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Replication Studies

Ensemble Calibration of lumped parameter retrofit building models using Particle Swarm Optimization

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ABSTRACT

Simulation-based building retrofit analysis tools and electricity grid expansion planning tools are not readily compatible. Their integration is required for the combined study of building retrofit measures and electrified heating technologies using low-carbon electricity generation. The direct coupling of these modelling frameworks requires the explicit mathematical representation of Energy Conservation Measures (ECMs) in building-to-grid energy system models. The current paper introduces an automated calibration methodology which describes retrofitted buildings as parametric functions of ECMs. The buildings are represented using a lumped parameter modelling framework. A baseline model, representative of the building prior to retrofit, and the retrofit functions are calibrated using Particle Swarm Optimization. Synthetic temperature and heating load time-series data were generated using an EnergyPlus semi-detached house archetype model. The model is representative of this residential building category in Ireland. It is shown that the proposed methodology calibrates retrofitted building models to an acceptable level of accuracy (*MAE* below 0.5 °C). The methodologies introduced in the current paper are capable of generating lumped parameter building models with similar dynamics for different ECMs for any archetype building energy model. The identified building retrofit models have the potential to be integrated with electricity grid models in a computationally-efficient manner.

1. Introduction

1.1. Decarbonization of the residential sector in Ireland

Current European policy targets a reduction of greenhouse gas (GHG) emissions by at least 80% below 1990 levels by 2050, including a 95% abatement of GHG emissions in the building sector [1]. Buildings represent 40% of global energy consumption and account for nearly 30% of energy related global GHG emissions [2]. In the Irish context, the residential sector represents 25% of the primary energy supply [3] and a quarter of energy related CO_2 emissions in 2015 [4]. One approach to decarbonise the Irish residential sector using current technologies is the implementation of effective Energy Conservation Measures (ECMs), including upgrades of heating systems [5]. Ahern et al. [6] determined that building retrofit measures have the potential to reduce by 65% the heating costs and CO_2 emissions for detached rural houses built prior to 1979 (approximately 20% of the Irish domestic dwelling stock). Ahern et al. conclude that government incentives (such as the Better Energy Homes scheme [7]) are required to incentivise retrofit, given the significant upfront cost for end users. Without monetary or economic incentives, home owners are unlikely to carry out energy efficiency measures [8].

The Irish Government estimates an investment of 35 billion EUR (20,000 EUR per dwelling) is required to bring the domestic stock (as of 2015) to an efficient level of energy performance (BER rating B) [9]. There is a need for the study of techno-economic mechanisms by which the environmental and economic benefits of government investment in Energy Conservation Measures are maximized. One such mechanism corresponds to the electrification of domestic space heating and domestic hot water supply. Under this mechanism, efficient electrified heating technologies such as heat pumps and storage heating [10] displace the CO_2 emissions arising from fossil fuel consumption for heating. The displaced CO_2 emissions are abated by the usage of low-carbon electricity generation assets. In 2015, fossil fuels accounted for 61% of energy-related CO_2 emissions in the residential sector [4]. During the same period, electricity accounted for only 25% of residential final energy use [3].

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Nomenclature

Variables and parameters

A	area [m^2]
α	calibration parameter (exponential approximation) [–]
β	calibration parameter (exponential approximation) [–]
C	Lumped capacitance [J/kg K]
d	weather disturbances
ΔR	variation in lumped resistance [m^2 K/W]
Δp	variation in calibration parameters
ΔT_{avg}	variation in annual average internal temperature [°C]
Δx	variation in layer thickness increment [m]
$\mathcal{F}$	set of fixed parameters (calibration)
$\mathcal{I}_n$	set of thermal nodes adjacent to node n
$J(\cdot)$	calibration cost function
g	solar transmittance (window) [–]
λ	thermal conductance [W/m K]
M	index for external insulation (ensemble)
n	number of insulation steps
nl	number of layers in a wall
nC	number of capacitances
nR	number of resistances
N	index for internal insulation (ensemble)
NH	calibration horizon [time steps]
O	index for ceiling insulation (ensemble)
p	set of calibration parameters
Q	heating load [W]
R	lumped resistance [m^2 K/W]
T	temperature [°C]
u	heating load [W]
U	thermal transmittance (U-value) [W/m^2 K]
$\mathcal{V}$	set of variable parameters (calibration)

Subscripts

0	baseline model (calibration parameters)
att	attic
amb	outdoor temperature
c	ceiling node
ceil	ceiling insulation
data	synthetic data
ext	external insulation
gnd	ground node
heat	heat input
int	internal insulation
inf	infiltration
k	time-step index (building model thermal evolution)
l	time-step index (Particle Swarm Optimization)
r	room temperature
M, N, O	calibration parameter point (ensemble)
s	solar gains
si	inside surface resistance [m^2 K/W]
so	outside surface resistance [m^2 K/W]
wall	external walls
win	window
theo	theoretical value (resistance or capacitance)
total	total construction resistance
w	wall node

Superscripts

$\star$	optimal (calibrated) parameter

Acronyms

ACH	air changes per hour
BEMS	Building Energy Model Simulation
CV(RMSE)	Coefficient of Variation of Root Mean Square Error
ECM	Energy Conservation Measure
EPS	expanded polystyrene
GA	Genetic Algorithm
GAMS	General Algebraic Modelling System
GHG	greenhouse gas (emission)
IWEC	International Weather Energy Conversion
LP	linear program
MAE	Mean Average Error
MILP	Mixed Integer Linear Program
MBE	Mean Biased Error
PSO	Particle Swarm Optimization
SEAI	Sustainable Energy Authority of Ireland
SQP	Sequential Quadratic Programming

Furthermore, wind generation represents 23% of electricity generation and it is likely to increase in order to meet the Irish Government target of 40% generation using Renewable Energy sources [11]. Storage heating becomes a technology of interest as it has the potential to provide power system operators with demand management alternatives while increasing the usage of electricity generation assets [12].

The interconnection between building retrofits, electrified heating technologies and low-carbon electricity generation is evident. If energy efficiency measures and electrified heating systems are combined, the carbon emissions associated with domestic space heating and domestic hot water can potentially be displaced by low-carbon power generation. At an aggregated level, building and grid model integration has the potential to reduce peak electricity consumption and defer future investments in electricity generation capacity. Furthermore, heating storage can further minimize generation cost by shifting demand from excess wind production to domestic heat storage units. The integrated assessment of building retrofit measures, electrified heating technologies and variable energy generation requires the development of an integrated building-to-grid retrofit modelling framework by which the overall environmental and economic benefits can be maximized.

1.2. Modelling integrated building and grid retrofit policies

Techno-economic building retrofit optimization often relies on the coupling of heuristic optimization techniques (e.g., Genetic Algorithms) and Building Energy Model Simulation (BEMS) tools [13–16]. In such a framework, the heuristic optimization solver uses BEMS models in an iterative manner for cost function evaluation purposes. However, power systems investment planning problems are often defined using classical optimization models such as Mixed-Integer Linear Problems (MILP) (e.g., [17,18]). Prior work that has addressed building-to-grid analysis focussed on methodologies that use BEMS and power systems optimization in a sequential manner. This typically involves the use of BEMS to generate synthetic building performance data as an input to power systems optimization tools. Ault et al. [19] adopted this approach by pre-calculation of heating demand profiles using the ESP-r simulation environment [20]. These heating profiles were used as input to a power systems optimization study.

A disadvantage associated with this approach is that BEMS are unable to adapt to dynamic events occurring in the power systems model (e.g., availability of variable generation or demand response events) unless a potentially sub-optimal iterative and