Knowledge-Based Systems 99 (2016) 10–18

Contents lists available at ScienceDirect

Knowledge-Based Systems

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

A novel battery network modelling using constraint differential evolution algorithm optimisation

Yang Liu[a,*], Matthew Rowe[b], William Holderbaum[b], Ben Potter[b]

[a] School of Engineering, Edinburgh University, UK
[b] School of System Engineering, Reading University, Reading, UK

ARTICLE INFO

Article history:
Received 3 July 2015
Revised 22 December 2015
Accepted 16 January 2016
Available online 21 February 2016

Keywords:
Optimisation
Constraint optimisation
Self-adaptive control
Distributed network model

ABSTRACT

The use of battery storage devices has been advocated as one of the main ways of improving the power quality and reliability of the power system, including minimisation of energy imbalance and reduction of peak demand. Lowering peak demand to reduce the use of carbon-intensive fuels and the number of expensive peaking plant generators is thus of major importance. Self-adaptive control methods for individual batteries have been developed to reduce the peak demand. However, these self-adaptive control algorithms of are not very efficient without sharing the energy among different batteries. This paper proposes a novel battery network system with optimal management of energy between batteries. An optimal management strategy has been implemented using a population-based constraint differential evolution algorithm. Taking advantage of this strategy the battery network model can remove more peak areas of forecasted demand data compared to the self-adaptive control algorithm developed for the New York City study case.

1. Introduction

Battery energy storage has found a wide range of applications in various fields of science. Batteries can improve the power quality (mainly voltage depressions and power interruptions) and reliability of power system [1]. Battery storage could also play a vital role in deferring the need to improve the transmission and distribution capacity to meet ever growing power demand by effectively increasing the capacity of a given network by reducing peaks. In recent years, the capital cost of battery storage technologies has significantly reduced, thus justifying a new study of its applications [2]. For example, some of earliest commercial use of battery storage device were at Bewag, Germany (17 MW/14 MWh battery for frequency regulation) and at Southern California Edison Chino substation (10 MW/40 MWh for load levelling, rapid spinning reserve and instantaneous frequency control) [3] and [4]. The earliest transportable battery (lead-acid), located at Phoenix distribution system is a multi-model battery [5]. The battery switches between improving power quality (2 MW up to 15 s) and improving power management (200 kW for 45 min) and uses a different mode for each model. The megawatt scale deployment of the Distributed Energy Storage system (DES) technology was also successfully carried out in the American electricity power grid in 2006 [6] and [7]. Higher peaks in demand will increase the electricity price and could cause blackouts and infrastructure damage. Lowering peak demand to reduce the use of carbon-intensive fuels and reduce the number of expensive peaking plant generators is thus of major importance. The Charleston storage project partially funded by the US Department of Energy (DOE) aimed to reduce the peak load on overloaded equipment in the distribution substation [7]. It has operated successfully for three winter and summer peak seasons. Realising multiple benefits that DES technology has to offer, the utility continued to install three 2-MW, 14.4-MWh NaS DES units of larger capacity in their distribution system in 2008 providing peak shaving. The key feature of the new system is triggered peak shaving that does not allow the battery to be discharged unnecessarily during daily peak hours and only discharges the battery when the load of a nearby “bottleneck” on the grid exceeds a certain “trigger”. This approach not only allows the battery to offer its peak shaving value but also increase the availability of the remaining storage energy to serve customers in the event of an outage. Despite the large number of investigations carried out to apply different storage technologies to power system, very few of them have been implemented in practice. One of the main reasons for this limited practical application is lack of practical experience and lack of availability of tools which could be used for optimal control of battery storage in the smart

* Correspondence to: School of Engineering, Cardiff University, Cardiff CF24 3AA, UK. Tel.: +44 7541749557; fax: +44 29208719150.
E-mail address: sharkyangliu@gmail.com, sharkyangliu916@gmail.com (Y. Liu).

http://dx.doi.org/10.1016/j.knosys.2016.01.019
0950-7051/

grid during planning. Lately there has been some development of different types of optimal control algorithms in smart grid [8–10].

Coppez et al. [9] has classified battery storage optimisations based on hybrid renewable energy system in four categories: graph construction, probabilistic and deterministic techniques, genetic algorithms and artificial neural networks. Main issues like cell battery technology and optimisation techniques were reviewed. The authors stated that the reliability of supply of the system must be kept in mind to ensure that the load will be met by the supply at all times and economically the system must be optimized to ensure the lowest cost possible whist maintaining the system integrity. A common parameter used to measure the system integrity and reliability is Loss of Power Supply Probability (LPSP). LPSP must be monitored as the key parameter to ensure that in optimising the system, the likelihood of the system supply not being able to meet the load at all times is kept very low. Graphical construction is used to optimise in terms of two criteria (either Photovoltaic (PV) and size of battery storage, or PV and wind turbine. However, some important factors (such as the PV module slope angle and the wind turbine installation height.) were completely neglected. Other techniques will prove more useful for a more complex system with high dimensional parameters because it is only useful for simple systems with few parameters.

Probabilistic techniques can be used in situations where actual hour by hour long-term data is not available and more general data needs to be used [9]. The probabilistic and deterministic techniques are achieved by initially creating a design space of feasible solutions which adhere to the maximum LPSP. The parameters such as the number of wind turbines, size of PV panels and size of battery storage are optimised using the objective function (e.g. cost of the system including PV modules, Batteries, wind turbines and the cost of design and installation). Disadvantage of this probabilistic approach is that it cannot represent the dynamic changing performance of the hybrid system [8].

Ould Bila et al. [11] show a case study of the optimisation of a wind, PV and battery distributed generation system in Senegal. A genetic algorithm (GA) was used to minimise the total cost of the system whist maintaining a low LPSP using the following parameters: number of PV modules, power output of wind turbines, battery capacity and number of inverters and regulators [11]. The system is now functioning optimally. GAs were selected because they have shown to be highly applicable to cases of non-linear systems, where the location of the global optimum is a difficult task [8]. A Neural Networks (NNs) was used to predict the fitness values of solutions in order to speed up the GA search process [12]. This approach substantially decreases the time taken to calculate the optimal solution, while keeping the accuracy of each of the methods. The system includes the photovoltaic arrays, the lead-acid battery and a flywheel. The optimal sizing can be considered as a constrained optimisation problem: minimisation the total capacity of energy storage system, subject to the main constraint of the Loss of Power Supply Probability (LPSP) [12]. The GA spent 45 min but the combinatorial optimisation by GA and NNs) spent only 3–5 min on calculation.

In addition, Vytelingum et al. [10] developed a novel agent-based micro-storage management of energy storage devices in UK homes that adapts to market condition using game theory optimisation. They show that using demand-side management (i.e., directly controlling the storage profile of a number of homes) coupled with storage can increase savings made in the system. In the UK electricity market, it is possible to achieve savings of up to 13% on average for a consumer on his electricity bill with a storage device of 4 kWh. In spite of benefits in using the advanced agent-based model for the smart grid, the cost of micro-storage devices for all UK homes makes it impractical to apply the proposed method and the optimal control of storage details have not been given in the paper. A self-adaptive control model (SACM) of individual battery storage was developed by Rowe et al. [13] to remove the peaks of forecasted demand. The SACM was applied to Bracknell, UK using individual battery. However, the self-adaptive control algorithm of individual battery is not very efficient to reduce peaks without sharing the energy among different batteries. This paper proposes a novel Battery Network Model (BNM) with optimal management between batteries in the network. Mathematically, the optimal management of battery network is a large scale constraint optimisation with the objective of maximally removing the peak areas of forecasted demand or actual demand.

The optimisation methods can be broadly divided into two groups: linear and nonlinear optimisation methods. Linear optimisation's characteristics are a linear objective function to be maximised (or minimised) and linear constraints (i.e. constraints are linear functions of the variables). For some nonlinear optimisation problems, due to non-convexity, the objective function may have many local optima, and an analytical expression of the objective function may not be available. Nonlinear optimisation methods may be classified into deterministic local optimisation methods (e.g., gradient methods or direct search methods) and stochastic global optimisation methods (examples are multiple local search, genetic algorithms, simulated annealing and tabu search) [14–17]. Stochastic optimisation refers to the minimisation (or maximisation) of a function in the presence of randomness in the optimisation process. Genetic algorithms (GAs) [15] and particle swam optimisation (PSO) [18] and differential evolution (DE) [19] are popular stochastic optimisations for better global optimisation frameworks to fully realise the full benefits to conducting mathematical model optimisation, because of their simplicity, global perspective, and inherent parallel processing [20–22].

In most cases of practical interest, global optimisation is very difficult. This is because of the omnipresence of local minimum, the number of which tends to increase exponentially with the size of the problem [17]. Conventional minimisation techniques, which are time consuming and tend to converge to whichever local minimum they first encounter in such cases. The solution in these cases may not be the global minimum but a local minimum sensitive to the starting point. Also these methods are unable to continue the search after a local minimum is reached. Mathematical models may have many local optima on the objective function surface, and in such cases local search is inappropriate because the estimated optimum will depend on the starting point of the search. Due to the high number of possible parameter combinations, computation becomes very expensive for complex models if using a method based on searching combinations of parameters [23]. The particle swarm optimisation and differential evolution are two efficient stochastic optimisation methods minimising an objective function that can model the problem's objectives while incorporating constraints, and have three main advantages: global search regardless of the initial parameter values, fast convergence and a few control parameters. Both techniques have shown great promise in several real-world applications [24–28]. Facts have proved that population based optimisations like GA, PSO and DE are suitable to handle complicated constrained optimisation problems [29] and [30]. Differential Evolution (DE) is used in the paper to optimise the high-dimensional battery network model parameters because of its robust search ability based on benchmark test functions and real applications among these algorithms [28] and [31].

The rest of this paper structured as follows. Section 2 and 3 formulate a self-adaptive control approach for an individual battery and our proposed battery network approach. Section 3 describes the constraint differential evolution algorithm for the battery network optimisation. Section 4 empirically studies this system for New York City peak demand reduction through simulation and