Sustainable Energy Technologies and Assessments 23 (2017) 73–82

Contents lists available at ScienceDirect

Sustainable Energy Technologies and Assessments

journal homepage: www.elsevier.com/locate/seta

Original article

Energy storage system scheduling for peak demand reduction using evolutionary combinatorial optimisation

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ARTICLE INFO

Keywords:
Algorithm design and analysis
Battery management systems
Energy storage
Heuristic algorithms
Power distribution
Smart grids

ABSTRACT

This paper is concerned with finding an optimal energy storage system (ESS) schedule for peak demand reduction and load-levelling given only the information certainly available to and controllable by the Distribution Network Operator (DNO) which are the substation demand profile information and the DNO-owned ESS parameters. Methods such as set-point control are usually suboptimal and can create new peaks. Other methods require more parameters and actions than the DNO can fully control to form the basis for optimisation and can be computationally complex. The method presented in this paper uses simple heuristics to find possible optimal operation points for the ESS and improves the solutions found using genetic algorithm optimisation. A case study is presented showing a UK distribution network with a peak capacity violation which is resolved using the method and the results are compared to a closed-loop set-point control method.

Introduction

Energy storage systems (ESS) are increasingly becoming vital components of smart electricity networks as a result of the services they can provide which include curbing the intermittency of renewable energy sources, power quality improvement, peak demand shaving, load-levelling, demand time shifting, energy cost savings, security of supply etc. [1–4].

Distribution network operators (DNO) operating medium voltage (MV) and low voltage (LV) networks typically face challenges regarding demand on the network exceeding installed firm capacity. The conventional approach to resolving these peak demand violations of network capacity is to reinforce the network by including more lines and transformers or replacing equipment, or in the worst cases load shedding [5,6]. The conventional reinforcement is sometimes costly and can also lead to addition of underutilised capacity.

ESS provide an alternative by supplying peak demand using energy stored at during periods of lower demand and implicitly provide a flatter demand profile to improve capacity headroom of the network. Several ESS control strategies have been formulated to achieve peak reduction and load-levelling either directly or as a side-effect of some other scheme. The two operations of peak shaving and load-levelling are different services, however in some cases are closely related and coupled and can be performed by the same storage technology depending on the frequency and duration of use [1]. The problem many of the schemes face are related to the amount of control a DNO has in markets that are deregulated and have different agents for transmission, distribution and generation. The optimisation parameters may also be limited in some cases which can be restricting

Dynamic programming (DP) methods while being detailed and effective in handling nonlinearity and stochastic operation also depend on a specific value function which is based on generation data or cost data for each time step and are usually also computationally complex. For example, in [7] researchers use a quadratic fuel cost curve and recursively solve finite space Markov decision processes for each subnetwork under consideration with AC power flow equations as part of a DP model. Sioshansi et al. in [8] assume knowledge of future energy prices and perform an optimal dispatch based on this and then assign probability distribution for the availability of storage based for each successive periods in the DP. In [9] Neves et al. use price based demand response and DP to determine the best transition state from one time step to the next via an economic dispatch which is based on quadratic programming.

Optimal power flow based methods also rely heavily on generation price information or other forecasts which are not always available or in the control of the DNO. The dynamic optimal power flow (DOPF) formulated by Gill et al. in [10] for using storage to reduce the curtailment of renewables and manage congestion in a distribution grid performs an OPF at each time step based on wind forecasts and exogenous electricity prices. The active-reactive power flow (AR-OPF) by Li and Gabash [11,12] uses wind forecasts and an electricity price model to determine the best periods to dispatch storage and maximise

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http://dx.doi.org/10.1016/j.seta.2017.08.003
Received 30 April 2017; Received in revised form 26 June 2017; Accepted 30 August 2017

profit and reduce constraints on wind generation integration.

Demand response (DR) schemes based on time-of-use (ToU) pricing may lead to peak demand reduction but are generally out of the control of the DNO. DR schemes depend on consumer behaviour in response to energy prices but the DNO in most cases do not set the energy prices, the energy supplier does. The consumer may also not respond to the prices in such a manner that it leads to peak demand reduction. In [13] for instance the peak demand increases as a result of a DR scheme that aims to reduce energy costs in households. The DR scheme in [14] requires control of "wet appliances" to reduce congestion by scheduling the time they use energy to coincide with low demand periods which customers may find intrusive.

Set-point control (SPC) methods operate by charging or discharging the ESS when the demand is below or above a fixed set-point. In [15] the set-point is based on the peak demand and periods of peak pricing while in [16] it is based on average demand throughout the day which is vulnerable in a profile with high variation in demand. SPC is usually based on real-time control and therefore does not take into account future events, which may lead to suboptimal solutions globally. Rowe et al. in [17] formulate a method using aggregated forecasts and an iterative scheduling algorithm. The method is based on operating a moving set-point which is determined for each iteration of the optimisation, hence it is a dynamic programming technique based on a moving set-point.

In this paper a method is presented for using a genetic algorithm (GA) to improve on schedules generated via simple combinatorial optimisation heuristics. Other methods such as in [6,9,18] use GA after applying either demand response or dynamic programming which has limitations from the DNO point of view.

The scheduling problem is first formulated in Section "Modelling the problem" as a combination of the bin-packing and subset sum problem of finding the best placement for energy storage in a demand profile. A basic methodology for solving the problem as described in Section "Methodology for obtaining solution" was formulated by the authors in [19] using heuristics such that several viable schedules are produced. This methodology now extends it by further optimisation using GA optimisation to evolve an entirely new schedule not generated in the first heuristic stage. In Section "Case study description" case study of the Leighton Buzzard smarter network storage [5] which highlights the exact problem of concern is presented and the methodology is applied to it alongside a closed-loop set-point control algorithm for comparison. The results are discussed in Section "Results and discussion".

The benefit of this method is that it uses only the information typically available to the DNO, which is a demand profile forecasted at a problem substation and DNO-owned ESS parameters to generate optimal schedules that are controllable by the DNO and do not have the limitations of other methods described previously from a DNO point of view.

In comparison to existing literature, this is the first time the classical algorithms are combined in this manner and applied to energy storage optimisation in electrical systems. By modelling the problem of optimising a given demand profile such that it can be viewed as a bin-packing problem, and storage allocation as a subset sum problem, then the solutions applicable to problems of those forms are also applicable to electrical energy systems.

Furthermore, it provides an additional option for generating schedules. In every unique scenario where optimisation is required, there are characteristics of the network or the system that impose constraints or impact the effectiveness of the solution. The methodology presented in this paper provides several solutions to the same problem, with adjustable parameters in the genetic algorithm scoring phase to allow flexibility and adaptability to any scenario where unique conditions and goals exist and then works to achieve those goals. These are the key contributions of the method to the literature and implementation of energy storage scheduling and optimisation.

Modelling the problem

Summary of parameters used

b	Number of discrete time intervals
D_t	Normalised demand at any time interval t
D_p	Normalised peak demand
F_N	Optimisation objective N
E_t	Energy stored or discharged at time interval t
P	ESS rated power
t	Time interval duration
C	Network energy transfer capacity over time horizon
μ	ESS round-trip efficiency

The problem of operating a network within thermal and capacity constraints using ESS is defined as a dynamic optimisation problem of selecting the best periods to charge and discharge the ESS to keep an otherwise overloaded network within operational limits. This is achieved by a peak shaving and/or load-levelling objective.

Transforming a continuous daily demand profile into b discrete time steps with normalized demand D_i in the ith interval, the objective is to minimise the peak demand given as D_p in Eq. (1) within the time horizon $t_1,\ldots, t_b$. The integer b will be 24 for an hourly resolution and 48 for half hourly, etc.

$$D_p = \max(\{D_1,\ldots,D_b\}) \tag{1}$$

$$F_1 = \min(D_p) \tag{2}$$

Eq. (2) is a peak shaving objective. The load-levelling is defined as the difference between the peak and trough demand, which gives an indication of how "flat" the demand profile is. It is given in (3) and the objective to minimise the variation in demand is given in (4).

$$D_L = \max(\{D_1,\ldots,D_b\}) - \min(\{D_1,\ldots,D_b\}) \tag{3}$$

$$F_2 = \min(D_L) \tag{4}$$

When combined with ESS utilisation F_1 and F_2 are constrained by ESS total energy storage capacity E, ESS rated power P, efficiency μ, and network capacity C. If the amount of energy stored (i.e. the positive values) or discharged (i.e. the negative values) during the ith interval is E_i the constraints are as follows:

i. ESS capacity constraint

$$\left|\sum_{i=1}^{b} E_i\right| < E \tag{5}$$

where: $-E \le E_i \le 0$ for discharging operations and $0 \le E_i \le E$ for charging operations

ii. ESS rated power constraint

$$\frac{E_i}{t_i} \leqslant P \tag{6}$$

for all i.

iii. Network capacity constraint

$$C = \sum_{i=1}^{b} D_i t_i \tag{7}$$

$$\sum_{i=1}^{b} D_i t_i + \mu \mathrm{E}_i \leqslant C \tag{8}$$

Eqs. (5)–(8) define the constraints for the optimisation. The solution will be an ordered set representing the ESS dispatch schedule $\{E_1, E_2,\ldots, E_b\}$and the final demand profile $\{D_1, D_2, D_3,\ldots,D_b\}$. The energy constraint defined in (7) and (8) may be treated as a power constraint for hourly time intervals. As a result of the initial discretization of the