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A method for aggregating external operating conditions in multi-generation system optimization models

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HIGHLIGHTS

- The CHOP method for aggregating energy system data is presented.
- The CHOP method is applied in a case study.
- The CHOP method is compared to three commonly used data aggregation methods.
- The comparison suggests that the CHOP method offers more accurate reduced datasets.

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ABSTRACT

This paper presents a novel, simple method for reducing external operating condition datasets to be used in multi-generation system optimization models. The method, called the Characteristic Operating Pattern (CHOP) method, is a visually-based aggregation method that clusters reference data based on parameter values rather than time of occurrence, thereby preserving important information on short-term relations between the relevant operating parameters. This is opposed to commonly used methods where data are averaged over chronological periods (months or years), and extreme conditions are hidden in the averaged values.

The CHOP method is tested in a case study where the operation of a fictive Danish combined heat and power plant is optimized over a historical 5-year period. The optimization model is solved using the full external operating condition dataset, a reduced dataset obtained using the CHOP method, a monthly-averaged dataset, a yearly-averaged dataset, and a seasonal peak/off-peak averaged dataset. The economic result obtained using the CHOP-reduced dataset is significantly more accurate than that obtained using any of the other reduced datasets, while the calculation time is similar to those obtained using the monthly averaged and seasonal peak/off-peak averaged datasets. The outcomes of the study suggest that the CHOP method is advantageous compared to chronology-averaging methods in reducing external operating condition datasets to be used in the design optimization models of flexible multi-generation systems.

1. Introduction

Large-scale integration of intermittent renewable energy sources (solar, wind, tidal and wave) in the energy system imposes a demand for generation–consumption balancing [1]. Flexible multi-generation systems (FMGs), here defined as flexibly operating facilities integrating the generation of two or more energy services (power, heating, cooling, fuels, etc.), may provide such balancing operation [2]. Furthermore, FMGs based on biomass may achieve high aggregated biomass conversion efficiencies through process integration [3], which is of crucial importance in sustainable energy systems as the biomass resource is limited on a global level [4,5]. Such process integration advantages may further be used for providing sustainable fuel and energy services in FMGs at competitive prices [6–8], thereby integrating various layers of the energy system. The development of efficient biomass-processing FMGs may therefore be seen as an integral part of the transition towards a smart energy system based on renewable energy sources [9].

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Nomenclature

Latin letters

C	cost (Euro)
C_v	ratio between lost power generation and increased district heating generation (–)
c	specific cost (Euro/MWh)
D	dataset
F	fuel consumption (MWh)
N	number of groups
n	number of characteristic parameter intervals
O	operating point
P	power (MWh)
p	operating condition parameter
Q	heat (MWh)
T	time of occurrence
t	duration (h)

Greek letters

α	back-pressure ratio (–)
λ	load (–)
σ	standard deviation (–)

Subscripts

aa	annually averaged
i	characteristic parameter interval index
j	data point index
k	EOC parameter index
l	CHOP group index
ma	monthly averaged
pot	potential
sp	seasonal peak/off-peak averaged

Superscripts

$*$	linearized

Abbreviations

CHOP	Characteristic Operating Pattern
CHP	combined heat and power
EOC	external operating condition
FMG	flexible multi-generation system

The design optimization of FMG concepts includes such challenges as synthesising processes from multiple technological alternatives, facility and process dimensioning, process integration, feedstock market-impacts, operation optimization, etc. In addition to this, a principal challenge is to optimize design and operational performance with respect to hourly fluctuations as well as long-term changes in demands and prices of various energy products. In principle, these data could be obtained by implementing a detailed energy system model [10] in the design optimization model, but the required data sampling, modelling, and computational effort can be prohibitive. It is therefore common to include external operating conditions (EOCs) that are hardly influenced by system operation, such as fuel price and heating demand, as fixed parameters in multi-period design optimization models. In a case study of a thermal energy system, Hindsberger and Ravn [11] demonstrated that robust results can be obtained by using fixed EOC datasets when external conditions are little affected by system operation.

A fundamental issue in mathematical optimization models is the trade-off between level of detail and ease of solving the model. As the complexity of multi-period optimization problems increases significantly with the number of periods defined [12], it is desirable to reduce the number of period datasets without plummeting result accuracy. One approach to reducing the number of periods is to average EOC parameter values over chronological time-periods. Among averaging methods, the simplest is to average the EOCs over the lifetime of a system (e.g. Ahmadi et al. [13], Gassner and Maréchal [14], and Chen et al. [15]). A related method is to assume annually static operating conditions, but defining each year as a period to allow for year-to-year variations caused by general energy system developments (e.g. Gerogiorgos et al. [16] and Liu et al. [17,18]). Another method is to consider monthly average values for one key operating parameter and static conditions for all other (e.g. Fazlollahi et al. [19,20]). A more detailed approach is to consider monthly averaged EOC parameter values in a first-step optimization model, and then conduct detailed hour-wise operation optimization in a sequential step for the most promising system designs (e.g. Rubio-Maya et al. [21] and Uche et al. [22]). However, neither monthly- nor annually-averaged operating parameter values provide information on short-term relations and variations between various operating conditions. While it may be acceptable to neglect this information for static operating facilities, it can be critical to the economy and thermodynamic performance of flexible facilities such as combined heat and power (CHP) plants [23] and FMGs [24,25]. Failing to consider short-term relations between relevant operating parameters may lead to sub-optimal solutions in the design optimization of FMGs [26].

One approach to reduce energy system data while maintaining details on hourly parameter relations is to represent each year by a small number of typical time-periods. Another approach is to define a number of characteristic periods, like peak-demand and off-peak-demand periods in each of the four seasons (e.g. Chen et al. [2,27]) or typical demand days for each month based on monthly average parameter values (e.g. Mavrotas et al. [28]). These approaches rely on the assumption that operating conditions and energy demands are linked and cyclic over the seasons, an assumption that may prove inaccurate in energy systems in transition and with large shares of intermittent renewable energy generation [1]. To overcome the assumption of cyclic behavior, several studies propose application of cluster analysis to identify typical periods that can be repeated in order to approximate the annual cumulative curves. Ortiga et al. [29] proposed a graphical method for selecting a few typical days that can be used for representing the annual cumulative heating and cooling demand curves. Domínguez-Muñoz et al. [30] and Fazlollahi et al. [31] used a partitional clustering analysis method, the k-Mediods method, to create k typical periods. However, such approaches may hide information on peak and extreme operating conditions and lead to significant errors on peak operation performance, as also reported by Fazlollahi et al. [31] in two illustrative examples. In order to overcome these drawbacks, the duration of the typical periods may be extended to several consecutive days or even weeks (e.g. Hedegaard and Münster [32]). However, this approach increases the computational effort significantly, thereby counteracting the initial ambition of reducing the number of period datasets. Instead, Bungener et al. [33] proposed a method that applied an evolutionary multi-objective optimization algorithm for identifying n sequential periods representing typical operations for an industrial cluster with the aim of minimizing standard deviation and, at the same time, maintain information on extreme operating conditions. Nemet et al. [34] presented a similar method for aggregating continuous thermal energy generation and demand into