Simulation Modelling Practice and Theory 126 (2023) 102770

Contents lists available at ScienceDirect

Simulation Modelling Practice and Theory

journal homepage: www.elsevier.com/locate/simpat

Co-simulation for buildings and smart energy systems — A taxonomic review

Qamar Alfalouji [a], Thomas Schranz [a], Basak Falay [b], Sandra Wilfling [a], Johannes Exenberger [a], Thorsten Mattausch [a], Cláudio Gomes [c], Gerald Schweiger [a,*]

[a] *Graz University of Technology, Graz, Austria*
[b] *AEE-Intec, Gleisdorf, Austria*
[c] *Aarhus University, Aarhus, Denmark*

ARTICLE INFO

Keywords:
Co-simulation
Functional mock-up interface
Modeling

ABSTRACT

Modeling buildings and smart energy systems requires coupling a wide range of components into one unified simulation process, which can be difficult given the complexity of these systems. Hence, a large number of researchers integrate separate simulations for each of the individual components in a co-simulation instead. To systematically analyze techniques, standards, tools and applications of co-simulation in the field of buildings and smart energy systems, the publications on co-simulations in this field are reviewed by means of taxonomic analysis. Furthermore, the reproducibility as well as the validation approach of the respective papers are evaluated. Results show that Functional Mock-up Interface (FMI) is the most prominent standard for co-simulation in modeling buildings and smart energy systems. Co-simulation is mostly used in Heating, Ventilation, and Air Conditioning (HVAC) and occupancy analysis applications. Since nearly 70% of publications are not reproducible, we advocate that journals and funding agencies adopt stricter data and code-sharing policies.

1. Introduction

Many real-world engineered systems integrate multiple components in one complex process, which includes physical parts, software, and their interconnection aspects. This complexity poses many challenges to the modeling and simulation of these systems. Each independent simulation is an experiment performed on a model with a set of variables that evolve over time [1]. One way to simulate systems that comprise several components is to model and simulate the entire system using one tool in the so-called monolithic simulation. Another widely known approach is to simulate the system in a co-simulation; a synthesis of separate simulations for each of the systems' components, coordinated and synchronized based on a coupling strategy, a coupling algorithm, as well as coupling and synchronization settings [2,3]. *Co-simulation can be seen as a generalized form of simulation, where a coupled system is simulated through the composition of simulation units* [4]; while *a simulation unit is an executable software entity responsible for simulating a part of the system* [5]. A co-simulation involves a closed-loop simulation of two or more subsystems. If there is no feedback between two subsystem models, they are coupled in a sequential or open-loop strategy [6]. By definition, these open-loop simulations are not considered co-simulations in this article.

Bringing together different subsystems in one co-simulation process allows for the behavioral integration of the subsystems, incorporating each system's simulation algorithm in one system, and exchanging variables without the need for a clear declaration of

* Correspondence to: Institute of Software Technology, Graz University of Technology, 8010 Graz, Austria
E-mail address: gerald.schweiger@tugraz.at (G. Schweiger).

https://doi.org/10.1016/j.simpat.2023.102770
Received 25 December 2022; Received in revised form 18 March 2023; Accepted 12 April 2023
Available online 20 April 2023
1569-190X/

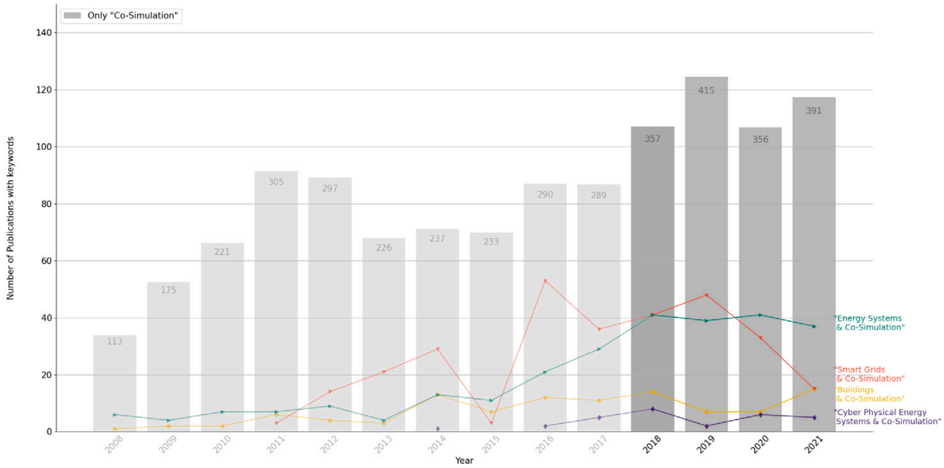

Fig. 1. Trend of articles published between 2008 and 2021 for Co-Simulation used for Buildings, Smart Grids, Energy Systems, and Cyber–Physical Energy Systems according to a Scopus search. The bar plot represents the publications for the "Co-simulation" terminology and aims to give the reader a scale of the keyword search. The selected articles in the last 4 years fall under the darker bar plots.

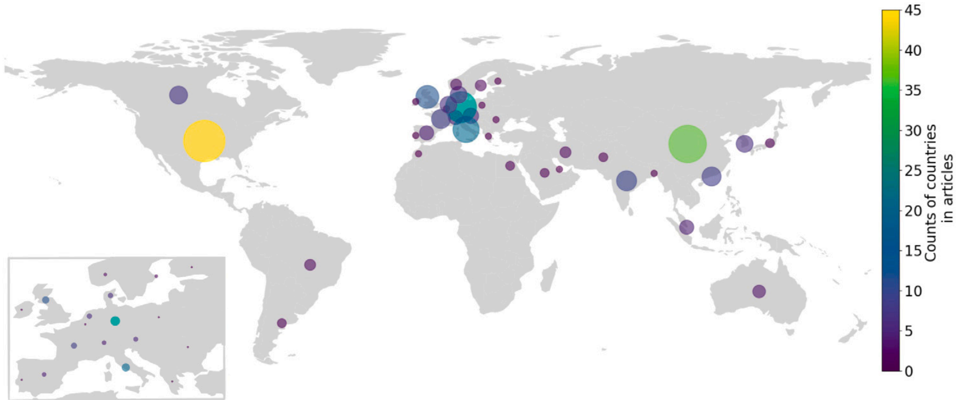

Fig. 2. Distribution of the publications reviewed between 2018 and 2021 for the selected keywords based on the authors' countries.

the content, protecting private information and avoiding problems such as license fees [7]. These benefits have led researchers to use co-simulation in different domains and resulted in a progressive increase in the number of publications in the field of co-simulation for various domains in the last decade, as shown in Fig. 1.

However, due to the complexity of the co-simulation process, it can be affected by factors such as the use of domain-specific software, the choice of programming languages, co-simulation solvers, other supporting tools, and the inter-operation of these tools. These challenges are generally addressed by collaborations within the research community. Therefore most of the implementations found in the literature are based on collaborations from different countries. Fig. 2 shows the distribution of the researchers working on co-simulation topics between 2018 and 2021 worldwide.

In the field of Smart Energy Systems, co-simulation plays a vital role in combining sets of powerful tools in one synchronized hybrid simulation. However, works in the literature sometimes lack a detailed description of the co-simulation process, which limits reproducibility and requires time and effort to find suitable configurations for each tool. In this paper, we analyze the literature on co-simulation in terms of the details of the co-simulation process described by each work and provide a summary of the details and set-ups that are necessary to reproduce the results.

1.1. Main contribution

To the best of our knowledge, there is no literature study that attempts to systematically analyze co-simulations in the field of smart energy systems. This paper closes this gap by presenting a taxonomic analysis of co-simulation in the field of smart energy systems. Based on this analysis, we intend to answer the following questions:

- Where is co-simulation applied in the field of smart energy systems?

- Which coupling techniques, standards, master algorithms, and tools are used?
- Is the work reproducible in terms of data, models, set-up, and co-simulation configurations?

By analyzing the results of a taxonomic review and comparing the results with other state-of-the-art reviews, we identify research gaps and propose best practices for co-simulation applications within smart energy systems.

2. Related work

There are several articles on implementing co-simulations, using various tools and methods, in different applications. A definition of co-simulation terminology, along with a description of state-of-art co-simulation frameworks can be found in [8,9]. Hafner and Popper [10] focuses on the classification and the structuring of the co-simulation methods, while [7] provides an empirical survey on current co-simulation challenges, research needs, standards, and tools.

Co-simulation has been used extensively in energy-related applications such as smart grids and smart buildings. Therefore, many existing studies discuss how to simulate large energy systems by combining more than one tool in a co-simulation process. Vogt et al. [11] surveys 26 smart grid co-simulation frameworks and shows different simulation tools, synchronization methods, and use-cases. Taveres-Cachat et al. [12] examines co-simulation for performance prediction of Advanced Building Envelops (ABEs) using ten questions that cover the co-simulation process. Tian et al. [13] conducts a systematic review, which points out that co-simulation is time-consuming and challenging, especially for practical applications with high computational load, due to the complication of each simulation tool. Singh and Sharston [14] provides a literature review on coupling Computational Fluid Dynamics with Building Energy Simulations (CFD-BES) and includes a review of different coupling techniques. The study concludes that combining such two simulations results in a powerful framework for building performance prediction. Additionally, it shows that the best coupling method always depends on the general goal of the co-simulation. A bibliographic analysis of co-simulation in district heating and cooling systems is presented in [15]. It demonstrates the importance of control strategies in these applications and highlights the importance of accurate system specifications in choosing the correct control method. However, no literature review systematically analyses the use of co-simulation in the field of smart energy systems. Hence, in this paper, we present a taxonomic analysis of state-of-art applications in terms of the simulation tools, standards, models, and co-simulation setup implemented in each work.

3. Method

We conducted a taxonomic literature review (as defined in [16]) to (i) identify common applications for co-simulation in smart energy systems; (ii); identify common co-simulation techniques, standards, and tools and (iii) evaluate the reproducibility of the results and the validation approach applied by each work. The structure of the taxonomy is based on existing review papers [2,11,17,18] and the expertise of the authors. The final taxonomy includes main categories, sub-categories, and keywords as shown in Fig. 11. As there was no review paper on co-simulation in smart grids and energy systems, we identified relevant journal publications by using a combination of the "Co-simulation" keyword in Scopus [19,20] with the following applications:"Buildings", "Smart Grids", "Energy Systems" and "Cyber-Physical Energy Systems". For this review, we selected all articles published in the last five years (2018–2022). We also used the keywords to produce Fig. 1 which shows the number of publications per year in each of these fields. As shown in Fig. 3 we identified 143 articles with the categories and keywords we defined.

A total of 46 articles had to be excluded due to at least one of the following reasons:

- Duplicated articles
- Review articles
- Articles describing any projects (H2020) without demonstrating and application of the workflow they present
- Articles not related to the energy domain but hunted by keyword searches such as Chen2020-Silicon photonic networks paper
- Articles listed because of a typo, such as "... and Belmar in Lakewood, CO. Simulations ..".
- Articles listed in Scopus but unavailable to download
- Articles not in English
- Articles presenting co-simulation methods in the discussion or the future work section, but not actually utilizing them.

Additionally, we removed 17 papers because they use sequential simulation processes as co-simulation, which does not align with the definition of co-simulation used in this paper so that in total we reviewed 80 articles [21–99].

Since co-simulation is an interdisciplinary field of research, the selection of the keywords can be seen as a threat to validity, however, to the best of our knowledge, this is the most transparent selection process that covers the scope of this paper. In addition, we selected a list of journal articles that describe the co-simulation process with all the needed details according to the criteria that we defined previously. We reviewed each of the articles by answering a list of questions that is available on the survey repository, in an effort to ensure consistency and transparency.

4. Results and discussion

In this section, we present the key findings from the taxonomy-based analysis. We provide an analysis of the co-simulation application, covering the input data, the domain, and the type of the system that is modeled in 4.1. We discuss the details of the co-simulation processes, including the techniques, standards, and orchestration algorithms in 4.2 and describe the modeling tools in 4.3. Other important considerations, such as the reproducibility of the results and the validation process are discussed in 4.4. The taxonomy-based review is available at https://github.com/tug-cps/CosimulationTaxonomy and contains all questions and answers formulated during the analysis process of the papers we reviewed.

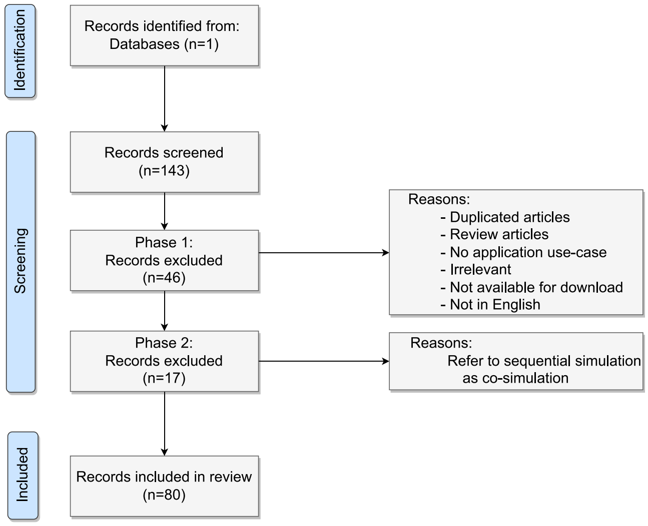

Fig. 3. A flow diagram shows the number of identified, excluded, and included articles in our study.

4.1. Application

In the field of buildings and smart energy systems, co-simulation is mainly used for two reasons: (i) What-if analyses can give system designers valuable insights into system-level properties and enable them to evaluate design decisions such as the impact of integrating storage or PV systems on self-consumption and demand peaks. (ii) In addition, co-simulation is widely used to control and optimize the operation of buildings and smart energy systems. The papers we reviewed describe various applications and use cases throughout different domains.

Fig. 4 groups the papers by their use-case: (a) virtual/synthetic systems using synthetic data and assumptions of the system and (b) real systems and subdivides each category by the use-case's application domain. It shows that 79% of the studies are conducted for operational analysis with 48% of real-world applications. The most common applications for co-simulation are Heating, Ventilation, and Air Conditioning (HVAC) systems and occupancy analysis.

In the case of modeling complex heterogeneous systems, one of the most interesting testing and development techniques is the so-called hardware-in-the-loop (HIL) method [21]. HIL is a technique to test physical systems on special test benches that receive data input from physical devices and test them within a simulation process. The analysis of the taxonomic review shows that more than 90% of the papers did not consider HIL in their systems. This might be due to the technical challenges in setting up a HIL experiment for complex systems requiring additional effort and introducing additional costs.

4.2. Co-simulation techniques, standards, and orchestration

There are different coupling techniques for co-simulation [12]:

- One-to-one coupling: Communication between submodels is accomplished through dedicated implementations such as TRNSYS type 155 that links the TRNSYS with Matlab, or S-function that links Matlab/Simulink with other software such as EnergyPlus [42,62,90,100].
- Middleware coupling: A third program implements a co-simulation orchestration algorithm that coordinates the simulation programs and manages the data exchange between them. The main advantage of using middleware coupling is that it can include more than two simulation programs in a very flexible way [101–103]. Middleware can work solely to connect submodels or as a connection and modeling tool; consider, for instance, the Building Control Virtual Test Bed (BCVTB) in [81].
- Standard interface coupling: Submodels communicate through a standardized interface for co-simulation, which allows for direct coupling between any software that implements the interface. The Functional Mock-up Interface (FMI) and the High-Level Architecture (HLA) are well-known examples of standardized co-simulation interfaces [50,72,104,105].

Fig. 5 shows the percentage of papers using each of these three techniques in the literature.

Co-simulation standards include rules and specifications for model initialization and synchronization. Standards, such as FMI or HLA, allow for data exchange and synchronization using high-level APIs and the deployment of distributed, network-based simulations on different machines. So-called master algorithms follow these standards and orchestrate the co-simulation coupling processes. In each co-simulation scenario, the master algorithm is responsible for setting the co-simulation process and defining the initial conditions, data and variables exchange, and time synchronization of the sub-models [106]. Fig. 6 shows a list of the co-simulation standards used in the publications we analyzed, with FMI being the most prominent standard. These findings are in

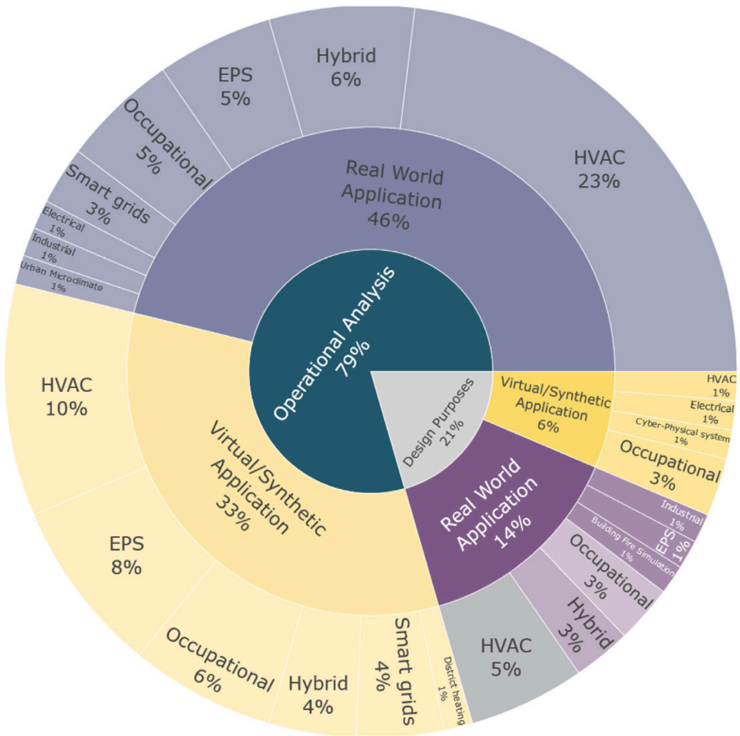

Fig. 4. Applications goals, Systems, and Domains of co-simulation in the reviewed papers.

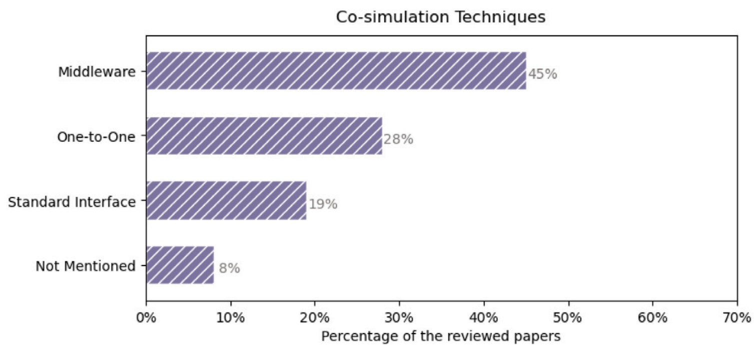

Fig. 5. Co-simulation techniques in the reviewed papers.

line with the results in Schweiger et al. [2], where empirical results show that experts consider the FMI standard to be the most promising standard for continuous time, discrete event, and hybrid co-simulation. There are multiple master algorithms for FMI such as Modelica tools [107] (Dymola, JModelica, OpenModelica), EnergyPlus [108], and Mosaik [109] as shown in Fig. 7.

4.3. Tools

Results show that the choice of tools typically depends on the application domain. Fig. 8 shows the most common modeling tools grouped by the main domains (keywords), independently of the coupling strategy. It shows that TRNSYS-Matlab and TRNSYS-EnergyPlus, are the dominant tool combinations in HVAC systems, while EnergyPlus-BCVTB is most commonly used in building applications.

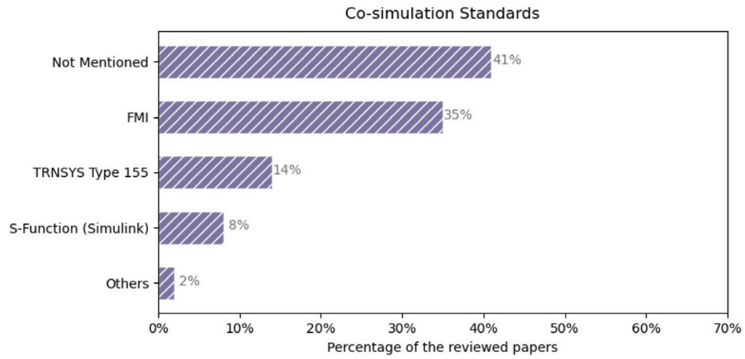

Fig. 6. Co-simulation standards in the reviewed papers.

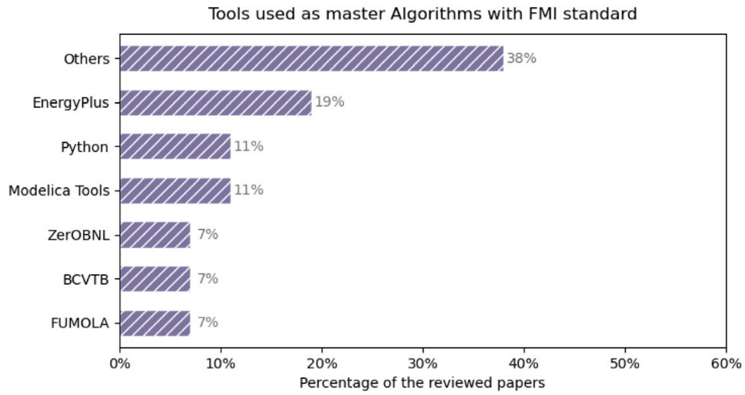

Fig. 7. Tools used as a master algorithm with FMI standard in the reviewed papers.

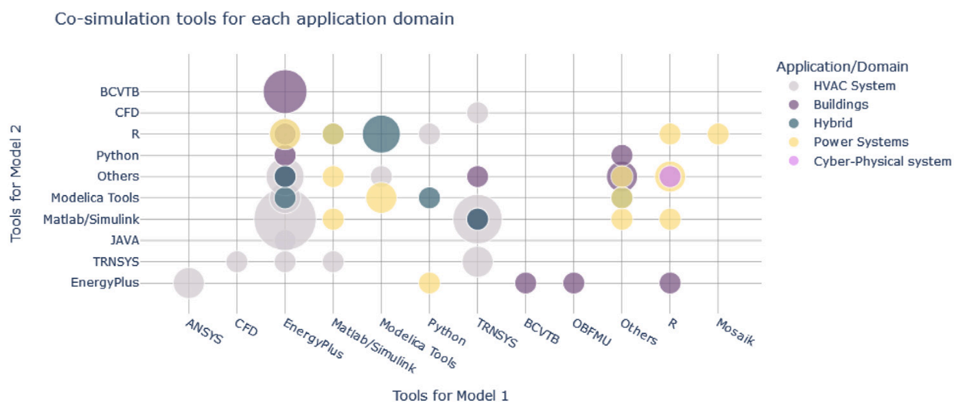

Fig. 8. How many times each combination of tools is used according to each application Circle size corresponds to the number of publications; circles color corresponds to the domain.

4.4. Reproducibility and validation

Reproducibility and validation are two important considerations when talking about co-simulation. A reproducibility crisis refers to circumstances where many scientific studies cannot be reproduced [110]. Goodman et al. [111] defines different types of reproducibility:

- Method reproducibility: provide sufficient detail about procedures and data so that the same procedures can be repeated exactly.

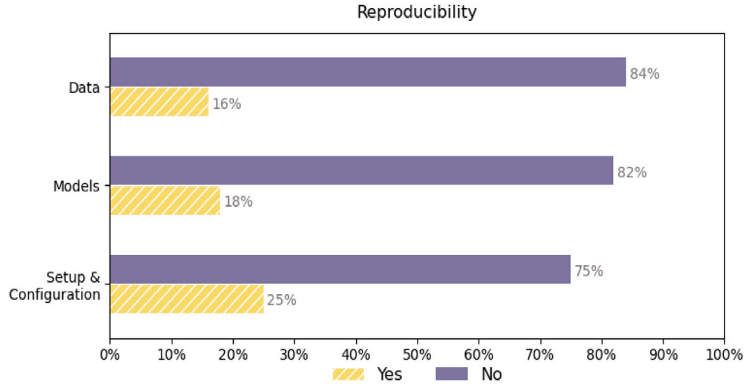

Fig. 9. Reproducibility possibility of the reviewed papers based on the reproducibility of data, models, configuration and setup.

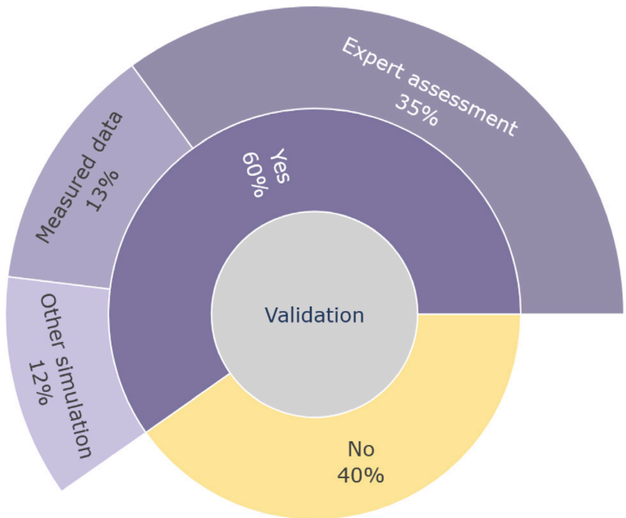

Fig. 10. Validation implementation in the reviewed papers.

- Result reproducibility: obtain the same results from an independent study with procedures as closely matched to the original study as possible.
- Inferential reproducibility: draw the same conclusions from either an independent replication of a study or a reanalysis of the original study.

From this, we can conclude that a work is only fully reproducible if (i) all data is accessible and (ii) all methods are described unambiguously [112]. While data sharing is one of the cornerstones of science, enabling large-scale analysis and reproducibility [113], the requirement that data (and code) need to be shared to consider a study reproducible is not so obvious. In certain disciplines, such as medicine, data sharing may be hampered by privacy concerns, for example.

In this work, we define reproducibility for simulation-based analysis similar to how it is defined in Malhotra et al. [114], i.e., as being able to reproduce an experiment/simulation from data acquisition to results. Accordingly, we classify articles as reproducible if (i) the data used during the co-simulation is available; (ii) the co-simulation models are open or available; (iii) the co-simulation setup parameters, such as the solver configuration, time-step, etc, are described in the paper. Fig. 9 shows that the majority of the papers are non-reproducible as 84% do not provide their data, 82% do not provide the models, and 75% do not mention which setup and configurations they use. Among all the papers we reviewed, only 8% provide all three factors for reproducibility, and only 14% provide two out of three (data and models, data and setup configurations, or models and setup and configurations). This could be due to various reasons, including:

- restrictions on the availability of some countries' information such as meteorological data;

- data sources and/or models are not open-source and/or open data (sometimes provided by commercial software);
- data sources are not mentioned;
- data pre-processing process is not mentioned in the paper; and
- configuration and setup of the co-simulation process are not described in detail, mainly because it combined more than one model.

This makes the absence of any setting significantly affect the entire reproducibility possibility. These results are in line with similar studies on simulation-based analysis in the field of building energy simulation [114], which found that about 95% of the studies were not reproducible due to the lack of information on crucial aspects such as data sources, or simulation set-up.

Validation checks how well the results of a co-simulation represent the real system that was used as the data source. The input data for the validation process can be measured data, simulated data, or based on the experts' assessment. Fig. 10 shows whether a paper included the validation step in their work or not, in addition to the data source. Results show that around 60% of the papers we reviewed included some means of validation, with expert assessment being the most common approach.

5. Conclusion

The complexity of many real-world applications poses challenges to the modeling and simulation of systems. In recent years co-simulation has become a common means to address the increasing complexity of systems by the behavioral integration of specialized submodels. In the field of buildings and smart energy systems, co-simulation plays a vital role in the development of synchronized, hybrid simulations. There is a large number of publications describing the application of co-simulation to the field of smart energy systems. For this paper, we systematically analyzed these publications through a taxonomic analysis and identified the most common co-simulation techniques, standards tools, and applications. Additionally, we evaluated the reproducibility of each of the co-simulations based on the information provided by the respective papers and examined the validation approach the authors of these papers applied. We summarize the most findings in the subsequent listing:

- Most common applications for co-simulation are HVAC systems (38%) and occupancy analysis (14%).
- 45% of the reviewed papers uses middleware to couple the sub-models together; while FMI is the most prominent standardized co-simulation interface; this is in line with previous work where experts consider the FMI standard to be the most promising standard for co-simulation.
- 67% of the analyzed studies were not reproducible because data and/or models are not openly available, and/or the co-simulation setup is not described in detail. There is (a) a need for stricter policies for data and code sharing by journals and especially by funding agencies which could have a great impact on the open science practice, and (b) researchers and reviewers should be more critical in ensuring the reproducibility of their work when conducting simulation-based analyses. For papers that apply co-simulations, we suggest including at least the following information: modeling tool and detailed specification of each sub-model; details co-sim "set - up"... (old "Master algorithm of co-simulation; Coupling technique and standard; Coupling variables; Coupling interval; Total simulation time; Input data".).
- About one-fifth of the articles refers to sequential simulations as co-simulation. Thus, the definition of co-simulation as a closed-loop simulation is not yet well understood in the community. For many open-loop applications that could simply be run as a sequential simulation, the reason for co-simulation, with its associated increased development effort and computational requirements, is not apparent.
- 43% of the analyzed works did not mention the used coupling interval, 32% did not mention the total simulation time, 41% did not mention which co-simulation standard they use, and 38% did not specify which master algorithm they use.

Data availability

Data will be made available on request

Acknowledgments

This project (GA numbers 879315, 887002, and 881150) is funded by the Austrian Research Promotion Agency and supported by TU Graz Open Access Publishing Fund.

Appendix

See Fig. 11.

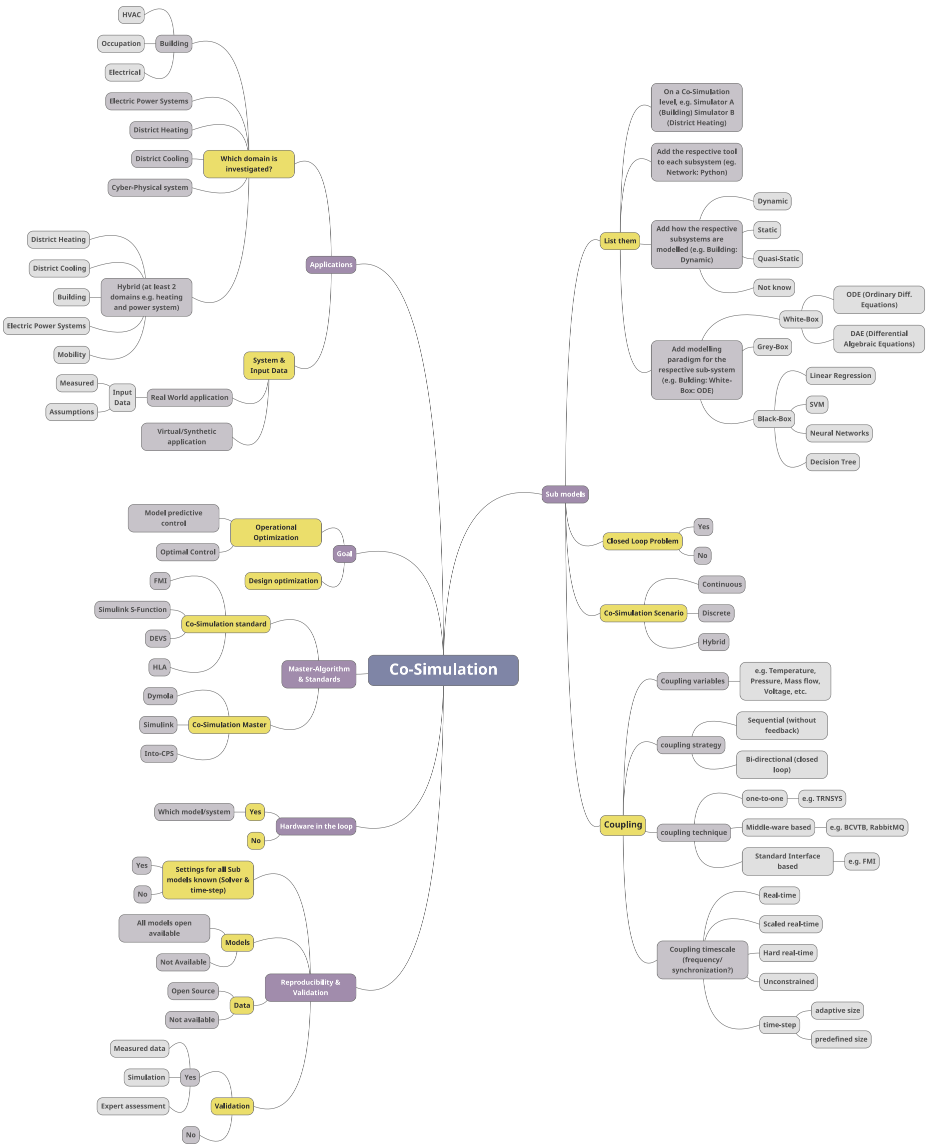

Fig. 11. Overview of the taxonomy.

References

[1] P. Fritzson, Introduction to modeling and simulation, in: Principles of Object-Oriented Modeling and Simulation with Modelica 2.1, 2004, pp. 2–18, http://dx.doi.org/10.1109/9780470545669.ch1.

[2] G. Schweiger, C. Gomes, G. Engel, I. Hafner, J. Schoeggl, A. Posch, T. Nouidui, An empirical survey on co-simulation: Promising standards, challenges and research needs, Simul. Model. Pract. Theory 95 (2019) 148–163.

[3] D.-C. Craciunean, D. Karagiannis, A categorical model of process co-simulation, Int. J. Adv. Comput. Sci. Appl. 10 (3) (2019) http://dx.doi.org/10.14569/IJACSA.2019.0100355.

[4] C. Gomes, C. Thule, P.G. Larsen, J. Denil, H. Vangheluwe, Co-simulation of continuous systems: a tutorial, 2018, arXiv preprint arXiv:1809.08463.

[5] C. Thule, C. Gomes, J. Deantoni, P.G. Larsen, J. Brauer, H. Vangheluwe, Towards the verification of hybrid co-simulation algorithms, in: Federation of International Conferences on Software Technologies: Applications and Foundations, Springer, 2018, pp. 5–20.

[6] V.F. Sánchez, A. Garrido Marijuan, Integrated model concept for district energy management optimisation platforms, Appl. Therm. Eng. 196 (2021) 117233, http://dx.doi.org/10.1016/j.applthermaleng.2021.117233.

[7] G. Schweiger, C. Gomes, G. Engel, I. Hafner, J.-P. Schoegg, A. Posch, T. Nouidui, Functional mock-up interface: An empirical survey identifies research challenges and current barriers, in: Linköping Electronic Conference Proceedings, Linköping University Electronic Press, 2019, http://dx.doi.org/10.3384/ecp18154138.

[8] C. Gomes, C. Thule, D. Broman, P.G. Larsen, H. Vangheluwe, Co-simulation: State of the Art, Technical Report, 2017, URL: http://arxiv.org/abs/1702.00686.

[9] C. Gomes, C. Thule, D. Broman, P.G. Larsen, H. Vangheluwe, Co-simulation: a survey, ACM Comput. Surv. 51 (3) (2018) 49, http://dx.doi.org/10.1145/3179993.

[10] I. Hafner, N. Popper, On the terminology and structuring of co-simulation methods, in: Proceedings of the 8th International Workshop on Equation-Based Object-Oriented Modeling Languages and Tools, ACM Press, New York, New York, USA, 2017, pp. 67–76, http://dx.doi.org/10.1145/3158191.3158203, URL: http://dl.acm.org/citation.cfm?doid=3158191.3158203.

[11] M. Vogt, F. Marten, M. Braun, A survey and statistical analysis of smart grid co-simulations, Appl. Energy 222 (2018) 67–78.

[12] E. Taveres-Cachat, F. Favoino, R. Loonen, F. Goia, Ten questions concerning co-simulation for performance prediction of advanced building envelopes, Build. Environ. 191 (2021) 107570, http://dx.doi.org/10.1016/j.buildenv.2020.107570, URL: https://www.sciencedirect.com/science/article/pii/S0360132320309379.

[13] W. Tian, X. Han, W. Zuo, M.D. Sohn, Building energy simulation coupled with CFD for indoor environment: A critical review and recent applications, Energy Build. 165 (2018) 184–199, http://dx.doi.org/10.1016/j.enbuild.2018.01.046.

[14] M. Singh, R. Sharston, A literature review of building energy simulation and computational fluid dynamics co-simulation strategies and its implications on the accuracy of energy predictions, Build. Serv. Eng. Res. Technol. 43 (1) (2021) 113–138, http://dx.doi.org/10.1177/01436244211020465.

[15] M. Abugabbara, S. Javed, H. Bagge, D. Johansson, Bibliographic analysis of the recent advancements in modeling and co-simulating the fifth-generation district heating and cooling systems, Energy Build. 224 (2020) 110260, http://dx.doi.org/10.1016/j.enbuild.2020.110260.

[16] M.J. Grant, A. Booth, A typology of reviews: an analysis of 14 review types and associated methodologies: A typology of reviews, *Maria J. Grant & Andrew Booth*, Health Inf. Libr. J. 26 (2) (2009) 91–108, http://dx.doi.org/10.1111/j.1471-1842.2009.00848.x.

[17] C. Gomes, C. Thule, D. Broman, P.G. Larsen, H. Vangheluwe, Co-simulation: a survey, ACM Comput. Surv. 51 (3) (2018) 1–33.

[18] F. Schloegl, S. Rohjans, S. Lehnhoff, J. Velasquez, C. Steinbrink, P. Palensky, Towards a classification scheme for co-simulation approaches in energy systems, in: 2015 International Symposium on Smart Electric Distribution Systems and Technologies, EDST, IEEE, 2015, pp. 516–521.

[19] J.F. Burnham, Scopus database: a review, Biomed. Digit. Libr. 3 (1) (2006) http://dx.doi.org/10.1186/1742-5581-3-1.

[20] Scopus, Scopus sources, 2021, https://www.scopus.com/sources. (Accessed 19 December 2021).

[21] M. Bacic, On hardware-in-the-loop simulation, in: Proceedings of the 44th IEEE Conference on Decision and Control, 2005, pp. 3194–3198, http://dx.doi.org/10.1109/CDC.2005.1582653.

[22] M.R. Alam, M.J.E. Alam, A. Somani, R.B. Melton, W. Tushar, F. Bai, R. Yan, T.K. Saha, Evaluating the feasibility of transactive approach for voltage management using inverters of a PV plant, Appl. Energy 291 (2021) 116844, http://dx.doi.org/10.1016/j.apenergy.2021.116844.

[23] M. Arnaudo, M. Topel, B. Laumert, Techno-economic analysis of demand side flexibility to enable the integration of distributed heat pumps within a Swedish neighborhood, Energy 195 (2020) 117012, http://dx.doi.org/10.1016/j.energy.2020.117012.

[24] P. Narendra Babu, B. Chitti Babu, R.B. Peesapati, G. Panda, An optimal current control scheme in grid-tied hybrid energy system with active power filter for harmonic mitigation, Int. Trans. Electr. Energy Syst. 30 (3) (2020) http://dx.doi.org/10.1002/2050-7038.12183.

[25] L. Barbierato, A. Estebsari, E. Pons, M. Pau, F. Salassa, M. Ghirardi, E. Patti, A distributed IoT infrastructure to test and deploy real-time demand response in smart grids, IEEE Internet Things J. 6 (1) (2019) 1136–1146, http://dx.doi.org/10.1109/JIOT.2018.2867511.

[26] M. Barsanti, J.S. Schwarz, L.G. Gérard Constantin, P. Kasturi, C.R. Binder, S. Lehnhoff, Socio-technical modeling of smart energy systems: A co-simulation design for domestic energy demand, Energy Inform. 4 (S3) (2021) 12, http://dx.doi.org/10.1186/s42162-021-00180-6.

[27] F. Bennai, M.Y. Ferroukhi, F. Benmahiddine, R. Belarbi, A. Nouviaire, Assessment of hygrothermal performance of hemp concrete compared to conventional building materials at overall building scale, Constr. Build. Mater. 316 (2022) 126007, http://dx.doi.org/10.1016/j.conbuildmat.2021.126007.

[28] B. Bhattarai, L. Marinovici, M. Touhiduzzaman, F.K. Tuffner, K.P. Schneider, J. Xie, P.T. Mana, W. Du, A. Fisher, Studying impacts of communication system performance on dynamic stability of networked microgrid, IET Smart Grid 3 (5) (2020) 667–676, http://dx.doi.org/10.1049/iet-stg.2019.0303.

[29] M. Blonsky, J. Maguire, K. McKenna, D. Cutler, S.P. Balamurugan, X. Jin, OCHRE: The object-oriented, controllable, high-resolution residential energy model for dynamic integration studies, Appl. Energy 290 (2021) 116732, http://dx.doi.org/10.1016/j.apenergy.2021.116732.

[30] H. Çakmak, A. Erdmann, M. Kyesswa, U. Kühnapfel, V. Hagenmeyer, A new distributed co-simulation architecture for multi-physics based energy systems integration: Analysis of multimodal energy systems, At - Automatisierungstechnik 67 (11) (2019) 972–983, http://dx.doi.org/10.1515/auto-2019-0081.

[31] G. Cucca, A. Ianakiev, Assessment and optimisation of energy consumption in building communities using an innovative co-simulation tool, J. Build. Eng. 32 (2020) 101681, http://dx.doi.org/10.1016/j.jobe.2020.101681.

[32] C. Dad, J.-P. Tavella, S. Vialle, Synthesis and feedback on the distribution and parallelization of FMI-CS-based co-simulations with the DACCOSIM platform, Parallel Comput. 106 (2021) 102802, http://dx.doi.org/10.1016/j.parco.2021.102802.

[33] T. Duan, Z. Huang, V. Dinavahi, RTCE: Real-time co-emulation framework for EMT-based power system and communication network on FPGA-MPSoC hardware architecture, IEEE Trans. Smart Grid 12 (3) (2021) 2544–2553, http://dx.doi.org/10.1109/TSG.2020.3039259.

[34] S. Duerr, C. Ababei, D.M. Ionel, A case for using distributed energy storage for load balancing and power loss minimization in distribution networks, Electr. Power Compon. Syst. 48 (9–10) (2020) 1063–1076, http://dx.doi.org/10.1080/15325008.2020.1825556.

[35] R. El Geneidy, B. Howard, Contracted energy flexibility characteristics of communities: Analysis of a control strategy for demand response, Appl. Energy 263 (2020) 114600, http://dx.doi.org/10.1016/j.apenergy.2020.114600.

[36] A. Elhefny, Z. Jiang, J. Cai, Co-simulation and energy management of photovoltaic-rich residential communities for improved distribution voltage support with flexible loads, Sol. Energy 231 (2022) 516–526, http://dx.doi.org/10.1016/j.solener.2021.11.051.

[37] A. Estebsari, L. Barbierato, A. Bahmanyar, L. Bottaccioli, E. Macii, E. Patti, A SGAM-based test platform to develop a scheme for wide area measurement-free monitoring of smart grids under high PV penetration, Energies 12 (8) (2019) 1417, http://dx.doi.org/10.3390/en12081417.

[38] M. Ferrara, J.C. Vallée, L. Shtrepi, A. Astolfi, E. Fabrizio, A thermal and acoustic co-simulation method for the multi-domain optimization of nearly zero energy buildings, J. Build. Eng. 40 (2021) 102699, http://dx.doi.org/10.1016/j.jobe.2021.102699.

[39] E. Hammad, M. Ezeme, A. Farraj, Implementation and development of an offline co-simulation testbed for studies of power systems cyber security and control verification, Int. J. Electr. Power Energy Syst. 104 (2019) 817–826, http://dx.doi.org/10.1016/j.ijepes.2018.07.058.

[40] T. Hong, H. Sun, Y. Chen, S.C. Taylor-Lange, D. Yan, An occupant behavior modeling tool for co-simulation, Energy Build. 117 (2016) 272–281, http://dx.doi.org/10.1016/j.enbuild.2015.10.033.

[41] K. Hoth, T. Steffen, B. Wiegel, A. Youssfi, D. Babazadeh, M. Venzke, C. Becker, K. Fischer, V. Turau, Holistic simulation approach for optimal operation of smart integrated energy systems under consideration of resilience, Economics and sustainability, Infrastructures 6 (11) (2021) 150, http://dx.doi.org/10.3390/infrastructures6110150.

[42] M. Hu, F. Xiao, J.B. Jørgensen, S. Wang, Frequency control of air conditioners in response to real-time dynamic electricity prices in smart grids, Appl. Energy 242 (2019) 92–106, http://dx.doi.org/10.1016/j.apenergy.2019.03.127.

[43] M. Jans-Singh, R. Ward, R. Choudhary, Co-simulating a greenhouse in a building to quantify co-benefits of different coupled configurations, J. Build. Perform. Simul. 14 (3) (2021) 247–276, http://dx.doi.org/10.1080/19401493.2021.1908426.

[44] M. Jia, R. Srinivasan, R.J. Ries, G. Bharathy, N. Weyer, Investigating the impact of actual and modeled occupant behavior information input to building performance simulation, Buildings 11 (1) (2021) 32, http://dx.doi.org/10.3390/buildings11010032.

[45] X. Kang, D. Yan, X. Xie, J. An, Z. Liu, Co-simulation of dynamic underground heat transfer with building energy modeling based on equivalent slab method, Energy Build. 256 (2022) 111728, http://dx.doi.org/10.1016/j.enbuild.2021.111728.

[46] T.Y. Kim, J.M. Lee, Y. Yoon, K.H. Lee, Application of artificial neural network model for optimized control of condenser water temperature set-point in a chilled water system, Int. J. Thermophys. 42 (12) (2021) 172, http://dx.doi.org/10.1007/s10765-021-02922-w.

[47] M. Knudsen, S. Petersen, Economic model predictive control of space heating and dynamic solar shading, Energy Build. 209 (2020) 109661, http://dx.doi.org/10.1016/j.enbuild.2019.109661.

[48] J.M. Lee, S.H. Hong, B.M. Seo, K.H. Lee, Application of artificial neural networks for optimized AHU discharge air temperature set-point and minimized cooling energy in VAV system, Appl. Therm. Eng. 153 (2019) 726–738, http://dx.doi.org/10.1016/j.applthermaleng.2019.03.061.

[49] B. Leitner, E. Widl, W. Gawlik, R. Hofmann, Control assessment in coupled local district heating and electrical distribution grids: Model predictive control of electric booster heaters, Energy 210 (2020) 118540, http://dx.doi.org/10.1016/j.energy.2020.118540.

[50] B.D. Less, S.M. Dutton, I.S. Walker, M.H. Sherman, J.D. Clark, Energy savings with outdoor temperature-based smart ventilation control strategies in advanced California homes, Energy Build. 194 (2019) 317–327, http://dx.doi.org/10.1016/j.enbuild.2019.04.028.

[51] Y. Li, Z. Tong, Model predictive control strategy using encoder-decoder recurrent neural networks for smart control of thermal environment, J. Build. Eng. 42 (2021) 103017, http://dx.doi.org/10.1016/j.jobe.2021.103017.

[52] X. Lu, T. Yang, Z. O'Neill, X. Zhou, Z. Pang, Energy and ventilation performance analysis for CO_2 -Based demand-controlled ventilation in multiple-zone VAV systems with fan-powered terminal units (ASHRAE RP-1819), Sci. Technol. Built Environ. 27 (2) (2021) 139–157, http://dx.doi.org/10.1080/23744731.2020.1831318.

[53] K.B. Mehboob, Development of energy saving technique for setback time using artificial neural network, Aust. J. Mech. Eng. 19 (3) (2021) 276–290, http://dx.doi.org/10.1080/14484846.2019.1605685.

[54] R. Mokhtari, M.H. Jahangir, The effect of occupant distribution on energy consumption and COVID-19 infection in buildings: A case study of university building, Build. Environ. 190 (2021) 107561, http://dx.doi.org/10.1016/j.buildenv.2020.107561.

[55] S.-H. Mun, Y. Kwak, J.-H. Huh, Influence of complex occupant behavior models on cooling energy usage analysis, Sustainability 13 (3) (2021) 1243, http://dx.doi.org/10.3390/su13031243.

[56] T.S. Nouidui, J. Coignard, C. Gehbauer, M. Wetter, J.-Y. Joo, E. Vrettos, CyDER – an FMI-based co-simulation platform for distributed energy resources, J. Build. Perform. Simul. 12 (5) (2019) 566–579, http://dx.doi.org/10.1080/19401493.2018.1535623.

[57] Z.D. O'Neill, Y. Li, H.C. Cheng, X. Zhou, S.T. Taylor, Energy savings and ventilation performance from CO_2 -Based demand controlled ventilation: simulation results from ASHRAE RP-1747 (ASHRAE RP-1747), Sci. Technol. Built Environ. 26 (2) (2020) 257–281, http://dx.doi.org/10.1080/23744731.2019.1620575.

[58] K. Pandakov, C.M. Adrah, H.K. Hoidalen, O. Kure, Experimental validation of a new impedance-based protection for networks with distributed generation using co-simulation test platform, IEEE Trans. Power Deliv. 35 (3) (2020) 1136–1145, http://dx.doi.org/10.1109/TPWRD.2019.2935834.

[59] B. Pandey, R. Banerjee, A. Sharma, Coupled EnergyPlus and CFD analysis of PCM for thermal management of buildings, Energy Build. 231 (2021) 110598, http://dx.doi.org/10.1016/j.enbuild.2020.110598.

[60] B. Pandey, B. Bohara, R. Pungaliya, S.C. Patwardhan, R. Banerjee, A thermal comfort-driven model predictive controller for residential split air conditioner, J. Build. Eng. 42 (2021) 102513, http://dx.doi.org/10.1016/j.jobe.2021.102513.

[61] H. Park, A. Easwaran, E. Borde, Online cycle detection for models with mode-dependent input and output dependencies, J. Syst. Archit. 115 (2021) 102017, http://dx.doi.org/10.1016/j.sysarc.2021.102017, arXiv:2102.01928.

[62] T. Péan, R. Costa-Castelló, J. Salom, Price and carbon-based energy flexibility of residential heating and cooling loads using model predictive control, Sustainable Cities Soc. 50 (2019) 101579, http://dx.doi.org/10.1016/j.scs.2019.101579.

[63] V. Reinbold, C. Protopapadaki, J.-P. Tavella, D. Saelens, Assessing scalability of a low-voltage distribution grid co-simulation through functional mock-up interface, J. Build. Perform. Simul. 12 (5) (2019) 637–649, http://dx.doi.org/10.1080/19401493.2019.1597923.

[64] T.P. Richert, T.V. Jensen, Simulating services from power-to-heat components in integrated energy systems, Electr. Power Syst. Res. 189 (2020) 106778, http://dx.doi.org/10.1016/j.epsr.2020.106778.

[65] M. Roccotelli, A. Rinaldi, M.P. Fanti, F. Iannone, Building energy management for passive cooling based on stochastic occupants behavior evaluation, Energies 14 (1) (2020) 138, http://dx.doi.org/10.3390/en14010138.

[66] A. Sachajdak, J. Lappalainen, H. Mikkonen, Dynamic simulation in development of contemporary energy systems – Oxy combustion case study, Energy 181 (2019) 964–973, http://dx.doi.org/10.1016/j.energy.2019.05.198.

[67] D.S. Schiera, F.D. Minuto, L. Bottaccioli, R. Borchiellini, A. Lanzini, Analysis of rooftop photovoltaics diffusion in energy community buildings by a novel GIS- and agent-based modeling co-simulation platform, IEEE Access 7 (2019) 93404–93432, http://dx.doi.org/10.1109/ACCESS.2019.2927446.

[68] D.S. Schiera, L. Barbierato, A. Lanzini, R. Borchiellini, E. Pons, E. Bompard, E. Patti, E. Macii, L. Bottaccioli, A distributed multimodel platform to cosimulate multienergy systems in smart buildings, IEEE Trans. Ind. Appl. 57 (5) (2021) 4428–4440, http://dx.doi.org/10.1109/TIA.2021.3094497.

[69] M. Schönemann, H. Bockholt, S. Thiede, A. Kwade, C. Herrmann, Multiscale simulation approach for production systems: Application to the production of lithium-ion battery cells, Int. J. Adv. Manuf. Technol. 102 (5–8) (2019) 1373–1390, http://dx.doi.org/10.1007/s00170-018-3054-y.

[70] S.T. Shams Abadi, N. Moniri Tokmehdash, A. Hosny, M. Nik-Bakht, BIM-based co-simulation of fire and occupants' behavior for safe construction rehabilitation planning, Fire 4 (4) (2021) 67, http://dx.doi.org/10.3390/fire4040067.

[71] J. Singer, T. Roth, C. Wang, C. Nguyen, H. Lee, EnergyPlus integration into cosimulation environment to improve home energy saving through cyber-physical systems development, J. Energy Resour. Technol. 141 (6) (2019) 062001, http://dx.doi.org/10.1115/1.4042224.

[72] C. Steinbrink, M. Blank-Babazadeh, A. El-Ama, S. Holly, B. Lüers, M. Nebel-Wenner, R. Ramírez Acosta, T. Raub, J. Schwarz, S. Stark, A. Nieße, S. Lehnhoff, CPES testing with mosaik: co-simulation planning, execution and analysis, Appl. Sci. 9 (5) (2019) 923, http://dx.doi.org/10.3390/app9050923.

[73] P.C. Tabares-Velasco, A. Speake, M. Harris, A. Newman, T. Vincent, M. Lanahan, A modeling framework for optimization-based control of a residential building thermostat for time-of-use pricing, Appl. Energy 242 (2019) 1346–1357, http://dx.doi.org/10.1016/j.apenergy.2019.01.241.

[74] J. Thompson, B. Ganapathysubramanian, W. Chen, M. Dorneich, P. Gassman, C. Krejci, M. Liebman, A. Nair, U. Passe, N. Schwab, K. Rosentrater, T. Stone, Y. Wang, Y. Zhou, Iowa urban FEWS: Integrating social and biophysical models for exploration of urban food, energy, and water systems, Front. Big Data 4 (2021) http://dx.doi.org/10.3389/fdata.2021.662186.

[75] C. Thule, K. Lausdahl, C. Gomes, G. Meisl, P.G. Larsen, Maestro: The INTO-CPS co-simulation framework, Simul. Model. Pract. Theory 92 (2019) 45–61, http://dx.doi.org/10.1016/j.simpat.2018.12.005.

[76] L.J. Underhill, C.W. Milando, J.I. Levy, W.S. Dols, S.K. Lee, M.P. Fabian, Simulation of indoor and outdoor air quality and health impacts following installation of energy-efficient retrofits in a multifamily housing unit, Build. Environ. 170 (2020) 106507, http://dx.doi.org/10.1016/j.buildenv.2019.106507.

[77] M. Usman, M. Ali, T. Rashid, H. Muhammad, G. Frey, Towards zero energy solar households – A model-based simulation and optimization analysis for a humid subtropical climate, Sustain. Energy Technol. Assess. 48 (2021) 101574, http://dx.doi.org/10.1016/j.seta.2021.101574.

[78] J. Wang, S. Li, H. Chen, Y. Yuan, Y. Huang, Data-driven model predictive control for building climate control: Three case studies on different buildings, Build. Environ. 160 (2019) 106204, http://dx.doi.org/10.1016/j.buildenv.2019.106204.

[79] C. Wang, K. Pattawi, H. Lee, Energy saving impact of occupancy-driven thermostat for residential buildings, Energy Build. 211 (2020) 109791, http://dx.doi.org/10.1016/j.enbuild.2020.109791.

[80] E. Widl, B. Leitner, D. Basciotti, S. Henein, T. Ferhatbegovic, R. Hofmann, Combined optimal design and control of hybrid thermal-Electrical distribution grids using co-simulation, Energies 13 (8) (2020) 1945, http://dx.doi.org/10.3390/en13081945.

[81] J. Yao, R. Zheng, Uncertainty of energy and economic performance of manual solar shades in hot summer and Cold Winter Regions of China, Sustainability 11 (20) (2019) 5711, http://dx.doi.org/10.3390/su11205711.
[82] J. Yao, The uncertainty of manual shade control on west-facing facades and its influence on energy performance, Appl. Therm. Eng. 165 (2020) 114611, http://dx.doi.org/10.1016/j.applthermaleng.2019.114611.
[83] J. Yao, Minimum number of simulation runs for reliable building energy and peak load prediction at different building scales: A study on stochastic shade adjustment, J. Asian Archit. Build. Eng. 19 (5) (2020) 527–540, http://dx.doi.org/10.1080/13467581.2020.1758112.
[84] H. Yi, Visualized co-simulation of adaptive human behavior and dynamic building performance: An agent-based model (ABM) and artificial intelligence (AI) approach for smart architectural design, Sustainability 12 (16) (2020) 6672, http://dx.doi.org/10.3390/su12166672.
[85] M. Young, B.D. Less, S.M. Dutton, I.S. Walker, M.H. Sherman, J.D. Clark, Assessment of peak power demand reduction available via modulation of building ventilation systems, Energy Build. 214 (2020) 109867, http://dx.doi.org/10.1016/j.enbuild.2020.109867.
[86] K. Zhang, M. Kummert, Evaluating the impact of thermostat control strategies on the energy flexibility of residential buildings for space heating, Build. Simul. 14 (5) (2021) 1439–1452, http://dx.doi.org/10.1007/s12273-020-0751-x.
[87] L. Zhao, M. Ni, H. Tong, Y. Li, Design and application of distributed co-simulation platform for cyber physical power system based on the concepts of software bus and middleware, IET Cyber-Phys. Syst. Theory Appl. 5 (1) (2020) 71–79, http://dx.doi.org/10.1049/iet-cps.2018.5084.
[88] X. Zhu, T. Shi, X. Jin, Z. Du, Multi-sensor information fusion based control for VAV systems using thermal comfort constraints, Build. Simul. 14 (4) (2021) 1047–1062, http://dx.doi.org/10.1007/s12273-020-0736-9.
[89] N. Carbonare, T. Pflug, C. Bongs, A. Wagner, Simulative study of a novel fuzzy demand controlled ventilation for façade-integrated decentralized systems in renovated residential buildings, Sci. Technol. Built Environ. 26 (10) (2020) 1412–1426, http://dx.doi.org/10.1080/23744731.2020.1797442.
[90] M. Azeroual, T. Lamhamdi, H. El Moussaoui, H. El Markhi, Archives of Electrical Engineering, Polish Academy of Sciences, 2020, http://dx.doi.org/10.24425/AEE.2020.131756, URL: https://journals.pan.pl/dlibra/publication/131756/edition/115086/content.
[91] M.H. Fathollahzadeh, P.C. Tabares-Velasco, Building control virtual test bed and functional mock-up interface standard: comparison in the context of campus energy modelling and control, J. Build. Perform. Simul. 13 (4) (2020) 456–471, http://dx.doi.org/10.1080/19401493.2020.1769191.
[92] J. Yao, The uncertainty of manual shade control on west-facing facades and its influence on energy performance, Appl. Therm. Eng. 165 (2020) 114611, http://dx.doi.org/10.1016/j.applthermaleng.2019.114611.
[93] S. Huang, D. Wu, Validation on aggregate flexibility from residential air conditioning systems for building-to-grid integration, Energy Build. 200 (2019) 58–67, http://dx.doi.org/10.1016/j.enbuild.2019.07.043, URL: https://www.sciencedirect.com/science/article/pii/S0378778819307534.
[94] M. Hu, F. Xiao, J.B. Jørgensen, R. Li, Price-responsive model predictive control of floor heating systems for demand response using building thermal mass, Appl. Therm. Eng. 153 (2019) 316–329, http://dx.doi.org/10.1016/j.applthermaleng.2019.02.107, URL: https://www.sciencedirect.com/science/article/pii/S1359431118361921.
[95] P. Shen, M. Dai, P. Xu, W. Dong, Building heating and cooling load under different neighbourhood forms: Assessing the effect of external convective heat transfer, Energy 173 (2019) 75–91, http://dx.doi.org/10.1016/j.energy.2019.02.062, URL: https://www.sciencedirect.com/science/article/pii/S0360544219302579.
[96] H. Tang, S. Wang, A model-based predictive dispatch strategy for unlocking and optimizing the building energy flexibilities of multiple resources in electricity markets of multiple services, Appl. Energy 305 (2022) 117889, http://dx.doi.org/10.1016/j.apenergy.2021.117889, URL: https://www.sciencedirect.com/science/article/pii/S0306261921012058.
[97] T.H. Pedersen, R.E. Hedegaard, K.F. Kristensen, B. Gadgaard, S. Petersen, The effect of including hydronic radiator dynamics in model predictive control of space heating, Energy Build. 183 (2019) 772–784, http://dx.doi.org/10.1016/j.enbuild.2018.11.015, URL: https://www.sciencedirect.com/science/article/pii/S037877881831301X.
[98] S.-H. Park, Y.-S. Jang, E.-J. Kim, Multi-objective optimization for sizing multi-source renewable energy systems in the community center of a residential apartment complex, Energy Convers. Manage. 244 (2021) 114446, http://dx.doi.org/10.1016/j.enconman.2021.114446, URL: https://www.sciencedirect.com/science/article/pii/S0196890421006221.
[99] R. Lv, Z. Yuan, B. Lei, J. Zheng, X. Luo, Model predictive control with adaptive building model for heating using the hybrid air-conditioning system in a railway station, Energies 14 (7) (2021) http://dx.doi.org/10.3390/en14071996, URL: https://www.mdpi.com/1996-1073/14/7/1996.
[100] A. Alzahrani, I. Petri, Y. Rezgui, A. Ghoroghi, Developing smart energy communities around Fishery ports: toward zero-carbon Fishery ports, Energies 13 (11) (2020) http://dx.doi.org/10.3390/en13112779.
[101] J. Singer, T. Roth, C. Wang, C. Nguyen, H. Lee, Energyplus integration into cosimulation environment to improve home energy saving through cyber-physical systems development, J. Energy Resour. Technol. 141 (6) (2019) http://dx.doi.org/10.1115/1.4042224.
[102] B. Bhattarai, L. Marinovici, M. Touhiduzzaman, F.K. Tuffner, K.P. Schneider, J. Xie, P.T. Mana, W. Du, A. Fisher, Studying impacts of communication system performance on dynamic stability of networked microgrid, IET Smart Grid 3 (5) (2020) 667–676, http://dx.doi.org/10.1049/iet-stg.2019.0303.
[103] B. Seo, Y.B. Yoon, B.H. Yu, S. Cho, K.H. Lee, Comparative analysis of cooling energy performance between water-cooled vrf and conventional ahu systems in a commercial building, Appl. Therm. Eng. 170 (2020) 114992, http://dx.doi.org/10.1016/j.applthermaleng.2020.114992.
[104] G. Cucca, A. Ianakiev, Assessment and optimisation of energy consumption in building communities using an innovative co-simulation tool, J. Build. Eng. 32 (2020) 101681, http://dx.doi.org/10.1016/j.jobe.2020.101681, URL: https://www.sciencedirect.com/science/article/pii/S2352710220303818.
[105] IEEE, 1516-2010 - IEEE standard for modeling and simulation (M&S) high level architecture (HLA), 2010, http://dx.doi.org/10.1109/IEEESTD.2010.5553440, IEEE Std 1516-2010 (Revision of IEEE Std 1516-2000).
[106] P. Palensky, A.A. Van Der Meer, C.D. Lopez, A. Joseph, K. Pan, Cosimulation of intelligent power systems: Fundamentals, software architecture, numerics, and coupling, IEEE Ind. Electron. Mag. 11 (1) (2017) 34–50, http://dx.doi.org/10.1109/MIE.2016.2639825, URL: http://ieeexplore.ieee.org/document/7883974/.
[107] M. Otter, H. Elmqvist, Modelica overview, 2001, URL:https://www. modelica. org/education/educationalmaterial/lecture-material/english/ModelicaOverview. pdf.
[108] D.B. Crawley, L.K. Lawrie, F.C. Winkelmann, W. Buhl, Y.J. Huang, C.O. Pedersen, R.K. Strand, R.J. Liesen, D.E. Fisher, M.J. Witte, J. Glazer, EnergyPlus: creating a new-generation building energy simulation program, Energy Build. 33 (4) (2001) 319–331, http://dx.doi.org/10.1016/S0378-7788(00)00114-6, URL: https://www.sciencedirect.com/science/article/pii/S0378778800001146, Special Issue: BUILDING SIMULATION'99.
[109] S. Schütte, S. Scherfke, M. Tröschel, Mosaik: A framework for modular simulation of active components in smart grids, in: 2011 IEEE First International Workshop on Smart Grid Modeling and Simulation, SGMS, IEEE, 2011, pp. 55–60.
[110] T. Miyakawa, No raw data, no science: another possible source of the reproducibility crisis, Mol. Brain 13 (1) (2020) 1–6.
[111] S.N. Goodman, D. Fanelli, J.P. Ioannidis, What does research reproducibility mean? Sci. Transl. Med. 8 (341) (2016) 341ps12.
[112] K.M. Merz Jr., R. Amaro, Z. Cournia, M. Rarey, T. Soares, A. Tropsha, H.A. Wahab, R. Wang, Method and data sharing and reproducibility of scientific results, J. Chem. Inf. Model. 60 (12) (2020) 5868–5869.
[113] L. Tedersoo, R. Küngas, E. Oras, K. Köster, H. Eenmaa, Ä. Leijen, M. Pedaste, M. Raju, A. Astapova, H. Lukner, et al., Data sharing practices and data availability upon request differ across scientific disciplines, Sci. Data 8 (1) (2021) 1–11.
[114] A. Malhotra, J. Bischof, A. Nichersu, K.-H. Häfele, J. Exenberger, D. Sood, J. Allan, J. Frisch, C. van Treeck, J. O'Donnell, et al., Information modeling for urban building energy simulation—A taxonomic review, Build. Environ. (2021) 108552.