Energy 36 (2011) 3933–3943

Contents lists available at ScienceDirect

Energy

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

A hybrid multi-level optimization approach for the dynamic synthesis/design and operation/control under uncertainty of a fuel cell system

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ARTICLE INFO

Article history:
Received 30 December 2009
Received in revised form
5 August 2010
Accepted 17 August 2010
Available online 8 October 2010

Keywords:
Proton exchange membrane fuel cell (PEMFC)system
Multi-level optimization
Physical decomposition
Uncertainty quantification
Response sensitivity analysis
Dynamic optimization

ABSTRACT

During system development, large-scale, complex energy systems require multi-disciplinary efforts to achieve system quality, cost, and performance goals. As systems become larger and more complex, the number of possible system configurations and technologies, which meet the designer's objectives optimally, increases greatly. In addition, both transient and environmental effects may need to be taken into account. Thus, the difficulty of developing the system via the formulation of a single optimization problem in which the optimal synthesis/design and operation/control of the system are achieved simultaneously is great and rather problematic. This difficulty is further heightened with the introduction of uncertainty analysis, which transforms the problem from a purely deterministic one into a probabilistic one. Uncertainties, system complexity and nonlinearity, and large numbers of decision variables quickly render the single optimization problem unsolvable by conventional, single-level, optimization strategies.

To address these difficulties, the strategy adopted here combines a dynamic physical decomposition technique for large-scale optimization with a response sensitivity analysis method for quantifying system response uncertainties to given uncertainty sources. The feasibility of such a hybrid approach is established by applying it to the synthesis/design and operation/control of a 5 kW proton exchange membrane (PEM) fuel cell system.

1. Introduction

Due to the complexities in structure and operation involved, the process of system synthesis/design and operation/control for large-scale energy system development requires a multi-disciplinary approach to achieve the quality, cost, and performance goals for the system. In general the typical approach to this process is to use simple trade-off analysis, rule-of-thumb, and both design and off-design simulations. Such an approach may not correctly predict the best interactions between subsystems, the impact of transient system/subsystem/component behavior during dynamic operation (e.g., the start-up and shutdown stages, or rapid load changes), the optimum system configuration and component designs, the optimum operating strategies, etc. Moreover, although controller design should be conducted during the system integration stage as a part of the system synthesis/design process, it is typically left as a secondary task to be completed after the system synthesis/design task has been completed.

Integration of all of these design issues (i.e., dynamic synthesis/design and operation/control) into a single optimization problem, which is solved simultaneously, is extremely difficult because of the complexities involved. This difficulty is further heightened once uncertainty analysis is incorporated into the problem. Even though optimization under uncertainty has been widely used for decision-making procedures in work done on product management and scheduling, it is difficult to apply to the large-scale system optimizations envisioned here because probabilistic approaches are very computationally expensive. Only a few cases have been reported in the literature and these have been limited to steady-state energy system synthesis/design [1,2] despite the fact that uncertainty analysis can significantly improve the quality of the analysis results. The stochastic programming needed for the uncertainty analysis transforms a deterministic problem into a probabilistic one, increasing system complexity and nonlinearity and rapidly rendering the single optimization problem unsolvable through typical single-level optimization strategies. To overcome this difficulty sophisticated multi-level optimization strategies (i.e., decomposition strategies) to facilitate the optimization process can be used [3–8]. In particular, decomposition approaches are very efficient for the optimization of dynamic systems that have highly

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0360-5442/$ – see front matter
doi:10.1016/j.energy.2010.08.024

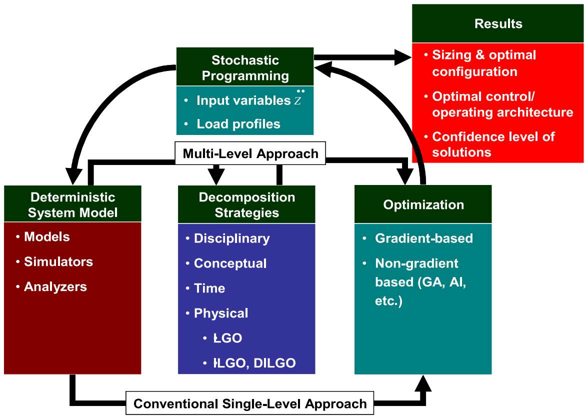

Fig. 1. Schematic of general modeling and optimization under uncertainty [7].

nonlinear characteristics with a great number of degrees of freedom. In this study, the dynamic synthesis/design and operation/control optimization strategy used is one based on physical decomposition only.

As to the many different uncertainty sources in the optimization problem, these include computational errors, load profile variability, cost information, thermodynamic properties, correlation equations, etc. Among these sources, the uncertainties in load profile and cost information significantly affect the system synthesis/design and operation/control optimization results. Thus, it is very important to quantify the uncertainties during system development. To quantify these uncertainties in the optimization problem, the response sensitivity analysis (RSA) method [9] is adopted and developed for our application. The load profile, cost models, and fuel cost are treated as probabilistic input variables and uncertainties in the output results are quantified. Fig. 1 schematically presents how these uncertainties and all of the other issues listed above are integrated here into one complete optimization process which simultaneously determines the dynamic system synthesis/design and operation/control optimization of a system and its components. The feasibility of such a hybrid approach is established by applying it to the synthesis/design and operation/control of a 5-kW PEMFC system and results are presented below. The focus of the present paper differs from previous papers by the authors [10,11] in that it illustrates how the multi-level optimization technique can be integrated with the uncertainty analysis process and be successfully applied to the development of an entire energy system.

2. Optimization

At the beginning stage of a system synthesis/design and operation/control optimization process, three things must be decided with regard to the optimization. The first is deciding what kind of optimization algorithm (e.g., gradient-based, nongradient-based, or hybrid) is to be employed. The second is deciding between either a single or multi-objective approach, while the third requires deciding between a single-level or a multi-level optimization strategy. In this work, Sequential Approximate Optimization (SEQOPT), a kind of surrogate-model-based optimization algorithm, is employed, because it is relatively computationally inexpensive and effective for solving complex DMINLP problems [10–12]. SEQOPT is a kind of hybrid heuristic/gradient-based optimization algorithms developed by Audet et al. [12] at Boeing. Readers are referred to the reference for more details.

Energy system synthesis/design and operation/control optimization problems consist of modifying the system configuration, component designs, and operation and control parameters according to a single or to multiple objective(s) such as thermodynamic performance, economic, and environmental impact factors [13]. In particular, multi-objective optimization is quite useful for decision makers but has not been applied widely to energy system optimizations because it is computationally expensive. The present authors have developed an effective strategy for multi-objective optimization problems, which appears in Kim et al. [10]. However, in the present paper, the optimization problems are treated as single-objective problems, focusing instead on the development of a multi-level optimization strategy for dynamic energy system development under uncertainty.

2.1. General concept of decomposition techniques

If a system optimization problem is uncomplicated enough to be solved using any of the typical optimization algorithms mentioned above, a single-level optimization approach is directly applicable. However, many energy system optimization problems are not that simple but can, nonetheless, be handled by sophisticated multi-level optimization strategies, which facilitate the optimization process. Decomposition breaks the large-scale optimization problem down into a set of approximately equivalent smaller optimization problems in order to facilitate the optimization procedure. Decomposition approaches are very effective for facilitating the optimization of dynamic systems which have highly nonlinear characteristics with a large number of degrees of freedom. Decompositions in the multi-level approach can be achieved in four ways: by disciplinary, conceptual, physical, and time decomposition.

Fig. 1 shows a schematic of the general single- and multi-level optimization process. Conceptually, the decomposition process is placed in between the deterministic model and the optimizer as shown in the figure. Examples of the application of such decomposition strategies to large-scale energy system synthesis/design and operation/control optimization problems can be found in [3,7,14].

2.2. Physical decomposition techniques for large-scale energy system optimization problems

Various physical decomposition techniques have been introduced in the literature and, in general, can be classified as methods of either local-global optimization (LGO) or iterative local-global optimization (ILGO). A dynamic version of the latter also exists designated as DILGO. Both ILGO and DILGO have been developed and their efficiencies validated in energy system synthesis/design and operation/control optimization applied to high performance aircraft and SOFC/PEMFC systems by [15,16].

The LGO technique has the advantage of breaking a large-scale optimization problem down into smaller unit-level problems. However, it is computationally expensive because each unit-level optimization must be carried out independently many times within the system-level (or global) optimization problem resulting in a set of nested optimizations. The nesting of optimizations in the LGO approach can be eliminated by recognizing that the system-level information of optimizing the system-level objective with respect to the coupling functions can be embedded directly into the unit-level objectives. Munoz and von Spakovsky [15] recognized this in developing their iterative local-global optimization (ILGO) approach which embeds this information at the local level in the form of gradient (i.e., shadow price) information of subsystem responses to variations in the coupling functions, which represent subsystem-to-subsystem interactions associated with strictly system-level optimization degrees of freedom.