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Optimal operation of interconnected energy hubs by using decomposed hybrid particle swarm and interior-point approach

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ABSTRACT

The Energy Hub has become an important concept for formally optimizing multi-carrier energy infrastructure to increase system flexibility and efficiency. The existence of energy storage within energy hubs enables the dynamic coordination of energy supply and demand against varying energy tariffs and local renewable generation to save energy cost. The battery lifetime cost may be included in the optimization objective function to better utilize battery for long term use. However, the operational optimization of an interconnected energy hub system with battery lifetime considered presents a highly constrained, multi-period, non-convex problem. This paper proposes Particle Swarm Optimization (PSO) hybridised with a numerical method, referred to collectively as the decomposition technique. It decouples the complicated optimization problem into sub-problems, namely the scheduling of storage and other elements in the energy hub system, and separately solves these by PSO and the numerical method 'interior-point'. This approach thus overcomes the disadvantages of numerical methods and artificial intelligence algorithms that suffer from convergence only to a local minimum or prohibitive computation times, respectively. The new approach is applied to an example two-hub system and a three-hub system over a time horizon of 24 h. It is also applied to a large eleven-hub system to test the performance of the approach and discuss the potential applications. The results demonstrate that the method is capable of achieving very near the global minimum, verified by an analytical approach, and is fast enough to allow an online, receding time horizon implementation.

1. Introduction

Energy hub modelling relates to the utilization of co-generation or tri-generation, which increases system flexibility by means of exploiting every available energy carrier, such as electricity, gas, and heat [1,2]. A typical energy hub contains multiple energy carriers, which achieves the function of importing, exporting, converting, and storing energy [3,4]. The energy hub approach takes advantage of existing infrastructures as much as possible and can be applied to various sizes of the energy system. Domestic buildings are modelled in this paper, which consume approximately 40% of society's total energy [5] but an individual domestic load profile is fairly stochastic such that it cannot always be met with onsite generation. Interconnecting heterogeneous energy infrastructure at local level can best leverage renewable generation and pooled storage without suffering large distance transmission losses and enable self-sufficient energy communities.

The optimal operation of an energy hub system enables the effective utilization of the elements within the system to minimize energy use, monetary cost or emissions, or some weighted combination of these objectives. Different algorithms have been applied to the multi-hub optimization problem. Ref. [6] presents a decomposed solution of a multi-agent genetic algorithm to optimize the power and gas flow between energy hubs. Papers [7,8] employ model predictive control (MPC) to optimally control the operation of three interconnected energy hubs, although numerical methods are applied within the MPC scheme, so a global minimum cannot be guaranteed in the solution. In [9,10], a grid of 10 hubs is modelled, where the energy transfer between hubs is formulated as a non-cooperative game. The existence of the unique Nash equilibrium is proved. Refs. [11,12] propose an integrated demand response program and simulate the scheme on a smart grid of six energy hubs. The integrated demand response problem is formulated as an ordinal potential game and the Nash equilibrium is proven to be unique. Ref. [13] investigates the performance of an energy management system under different energy pricing schemes for a group of 10 hubs. Ref. [14] introduces the "smart

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energy hub" system which uses a cloud computing platform to enable customers with must run loads to participate in a demand side management program. Ref. [15] investigates the optimization performance between deterministic and stochastic approaches applied to multi-period optimization for a 3-hub system over a mixed industrial and residential area. Ref. [16] generates a novel mathematical model for storage, general appliances, and other renewable components in residential houses. Mixed integer linear programming (MILP) is applied to optimize the control for residential energy hubs considering end-user preferences.

Refs. [9–15] propose the optimization for multi-hubs. However, storage is not considered when the problem is formulated as a non-convex problem in [9–12]. In Ref. [13], the storage is modelled in the energy hub optimization, but the problem is formulated as a convex problem. The optimal operation of multiple hubs with energy storage and interconnection available between hubs has hitherto been formulated as a highly constrained, non-linear multi-period optimization. However, the lifetime of the battery system suffers as its utilization increases, an aspect which has not been addressed in previous energy hub literature. In this paper, the battery lifetime cost is calculated and included in the objective function based on the method proposed by [17]. Therefore, the optimization problem is formulated as a non-convex, multi-period problem.

Numerical algorithms such as MILP provide fast computation times, but perform poorly when solving non-convex problems, because the solver can easily fall into local minima. Alternatively, particle swarm optimization (PSO) and related optimization approaches have been applied to optimize the operation of power systems due to their straightforward implementation and high efficiency [18]. For example, multi-pass iteration PSO was applied to the optimal scheduling of a battery coupled with wind turbine generators [19]. Co-evolutionary PSO was applied to smart home operation strategies [20]. A hybrid algorithm combining PSO and a bacterial foraging algorithm was proposed and applied to the optimal scheduling of an active distribution network [21].

Despite high robustness and accuracy compared with other algorithms [19], PSO has never been applied to solve energy hub optimization problems. However, conventional PSO is not suitable for solving highly-constrained non-linear problems with a large number of variables where the feasible region is narrow in hundreds of dimensions, meaning the time spent on finding feasible particles is considerable. Thus, improvement to conventional PSO is required in order to fully harness its potential for multi-hub optimization. This paper proposes a decomposed solution by applying a novel hybrid PSO and numerical optimization by combining conventional PSO with the 'interior point' method. Each particle in the PSO routine represents the storage operations over the whole optimization time horizon (24 h in this paper). Based on the storage operation, the 'interior-point' algorithm is applied to optimize the operations of other elements in the system of energy hubs over 24 h. The resulting energy cost over the full 24 h time horizon is formulated as the fitness score. All particles then are updated based on the conventional PSO routine until the optimization completes. The decomposition technique is demonstrated to be capable of optimizing multi-energy hubs efficiently, and the storage operation obtained from the decomposition technique is benchmarked to be very close to the theoretical optimal strategy of storage. Additionally, the decomposed PSO yields better optimization results with less computation compared with the conventional PSO. The approach is applied to two energy hub systems to illustrate its effectiveness. The main contributions of this paper are illustrated as follows:

(i) A decomposition technique of applying particle swarm optimization is proposed in this paper, and it is capable of solving the non-convex multi-period optimization problem. The decomposition technique is validated by a simple two-hub system for which the theoretical minimum can be derived empirically.
(ii) A group of residential houses is simulated as an interconnected energy hub system, an optimization problem is expressed to minimize the total cost of the energy hub system over 24 h. With the battery lifetime cost considered in the optimization, the problem is formulated as a non-convex problem. The decomposed PSO approach is applied to optimally solve the problem. The optimization results indicate that the battery SOC varies between 60% and 90% to avoid unnecessary degradation of the battery lifetime for three residential hubs.
(iii) The performance of the decomposed PSO approach is compared with the conventional PSO being applied to solve a same three-hub problem. The decomposition technique achieves a 58% greater energy saving for three-hub optimization with 98% saving of computation time comparing with the conventional PSO.

This paper is organized in six sections. Section 2 illustrates the general optimization problems for multi-energy hubs which the energy interconnection is enabled between hubs. An explicit description of the decomposition technique applying PSO is presented in Section 3. Section 4 presents the case studies and related results. Section 5 concludes the paper.

2. Energy hub optimization

2.1. Energy hub modelling

A typical energy hub model that enables energy sharing between hubs is shown in Fig. 1. It consumes various input resources including electricity from grid (P_{ele}), solar energy (P_{so}), and gas (P_{gas}) to meet the electricity load (L_{ele}) and thermal load (L_{th}). The energy flow between hubs is denoted by E_{rh} and H_{rh} , which indicate the power and heat exchange with other hubs. The mathematical formulation between hub inputs and outputs under steady state operation is shown in (1).

$$\begin{bmatrix} L_{ele}(t) \\ L_{th}(t)+H_{rh}(t) \end{bmatrix} = \begin{bmatrix} \eta_{PV}\cdot(1-v_1(t)) & 1-v_1(t) & v_2(t)\cdot\eta_e \\ \eta_{PV}\cdot v_1(t)\cdot CoP & v_1(t)\cdot CoP & v_2(t)\cdot\eta_{th}+\eta_{bo}\cdot(1-v_2(t)) \end{bmatrix} \times \begin{bmatrix} P_{so}(t) \\ P_{ele}(t)+E_{sh}(t)-E_{hs}(t)+E_{rh}(t) \\ Pgas(t) \end{bmatrix} \tag{1}$$

The first matrix on the right hand side is the coupling matrix C, which defines the relationship between inputs P and outputs L. The parameter t within the brackets indicates that these variables are time dependent. Since the problem is considered in a discretized time domain, they are fixed in each time step. The coefficient v is the dispatch factor between 1 and 0 which generally denotes the portion of the energy injected to a certain converter. For the example energy hub model, υ_1 is the portion of electricity injected to