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Novel method to simulate large-scale thermal city models

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ABSTRACT

This study presents a method used to simulate large-scale thermal models of cities that achieves two improvements compared to the state-of-the-art techniques: 1) Current state-of-the-art methods cannot simulate the dynamic interaction between subcomponents of a smart energy system at urban scale. This method proposes detailed dynamic simulation approaches for large-scale thermal models. 2) Currently applied co-simulation frameworks are not applicable to large-scale models. In the present study, the dynamic building simulation tool IDA Indoor Climate and Energy, which uses parallelization methods for large-scale models, is coupled with a co-simulation platform. The methods are applied to a semi-virtual case study, which consists of 1561 buildings and a new development area. The building stock is analyzed using an automated method based on publicly available data. In contrast, the virtual urban development area is investigated using a co-simulation framework with three dynamic simulation tools: IDA Indoor Climate and Energy for buildings (256 thermal zones and 29 heating systems), TRNSYS for the energy supply unit and Dymola/Modelica for the district heating network. The influence of co-simulation on the accuracy and on the computation time are investigated. The major finding of this study is that the computation time can be significantly reduced by decoupling methods.

1. Introduction

Driven by growing environmental consciousness, international energy policies have been formulated to reduce the global energy demand and the carbon dioxide emissions [1]. Therefore, the European Commission is committed to reducing the European greenhouse gas emissions by 40% (compared to the levels recorded in 1990) by 2030 [2]. Integrating the buildings in future energy systems can be an important contribution towards the achievement of this aim since European buildings account for approximately 37% of the total final energy use, 26% of this in residential, and 11% in commercial buildings [3].

An analysis of the actual building stock is thus necessary to identify and quantify the energy demand, the refurbishment potential of buildings, the usage of decentralized heating supply units, or the expansion potential of district heating networks (DHN). Kavgic et al. [4] presented a review of bottom-up building stock models for the residential area. Keirstead et al. [5] went one step further and described five sub-areas of urban energy system models: technology design, building design, urban climate, systems design, and policy assessment. State-of-the-art building models for heating and cooling energy demand at city scale are discussed by Frayssinet et al. [6]. Dynamic urban energy modeling tools are discussed by Reinhart et al. [7]. State-of-the-art dynamic urban modeling approaches can be broken down into statistical and physical approaches. Statistical models use a mathematical description of the system based on measurement data [8]. These data-driven models can be divided into black box models and grey box models also known as energy signatures. The black box approach defines the input and output relation by means of training data without describing the physical properties [9]. A more sophisticated approach is that of energy signatures [10], which consider building archetypes and the dependency of heating demand and environmental variables such as the outdoor temperature. Physical modeling approaches are classified by Kämpf [11] according to the heat transfer calculation in buildings as explicit solution, model order reduction techniques and model simplification techniques. Explicit solutions are computational expensive such as the finite difference method [12]. Kim et al. [13] reduced the physical system of a detailed building model into a 6-order model using a balanced realization reduction technique. Fonesca and Schlueter [14] used a resistance-capacity model simplification

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Nomenclature

Abbreviations

BCVTB	Building Controls Virtual Test Bed
DB	database
DHN	district heating network
DHW	domestic hot water
GIS	geographic information system
IDA ICE	IDA Indoor Climate and Energy
PI controller	proportional-integral controller
SFH	single family houses

Symbols, unit

GFA	gross floor area, m^2
K	proportional gain
$\dot{m}$	mass flow, kg s^{-1}
$\dot{Q}$	heat flow, W
t_E	extrapolation time, s
t_i	integration time, s
t_t	tracking time, s
Δt	simulation timestep, h
ε	tolerance
ϑ	temperature, °C
%Error	percent error, %

Subscript

Air	room air
Conv	convective
D	district
max	maximum
min	minimum
n	number of district heating substations
R	return
rad	radiative
S	supply

technique in order to model buildings at urban scale. An important point in the modeling process is the data acquisition, since the collection of all the necessary data for the energy analysis of a building can be difficult owing to the data protection rules that apply for individuals and corporations. The data of the building stock, which include the material layers and the respective thicknesses of the building envelope, the year of construction, the type of use, and the behavior of the building users, are mostly unknown. Aksoezen et al. [15] have thus identified the building age as an indicator for the building's energy consumption. Loga et al. (TABULA project) [16] have assigned age-related building envelopes for the residential building stock. Nageler et al. [17] used these building archetypes and presented a validated method for fully automated, detailed, dynamic building modeling within urban districts based on publicly available data. Additional methods have been presented in the literature by Fuchs et al. [18], which have developed an automated workflow for combined modeling of buildings (resistance and capacity models), and district energy systems. Characteristically, Eicker et al. [19], used a standardized geometrical format (CityGML) for the building geometry. Dogan and Reinhart presented an automated multizone method to perform urban simulations [20]. All these methods have used building model generation tools to reduce the considerable time needed for manual input, and have minimized the error rate caused by to typographical errors. Leal et al. [21] used a detailed building model generation tool based on the ASHREA Standard [22] for model creation, calibration and analysis according to ISO 50001. The Autozoner zoning algorithm [23] is even capable to generate thermal building models of floor plans with complex multi-polygons. Nageler et al. [24] used a building model generation tool, which have implemented automatic zoning algorithms that zones the building according to different uses and is applicable at district level due to the lower number of thermal zones.

In addition to the building stock, many new urban development areas are arising owing to the growing urbanization (e.g., the projections in Europe refer to increases from 54% in 2014 to 66% in 2050 [2]). Urban development areas comprise a mixture of already existing buildings, which have either been planned to detail, or are at the planning stage, whereby less information is available. This has led to different levels of detail in the context of building modeling. Furthermore, a transformation of the old energy systems in new smart energy systems is essential given the anticipated increased share of renewable energy sources to 27% by 2050 [2]. The 4th generation district heating network [25] provides a promising approach, which integrates renewable energy sources exhibiting increased fluctuations, such as those pertaining to wind or solar energies, into low temperature DHN. Schweiger et al. identified the potential of power-to-heat in Swedish DHN [26]. The main challenge is to match the available energy from renewable sources with the energy demand in space and time. Consequently, the dynamic modeling of DHN, the buildings, and the heat supply units, are essential in understanding their dynamic interactions [50]. At present, science is mainly concerned with the modeling of DHN dynamics [27]. In this respect, pipe models have been developed to represent heat losses, temperature propagation, and pressure drops. Subsequently, these models are applied at district level [28]. Schweiger et al. used these models for dynamic optimization of large-scale district heating and cooling systems [29]. A general overview of different modeling approaches for pipes in district heating systems was presented by Pálsson et al. [30]. Two widely used methods are the so called element method and the so called node method; a detailed discussion and comparison of both methods was presented by Bøhm et al. [31]. On the other hand, energy supplier engineers make extensive use of commercial software solutions (e.g. TERMIS [32]) to design or optimize DHN, but these programs cannot be used to investigate the dynamic network interactions with the buildings, or with the energy supply unit, because they do not have integrated solutions or APIs to interface with other simulation tools.

Two problems arise in the dynamic simulation of urban areas. The first is that detailed models have become too large (in terms of the number of equations). In this way, developed models have to be split in several parts, and each of these parts be simulated in parallel [33]. The second problem is that the modeling of different subtasks is necessary, such as the modeling of the building envelope, the heating system of the building, and the DHN, or the energy supply system to analyze the thermal energy flows in cities. Consequently, no simulation tool provides optimum coverage for each subtask [34]. Co-simulation provides the opportunity to couple the best and most computationally efficient tool for each subtask. In this context, co-simulation is an application that employs at least two simulation tools to solve differential equations that are coupled to exchange data depending on state variables. The tools are coupled via a co-simulation interface such as the