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Decomposition method for optimizing long-term multi-area energy production with heat and power storages

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HIGHLIGHTS

- A decomposition method for optimizing long-term heat and power production is developed.
- The energy system includes multiple areas with power transmission and energy storages.
- The method solves three kinds of sub-models iteratively.
- Proposed method solves long-term problems fast.

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ABSTRACT

To achieve efficient transition towards climate and energy framework targets, improvement in energy efficiency is important. This paper presents a model for long-term multi-area combined heat and power production with heat and power storages, and power transmission between areas. Assuming fixed unit commitment, the model minimizes total production and transmission cost. The model can in principle be solved as a linear programming model. However, energy storages impose dynamic constraints to the model, making the long-term model very large and slow to solve. To speed up solution and to allow larger models to be solved, we develop a novel decomposition method that solves three kinds of smaller sub-models iteratively. The method is validated by comparing it with the integrated linear programming model using realistic demand data generated by a forecasting model. The method produces near-optimal solutions within three iterations. The decomposition method can also solve larger models much faster than the integrated model.

1. Introduction

The key targets of climate and energy framework in the EU by 2030 are reducing greenhouse gas emissions by 40%, improving energy efficiency by 32.5%, and increasing renewable production by 32% [1]. Combined heat and power (CHP) is the most efficient form of electric power generation. Energy saving by CHP is in the range of 15–40% in comparison to separate condensing power production and heat-only boilers (HOBs). Good energy efficiency of CHP means that the same amount of power and heat can be produced from a smaller amount of fuel, which leads directly to lower CO_2 emissions [2]. In the case of renewable fuels, CO_2 emissions can be near-zero, and in that case, CHP allows scarce renewable fuels to be used more efficiently. In Nordic countries, such as Finland, power and heat consumption fluctuates intensely [3]. This makes it challenging to plan CHP production where power and heat production are interconnected.

Today, CHP contributes to 21% of the CO_2 emission reduction in Europe and 14% of the energy efficiency improvement. The vision for the CHP pathway is to reduce CO_2 emissions by 23% and improve energy efficiency by 18% by 2030. The EU goal is to double CHP capacity in order to replace separate power and heat production by 2050 [4]. In Finland, almost 32% of total power production and 64% of total district heat was produced by CHP in 2017. Of total power consumption, 76% was covered by domestic production while 24% was imported from other countries [5]. Optimization of CHP leads to energy efficiency improvement, and reduction in both production cost and greenhouse gas emission.

The coupling of heat and power in CHP production together with power transmission across areas impose complexity on CHP optimization models. The models define optimal operation with minimal production and transmission costs. Dynamic constraints for heat and power storages also increase the complexity. The CHP problems can be

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Nomenclature

Abbreviations

CHP	combined heat and power
HOB	heat only boiler
LP	linear programming
MILP	mixed integer linear programming

Symbols

C	production cost (€)
P	power demand (MWh)
Q	heat demand (MWh)
c_j, p_j, q_j	production price, power generation, and heat production at characteristic point j (MWh)
x_j	variables used to encode convex combination of operating region
C_{ik}	power transmission price from area i to k (€/MWh)
y_{ik}	electricity transmitted from area i to k (MWh)
η	efficiency factor
s_{in}^q, s_{in}^p	heat and power charge to storage (MWh)
s_{out}^q, s_{out}^p	heat and power discharge out of storage (MWh)
s^q, s^p	heat and power storage level (MWh)
x^{q+}, x^{p-}	surplus and slack variables
C^{q+}, C^{p-}	surplus and slack variable prices
$S^{q,max}$, $S^{p,max}$	capacity of heat and power storages
Y_{ik}	capacity for transmission line from area i to k (MWh)
x_i^l	production in area i and line segment l (MWh)
$\dot{P}_{prod}^t$	combined power production and storage (MWh)
L_i	number of line segments in production area i
c^l	marginal production costs (slope of line segment l) (€/MWh)

Index sets

N	set of areas or nodes in network
U_i	index set for production unit at area i
J_u	extreme characteristic points of production unit u
A	set of arcs in network
l	point or line segment of piecewise linear curves

Superscripts and subscripts

t	time
i,k	areas i and k
0	initial content
in	charge into storage
out	discharge out of storage
u	unit
prod	production

considered convex, which allows applying linear programming (LP) to solve the problem [6]. Non-linear models are computationally even more complex, and the optimum is difficult to reach. In [7], authors performed an uncertainty analysis for non-linear energy systems using a linear substitute model. The computational time was reduced by 200 times in comparison to the non-linear model with only a small approximation error in the performance of a gas turbine. The authors in [6] developed a Simplex algorithm to solve hourly CHP as an LP problem. The solution time of the model was improved and the model was applied for commercial industry use. The Simplex algorithm was used for optimization of hourly transmission-constrained multi-site CHP system formulated as an LP model [8]. The algorithm was in average 30 times faster than a commercial LP code. LP modelling was also applied to determine the optimal capacity of a 100% renewable energy system for a building in terms of total cost [9]. Considering the unit commitment (on/off status of plants) typically requires non-convex modelling. Such non-convex problems can be solved using different techniques such as heuristic algorithms, Lagrangian relaxation, and mixed integer linear programming (MILP). An algorithm was developed to address unit commitment in a multi-period CHP problem [10]. A heuristic procedure utilizing both Lagrangian relaxation and linear relaxation improved the initial solution. Numerical results showed an improvement in the results for costs and solution time. A heuristic method was applied for optimization of CHP production with power ramp constraints and reducing CO_2 emissions [11]. The heuristic gave efficient and high-quality solutions with test runs for real data over different time horizons. The Lagrangian relaxation technique was illustrated for non-convex CHP problems and tested using three test cases [12]. Study [13] showed that Lagrangian relaxation algorithm solves large-scale unit commitment problems faster than MILP. A MILP model was applied to non-convex bi-objective CHP problems [14]. The characteristic areas were divided into convex sub-areas. The two objectives were minimizing production cost and reducing emission costs. The problem was decomposed into thousands of hourly sub-problems and was formulated as MILP. The results using real plant data showed that the method is efficient enough and applicable for analysis and decision making of medium-term problems. A rolling-horizon algorithm was developed for long-term CHP systems [15]. The whole time horizon was split into a sequence of weekly sub-models and solved by a MILP model. The model was tested using a real test case and found a near-optimal solution with a reasonable computational time. A MILP model based on representative days technique was proposed to reduce the computational complexity of a full-year optimization for a solar district heating system with seasonal heat storage [16]. The speed of the solution was improved by 10–30 times with representative optimization for the full-year in comparison with different representative days selections. In [17] a MILP model was applied to determine the optimal size of remote renewable power systems when electricity curtailment decreases. An iterative process without using binary variables was used to find the optimal solution. The developed process solved the problem in a shorter time than the model with binary variables, and found sub-optimal annual costs with less than 0.5% difference. In [18], a typical time series aggregated method was introduced based on inter-period and intra-period states for the modelling of long-term energy systems with seasonal storage. Each time period determines a closed operational time. The method was solved by MILP model and results indicated that the accuracy of the solution is high. A non-convex mixed-integer non-linear problem was reformulated to a sequence of MILP problems and solved by branch-and-bound algorithm in [19]. The model was used to minimize levelized cost of a heating and cooling system. Electric power from natural gas and geothermal source were compared, and the results showed that the environmental benefit of applying geothermal power is higher than the increment in levelized cost. In [20], the non-linear objective functions and constraints were linearized to apply MILP for optimization of a power plant connected to a gas storage tank. A three-step iterative algorithm solved the problem faster than other algorithms and found a better optimal solution.

The intermittent nature of renewable production has promoted solutions to improve the flexibility of supply and to balance the production with fluctuating demand. Energy storage [21,22,23,16,24,25], flexible demand response [26,27] and extension of power transmission [28,29] are among technologies to enhance flexibility. Power storages can balance power production with variable power demand and intermittent wind and solar power to improve the flexibility of supply.