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Authors
Wetter, Michael
Sulzer, Matthias

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A call to action for building energy system modelling in the age of decarbonization

Michael Wetter and Matthias Sulzer

Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA

ABSTRACT
As urban energy systems become decarbonized and digitalized, buildings are increasingly interconnected with one another and with the industrial and transportation sector. Transformation strategies to cost-effectively integrate distributed energy sources, and to increase load flexibility and efficiency, generally increase complexity. This complexity causes challenges that the industry is unprepared to deal with. Today's simulation programs, and the processes in which they are used, have not been developed to meet the challenges of decarbonization. Nor have they been designed for, or do they keep pace with, the energy system digitalization. Modeling, simulation and optimization tools, and the processes in which they are used, need to undergo an innovation jump. We show a path to more holistic tools and workflows that address the new requirements brought forward by the increased complexity. Without concerted actions, the building simulation community will fall short of supporting the 2050 decarbonization targets declared by many governments.

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Decarbonized energy systems; optimization; modelling; complexity; risk; building energy model

1. Introduction

The need to decarbonize the energy sector by 2050 increases complexity and risk in design, deployment, and operation of building and district energy systems. Systems become increasingly integrated, not only among energy carriers such as thermal, electrical, and natural or synthetic gas, but also among sectors such as buildings, industry, and transportation. The urgency to succeed on the rapid decarbonization path of many governments, coupled with the large capital investments of renewable energy infrastructure, puts pressure on the timeline and robustness of the transformation. Future energy systems will be decentralized and integrated to harvest renewable energy, provide storage, and enhance efficiency in a cost-effective way. Flexibility in these systems' design and operation will be essential to manage the distributed assets and ensure the greatest security of supply. Demanding integration, modular decentralization and flexible operation on a rapid timeline poses unique design and operational challenges.

To comprehend the scale of building decarbonization, consider the US, which has around 110 million buildings. To decarbonize them in the next 25 years will require decarbonizing around 10,000 buildings *per day*. To stay on such a rapid decarbonization path, industry is being asked to rush the deployment of established equipment in new, unproven system designs. This will likely lead to unmet performance goals, extensive retrofits, and even stranded assets, as is frequently observed when novel system configurations are deployed. While such problems are reported rarely in the literature, as they can taint one's reputation and can have legal implications, challenges in the deployment of new building energy systems can be found; see, for example, Scofield (2002), Vetterli and Sulzer (2015), Egger (2015), and Fumagalli et al. (2017).

As will be shown below, modelling can help to address these challenges if modelling supports a holistic design-build-operate process. Before we discuss modelling needs in support of a process that can manage the complexity and reduce the technical risks of decarbonized energy systems, let us revisit the current situation and discuss the upcoming challenges.

2. Current situation and emerging challenges

Today, building energy systems are typically selected based on a limited set of technology options, such as oil, gas, or wood-fired boilers or heat pumps for heating, and chillers with dry or wet cooling towers for cooling. The supply of electricity is typically settled with the specification of the grid connection. Generally, the technologies being installed are sized either using design-day calculations assuming continuous system operation, or, particularly for larger plants, using a load duration curve

CONTACT Michael Wetter MWetter@lbl.gov Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA

or a static operation schedule for selected typical weeks that allows partial curtailing of peak loads with the use of thermal storage. Similarly, district heating systems are designed using a high-temperature distribution network for heating and a separate low-temperature distribution network for cooling (Lund et al. 2014). Energy and water flow are uni-directional, from plants to consumers. Heating and cooling systems are generally designed in a siloed approach, in which designing the control strategy and control sequences is not an integrated part of the design process, but rather a subsequent task in the construction phase. Optimization is almost never used in practice to select and size components and configure systems; at best simulation is used to inform and analyse proposed design solutions.

Newer district energy systems often have bi-directional energy flow, and sometimes bi-directional water flow, to share low-grade waste heat, to shift loads, and to convert and optimize between different energy carriers including thermal heat at different temperature levels, electricity, and natural or synthetic gas (Buffa et al. 2019). This decentralization and integration lead to increased complexity due to the need to match fluctuating distributed energy resources with the temporal requirements of loads. To manage this complexity, we argue that model-based engineering is needed. The need for model-based engineering, as a step within a Platform-Based Design Process, is explained in a companion paper (Sulzer et al. 2023). This poses new opportunities, but also new challenges and requirements on energy modelling. These include

- **Selection and sizing of technology assets for energy conversion and storage:** The types of viable energy conversion and storage technologies are rapidly expanding and may include: for thermal energy conversion (beyond the conventional boilers and chillers), heat pumps, biomass combined heat and power (CHP) facilities, waste heat integration (industrial or sewage), and solar collectors; for daily and seasonal thermal storage, geothermal systems and sensible or latent storages; and for electrical systems, solar photovoltaics (PV), wind turbines, batteries, and storage systems such as vehicle-to-grid and power-to-X. In addition, energy systems may be designed to exchange energy with each other by importing and exporting energy between the electricity grid, gas system, and a thermal grid. The appropriate configuration of such technology assets needs to consider local demand and supply, sector integration, and current as well as anticipated evolution of the district heating and cooling system.
- **Selection and conception of network technologies and topologies for energy distribution:** Network technologies need to be selected and designed in order to integrate and connect the above technology assets. These networks need to provide a conduit to transfer thermal energy at different temperature levels, transfer alternating current and direct current (AC and DC) power, and transfer natural and synthetic gas among plants, storage devices, buildings, and industrial processes. The design has to take into account not only the current conditions but also future scenarios, allowing for expansion and adaptation.
- **Configuration of equipment and networks under consideration of dynamic operation:** The selection, layout, and sizing of the above assets and networks needs to be undertaken in a way that leads to a Pareto-optimal system solution. Multi-criteria optimization, e.g. in terms of life-cycle costs and carbon emissions, must be weighed against each other to find the preferred design. System complexity increases even more as assets need to be operated dynamically to account for the variability of loads and renewable resources.

Key metrics for optimizing the selection and sizing not only include life-cycle costs and carbon emissions, but need to consider dynamic energy prices, time-dependent carbon intensity of electricity, local regulations, and business models of investors and operators. These diverse and intersecting requirements makes it natural to formulate the design problem as a multi-objective optimization problem.

2.1. Shortfalls in energy and building system optimization

The Pareto-optimal configuration and operation of the energy system requires optimization under consideration of the system dynamics. Design day sizing calculations, or static calculations such as load duration curves, are no longer appropriate.

For electrical systems, optimization tools that optimize selection and sizing of technology assets under consideration of hourly or sub-hourly optimal dispatch schedules have existed for some time; in some cases they have been expanded to cover certain thermal systems, and more recent software also covers multiple energy carriers and optimize over multiple investment stages of the system life-cycle (Cutler et al. 2017; Evins et al. 2014; Mashayekh et al. 2017; Petkov et al. 2022; Terlouw et al. 2023; Wu et al. 2022). These types of optimization software typically formulate an optimization problem using Mixed Integer Linear Programming (MILP). One advantage of MILP is that optimization problems can be solved efficiently. However, formulating cost and constraint functions for MILP requires significant model simplifications to make models piece-wise linear and to remove fast dynamics that may require an excessively fine temporal grid. Another approach is to use nonlinear dynamic models and optimization using collocation as is used in Köppen et al. (2022) to co-design a carbon-neutral manufacturing plant. Since this method only handles continuous decision variables, the decision of whether an asset should be installed can be made based on its optimal size, as assets that are not technically or economically viable will have zero sizes. Naturally, collocation also requires model simplifications such as the removal of fast dynamics and non-differentiabilities, as are commonly introduced by controllers.

While either approach is well suited to handle optimal technology selection and sizing, both are based on idealized models representing the real-world system in an abstract, highly idealized and imprecise way. Moreover, MILP satisfies the first but not necessarily the second law of thermodynamics, as flows of each energy carrier are considered as 'buses', balancing inputs, outputs, and energy of storage devices. They do not account for temperature differentials and pressure differentials that drive heat and mass flow. Moreover, in general, both approaches assume perfect control, perfect knowledge of the system, and perfect foresight. Thus, they abstract actual systems at a very high level, and implementation still bears significant design and operational risks because such models lack: (i) implementable control logic, (ii) reliable operation based on temperature and pressure differentials, (iii) subsystem coupling that can cause control instability, and (iv) nonlinear physical phenomena that can impede performance. By omitting such real-world effects, systems might not behave as expected or could fail in operation. For example, reports that show the importance of these effects include the following:

- **Control sequences**: A survey by Barwig et al. (2002) found that control programming errors were the most frequent control-related problem in commercial buildings with built-up heating, ventilation, and air conditioning (HVAC) systems, accounting for one-third of all reported problems. Crowe et al. (2020) show that control problems persist to be a key impediment to achieve high operational performance. Zhang et al. (2022) showed that advanced control sequences for variable air volume flow systems can reduce HVAC energy consumption by a wide range with an average of 31%, and Sommer et al. (2020) showed that in a reservoir district energy system, dynamic control of the distribution pump reduced total electric energy use for circulation pumps and heat pumps by about one-third.
- **Hydronic system**: Pressure problems in district energy systems at ETH Zurich caused pump cavitation and required retrofit measures (Egger 2015). Monitoring at an installation called Suurstoffi in Switzerland showed that shortcomings in the hydronic system caused high pump energy (Vetterli and Sulzer 2015).
- **Subsystem coupling**: Renewable systems generally have a tighter coupling of subsystems at the district level, at the building level, and across these scales. At the district level, consider the Quayside Toronto district energy system that was planned as part of a major urban retrofit. The initial hydronic configuration that allowed for reversing the water flow in pipes, which would have reduced electricity demand for the heat pumps, was abandoned due to fundamental control instabilities caused by the hydronic configuration (Wetter and Hu 2019). At the building level, a helpful explanation of the problem of tightly coupled control loops can be found in Bortoff et al. (2022). The authors developed an H_∞ Loop-Shaped Model Predictive Controller for a variable refrigerant flow system that enforces constraints while exhibiting excellent stability margins. To see coupling effects among the space heating system and the district heating distribution network, consider the fifth-generation combined district heating and cooling system presented in Maccarini et al. (2023). The authors show that for such systems in which a heat pump boosts temperature from a reservoir network to the building heating system, the design temperatures of the building heating system impact sizing of the reservoir network loop, because the needed capacity of the heat pump evaporator depends on the required condenser temperature. Another example of coupling between buildings and district is the need to thermally balance geothermal borefields, which has been shown to lead to operational problems (Vetterli and Sulzer 2015) that can lead to year-long retrofit measures.
- **Nonlinear phenomena**: Nonlinear phenomena such as the presence of moving groundwater in geothermal applications require detailed nonlinear models (Doughty et al. 2021; Hu et al. 2020) that are not applicable for use with MILP or collocation-based optimization. MILP simplifications that optimize only for energy flows but neglect nonlinearity due to fluctuating temperatures (which show up as the bilinear product of mass flow rate times temperature) have shown to lead to considerable errors and solutions that are infeasible in practice (Moretti, Manzolini, and Martelli 2020). Also, pumping energy in fifth-generation district energy systems can be quite high, but can be reduced with proper sizing and flow rate control (Sommer et al. 2020; Vetterli and Sulzer 2015) which requires inclusion of nonlinear effects.

2.2. Shortfalls in mechanical system and controls simulation

In view of the above simplifications that are needed to solve the optimization problem efficiently, models that are more refined than those used for optimization are needed for developing design specifications for implementation. Only by holistically considering all major physical effects, which includes mass transport, temperature, and pressure changes, can mechanical systems and their controls be developed in a way that ensures stable and reliable operation, guaranteeing that equipment operates within permissible operation envelopes. Consequently, models need to account for the pressure and temperature differentials that drive mass and heat flow, e.g. they need to properly model the 2nd law of thermodynamics and the transport equations, which generally are not regarded in MILP formulations.

Above, the risk in deploying decarbonized, grid-responsive energy systems has been shown. In addition, design and operational problems incurred expensive retrofit and potential reputational damages. It is therefore prudent to manage and reduce such risks. This can be done using refined models that capture the physics and dynamics of mass, temperature, and pressure of energy systems, coupled to feedback control loops that determine how the system operates over time. The problem here is not whether simulations for de-risking systems can be done, as various publications showed how simulations could verify the design prior to deployment. Rather, the problem is whether risk-reducing simulations can be conducted at scale by energy modellers beyond a few experts.

To discuss shortfalls, let us look at the intersection of the mechanical design and controls of an energy system: Similar to the islands of tools that are suited either for optimized asset selection or for system simulation, there are islands of tools for modelling building or HVAC systems and testing and verification of controls. As a consequence, in many projects that require control developments, whether predictive control or classical regulatory feedback control, mechanical, electrical and control engineers are developing their own tool sets or models, respectively. Common reasons for such bespoke model development are as follows:

- Many building energy simulators operate HVAC equipment based on load. They calculate how much energy needs to be provided over the next simulation time step to meet a room temperature set point, and then try to dispatch HVAC equipment at some fictitious part load operation that provides the required energy. In contrast, real control measures a quantity, for example, a room temperature or air flow rate, and then computes an actuation command for a compressor, damper, or fan speed using a feedback controller that takes as input the error between setpoint and measurement. Thus, the inputs, outputs, and the control logic are fundamentally different from load-based simulators.
- Many building energy simulators are just simulators; they don't expose the equations but rather are monolithic tools that make it hard to conduct controls analysis as for the above-mentioned Model Predictive Controller by Bortoff et al. (2022), for development of an observer that estimates non-measurable disturbances as shown in Bortoff and Laughman (2019), or for gain scheduling as shown in Wetter (2009). Moreover, their monolithic software architecture makes it hard to isolate a subsystem and design a controller for it. They also lack real-world effects because of their simplified models and solving principles.
- The use of classical linear and nonlinear control theory, as well as many optimization-based predictive control algorithms, requires models to be differentiable, which is not the case for models in typical building energy simulators. Moreover, most building energy simulators do not allow reinitializing state variables as required for Model Predictive Control algorithms.
- The time steps of many building energy simulators are too large to resolve the fast dynamics of control loops, or the simulators use fixed time steps that, if selected to be sufficiently small to resolve fast dynamics of controls within the required error tolerance, lead to excessively high computing time.
- Many building energy simulators are unable to model the physics that is needed for pressure calculations in duct or pipe networks, transport delay in ducts or pipes, or computational fluid dynamics in rooms. These effects are important for proper calculation of the physics and dynamics of feedback control loops (see, for example, Qiao et al. 2019; Wetter and Hu 2019; Zuo et al. 2016). However, for historical reasons that prevented pressure-driven flow distributions in pipe and duct networks, most building energy simulators balance heat and mass flow rates, but they do not compute mass flow rates based on pressure distribution in piping and/or duct networks. (Some tools allow coupling with airflow network simulations, or they approximate pressure in piping networks, although such approximations balance flow without satisfying pressure balance at flow junctions (EnergyPlus Engineering Reference 2023, Sec 9.9.12)).

2.3. Shortfalls in supporting verification of design intent versus as-installed control logic

Above, it was shown that programming errors account for a large majority of control-related problems, that controls are critical to reduce energy use and shift loads, and that control logic is inherently more complex in decarbonized energy systems. Complexity can be managed through appropriate design processes and formal verification; however, today's energy modelling tools and building control systems fall short in supporting formal verification of installed control logic. The shortfall is caused by a lack of building simulation programs to model actual control, as was discussed above. It is also caused by a lack of support by building automation systems for formal verification of control logic due to three main reasons: First, many building automation systems do not support testing faster than in real time. Second, they have models of computations (Lee and Sangiovanni-Vincentelli 1998) – e.g. rules that describe when outputs are computed – that are not documented. Third, they do not guarantee deterministic execution, meaning that for two executions with the same set of inputs and initial state variables, one cannot expect identical output. In fact, such behavior, while critically important for formal verification, is also not guaranteed for programmable logic controllers that are governed by the International Electrotechnical Commission (IEC) 61131 Standard, as Sehr et al. (2021) argue:

> Future programmable logic controller (PLC) designs must rely less on priority-based cyclic execution models whose timing depends on unrelated tasks running on the PLC or elsewhere in the network. Instead, PLC designs should specify timing behaviours, such as deadlines, and hardware and operating system infrastructure should ensure that the behavior is as specified. This implies less reliance on priorities because, given only priorities, the actual behavior of one component depends on other, unrelated components. Instead of priorities, software components should specify timing requirements and the compilers and operating systems should ensure these timing requirements are met.

Thus, today's building automation product lines were not designed with formal verification of the control logic in mind.

2.4. The missing link between design and operation

Our building energy modelling community has developed many powerful tools for specific applications that support individual steps within the design-build-operate process. Notable initiatives include design analysis integration (Augenbroe, Malkawi, and de Wilde 2004) and analytic target cascading which decomposes the design problem (Choudhary, Malkawi, and Papalambros 2005). However, despite these efforts, sharing data among applications for energy system design, construction and operation remains a big challenge and causes considerable workflow inefficiencies and inconsistencies. There are also fundamental gaps: While many tools have import and export capabilities for different data formats such as IFC or gbXML, these data formats need to be enriched with other, ad-hoc, custom data. For example, neither IFC nor gbXML has the capability to express how HVAC systems are controlled beyond very high-level information such as IfcBuildingControls, which only supports types such as sensors, actuators, and very basic controllers. IfcBuildingControls does not support expressing control logic in a way that allows its use to generate a specification or a simulation model suitable to simulate or verify system behavior. This is perhaps because a couple of decades ago, energy modelling was simply not advanced enough to use realistic control implementations. Therefore, tools are missing for integrating control workflows with energy system design. However, since control implementation choices can affect HVAC energy use, with savings in the range of 23% to 30% being common for most building types (Fernandez et al. 2017; Zhang et al. 2022), and implemented control logic often have errors (Barwig et al. 2002; Crowe et al. 2020), a new standard is needed.

The need is for a standard for the digital specification of control logic. Such a standard should enable testing correctness of building control logic, improving the control logic to increase system performance in model-based design with an energy model in the loop, and providing a digital specification for bidding, implementation, and verification as part of formal commissioning. In response to these needs, a Control Description Language (CDL) and associated workflow for digitalized control delivery has been developed (Wetter et al. 2022; Wetter, Grahovac and Hu 2018). CDL serves as the basic framework for a standardization process by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) that develops ASHRAE Standard 231P, 'CDL – A Control Description Language for Building Environmental Control Sequences'. This standard is orthogonal and complementary to semantic models such as Brick (Balaji et al. 2016) and the currently developed ASHRAE Standard 223P 'Semantic Data Model for Analytics and Automation Applications in Buildings'. Together, the digital specification of control logic and semantic models are poised to enable simulation-based control testing and performance assessment and a highly automated, digitalized deployment, configuration, and commissioning of control logic, system-level automated fault detection, diagnostics and correction, including the required communication. In such a workflow, the semantic model streamlines pairing sensor and actuator signals of actual control systems with the corresponding inputs and outputs of the model of the control logic. During commissioning, the control model takes as input the trended building automation data, and it outputs the anticipated response. If the actual response from the building automation system is within a prescribed tolerance of the simulated response, the control logic is implemented correctly (Wetter et al. 2022, 2019). Such a pairing between building automation system and model then also opens up the opportunity to use physics-informed data-driven methods for predictive control, which has shown to have high performance with lower data requirements compared to purely data-driven methods (Büning et al. 2022). Another frontier will be how to integrate models that encode design specifications not only for predictive control, but also for system-level automated fault detection, diagnostics and correction of integrated energy systems.

2.5. *Conclusions regarding the current situation*

A model is always a mathematical abstraction, designed to answer specific questions, or – ideally, as we will see below – to provide a specification for how to build an engineered system. Tools that incorporate such models and provide capabilities for model authoring, compilation, simulation or optimization, and inspection of results should be designed to support the intended modelling use cases. We will never avoid the need for specialized tools for designing, building, commissioning, and operating energy systems, for several fundamental reasons.

First, the mathematical properties needed for effective optimization, simulation, and control are distinct from one another. Second, the fact that data availability is scarce in early design and increases along the design-build-operate process naturally lends itself to using models at different levels of abstraction. Third, experience in Platform-Based Design for complex systems shows that generally better system-level performance is obtained by constraining the design space and by applying suitable abstractions at each level of the design. Otherwise, complexity would overwhelm the designer and render the design optimization intractable (Sangiovanni-Vincentelli 2007). Therefore, having an all-encompassing model that supports all major use cases is a pipe dream.

Similar to models being developed for a specific use case, data formats are developed to describe elements in a virtual environment. Domain-specific data lead to siloed databases that are not able to represent other domains. For example, trying to represent a control logic in IFC would be unwise. The challenge is to create these domain-specific data in a way that allows them to be linked to one another so that system queries can be done across domains. Such queries across domains would allow for holistic data modelling of integrated systems.

3. Model-based engineering is the new normal

3.1. *Seamless design-build-operate workflow*

The above discussion shows that many solutions exist to address specific use cases, but these solutions are insular. Progress needs to be made to ensure that these insular tools and workflows are interoperable, in order to ensure fluidity of performance requirements, fluidity of data that specify system configuration and equipment performance, and fluidity of control specification. Also, the design process for building energy systems is still structured around a paper-based process used 30 years ago. While simulation models are used for certain energy compliance verifications, and are used to support design decisions and sizing of equipment, the overall design-build-operate process has not evolved to effectively address the new needs. Converting models (meaning a set of requirements, systems, and equipment specifications) from one stage of the process to the next, which may require the use of different tools, can be so prohibitively time-intensive that users often abandon model-based engineering. Consequently, models for early design are seldom refined for detailed design, and practically never used as a specification of the construction or to support commissioning and operation. However, modelling should not be an isolated task within particular design steps. Instead, modelling should be fully integrated into the whole design-build-operate process. At any stage, models should provide a *specification* of the design. Integrating interoperable, modular tools into a holistic ecosystem will support an efficient and effective workflow to tackle the challenges of future energy systems.

3.2. *Usability of interoperable tools*

In the rare cases in which models are reused and refined throughout the different stages of the building life cycle, this is done today using an ad hoc process. This inherently poses a risk, is expensive, time-consuming and does not scale. Often, models are not built to be reused in subsequent tools that would answer more refined questions, such as when progressing from conceptual to detailed design and to construction and commissioning. Moreover, we regularly see users applying a tool that is not appropriate because it lacks the required physics or dynamics. In some cases, users resort to patching the tool deficiencies with fragile spreadsheet calculations to squeeze some plots out of it that may lead to questionable decisions.

In our opinion, there are two reasons that people use such patch solutions. First, users tend to keep using tools with which they are familiar due to the lack of time, resources, and management support to learn a more suitable tool. Second, many building energy modelling tools are difficult to expand to include new components and systems, or to add the physics and dynamics needed in the next, more refined stage of the planning process. This makes it impractical for users to add new capabilities, and it often takes years for development teams to add user-requested new capabilities. However, using such patch solutions is inappropriate because creating them is time consuming, there is a high risk of not considering the needed system dynamics, and reusability in a subsequent step of the planning process is low, as is reuse in similar projects.

What our community should strive for is an ecosystem of interoperable tools that can be applied in different configurations as use cases require. Users should be able to rapidly add new models or reuse models. This will also reduce human bias introduced by a user's choice of a system that is well supported by the tool being used. Just because a system design is time-consuming or difficult to model due to lack of tool support should not exclude it from the set of possible design options. Energy modelling tools should also better support collaboration between modelling and application experts. In other industries, a more formal separation exists between those who develop a model, such as for a car engine, and those who use the model, for example, to develop a controller for that engine. But in our industry, collaboration in which different experts share their models and possibly extend and refine their models is rare.

3.3. Harmonization of tools and processes

What is needed, in our view, is a formalization of the design-build-operation process for building and district energy systems. However, such a process needs clear steps in which requirements for functionality and performance are explicit and are used to select a realization from a set of candidate solutions; at every level of abstraction or at every process step, respectively, the selection of the most appropriate solutions has to be performed. At the next process step, the selection made serves again as requirements for functionality and performance, but is now enriched with additional requirements for that new, refined level of abstraction, and the process is repeated until an implementation is fully specified. Platform-Based Design, as described by Sangiovanni-Vincentelli (2007), formalizes such a process and is a promising approach to master these complex design challenges. Sulzer et al. (2023) propose a new design-build-operate workflow based on Platform-Based Design to achieve rapid, cost-effective and reliable decarbonization of energy systems, and present an example of how to apply Platform-Based Design to a pareto-optimal district energy system design. This Platform-Based Design process requires suitable tools to evaluate design compliance and system performance at the various levels of abstraction. Platform-Based Design also needs the fluidity of functional requirements, performance targets, and equipment and system specification in a way that allows the successive refinement of the design. It also allows the verification of the performance at each layer of abstraction. The subsequent implementation step allows for the digitalized deployment of the controls, ensuring correct-by-construction, thereby providing as-designed operational performance. Thus, interoperable tools and associated models must be modular and extensible so that they can be used throughout the life cycle of buildings and energy systems.

3.4. The purpose of the model matters – we building engineers use models the wrong way

At this point, it is worth noting that one key impediment to the digitalization of the design-build-operate process is caused by our community's relation between a model and an energy system. In the buildings industry, engineers generally build a model to be sufficiently faithful to the expected behavior of an energy system. The model may then be updated to reflect changes during the design-build-operate process – or, more often, it may be abandoned, as explained above. However, models can serve better use cases. Consider, for example, the electronic design automation industry, in which engineers write models, and products are developed to conform to the model. As Lee (2018, p. 42) explains, we have two different mechanisms available to get a good model fidelity:

> We can either choose (or invent) a model that is faithful to the [system], or we can choose (or invent) a [system] that is faithful to the model. The former is the essence of what a scientist does. The latter is the essence of what an engineer does.

He summarizes:

> In engineering, a model is useful if we can find an implementation that is reasonably faithful to the model. In science, a model is useful if it is reasonably faithful to a system given to us by nature. In other words, a scientist asks, 'Can I make a model for this thing?' and an engineer asks, 'Can I make a thing for this model?'

Furthermore, Lee and Sirjani (2018) state:

> …we distinguish models that we call scientific models, which are intended to reflect the behavior of a pre-existing system, from models that we call engineering models, which are intended to specify the behavior of a system to be built. It is important to recognize whether a model is to be used in a scientific way or an engineering way. For example, adding detail may enhance a scientific model and degrade an engineering model.

As we reflect on how building energy engineers use models, we see that we use models like scientists, rather than engineers. In view of the daunting task of mastering the complexity of decarbonized energy systems, and the need to accelerate the deployment of such systems in a robust way, it is time to change how models are used in our field. This requires a transformative change in how models are built and evolve so that they represent engineering specifications for how energy systems and buildings are designed, built, commissioned, and operated.

4. A call to action

The integration of distributed energy resources can efficiently be achieved by buildings. Through the deployment of 'behind-the-meter' technologies such as PV, heat pumps, electrical vehicles, and batteries, buildings are evolving as active nodes in the future energy system. Such a transformation causes a rapid increase of requirements for building and district energy systems to meet decarbonization challenges. Designing and operating such systems in a cost-effective, robust way that scales at the rate needed to achieve the decarbonization goals of various governments is a challenge that our industry is not equipped to meet.

IBPSA should take responsibility for providing the foundation that the building industry needs to succeed in decarbonizing building and district energy systems. IBPSA should establish a roadmap for the development of tools, models, and data formats needed by its members in their efforts to decarbonize the sector. The research and development activities of IBPSA members should be oriented on such a roadmap to ensure the fast, cost-effective, and reliable transition of our industry. A continually renewing expert committee would review the state of national and international R&D development every two years and, as necessary, adapt the roadmap to the latest research findings.

To take advantage of digitalization and to achieve the transformation needed, the workflow and the role of engineers, architects, contractors and other actors within our highly fragmented buildings industry will need to be restructured. Forty years ago, designing and installing a PV system was a difficult pioneering task using an ad hoc workflow. Today there is a vibrant industry that delivers PV, batteries, and financing on a routine basis. The IBPSA community should work on implementing a digitalized, formal workflow that uses computational tools and data formats that enable a similar transformation process for the design, deployment, and operation of decarbonized building and district energy systems.

Our vision is a set of interoperable tools that allow hierarchical design space exploration and refinement; risk quantification and management under consideration of the inherent uncertainty and variability of external factors and users; and digitally supported installation, commissioning, and operation. In a seamless design-build-operate process, models need to be modular and formal to allow the abstraction and refinement of systems and subsystems. They need to serve as specifications for how systems are built, with a fidelity that allows formal verification of installed systems relative to these specifications. Orthogonal, open standards should be leveraged, and further advanced as needed,

- to express the cyber-physical behavior of building and energy systems, using different facets for optimization; for code generation for simulation or real-time operation; for verification, and for operational monitoring, and
- to represent data that show how requirements, system specifications, and performance evolve during design and operation.

Our field can learn from how other industries tamed the complexity through workflows such as Platform-Based Design, and enabled collaborative design and manufacturing of engineered systems through open standards such as Modelica, FMI, eFMI and SSP (Fritzson and Engelson 1998; Junghanns et al. 2021; Lenord et al. 2021; Mattsson and Elmqvist 1997; Modelica Association 2019). Some advances have been made via collaborations such as IEA EBC Annex 60 (Wetter and van Treeck 2017), IBPSA Project 1 (Wetter et al. 2019), and the recently formed IBPSA Modelica Working Group, as well as through the ongoing standardization of CDL and semantic models via the currently developed ASHRAE Standards 231P and 223P. These collaborative efforts advanced modular modelling and work toward digitalization of the control delivery process. The anticipated outcome of these efforts includes modular, multi-fidelity models that bridge energy modelling and controls, provide interoperability of control logic among control modelling software and commercial control product lines, and lead to standardization of the graph representation of building systems. When integrated, these technologies provide a path toward digitalized, performance-based HVAC control delivery and operation (Roth et al. 2022).

However, much more remains to be done on a comprehensive and holistic workflow and on supporting tools and data representations to enable a robust, rapid decarbonization of energy systems. For example, we need education in model-based engineering for all stakeholders of the building delivery process, ensuring not only that designers can conduct it, but also that building owners demand a design process that delivers high-performance systems in a robust, cost-effective, predictable way.

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ORCID

Michael Wetter http://orcid.org/0000-0002-7043-0802
Matthias Sulzer http://orcid.org/0000-0003-2094-2460

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