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Greenhouse gases emission assessment in residential sector through buildings simulations and operation optimization

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A B S T R A C T

Buildings use a significant amount of primary energy and largely contribute to greenhouse gases emission. Cost optimality and cost effectiveness, including cost-optimal operation, are important for the adoption of energy efficient and environmentally friendly technologies. The long-term assessment of buildings-related greenhouse gases emission might take into account cost-optimal operation of their energy systems. This is often not the case in the literature. Long-term operation optimization problems are often of large scale and computationally intensive and time consuming.

This paper formulates a bottom-up methodology relying on an efficient, but precise operation optimization approach, applicable to long-term problems and use with buildings simulations. We suggest moving-horizon short-term optimization to determine near-optimal operation modes and show that this approach, applied to flexible energy systems without seasonal storage, have satisfactory efficiency and accuracy compared with solving problem for an entire year. We also confirm it as a valuable pre-solve technique.

Approach applicability and the importance of energy systems optimization are illustrated with a case study considering buildings envelope improvements and cogeneration and heat storage implementation in an urban residential settlement. EnergyPlus is used for buildings simulations while mixed integer linear programming optimization problems are constructed and solved using the custom-built software and the branch-and-cut solver Gurobi Optimizer.

1. Introduction

Tackling climate changes and providing secure energy supply are among the most important challenges of mankind today. Buildings consume a significant share of total energy. According to [1], they use 40% of global primary energy and contribute to 30% of CO_2 emissions.

Cost optimality is very important for the effective expansion of energy efficient heating and cooling of buildings [2]. The (European Union) EU has ambitious goals related to the increase in energy efficiency in buildings. However, Ref. [3] underlines the importance of cost-optimal energy efficiency levels and cost-effective measures when moving towards nearly zero energy buildings.

References [3,4] suggest estimating economic and environmental impacts for entire lifetimes. According to [5], the major approaches to estimate buildings-operation-related energy use, within a (life-cycle analysis) LCA, include: relying on the actual consumption records, estimation based on referencing to databases and using energy simulation tools that might be static or dynamic.

For a successful evaluation of energy supply options, it is important to have accurate and sophisticated procedures for assessing buildings-related greenhouse gases (GHG) emission (GHGE) and (primary energy consumption) PEC assessment that take into consideration as many relevant parameters as possible. Forecasting buildings energy needs, GHGE or PEC is often not a straightforward task, especially when there are no relevant measurements. In the cases of complex energy supply systems with several different types of components – (cogeneration unit) CG, (thermal storage) TS, heat pump, chillers, solar thermal, electrical or hybrid technologies *etc.* – the choice of the operation strategy may significantly influence costs or environmental impact. Thus, when considering cost optimality and cost effectiveness, one should take into account the cost-optimal operation of energy supply plants.

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1.1. Energy supply operation optimization

In order to ensure positive financial and other effects, plants have to be carefully designed and managed. A complex (energy supply system) ESS, especially with CGs and TSs, can be operated in a variety of regimes and any analysis of cogeneration system economics must consider operating modes [6], because the operation cost of a plant largely depends on planning methods and operation parameters [7]. Reference [8] emphasizes the importance of permanent control and (operation optimization) OO for a better plant economy, higher energy efficiency and lower GHGE.

There are many different models and methods for finding the (optimal operation regime) OOR of ESS in the literature. The simplest and the easiest to solve are based on (linear programming) LP. The use of binary variables to indicate the on/off states of components and set lower bounds of load levels leads to more realistic models and solutions, but requires computationally intensive (mixed integer linear programming) MILP methods. Nonlinear and complex problems are often solved with metaheuristic methods – (genetic algorithms) GA, (particle swarm optimization) PSO *etc.* Refs. [9,10] compare simpler and more detailed OO approaches.

In Refs. [11,12], LP is used for OO of a trigeneration system. In Ref. [12], LCA and thermoeconomic analysis are combined and GHGE is minimized to allocate environmental loads. In Refs. [13,14], LP is exploited to find the cost-optimal regime that satisfies energy demand.

In Ref. [15], MILP is applied to evaluate and compare CGs and TS options for a (district heating) DH system under cost-optimal operation assumption. A comprehensive MILP-based general modeling framework for OO of cogeneration plants under liberalized electricity market conditions is presented in Ref. [16]. Object-oriented programming languages are found convenient to create optimization models. Another approach to optimize power generation in liberalized markets is shown in Ref. [17].

GA are used in Ref. [18] to determine on/off variables of ESS and LP to optimize load levels of components. A similar approach is applied in Ref. [19] for OO of trigeneration systems, combining both GA and simulated annealing with LP. In Ref. [20], a multiobjective nonlinear OO problem related to a DH and cooling plant is defined using fuzzy sets and solved with PSO. Ref. [21] presents a model suitable for OO-based control of CGs. Mixed integer nonlinear optimization problem is represented as a dynamic programming problem. This approach has the re-optimization option useful in the cases of wrong predictions of input parameters.

Many papers are dedicated to OO of interconnected buildings or ESSs, often with CGs and TS. In Ref. [22], a MILP model is proposed for design and OO of multiple small cogeneration systems located in the buildings of an urban area, as well as the heat distribution network that connects the systems. The approach is multiobjective and considers costs and GHGE. A methodology for daily OO of a polygeneration microgrid is shown in Ref. [23]. The goal is to minimize overall operation costs and special attention is paid to GHGE and PEC reduction. It is concluded that following OOR strategies is crucial for achieving economic, energy efficiency and environmental benefits. In Ref. [24], the design of microgrids connected to the buildings that have TS, HPs, CGs and boilers is analyzed under the assumption that control strategies are based on OO and the model predictive control approach. The importance of operational planning and OO for microgrids proper functioning is underlined again. Ref. [25] employs MILP for OO of a small residential system with CG, where PEC is the objective.

OO, often based on LP or MILP, is exploited in the frame of synthesis and design optimization of ESSs as shown in Refs. [22,26] and summarized in Ref. [27].

Long-term OO problems, where one or several years are considered with the time resolution of 1 h, are large-scale problems containing both integer and binary variables. Some common nonlinear relations can be formulated as linear using appropriate transformations which often require additional variables and constraints [28–30]. Such problems can be computationally very intensive, requiring long solving time, fast computer processors and large amounts of memory, especially for complex plants. Some approximations are necessary to make long-term OO problems suitable for efficient solving with available resources – either simplifying mathematical models, using approximate solving techniques or representing the entire horizon with several typical days.

Table 1 summarizes the advantages and the disadvantages of the most common approaches to long-term OO of energy supply systems. Approximating the entire horizon with several typical days and solving OO problem for each day separately or all together significantly reduces the problem size and allows short solving time. As a consequence, more detailed models are acceptable. Since MILP is usually used to solve such problems, the exact solution can be obtained or the error can be tolerated. It is possible to include the constraints that connect time-dependent variables over the entire year. On the other hand, a careful selection of typical days is required, as well as the additional inputs approximations (demand patterns, electricity prices *etc.*), which can strongly influence the quality of the solution. In addition to that, this approximation can be used to model only daily storage charging and discharging cycles. The above disadvantage can be partially avoided by using typical weeks instead of days [31].

Optimization of the entire year using MILP, although possible [32], can be a very time consuming and computationally intensive process. As such, it may require larger error tolerance or significant simplifications in the mathematical model. They might be related to extending the time step duration (lowering the time resolution) and decreasing the level of details. Mathematical model simplifications often assume the reduction of the number of integer variables, sometimes completely relaxing a MILP problem to an LP one. Such problems are solved much faster, but they neglect lower bounds on load levels, start-up and shutdown operation and often part-load characteristics. As observed in Ref. [9], they can result in operation regimes that are infeasible in practice. In Ref. [33], heuristic techniques are used to find good feasible starting values for the MILP procedure and thus improve solving efficiency. The advantage is the possibility to take into account seasonal energy storage and the constraints that connect time-dependent variables over the entire year.

Computationally demanding problems can sometimes be solved more efficiently using metaheuristic metods (GA, PSO *etc.*) instead of MILP. Such methods allow much higher flexibility in mathematical modeling, but finding the optimal solution is never guaranteed and the error cannot be controlled. The adjustment of input parameters that control the execution of such algorithms is rarely straightforward.

1.2. Buildings simulations

Authors often use buildings simulation software to calculate energy demand needed for analyses. This is especially useful when an hour-by-hour demand is required and there is no relevant measured data available, either due to the lack of equipment, expected significant changes in demand or because non-existing