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Incorporating domain knowledge into the optimization of energy systems

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ABSTRACT

Energy plays a key factor in the advancement of humanity. As energy demands are mostly met by fossil fuels, the world-wide consciousness grows about their negative impact on the environment. Therefore, it becomes necessary to design sustainable energy systems by introducing renewable energies. Because of the intermittent availability of different renewable resources, the designing of a sustainable energy system should find an optimal mix of different resources. However, the optimization of this combination has to deal with a number of possibly contradictory objectives.

Multi-objective evolutionary algorithms (MOEA) are widely used to solve this kind of problems. As optimizing an energy system by using a MOEA is computationally costly, it is necessary to solve the problem efficiently. For this purpose, we propose the incorporation of domain knowledge related to energy systems into different phases (i.e., initialization and mutation) of a MOEA run. The proposed approaches are implemented for two widely used MOEAs and evaluated on the Danish Aalborg test problem. The experimental results show that each approach individually achieves significant improvements of the energy systems, which is expressed in better trade-off sets. Moreover, a state-of-the-art stopping criterion is adapted to detect the convergence in order to save computational resources. Finally, all proposed techniques are merged within two MOEAs with the result that our combined approaches yield significantly better results in less time than generic approaches.

1. Introduction

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Most energy generated all over the world is based on fossil fuels [1]. As energy generated by fossil fuels has harmful effects on the environment, recent interest is directed towards the employment of green or renewable sources to generate energy [2]. However, due to their intermittent availability, it is not easy to integrate renewable energy into a larger energy system [3].

In order to solve the integration problem, two optimization phases can be considered [4], i.e., (i) operational optimization and (ii) capacity/sizing optimization. While the day-to-day operations of resources of a given energy system are optimized in the first phase, the second phase is mainly concerned with the design of future energy scenarios to integrate renewable energies. For the first phase, many optimization models such as energy system simulation models are available (e.g., see the comprehensive review article by Connolly et al. [5]). For the second phase, however, only few attempts have been made when the considered energy system consists of inter-connected sub-systems from electric, thermal and transportation sectors [6]. Of the existing approaches, several consider the optimization of the second phase as a multi-objective optimization problem [7–9], where the different objectives can be *total cost*, *unmet load* and *fuel emission* (i.e., CO_2 emission) [8]. In this article, we focus on the optimization of energy systems in the second phase. Capacity/sizing optimization is an active research topic in the energy domain, where it is possible to leverage synergies between different energy sub-systems [10].

The objectives of real-world problems can often be in conflict with each other. The goal of solving a multi-objective optimization (MOO) problem is to find a (not too large) set of compromise solutions. The Pareto front of a MOO problem consists of the function values representing the different trade-offs with respect to the given objective functions. In practice, it is computationally infeasible to compute the whole Pareto front, and MOO problems

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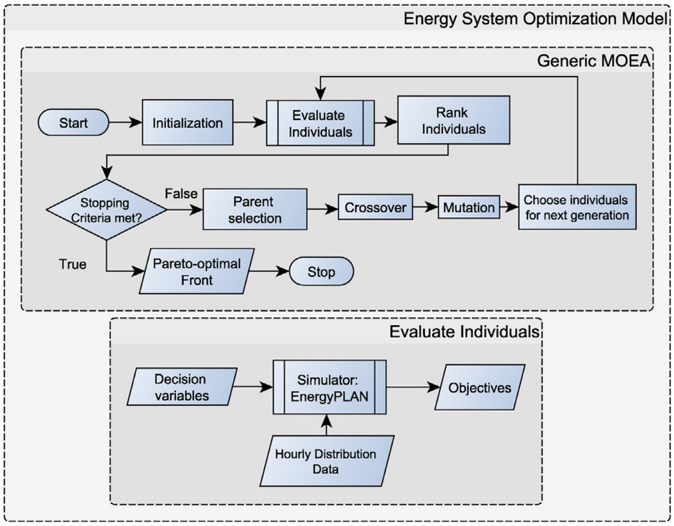

Fig. 1. Energy system optimization model.

often can only be solved approximately by heuristic approaches. Evolutionary algorithms have been widely used to tackle multi-objective problems, and recently, efforts have been made to employ multi-objective evolutionary algorithm (MOEA) to solve the problem of optimizing energy systems [11,12]. In addition, as the energy system optimization problem we want to tackle is non-linear and discontinuous in nature [10], we apply stochastic method such as evolutionary algorithm instead of gradient-based methods (such as used in [13]).

Fig. 1 presents our model for optimizing energy systems. The upper part of the model illustrates the steps undertaken by classical MOEAs such as Non-dominated Sorting Genetic Algorithm (NSGA-II) [14] and Strength Pareto Evolutionary Algorithm (SPEA2) [15]. MOEAs are bio-inspired algorithms, which mimic some fundamental aspects of the neo-Darwinian evolutionary process. They simultaneously search with a *population* of candidate solutions and associate objective scores as fitness values for each candidate solution. The algorithms then select among the population to favor those solutions that are more fit. The next generation (i.e., a new population) consists of replicates of the fitter solutions that have been *genetically mutated* and *crossed over* in a biological metaphor: the decision variables were perturbed such that they inherit characters of their parents, as well as change in random ways. NSGA-II and SPEA2 are nearly identical, but differ in the way they rank solutions within the set of trade-offs, and in the way the individuals for next generations are selected.

The lower part of Fig. 1 shows our steps of evaluating individuals. The core component is the simulator for energy systems, and Connolly et al. [5] provide a detailed review of different computer tools for performing such simulations. The classification of tools mainly depends on the simulated time step and the modeled energy sub-systems. Time steps are important when modeling the intermittent availability of renewable resources. There are several simulation models that consider different time step sizes: HOMER [16,17] for minutes, EnergyPLAN and H_2RES [18,19] for hours, and INFORSE [20] and LEAP [21] for years. However, very few models (e.g., EnergyPLAN, INFORSE) are capable of simulating different levels of penetration of a renewable energy system (electricity, thermal and transportation). We choose EnergyPLAN because it is freely available and it provides fairly detailed (i.e., hourly) analyses of operations of different energy generating sources. It is capable of simulating all the main inter-connected sub-systems of an energy system. In addition, EnergyPLAN also optimizes the operations of a given system (i.e., capacities of different power generations components, demands, efficiencies, and other relevant data) and produces annual indicators (e.g., total emission, primary energy consumption, cost and others).

Generally, simulation models are computationally costly, therefore, we want to optimize energy systems more efficiently. In particular, we want to achieve this by generating a high-quality approximation of the Pareto front [22] at reduced computational cost. To reach this goal, we investigate the incorporation of domain knowledge related to energy systems into the different phases of a MOEA. Firstly, we propose a smart initialization technique and secondly, incorporate a smart mutation [23]; both exploit domain knowledge. Additionally, to detect convergence of the algorithm, we apply the stopping criterion proposed by Mahbub et al. [24] that has proven to work reliably when used in the optimization of a real-world problem (i.e., energy system optimization problem). This way the MOEA stops when no improvements are achieved, which saves computational resources that would otherwise be wasted. We integrate smart initialization, mutation and stopping criterion into MOEAs to form *informed MOEAs* and compare them with generic MOEAs. The results clearly show that all these individual methods work together and have an overall very good impact on the optimization of an energy system. To the best of our knowledge, this is the first attempt to incorporate energy system domain knowledge into different operators of MOEAs.

In this study, we focus on the Danish Aalborg energy system [25] to demonstrate the feasibility of our approach. It is a well-understood problem, and the details are readily available. It is important to note that more and more aspects have been investigated in the recent past, giving rise to a large number of optimization problems about renewable energy management and electricity market operation. For instance, energy bidding and reservation [26], economic dispatch [27] and microgrids management [28] have been considered in the last few years. As our proposed improvements are independent of the particular framework used (i.e., as the approach is generic), we conjecture that they can be applied to these problems as well to improve the outcomes.

The paper is organized as follows. Most of Section 2 discusses how domain knowledge is represented and how it can be incorporated into a MOEA through problem-specific initialization. A brief description of smart mutation and stopping criterion is presented in Sections 2.3 and 3. We present our test problem in Section 4. Then, we describe in Section 5 the details of all experiments and the corresponding discussions of the results. Finally, we draw our conclusions in Section 6.

2. Incorporating domain knowledge

In general, a typical MOEA cannot perform well for all classes of problems, as this would be contradictory to the No Free Lunch Theorem [29]. According to this theorem, the average performance of an algorithm over all possible classes of problems is constant. Hence, the good performance of an optimization algorithm on one class of problems is balanced out by the bad performance of the algorithm on another class of problems. However, this also means that problem-specific algorithms with above-average performance are possible. Bonissone et al. [29] define two different ways to achieve this by incorporating domain knowledge: *implicitly* and *explicitly*. Encoding, design of data structures and constraints representation are categorized as an implicit incorporation of domain knowledge. Our article mainly focuses on the explicit incorporation (i.e., smart seeding of initial population, mutation exploiting domain knowledge) for the energy system optimization problem. In the following sections, we will discuss how we represent domain knowledge of energy systems and how we incorporate this knowledge into initialization and mutation.

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