The EMS is tested using real-world data collected from the distribution network in Bedfordshire, England. The EMS uses information about local Distribution Use of System (DUoS) charges when creating the operational schedules for the BESS; the impact of these charges, and their variation in different regions, on the operation and profitability of the system are investigated.

INTRODUCTION

Battery Energy Storage Systems (BESSs) are increasingly being installed in distribution networks, delivering services to distribution and transmission system operators. BESSs require an energy management system (EMS) allowing them to operate in optimal way with minimum energy losses, capacity loss and operational cost while meeting the requirements of the local and wider networks. Battery energy management systems (BEMS) have different general objectives, which can include a focus on the State-of-Charge (*SoC*) [1] and minimizing battery degradation [2, 3, 4] (the loss of battery capacity as the system ages). Degradation is driven by several parameters, including Depth of Discharge (*DoD*), number of the cycles, *SoC*, and energy throughout. In conventional BEMS, the degradation model is either static or based on a simplified dynamic representation. Other BEMSs used a degradation model which is valid for a limited operating range [4, 5]. This paper aims to consider a dynamic representation of the BESS degradation and be also able to consider a wide range of the BESS's operation. For this reason the authors use a Material Properties Model (MPM) of the BESS [6] to estimate the degradation and energy losses within the optimal BEMS. This MPM, which is able to consider a wide range of BESS operation conditions, will continuously update the BEMS about the evolution of key parameters affecting the operational cost, including energy losses, power converters losses, the capacity loss, and the efficiency.

Recently, more energy management systems are based on Fuzzy Logic Control (FLC) [7] and Model Predictive Control (MPC) [3], which deliver better performance than those based on the traditional control methods [8, 9]. This paper presents a BEMS based on Model Predictive Control (MPC-BEMS) to control a BESS used for reducing the peak demand in a distribution network. The MPC-BEMS minimizes operational costs, a function of battery degradation, efficiency, energy prices, and Distribution Use of System (DUoS) charges.

In the UK, the distribution network in each region is managed by an operator which has its own DUoS cost parameters. This paper aims to show that the schedule of charging and discharging of the BESS depends on its location in the UK distribution network, and that there is the potential for network operators to achieve desirable outputs from locally connected BESSs through the use of these charges, without necessarily entering into a direct contract with the BESS operator.

STUCTURE OF BATTERY ENERGY MANAGEMENT SYSTEM

Figure 1 shows the block diagram of the MPC-BEMS employed to reduce peak demand in a distribution network. The MPC-BEMS comprises the following main components: an optimal scheduler, a MPM, and a forecast model. The inputs to the MPC-BEMS are the battery energy prices, the degradation cost, the initial conditions of the BESS, and real-time demand of the distribution network. The output of the MPC-BEMS is a sequence of charging and discharging power set-points over a future 24 hour time horizon, at a half-hourly time resolution. As can be seen in Figure 1, the optimal scheduler receives updated values of SoC, State-of-Health (SoH), energy losses (E_{Losses}), capacity loss (Cap_{Loss}), and efficiency (η) from the MPM. The MPM needs, in its turn, to know the power scheduled during this time step (P_{Batt}), and the *SoH* and *SoC* at the start of this time step, corresponding respectively to SoH_{init} and SoC_{init} in Figure 1.

The MPM used in this paper was developed by *Patsios et al.* [6]; it uses robust physics-based models which can be simulated approximately 100 times quicker than real time. The model incorporates accurate calculations of the key battery and power converter properties. The Li-ion battery model includes one of the major degradation mechanisms for Li-ion: solid-electrolyte interphase (SEI) layer formation. A time-averaged model is used to represent the power conversion system; this enables accurate and computationally efficient estimation of the full system efficiency.

A crucial aspect of the MPC-BEMS is the forecast, which has a direct impact on the controlled system. The authors have previously developed a forecast model developed specifically to fulfill a demand peak shaving application [10], which is based on linear- and auto-regressive methods. In this paper, the future time horizon is 24 hour at a half-hourly time resolution.

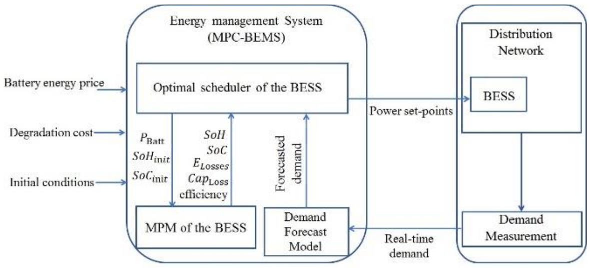

Figure 1: The block representation of MPC-BESS

OPTIMAL SCHEDULER OF THE BESS

The mathematical formulation of the optimal scheduler is described in this section.

Objective function:

$$F(X) = \min(C_{\text{elec}} + C_{\text{deg}}) \quad (1)$$

where: $X = [P_{\text{Batt}}(1), \ldots, P_{\text{Batt}}(48)]$

Equation (1) is detailed with equation (2) to (4) below:

$$C_{\text{elec}} = \sum_{i=1}^{N=48} E_{\text{price}}(i).P_{\text{Batt}}(i).\tau \quad (2)$$

$$E_{\text{Losses}}(i) = 1 - \eta(i) \quad (3)$$

where: $\eta(i) = f_1(P_{\text{Batt}}(i), SoC(i))$

$$C_{\text{deg}} = D_{\text{price}} \sum_{i=1}^{N=48} Cap_{\text{loss}}(i) \quad (4)$$

$$Cap_{\text{loss}}(i) = f_2(SoC(i), SoH(i)) \quad (5)$$

where:

C_{elec}	Energy cost delivered by the BESS (£)
C_{deg}	Degradation cost of the BESS (£)
$E_{\text{price}}(i)$	Energy price at the *i*th discrete time sample (£/kWh), including the cost of energy losses, and DUoS charges.
$P_{\text{Batt}}(i)$	Power of the BESS at the *i*th discrete time sample (kW). $P_{\text{Batt}} > 0$ or P_{Batt}^{+} represents the battery charging and $P_{\text{Batt}} < 0$ or P_{Batt}^{-} represents the battery discharging
τ	Size of the time sample. In this paper, $\tau =$ 30 minutes
$E_{\text{Losses}}(i)$	Energy losses at the *i*th discrete time, which are composed of battery losses and power converter losses (kWh)
$\eta(i)$	BESS's efficiency at the *i*th discrete time.
$\eta^{+}(i), \eta^{-}(i)$	Efficiency of charging and discharging process
D_{price}	Cost of degradation (£/kWh)
$Cap_{\text{loss}}(i)$	Capacity lost from the BESS during time sample *i*

Equation (2) calculates the total of energy cost delivered by the BESS according to the DUoS charges and includes the cost of battery and power converter losses. Equation (4) calculates the degradation cost of the BESS. Using the MPM, equations (3) and (5) calculate the energy losses, efficiency, and the capacity loss at the *i*th discrete time.

Constraints:

$$E_{\text{Batt}}(i+1) = E_{\text{Batt}}(i) + \tau.\eta(i).P_{\text{Batt}}(i) \quad (6)$$

$$PS_{\text{req}}(i) = P_{\text{N}}^{\max} - P_{\text{D}}(i) \quad (7)$$

$$\frac{abs\left(P_{\text{Batt}}^{-}(i)\right)}{\eta^{-}(i)} \geq PS_{\text{req}}(i) \ if \ P_{\text{N}}^{\max} - P_{\text{D}}(i) < 0 \quad (8)$$
$$P_{\text{Batt}}^{+}(i).\eta^{+}(i) \leq PS_{\text{req}}(i) \ if \ P_{\text{N}}^{\max} - P_{\text{D}}(i) > 0$$

$$\sum_{ii=1}^{n_{\text{d}}} \frac{abs\left(P_{\text{Batt}}^{-}(ii)\right)}{\eta^{-}(ii)}.\tau \leq \sum_{jj=1}^{n_{\text{c}}} P_{\text{Batt}}^{+}(jj).\eta^{+}(jj).\tau \quad (9)$$

$$E_{\text{nom}}.\left(SoC_{\min} - SoC(i)\right) \leq P_{\text{Batt}}(i).\tau \leq E_{\text{nom}}.\left(SoC_{\max} - SoC(i)\right) \quad (10)$$

$$P_{\min} \leq P_{\text{Batt}}(i) \leq P_{\max} \quad (11)$$

$$SoC_{\min} \leq SoC(i) \leq SoC_{\max} \quad (12)$$

$$SoH_{\min} \leq SoH(i) \leq SoH_{\max} \quad (13)$$

$$SoC_{\text{final}} \leq SoC(N) \quad (14)$$

$$0 \leq P_{\text{D}}(i) + P_{\text{Batt}}(i) \leq P_{\text{N}}^{\max} \quad (15)$$

where:

E_{Batt}	Battery energy
$PS_{\text{req}}(i)$	Peak shaving requirement during the time period *i*
$P_{\text{N}}^{\max}$	Capacity limit of the network (kW)
$P_{\text{D}}(i)$	Network demand at the *i*th discrete time sample (kW)
$n_{\text{d}}, n_{\text{c}}$	Number of discharging and charging periods during the considered time horizon, respectively.
E_{nom}	Nominal energy of the BESS
$SoC_{\min}, SoC_{\max}$	Minimum and maximum limit of *SoC*
$P_{\min}$	Minimum power limitation
$P_{\max}$	Maximum power limitation
$SoH_{\min}, SoH_{\max}$	Minimum and maximum limit of *SoH*
SoC_{final}	Value of *SoC* by the end of considered time horizon

Constraint (6) represents the battery model. Constraints (8) define the limit of charging and discharging powers of the BESS to meet the peak shaving requirement calculated by equation (7). Constraint (9) expresses that the energy charged in the BESS must be sufficient to cover the energy required from the BESS during the discharging periods. Constraint (10) ensures the BESS is operating within SoC limit. Constraint (11) shows that the battery charging and discharging power are within the minimum and maximum power limitation, defined by the power converter capacity. Constraints (12) and (13) express the *SoC* and *SoH* must be within their limits. Constraint (14) means that the value of *SoC* by the end of considered time horizon must be greater than SoC_{final}, thereby ensuring that sufficient energy is available for the next day's operation. Constraint (15) ensures that the total demand of the battery and the customers does not exceed the network capacity

CASE STUDY : RESULTS AND DISCUSSION

Table 1: Specifications of the Case study

Specification	Value	Unit
E_{nom}	60	kWh
SoC_{init}	50	%
SoC_{final}	50	%
SoC_{max}	95-100	%
SoC_{min}	15	%
SoH_{init}	100	%
$P_{\text{max}}, P_{\text{min}}$	100,-100	kW
$P_{\text{N}}^{\text{max}}$	129	kW
C_{Deg}	1050	£/kWh

In this section, the MPC-BEMS described previously is demonstrated. Simulation results are used to analyze the performance of the energy management system in terms of the energy losses, capacity loss, and total operating cost. The simulations were created using half-hourly (known as settlement periods) demand data from a real distribution network in Bedfordshire, England. Table 1 gives the specification of the case study. The distribution network in each region has a given energy price which is different from that of other regions due to levies imposed by the DSO and TSO. To show the impact of the energy price on scheduling the BESS, it is assumed that the same BESS is connected to different distribution networks in different regions in the UK and these networks have the same demand profile, but different energy prices. Figure 2 shows the sell and buy energy prices including the DUoS charges of five distribution networks in the UK. Figure 3 shows the time series of power and *SoC* over a 24 hour period of the different identical BESSs implemented in different regions in the UK. From Figure 3, it can be seen that the scheduled power and resulting *SoC* of the BESS is different for each of the considered regions of the UK distribution network; this is because a different energy price in used each case. It is noticed, for example, the BESS used in London distribution network charged to around 90% and 98% as there are two peak price, and this is to avoid buying energy during the peak periods.

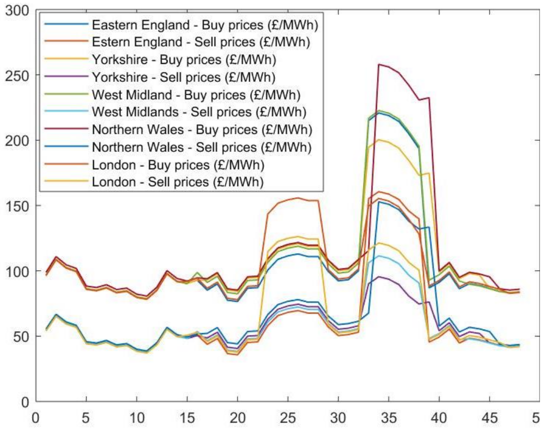

Figure 2: Buy and sell energy prices in five regions in the UK

To assess the performance of the developed MPC-BEMS, a typical BEMS is used as a reference case. In this reference energy management system, the BESS charged to full power at the first opportunity, delivered the energy

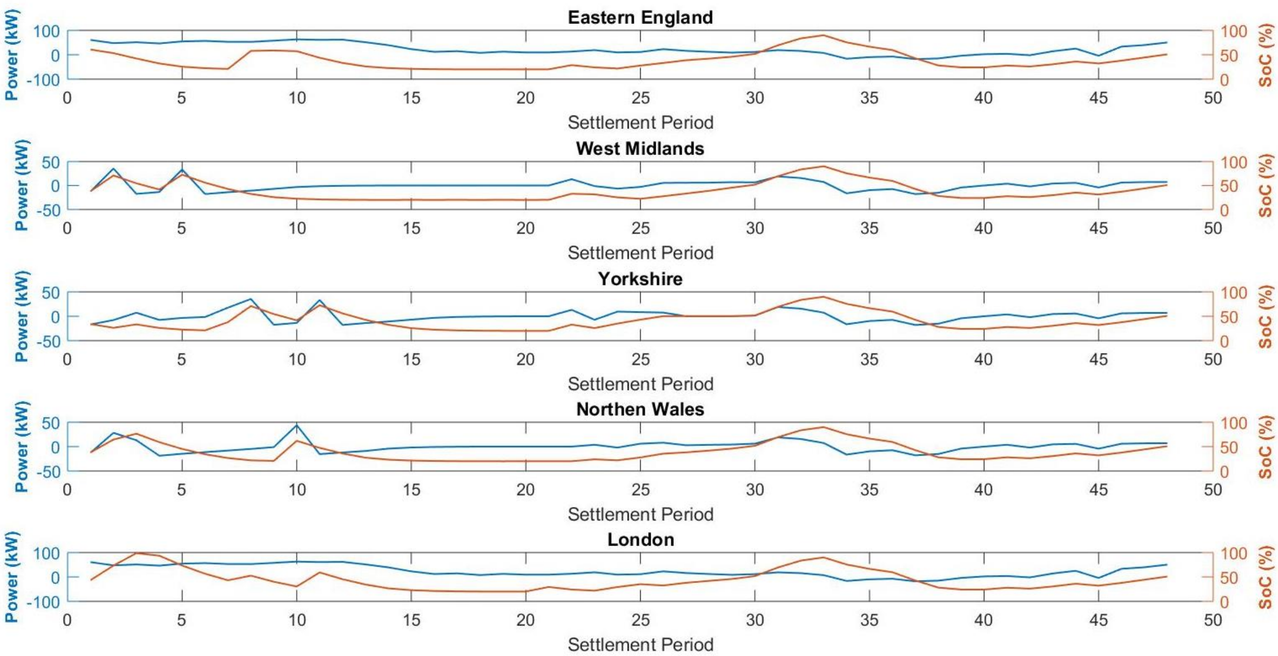

Figure 3: Time series of power and *SoC* over a 24 hour period of different identical BESSs implemented in different regions in the UK

Table 2: Simulation results of the considered case study: Typical-BEMS & MPC-BEMS								
Region in the UK	Capacity loss (%)		Cost of Capacity Loss (£)		Energy losses (kWh)		Operational cost (£)	
	Typical-BEMS	MPC-BEMS	Typical-BEMS	MPC-BEMS	Typical-BEMS	MPC-BEMS	Typical-BEMS	MPC-BEMS
Eastern England	0.168	0.085	105.8	53.6	2.32	1.475	179	91.9
Yorkshire	0.168	0.088	105.8	55.4	2.32	2.02	179.95	96.3
West Midlands	0.168	0.0853	105.8	53.7	2.32	1.79	179.3	92.7
Northern Wales	0.168	0.086	105.8	54.2	2.32	1.98	179	92.3
London	0.168	0.0857	105.8	54.0	2.32	1.47	179	91.95

for the peak shaving when required, then recharged to the mandated 50% *SoC* at the end of the day. Table 2 summarizes the values of energy losses, capacity loss, and the operational cost of the BESS managed using the Typical-BEMS and MPC-BEMS and implemented in different regions in the UK

In comparison with the Typical-BEMS, applying the MPC-BEMS on a BESS connected to a distribution network in Eastern England decreased the capacity losses by 50.6%, the energy losses by 36% and the operational cost by 48%. Making the same comparison for the BESS connected to the distribution network in London, the capacity losses, the energy losses, and the operational cost are decreased by 45%, by 10% and by 42%, respectively.

In all cases, the cost of battery degradation is the most significant component of the overall operating cost, which the MPC-BEMS was able to reduce by around 50% in all cases. The impact of different DSO regions on operational cost is minor, but the impact on the optimal schedule is significant. If battery costs continue to fall, and the cost of degradation is therefore reduced, then the impact of the local network charges will be more impactful overall on the operation of the BESS.

The regions with higher DUoS charges – which result in higher costs of energy for the BESS – result in lower overall operating costs for the BESS, as it is incentivized to discharge during high price periods. As things stand, these charges would not be sufficient to incentivize the BESS to carry out peak demand shaving without an explicit contract (as demonstrated by the positive operational cost). However, in a future system with a lower cost of degradation, it could be possible to incentivize this behavior through reformed DUoS charges rather than through bilateral contracts with each BESS operator.

CONCLUSION

An optimal energy management system for a BESS has been presented to minimize the operational cost, degradation, and losses of a BESS which supplements its primary function of reducing the peak demand on a distribution network with price-based energy arbitrage. The case study results show that the developed energy management system is effective at reducing the operational cost, degradation, and energy losses relative to a naïve set point controller. The local network charges of the region in which the BESS operates have a significant impact on its optimal operation, but are not as yet adequate to incentivise the demand peak shaving behaviour without an explicit contract between the DSO and the BESS operator.

REFERENCES

[1] Lu, C., Xu, H., Pan, X. and Song, J., 2014. Optimal sizing and control of battery energy storage system for peak load shaving. Energies, 7(12), pp.8396-8410.

[2] Tran, D. and Khambadkone, A.M., 2013. Energy management for lifetime extension of energy storage system in micro-grid applications. IEEE Transactions on Smart Grid, 4(3), pp.1289-1296.

[3] Han, S., Han, S. and Aki, H., 2014. A practical battery wear model for electric vehicle charging applications. Applied Energy, 113, pp.1100-1108.

[4] Abdulla, K., De Hoog, J., Muenzel, V., Suits, F., Steer, K., Wirth, A. and Halgamuge, S., 2018. Optimal operation of energy storage systems considering forecasts and battery degradation. IEEE Transactions on Smart Grid, 9(3), pp.2086-2096.

[5] Shi, Y., Xu, B., Wang, D. and Zhang, B., 2018. Using battery storage for peak shaving and frequency regulation: Joint optimization for superlinear gains. IEEE Transactions on Power Systems, 33(3), pp.2882-2894.

[6] Patsios, C., Wu, B., Chatzinikolaou, E., Rogers, D.J., Wade, N., Brandon, N.P. and Taylor, P., 2016. An integrated approach for the analysis and control of grid connected energy storage systems. Journal of Energy Storage, 5, pp.48-61.

[7] Arcos-Aviles, D., Pascual, J., Marroyo, L., Sanchis, P. and Guinjoan, F., 2018. Fuzzy logic-based energy management system design for residential grid-connected microgrids. IEEE Transactions on Smart Grid, 9(2), pp.530-543.

[8] Lee, C.S., Lin, H.C. and Lai, S.Y., 2013. Development of fast large lead-acid battery charging system using multi-state strategy. International Journal on Computer, Consumer and Control (IJ3C), 2(2).

[9] Lin, H.C., He, Y.J. and Liu, C.W., 2016, July. Design of an Efficient Battery Charging System Based on Ideal Multi-State Strategy. In Computer, Consumer and Control (IS3C), 2016 International Symposium on (pp. 956-959).

[10] Greenwood, D., Wade, N., Papadopolous, P., Heyward, N. and Mehtah, P., 2015. Scheduling power and energy resources on the smarter network storage project., CIRED 2015, Lyon, France