Challenges in the Modeling and Simulation of Green Buildings

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Abstract

Green buildings are environmentally bearable and economically viable buildings that are designed, constructed, and operated in order to minimize their environmental impact on the planet and maximize the quality of human life. Achieving a green building is hence a wide, complex, and ambitious challenge that requires close cooperation of all the stakeholders involved in the life cycle of the building, multidisciplinary competencies and field experience, as well as extensive

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computational skills. In this last regard, building performance simulation, which is a computer-based and multidisciplinary mathematical model of given aspects of building performance, is emerging as a promising support for designers and consultants. Unfortunately, although building performance simulation is renowned to be a powerful, comprehensive, flexible, and scalable tool, its use is not trivial, and, even today, modelers have to face several challenges for employing it to support the design and operation of green buildings. In this chapter, the main features of green buildings will be, first, mentioned. Next, typical mistakes, errors, and uncertainties that can spoil a building model will be presented. Then, a few modeling and simulation challenges – ranging from the model creation, through modeling under aleatory uncertainty, quality assurance, tool integration, simulation-based optimization, visualization and communication issues, to the selection of an appropriate tool – will be presented. Finally, a few final conclusions and future directions are drawn.

Keywords
Building performance simulation · Building modeling · Computer simulation · Simulation-based optimization · Building information modeling · Numerical models · Quality assurance · Verification · Validation · Calibration

Introduction

The buildings we use and in which we live have weighty environmental, social, and economic impacts on the earth and the human ecosystem. These three impacts are used to express the concept of sustainability. In this regard, a commonly pursued strategy for increasing the sustainability of the building sector is represented by *green buildings*. In general terms, a green building is an environmentally bearable and economically viable building that is, therefore, designed, constructed, and operated to minimize its environmental impact and to maximize the quality of human life. In more technical terms, the expression *green building* can refer to both a facility and the use of processes that have to (i) protect people's health, improve occupants' well-being, and enhance employees' productivity; (ii) result resource-efficient – in terms of energy, construction materials, and water – throughout a building's life cycle that covers from siting to its design, construction, operation, maintenance, refurbishment, till disassembly and demolition; and (iii) reduce waste, pollution, and environmental degradation [1]. Achieving a green building is hence a wide, complex, and ambitious challenge that requires (i) close cooperation of all the stakeholders involved in the whole life cycle of a building, from the client (owner and/or tenant) to the design team (architects, engineers, consultants), developer, and facility manager [2], (ii) multidisciplinary competencies and field experience, as well as (iii) extensive computational skills.

Focusing on the design and operation of a green building, a tool that has proven to be effective to support designers during the design decision-making process is building performance simulation (BPS). BPS is a computer-based, multidisciplinary, and problem-oriented mathematical model of given aspects of a building performance that is based on fundamental physical principles and engineering models. It assumes dynamic boundary conditions and is normally based on numerical methods that aim to provide a simplified and approximate solution of a real physical phenomenon. It is typically adopted for estimating the behavior of the built environment and improving its design and operation [3].

Although BPS is renowned to be a powerful, comprehensive, flexible, and scalable tool, unfortunately, its use is not trivial, and, even today, modelers have to face several challenges for employing it to support the design and operation of green buildings. For instance, it is common knowledge that the impact of design decisions is greatest in earlier design stages, but detailed BPS software is rarely used to support early decisions for optimal green buildings [4, 5].

The purpose of this chapter is to provide an overview of a few modeling and simulation challenges related to the design and operation of green buildings. In order to make easier the reading, the next section presents the main features characterizing a green building that shows intriguing modeling and simulation challenges. Next, a framework for presenting typical mistakes and uncertainty that can affect a building model development is proposed together in a discussion where all the challenges hereby mentioned are contextualized. Finally, each mentioned challenge is specifically addressed in the last sections.

The Green Building Challenge

Green buildings are a promising solution to minimizing the environmental impact of the building sector and are emerging through different sustainable and quantifiable design concepts [6] such as net zero-energy buildings, nearly zero-energy buildings, zero-emission buildings, zero-carbon buildings, carbon-neutral buildings, etc. The majority of these concepts explicitly aims at a substantial reduction of the energy required by a building during its operation and to cover it thanks to a local transformation of renewable energy sources into usable energy (electricity or thermal energy). In addition, a few later definitions expand to the energy embodied in or the emissions caused by the construction materials used to realize the building, and, in some attempts, also they aspire to consider the end of life of the building [7].

The aim of this chapter is not to describe or deal with any of these individual and specific design concepts rather hereby refer to generally *green buildings* and focus on their operational behavior in terms of energy demand and comfort performance.

Features of Green Buildings

Even if all the main sustainable building concepts and definitions share a few similar aspects, the design of a green building presents an inherited challenge represented by the shortage of established design strategies to systematically achieve this goal, and many of the BPS tools today available on the market have limited applicability for such advanced building concepts. A possible manner to describe the challenge of developing the model of a green building is to refer to the typical strategies adopted to achieve this target. In this regard, it is common to refer to passive and active systems [8]. *Passive systems* are materials and technological components that are typically integrated into the building fabric and have the capacity to modulate, store, absorb, and release air, vapor, water, thermal energy, or daylighting without any, or very limited, use of external energy, thus diminishing the energy needed for an active control of the building. *Active systems* are, in contrast, systems made of technological components, such as boilers, heat pumps, air handling units, fans, circulation pumps, lamps, etc., connected by pipes, channels, and wires, which are controlled and operate to provide space heating and cooling, humidification and dehumidification, ventilation, domestic hot water (DHW) production, and artificial lighting.

While in the past decades passive and active strategies were somehow considered as antagonistic design options, current international trends in green building design are increasingly relying on their synergic integration as enabling technologies for achieving high-performance buildings [8]. This approach was first formalized in the so-called Trias Energetica that is a design strategy consisting originally of three progressive steps [9]: (1) energy sufficiency, (2) energy change from fossil fuels to sustainable energy sources, and (3) energy-efficient use of fossil fuels, meaning that the demand for energy has to be first reduced through energy-saving measures for all the given energy services provided by a building; next, renewable energy sources (RES) have to be exploited to meet the building's energy demand; and, finally, if still active systems are required to meet essential requirements, fossil energy has to be used as efficiently and cleanly as possible. This synergic integration of passive and active systems has boosted the popularity of *hybrid systems*, which combine active and passive strategies and combined thermal and electric systems. This section deals primarily with the challenges in modeling passive systems and some building-integrated hybrid systems.

Passive systems, generally, do not use auxiliary energy in the harvesting and usage of solar heat, fresh air, daylight, etc. They rather rely on spontaneous modes of heat and mass transfer and daylighting to supply and distribute heat, air, and light in the built environment, such as the redistribution of absorbed direct solar gains, night ventilative cooling, or daylighting penetration. Design strategies typically adopted in green buildings are [10]: high airtightness of the facility, highly insulated building envelopes, advanced windows and solar control systems, energy storage, building-integrated solar thermal collectors and photovoltaic panels.

A high level of airtightness is useful to limit heat and mass exchange by natural convection due to involuntary infiltration to and from the outdoor environment through the building envelope. This enables the adoption of a demand-controlled mechanical ventilation strategy that offers a high indoor air quality by controlling the air-change rate and avoids wasting energy need for space heating and cooling due to unwanted draughts. This aspect does not apply only to the building envelope because airtightness depends also on the quality of the installation of the pipes and electric conduits that pass through the building envelope.

Very low U-values of the building envelope's components reduce heat exchange by transmission to and from the outdoor environment. However, the appropriate performance of each type of component has to be identified on the basis of the specificities of the local climate. For example, in summer-dominated climates, a *not-too-low* U-value for the external floor is appropriate for use in the adjacent ground or basement as a heat sink [11–16] and, hence, significantly reduces the energy need for space cooling. But care is to be put to assess the inner surface temperature for avoiding condensation issues in winter.

Windows, and more generally (semi)transparent (Glazing systems are characterized by a visible transmittance that is lower than the unit. Therefore, they are not perfectly transparent.) facade components, provide a visual connection between the indoor and outdoor environments and admit daylighting into the built environment but have a direct and significant impact on the comfort and energy performance of a building. Therefore, advanced and interactive windows and facades are typically used in green buildings. As summarized by Selkowitz et al. [17], they aim, at the same time, at (i) controlling winter heat losses for reducing the energy need for space heating, low-temperature radiation draught, cold surface convention flow, and superficial condensation and mold growth; (ii) controlling summer solar gain for reducing the energy need for space cooling, direct radiation gain in occupied zones, and indoor summer overheating; and (iii) controlling daylighting to reduce glare from high luminance sky, reflected daylight and direct sunshine, and veiling reflections in computer screens. Furthermore, double facades may (iv) integrate options that enable advanced natural or mechanical ventilation modes and (v) increase acoustic comfort with respect to open windows in case of outdoor noise. In addition, skylights may be employed (vi) for enhancing daylighting in deep buildings, and electro-chromic and thermochromic coatings are today-available technologies for the modulation of the light transmission. Regarding the solar control systems, (vii) motorized shading can be integrated both internally and externally a window and can be automatically and/or remotely controlled. Moreover, newer technologies are appearing on the market, such as (viii) (semi)transparent photovoltaic panels that simultaneously produce electricity and have direct and indirect impacts on cooling loads, as well as electricity consumption for lighting [10].

Thermal energy storage is a strategy that is increasingly adopted in the green building design. It can be used to smoothen the temperature fluctuations of the inner surfaces or to shave energy peaks required by active systems for space heating and cooling. Thermal energy storage can be integrated into the building fabric or added to the building. Building-integrated thermal energy is stored using (i) sensible energy storage materials that are commonly referred to as thermal mass; (ii) latent energy storage materials that are referred to as phase changing materials (PCM); (iii) thermochemical energy storage materials that are materials that can store energy as a product of a chemical reaction and, later, can pour (almost) the same amount of energy into the environment when the reverse reaction takes place [18]; (iv) thermo-active building systems (TABS) [19]; and (v) dynamic insulating walls. (vi) Additional thermal mass can be provided by coupling a building with the ground or water tanks.

Some type of solar thermal collectors and photovoltaic panels (PV) can be integrated into the building fabric serving as roof shingles or exterior cladding while producing hot water and electricity, respectively. Furthermore, a hybrid technology is also today available on the market for green buildings. Building-integrated solar and photovoltaic panels (commonly indicated with BIPV/T) consist of a PV coupled with an active heat recovery through a closed loop (e.g., water pipes as in solar collector absorber plates) or an open loop (e.g., flowing air in a cavity behind the PV panels), which is integrated into the building envelope. These new components produce at the same time electricity and useful heat [8].

Mistakes and Inaccuracies in Building Modeling and Simulation

Modeling of a building and simulation of its performance are quite complex matters especially if the purpose is to obtain plausible results. To this aim, good knowledge of building physics and skills in statistics and computer science are necessary [20]. A building model delivers plausible results when it represents a given behavior of the actual building in an accurate manner. However, the physical fidelity of a building model is often spoiled by mistakes and inaccuracies due to the modeler itself or other sources that can arise in any of the phases of the modeling and simulation process: from conceptual modeling of a physical system, through mathematical modeling of the conceptual model, discretization and algorithm selection for the mathematical model, computer programming of the discrete model, and numerical solution of the computer program model, to the representation of the numerical solution [21].

Judkoff et al. [22] propose seven possible sources of mistakes and/or inaccuracies that can affect the creation and development of a building energy model (BEM):

- Differences between the actual thermal and physical properties of materials constituting a building and those input filled in by the modeler, typically default or handbook values
- Differences between the actual heat transfer mechanisms operative in individual components and their algorithmic representation used in BPS
- Differences between the actual heat transfer mechanisms describing interactions between components and their exemplification in BPS
- Differences between the actual effect of occupant behavior and the simplifications assumed by the modeler
- Differences between the actual weather surrounding the building and the statistical weather input used with BPS
- Modeler's errors in deriving the building's input files
- Program errors in implementing correctly the intended algorithms in BPS

This classification may result very useful for a modeler because it can be used to double-check the quality of the modeling task like a checklist.

More generally, it is also possible to classify the deviations of the simulation outcome from the true value into three types: *epistemic uncertainties*, *aleatory uncertainties*, and *errors*.

Epistemic uncertainty is a potential inaccuracy in any phases of the modeling and simulation process that is due to lack of knowledge or incomplete information about a given physical system or environment [21]. Therefore, further information is beneficial to reduce this uncertainty that, at least in theory, can be nullified. According to Oberkampf et al. [21], sources of epistemic uncertainty are *vagueness*, *non-specificity*, or *dissonance*. Vagueness is primarily related to communication by language and refers to information that is unclear, indistinct, or imprecisely defined. Non-specificity indicates a condition when a variety of alternatives are all possible in a given situation and the true alternative is not specified. Dissonance denotes a situation where specifications are partially or totally conflicting. However, the quantification of epistemic uncertainty is difficult because it is complex to compare the outcomes due to the data already included into a model with what might be discovered with an additional investigation [23]. For example, Schlosser and Paredis [24] recurred to the principles of utility theory, information economics, and to the probability bounds analysis to establish to what level supplementary information had to be acquired for each uncertain quantity of an engineering decision problem to improve the overall quality of the design decision. In scientific literature, epistemic uncertainty is also referred as cognitive uncertainty, reducible uncertainty, and subjective uncertainty.

Aleatory uncertainty is used to indicate the innate variation of a given physical system or environment and does not depend on lack of knowledge. Thus, the acquisition of more information is not helpful to reduce this type of uncertainty [23]. It has the peculiarity to be random and, if sufficient information is available, is generally quantifiable by a probability or frequency distributions [21]. Therefore, for its specific nature, aleatory uncertainty is also named in the scientific literature as irreducible uncertainty, inherent uncertainty, stochastic uncertainty, and (even) variability. Typical sources of aleatory uncertainty in modeling and simulation are occupant behavior and the weather conditions under which to simulate a building.

Errors are a recognizable inaccuracy that can occur in any phase of the modeling and simulation process and is not due to lack of knowledge or incomplete information [21]. This recognizable inaccuracy can be either *acknowledged* or *unacknowledged* by the modeler. Acknowledged errors are assumptions, approximations, or simplifications introduced by the modeler who has typically some ideas about their magnitude or impact of the simulation outcomes. On the contrary, unacknowledged errors are typically blunders or mistakes that have not been recognized by a specific modeler, but are in general recognizable [21].

Unfortunately, uncertainties and/or errors affect all phases of BPS, from the development of the individual algorithms, through the implementation of them in a software package, to the use of the resulting program by the user [25]. One of the most important challenges in modeling and simulation is to nullify errors, to reduce as much as possible epistemic uncertainties, and to quantify the propagation of aleatory uncertainties to the simulation outcomes through probability and statistics (“Challenge No. 3: Quality Assurance”). A few researchers in BPS have already addressed the issue of uncertainty in building performance simulations [25–28].

Modeling and Simulation Challenges

As sustainability has become a standard practice in the building industry, greater levels of energy and resource efficiency have been required to buildings [29]. Higher energy standards and efficiency requirements impose greater complexity on the building design process. Consequently, the design process of new and retrofit buildings has become increasingly complex and necessitates advanced digital planning, that is, BPS [30]. Several approaches have been proposed to represent a typical modeling and simulation process also outside the domain of BPS. Built upon the schemes proposed by Schlesinger [31] and Oberkampf et al. [21], Fig. 1 proposes a diagram that identifies the major phases and activities of a BPS process. It is a conceptual representation that might not apply to all the BPS tools but aims at representing the flux of information and data between the different phases of building modeling and simulation.

Since the mid-1970s, BPS has become an integral part of the building design process to improve traditional manual methods of studying and optimizing the building's energy performance [32]. BPS is a large and diversified family of computer-based tools [33] that supports designers and consultants throughout the entire building's design process, from the schematic to the detailed design phases. Nevertheless, not all tools can be used in all the design phases or are suitable for supporting

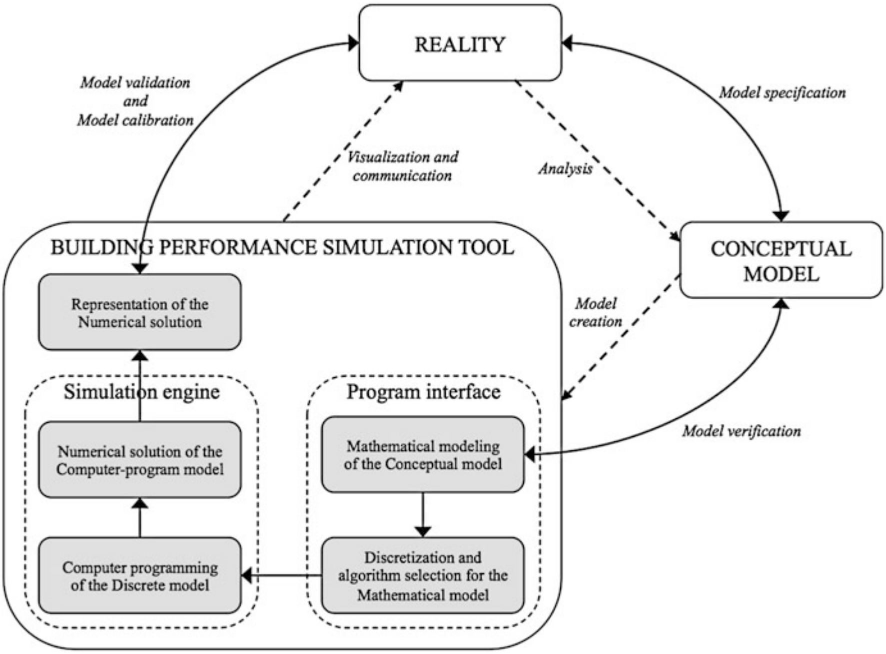

Fig. 1 Diagram identifying the main phases and activities of the BPS process (Developed from Refs. [21, 31])

all types of analysis. Therefore, the first challenge a modeler has is to select the tool that better suits his/her needs ("Challenge No. 10: Selection of a Suitable BPS Tool"). However, though it may appear the first action of the modeling and simulation process, the selection of an appropriate BPS tool requires the modeler to have a broad and deep knowledge of the BPS tools' capabilities and of the fundamental physical phenomena ("Challenge No. 1: Conceptual Modeling of the Building") that he/she wants to model, which are of paramount importance to build a reliable model ("Challenge No. 2: Construction and Development of a Building Model"). To this purpose, the physical fidelity of a numerical model needs to be checked through a rigorous quality assurance procedure ("Challenge No. 3: Quality Assurance") that will reduce and provide an estimation of the impact of uncertainty due to the lack of information (epistemic uncertainties) on the simulation outcomes. However, it would be also appropriate to estimate the sensitivity of the model against those sources of uncertainty that cannot be predicted and are inherent into the behavior of a building (aleatory uncertainty) such as how to represent weather variation and future climate conditions that affect the energy behavior of a building ("Challenge No. 4: Modeling Weather and Climate Scenarios") and how to model occupant behavior in a BPS ("Challenge No. 5: Modeling Occupant Behavior"). Furthermore, since the design and operation of a green building may require a quite vast variety of strategies, in some complex cases, no BPS tool can provide a full coverage of the models and approached that better fit in a design concept. In those cases, the capability of individual BPS packages can be expanded through software coupling ("Challenge No. 6: Expanding BPS Tools' Capabilities Through Software Coupling"). Furthermore, BPS can be used as an engine that boosts advanced analysis techniques that substantially expand the capability of designers using automatized workflow. This is the case, for example, of BPS-based optimization where large and complex design problems can be investigated by smartly selecting a limited number of building variants to be simulated ("Challenge No. 7: Applying BPS-Based Optimization in Design Practice"). Moreover, integrating a BPS into a building information modeling (BIM) platform can substantially constitute a step toward an actual multidisciplinary analytical procedure where only one building model is used by several and different simulation engines that will assess different performances of the same building model ("Challenge No. 8: Expanding BPS Potential Through Building Information Modeling"). Another challenge related to the modeling and simulation of buildings, which will be addressed in this chapter, is the capability of tools to post-process simulation outcomes and be effective in the communication with the different stakeholders involved in the design and operation of a building ("Challenge No. 9: Visualization and Communication Skills of BPS Tools").

In the more recent years, further developments aimed at integrating BPS tools into building energy management systems (BEMS) and enabled BPS to be exploited also during the post-construction and post-occupancy phases [3]. Therefore, this large family of versatile and flexible tools started to be adopted to improve building's energy efficiency through adjustments to energy system operations and fine-tuning of a building retrofit [10, 34].

Challenge No. 1: Conceptual Modeling of the Building

Referring to Fig. 1, a BPS process starts with the creation of a *conceptual model* of the building that the modeler wants to analyze. This phase requires the specification of all the physical attributes of the building and its systems and of the environment surrounding it. Thus, the geometrical dimensions of the facility and its components, the physical properties of materials and installations, the strategies intended to be used, and the tentative outcomes of the simulation have to be determined. Although all these aspects are not deterministic in the reality, the large majority of BPS tools are modeled using only one single value. More complex analysis, such as uncertainty analysis, enables some of them to be treated as nondeterministic input. In this phase, no major differences exist between an existing building and a proposed design concept. Moreover, even if no mathematical model of the building is required, all fundamental assumptions regarding possible design alternatives and the physical phenomena to account into the analysis have to be made, and the level of detail of the simulation has to be chosen. In a nutshell, during the conceptual modeling, all the conceptual issues have to be addressed together with all possible factors meaningful for the analysis, and all useful scenarios have to be identified.

After that the building's and the surrounding environment's specifications have been carefully identified, options for the various levels of input variables should be itemized. Therefore, for an existing building, the modeler shall be capable to derive the building input data from the field, possibly without mistakes, as mentioned earlier.

The assumptions made in this phase will influence the creation of the mathematical/digital model; thus if a change will be required later in the process, then either the modeler shall return to the conceptual modeling and check the appropriateness of the model with respect to the change or a new mathematical/digital model has to be built. For example, if the purpose of a simulation is to estimate the energy performance of a building, the modeler may decide for a coarse thermal zoning of the building to speed up the simulation time. But, if later he/she decides to analyze the thermal evolution of the indoor environment, then the previously developed energy model of the building may result unreliable, and he/she needs to develop another model with a much fine thermal zoning and longer computational times.

Challenge No. 2: Construction and Development of a Building Model

Neophytes to BPS often believe that creating a model means to draw the geometry of a building in a geometric modeling environment (GME) and fill a few data in a graphical user interface (GUI). Essentially, these are only some aspects of building modeling and simulation. The real goal of every GUI and GME, which are often provided together with simulation engines and incorporated in BPS (Fig. 1), is to generate the *mathematical model* of a building, which will be later discretized in space and time and, then, solved numerically by the simulation engine. In other words, the main purpose of using GUI and GME is to provide a detailed, precise, and solid analytical statement of the simulation problem. Since the majority of the physical phenomena described in BPS are represented with partial differential equations (PDE), the formulation of the statement of the simulation problem means to specify all boundary conditions, initial conditions, and possibly auxiliary conditions for the PDE of the physical phenomena considered into the analysis. The considered physical phenomena must be modeled as accurately as necessary; however, "while an acceptable level of precision is desired, too much complexity can limit the model usefulness in analysis and design" [10].

Focusing for simplicity on the calculation of the energy fluxes in a building, the mathematical modeling requires to specify all boundary conditions (e.g., weather conditions, contact condition between the building and the ground, etc.), initial conditions (e.g., the initialization temperature of the model), and system parameters (e.g., set-point temperatures, period for the update of the sun path, etc.) together with the geometry of the building. Energy fluxes that are relevant in the assessment of a building's thermal behavior are [35]:

- Heat conduction through exterior walls, roofs, ceilings, floors, (vertical and horizontal) interior partitions, doors, windows, and skylights
- Long-wave radiant heat exchanges among the zone interior surfaces
- Solar radiation reflected and absorbed by and transferred through windows and skylights
- Latent or sensible heat generated in the built environment by occupants, vegetation, lights, appliances, and, in special cases, water pools (swimming pools) and frozen surfaces (ice rinks)
- Heat transfer through ventilation and infiltration of outdoor air
- Other miscellaneous heat gains

Next, appropriate algorithms have to be chosen among those implemented in a given BPS tool, and, if required, the model has to be verified against recommended quality criteria to guaranty consistent, convergent, and stable results. For instance, transient heat conduction through a conducting medium is governed by the Fourier equation that is a parabolic, diffusion-type partial differential equation, which can be numerically computed using:

- The finite difference method
- The finite volume method
- The finite element method
- The transform methods, including the transfer function method and the time-series methods

In special cases, some of the abovementioned methods might not be appropriate. For instance, the transfer function method proved to be not reliable to analyze massive buildings, i.e., building with an intensive use of sensible energy storage materials [36].

Similarly, it happens for solving the long-wave radiant heat exchanges among the zone interior surfaces. Several methods are available, and, among all, it is worthy to mention:

- The star-network method by Seem [37] that is implemented in TRNSYS
- The ScriptF method by Hottel and Sarofim [38] that is implemented in EnergyPlus [39]
- The absorption factors by Gebhart [40] that are available in TRNSYS from version 17

The selection of the method and the modeling details depend on a few features that the modeler should have identified during the conceptual design phase, for example, the presence of a floor heating systems, a cooling beam, or a large unshaded windows or skylight. Another critical aspect strictly related to the solution of the long-wave radiant heat exchanges is the method used for estimating view factors. Several methods are available such as [41]:

- The double area summation
- The Nusselt sphere technique
- The crossed-string method
- The Monte Carlo ray tracing that is implemented in ESP-r [42]
- The contour integration
- The hemi-cube method

Special problems may require the selection of a specific solving approach that is implemented in given BPS tools, and this should guide the selection of the appropriate BPS. Similar examples can be presented with the other energy fluxes mentioned above. For a detailed discussion, it is suggested referring to dedicated references like [3, 8, 41, 43, 44].

In general, when modeling advanced technologies exploited in a green building design, the modeler has to keep in mind at least a few important *approximations* that are commonly introduced in mathematical and physical models to facilitate the computation of a building's thermal behavior:

1. *One-dimensional heat conduction*. Most of the BPS tools can solve transient heat conduction problems in the building envelope, but, they generally assume one-dimensional heat conduction. Deviations from this assumption are in some tools modeled using dedicated options to specify the magnitude of thermal bridges. Thermal bridges, both due to geometric discontinuity and material heterogeneity, have to be accounted for calculating the effective thermal resistance of building envelope components.
2. *Linearization of heat transfer phenomena*. Convection and radiation are intrinsically nonlinear heat transfer phenomena. However, when applied to buildings, it is common to linearize them using either one global heat transfer coefficient for both phenomena or two heat transfer coefficients for the convective and the

radiative shares separately. The main advantage is that the energy balance equations written for the indoor air volumes of building's thermal zones can be represented by a linear thermal network and solved by direct methods for linear systems. In general, the error in the calculation of the convective exchange between room surfaces and indoor air is larger than the error for long-wave radiant heat exchanges between room internal surfaces [8].

3. *Spatial and temporal discretization*. Heat transfer phenomena are governed by a few partial differential equations that are typically solved using numerical methods like finite difference, finite volume, and finite element methods. In such cases, all conductive building envelope components need to be discretized into a number of control volumes. This process is called spatial discretization. Furthermore, due to the dependency of the heat transfer phenomena on time, the time domain needs to be discretized in a number of appropriate time steps for the update of the energy calculations. This is called time discretization. Transform methods only require time discretization.
4. *Appropriate model resolution*. Model resolution is a term used to refer to the degree of detail of a building model. Since available information is different in the different life-cycle phases of a building, the model resolution required during the energy and thermal analysis of a building needs to be tailored on the specificities of the given design or analysis stage. For early design stage, when, for example, the building geometry is not decided yet, a steady-state or an approximate transient model is often adequate to support preliminary decision-making. However, an increasing level of the detail is required as the building design gets more refined. For example, starting from the preliminary design, it will be important to account for all objectives of the building thermal design and all the specifications of the systems that provide heating, ventilation, and air-conditioning (HVAC) and deploy renewable energy sources.

In conclusion, the knowledge of the principles, assumptions, and approximations underneath the calculation of a BPS tool coupled with the knowledge of the capabilities of BPS tools are important aspects for properly modeling and simulating the most critical features that characterize green buildings that were mentioned above in section "Features of Green Buildings."

Challenge No. 3: Quality Assurance

Since every model is a simplified representation of a real-world problem, it is necessary to be confident that a building model provides an accurate representation of how the building and its systems would behave in reality. Quality assurance is a process that aims to develop confidence in the predictions of a simulation tool [3]. This is of fundamental importance because designers base design decisions on the results of simulations. The main strategies used to enhance the quality of a BPS are undertaking rigorous *verification* of the BPS tools and comprehensive *validation* and *calibration* of a building model.

Verification "is the process of determining that a model implementation accurately represents the developer's conceptual description of the model and the solution to the model" [45]. Therefore, verification aims at determining whether a conceptual simulation model has been correctly translated into a computer program. Thus, its purpose is basically oriented to assess the mathematical accuracy of the numerical solutions.

Validation is "the process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model" [45]. Its purpose is hence to assess the *physical fidelity* of a model for a specific predictive application [23]. Operationally, this procedure uses statistical metrics to evaluate the deviation in the prediction of a model built on a data sample commonly called *training set*, with respect to the actual data of the sample used to carry out validation that is commonly called *test set*. If a training set and a test set belong to the same population of data, this assessment process is called *internal validation*, while, if they belong to different populations of data, it is called *external validation*. *Internal validation* results in an evaluation of the reproducibility of a model on a different data set belonging to the same population of data, whereas e*xternal validation* evaluates the generalizability, or transportability, of a model to a related, but different, population from that used for developing the model itself. In the specific case of BPS, the model is not built on data collected from the field using, for example, regression techniques, but is a mathematical system of partial differential equations that represents physical phenomena and is solved by approximation using adequate numerical methods. In order to assess the accuracy of a model in representing the behavior of an actual building, *aleatory uncertainties* have to be minimized, and, hence, a building model should be simulated using the most accurate boundary conditions, for example, weather conditions and occupancy profiles that represent, as much as possible, the real conditions to which the actual building is exposed. Therefore, only external validation can be employed to evaluate the quality of a BPS model.

Calibration "is the process of improving the agreement of a code calculation or set of code calculations with respect to a chosen set of benchmarks through the adjustment of parameters implemented in the code" [23]. Its purpose is hence to help the modeler to choose those values of the design variables that improve the agreement of a simulation model with a defined set of physical benchmarks, increasing the *credibility* of the model. Operationally, this process starts with choosing a physical benchmark (e.g., the delivered energy of a whole building model, the indoor air temperature in a given room, etc.) with respect to which calibrating the building model. At the same time, the *epistemic uncertainty* of a set of design variables has to be quantified, and an acceptable interval has to be set for every design variable according to which carry out the calibration. Several versions of the model are then generated (manually or automatically), setting different values for each design variable, which are hence compatible with the already identified epistemic uncertainties. Finally, all models are simulated, and the individual simulation outcomes are collected and compared with the measured values for the same benchmark. The agreement between simulation outcomes and measurements is assessed via statistical metrics. ASHRAE Guideline 14 [46] suggests the use of the *mean bias error*, *MBE*, and the *coefficient of variation of the root mean square error*, $C_V(RMSE)$. *MBE* is a nondimensional measure of the overall bias error between the measurements and the simulation outcomes in a known time resolution, and it is usually expressed as a percentage:

$$MBE = \frac{\sum_{i=1}^{N_p} (m_i - s_i)}{\sum_{i=1}^{N_p} (m_i)} \quad [\%] \tag{1}$$

where m_i ($i = 1, 2, \ldots, N_p$) are the measured data, s_i ($i = 1, 2, \ldots, N_p$) are the simulated data at the time interval i, and N_p is the entire number of data values. Positive values indicate that the regression underpredicts experimental values; on the contrary, negative values indicate that the model predicts values for the benchmark, which are higher than the actual ones. Next, $C_V(RMSE)$ indicates the overall uncertainty in a model. The lower $C_V(RMSE)$ is, the smaller the residuals between the measurements and the simulation outcome are. This is defined as:

$$C_V(RMSE) = \frac{1}{\overline{\overline{m}}} \sqrt{\frac{\sum_{i=1}^{N_p} (m_i - s_i)^2}{N_p}} \quad [\%] \tag{2}$$

where, besides the quantities already introduced in Eq. 1, $\overline{m}$ is the average of measured data values.

ASHRAE Guideline 14 [46] also provides useful criteria that can be used to declare a model calibrated (Table 1).

As argued by Hensen and Radošević [47], "the main ingredients of a professional and efficient quality assurance are domain knowledge and simulation skills of the user in combination with verified and validated building performance simulation software." Therefore, the user should be aware of the uncertainty associated with their modeling and design. To this aim, it would be a good practice to take into account uncertainty of input variables in order to estimate their propagation to the simulation outcomes and to assess how it causes variations in the simulation outcome [27], for example, through a global sensitivity analysis.

Challenge No. 4: Modeling of the Weather and Climate Scenarios

About 40 years ago, the National Climatic Data Center [48] created one of the first weather data sets, named test reference year (TRY). The purpose of this work was to provide weather input data for BPS. The TRY file contains data for hourly dry-bulb temperature, wet-bulb temperature, dew point, wind direction and speed, barometric pressure, relative humidity, cloud cover, and cloud type, but no measured or calculated solar data [49]. Since then, several organizations participated in creating worldwide weather data sets such as Weather Year for Energy Calculations (WYEC), Typical Meteorological Year (TMY), Canadian Weather for Energy

Table 1 Acceptable calibration tolerances according to ASHRAE Guideline 14

Calibration type	Acceptable value of *MBE*[a]	Acceptable value of $C_V(RMSE)$[a]
Monthly	±5%	15%
Hourly	±10%	30%

[a]Lower values indicate better calibration

Table 2 Different institutions or countries created weather files on the basis of different periods of observed data. Selected example weather data sources on EnergyPlus weather database

Source	Region	Number of files	Period of observation
Canadian Weather for Energy Calculations (CWEC)	Canada and others	80	1953–1995
Chinese Typical Year Weather (CTYW)	China	57	1982–1997
Climatic data collection "Gianni De Giorgio" (IGDG)	Italy	66	1951–1970
International Weather for Energy Calculations (IWEC)	Locations outside the USA and Canada	227	1982–1999
Australia Representative Meteorological Years (RMY)	Australia	69	1967–2007
Spanish Weather for Energy Calculations (SWEC)	Spain	52	1961–1990
Typical Meteorological Year 3 (TMY3)	USA and others	1020	1991–2005

Calculations (CWEC), and California Climate Zones (CTZ) [50]. One of the most popular weather file formats is the EnergyPlus weather format indicated by the extension .epw. Weather data for more than 2100 locations are available on the EnergyPlus weather online database. These weather data are derived from 20 sources, and selected example sources are listed in Table 2. The full list can be found at EnergyPlus weather webpage [51]. As mentioned before, these files are based on historical data.

As Table 2 shows, different institutions or countries created weather files on the basis of different periods of observed data. These attempts provided building simulation users a single year typical weather data that represents weather conditions at a location, but studies have shown that a single year of weather data cannot be a proper representation of the range of climate conditions [49], and the difference in the time period of observed data can influence the results of building performance simulation [52]. This can be due to the impact of climate change in last decades or the recent growth of a city and consequently increase in urban heat island effect that has not been captured into these files. These are some of drawbacks of using typical weather years based on historical data. Some cases, for example, Canadian Weather for Energy Calculations (CWEC) and California Climate Zones, tackled these issues by providing updated new weather data set, which are derived from 30 years of gathered data ending in 2014. Furthermore, the typical weather year files are based on identifying average weather period over the basis years which are not able to take into account extreme weather conditions such as the summer of 2003 that was extremely hot at least in Europe [53]. With this challenge, there is a risk that buildings that are designed and optimized using single typical year of weather data do not provide the expected performance after construction. Crawley and Lawrie [49] propose to use more than one weather file in building simulation. They suggest using three weather files, one typical meteorological year (TMY) and two extreme meteorological years (XMY), to induce a range of building performance.

Another important challenge that has been given much attention lately is the climate change phenomenon and its impact on the future building performance [54]. de Wilde and Coley [55] give an overview on the relationship between climate change and buildings. Future weather files are required to evaluate the impact of climate change on buildings using BPS. There are several methods available today on creating future weather files ready for use in building performance simulation programs [56]. A brief look into these methods and the background of climate projections follows.

The Intergovernmental Panel on Climate Change (IPCC) created a number of possible scenarios of future anthropogenic greenhouse gas emissions assuming certain socioeconomic story lines as a basis for projecting future changes in climate. These emission scenarios are the input data that provide initial conditions for the so-called general circulation models (GCMs) that are numerical models of global climate system. These models are able to simulate climate in defined future conditions and create future climate projections. A GCM output represents averages over a region or globe and is expressed with a spatial resolution above 100 Km^2 and a monthly temporal resolution. This resolution of data is not suitable to use for certain research fields, such as building performance simulation, which require local weather data with daily, hourly, or even minute resolution. In order to provide weather data in a format readable by building performance simulation programs (e.g., in ".epw" format), the outputs of GCMs should undergo both spatially and temporally downscaling. In this regard, there are three possible options. The first option is to use regional climate models (RCMs). RCMs are similar to GCMs in principle but with high resolution. RCMs take the GCM outputs as boundary conditions and integrate more complex topography with physical processes in order to generate climate information at much finer resolution down to 2.5 km^2. This method has many advantages, but it needs high amounts of computational power and large storage for the created data. The process involves high level of expertise to implement and interpret results.

The second option was introduced by Belcher et al. [57] and is called "morphing." It is a downscaling method that applies three transformation algorithms (*shift*, *stretch*, and *combination of shift and stretch*) to derive hourly typical weather data of a location from the monthly climate change prediction values of a GCM. Depending on the parameter to be changed, one of the three algorithms is applied. For example, Pagliano et al. [58] in their study used morphing method to assess the performance of a deep energy retrofit of a child care center for current and future weather scenarios. The simplicity and flexibility of this method are few of its key advantages, but it has been also widely criticized [59]. There are also two available software tools, CCWorldWeatherGen and WeatherShift™ [60, 61], which are developed based on the morphing method. These tools generate future weather files ready to use in building performance simulation. Moazami et al. [62] had a critical look and compared the output of the tools to identify possible consequences when applied into BPS.

The third option consists in using a weather generator that uses computer algorithms to statistically derive synthetic weather time series for a location. These weather time series are comparable in characteristics to historical observed data from that location. A stochastic weather model is then developed based on the observed data. This model is used to downscale stochastically the monthly values of climate projections derived from GCM into hourly resolution. Considering the limitations in the length of historical weather records in many locations, interest in producing synthetic weather data by weather generators has grown recently [63]. A summary of the possible options described above is shown in a flowchart in Fig. 2.

The key assumption of the two last options is that the future climate characteristics are similar to the historical data, but this is going to be very unlikely. Nik [64] discusses this issue and proposes that, due to the significant uncertainties in climate

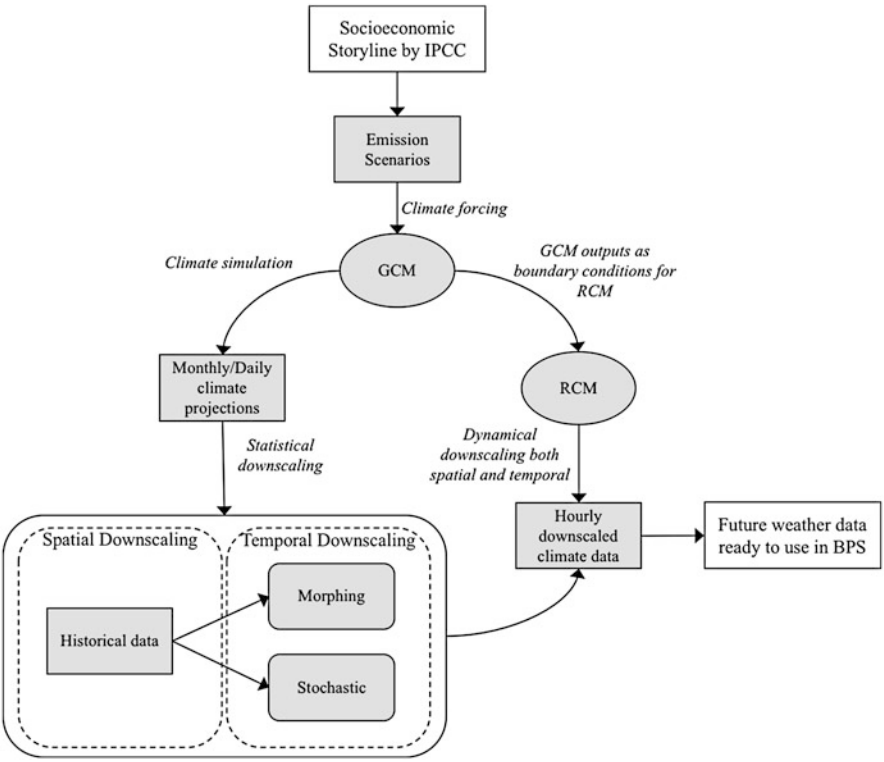

Fig. 2 Flowchart of different stages for preparing a typical future weather data file to use in BPS

modeling, several climate scenarios should be considered in impact assessment. He recommends using a method based on synthesizing three sets of weather data out of one or more regional climate models.

All the abovementioned challenges make weather inputs one of the main sources of uncertainties in building performance simulation [27]. It also highlights the need for more accurate weather data and new methodologies for guiding the impact assessment of climate change.

Challenge No. 5: Modeling of the Occupant Behavior

Modeling occupant behavior in a building is another major source of aleatory uncertainty in BPS. However, an international survey on occupant modeling approaches used in BPS has found that practitioners have not kept pace with latest research developments in building occupant behavior modeling and their attitude regarding occupant behavior modeling is not well understood [65].

Often the impact of this uncertainty is estimated through the measurement or calculation of building energy use. For example, the International Energy Agency (IEA), Energy in the Buildings and Communities Program (EBC), and Annex 53 entitled *Total Energy Use in Buildings* recognize occupants' behavior as one of the six factors directly influencing buildings' energy use. Several studies estimate that occupants' control actions and occupancy patterns explain variations in the energy use of identically built homes by a factor of two or higher [103, 105, 106, 107]. Furthermore, O'Brien [66] demonstrates that, without the adoption of accurate occupant models, BPS can drive toward poor building design choices. Indeed, Clevenger and Haymaker [67] found that the predicted energy use in an elementary school can increase more than 150% using from lowest to highest occupant behavior-related input values in BPS.

Here, sources of uncertainty are the methods used to model both the presence of occupants in a building – and their movement between rooms – and the actions that they execute to adjust the indoor environment conditions.

Yan et al. [68] provides a comprehensive overview of the state of the art on occupant behavior modeling for BPS, pointing out challenges and future needs. They also described the whole process of occupant behavior modeling and simulation recurring to four-step iterative steps:

1. Occupant monitoring and data collection
2. Model development
3. Model evaluation
4. Model implementation into BPS tools

The following are some of the challenges identified for the aforementioned four steps:

- Data availability and quality issues regarding data on occupants' presence and control actions

- Derivation of occupants' action models
- Generation of realistic action patterns and of reliable predictive performance
- Models' applicability
- Implementation of a sound model evaluation
- Integration of occupants' presence and action models in the disparate BPS tools

To tackle most of the challenges related to occupant behavior modeling, the IEA EBC Annex 66 "Definition and simulation of occupant behavior in buildings" was approved in 2013. The purposes of this project were to (i) set up a standard occupant behavior definition platform, (ii) establish a quantitative simulation methodology to model occupant behavior in buildings, and (iii) understand the influence of occupant behavior on building energy use and the indoor environment. This Annex, which is nowadays close to the end, has addressed many of the aforementioned challenges and has provided a comprehensive support to modelers by organizing many of the discussions in a book entitled *Exploring Occupant Behavior in Buildings* [69]. Furthermore, it has established an international large-scale occupant behavior survey and has collected case studies on the applications of occupant behavior simulation in the industry.

Challenge No. 6: Expanding BPS Tools' Capabilities Through Software Coupling

Designing green buildings is not intuitive [13, 33, 70, 71], and interactions among various parameters of these buildings are best studied using simulation tools [72]. Green buildings' HVAC systems typically combine multiple systems (e.g., equipment, passive or active heat recovery and storage systems, as well as renewable energy technologies) that are more than often one-of-a-kind and innovative solutions. Such innovative technologies and technology mix are not necessarily implemented in commercial building design tools [73]. New requirements that were not yet recognized when the development of current BPS programs began include "model-based design of integrated building systems by design firms and of products by equipment and controls providers to optimize energy efficiency and peak load, and to reduce time-to-market for components, systems and advanced control systems" (Wetter et al. 2013).

Detailed simulation software (e.g., EnergyPlus and TRNSYS) are well suited for simulating integrated energy building models even though, sometimes, they cannot support the full model implementation and some assumptions are required. Coupling HVAC and the RES systems with the building model is ideal but often difficult because some models are not available or the coupling is not easy to achieve, especially for controls. In this case, another procedure can be followed that consists of integrating HVAC systems into the building model without the production unit (assuming the availability of the resource) and using the energy need of the building as the input of the HVAC systems. Then, the production unit can be simulated separately (e.g., solar photovoltaic panels, heat pump with ground coupling, solar thermal, etc.) to obtain the resource availability and the energy demand and production can be compared to further optimize the coupling. This is of course an incomplete procedure, but it allows sizing the production unit and estimating how far the building is from reaching the energy goal. Dynamic tools such as TRNSYS and EnergyPlus might be able to capture the salient physical interactions between energy supply systems and the built environment, but it is computationally expensive and technically complex to use them for implementing green building full models that combine passive and active design strategies. Instead, multiple tools have been used to encapsulate the interactions between the different building and energy system components and obtain the necessary feedback to complete the design [74].

Challenge No. 7: Applying BPS-Based Optimization in Design Practice

There is not a predefined archetype of a green building. Therefore, in order to find a cost-optimal solution for a green building, the designer usually runs simulations for a few experience-based combinations for the values of the design variables, including the building envelope, the HVAC system, and the technologies for on-site energy generation. This conventional engineering procedure is inefficient in terms of time and labor, particularly if an increasing number of decision variables are considered as part of the solution space. Besides, the relation between the simulation variables and the system performance may not be inferred, especially when there are many parameters to be studied and given the nonlinearity of the problem. Therefore, finding optimal solutions by means of this trivial methodology is doubtful. To overcome such difficulties, automated simulation-based optimization search techniques proved to be an effective tool [11–13, 15, 71, 75–78]. However, results should be examined carefully because the optimization may produce mathematically correct but physically meaningless results [79].

Figure 3 shows the usual computational structure applied to simulation-based optimization in building performance studies. In this approach, the optimization program calls for the full system and building simulation to be run for each new design variable combination. This simulation-based optimization approach is clearly better than the conventional engineering method (e.g., trial-and-error evaluation). However, finding optimal solutions for a large case can be very time-consuming if dynamic interactions between the building and the energy systems are considered using high-resolution simulations. Furthermore, the optimum can be missed to some extent if a stochastic optimization algorithm is employed and only a limited number of evaluations are available. Given the stochastic nature of the evolutionary optimization algorithms (e.g., genetic algorithms), there is no proof that they converge to the same result each time they run [77]. Highly repeatable optimums should be guaranteed in order to quantify the sensitivity of the optimal solution for each input parameter (technical/financial assumption) and/or for assessing the uncertainty in the optimal solutions. In order to guarantee sufficiently accuracy, a large number

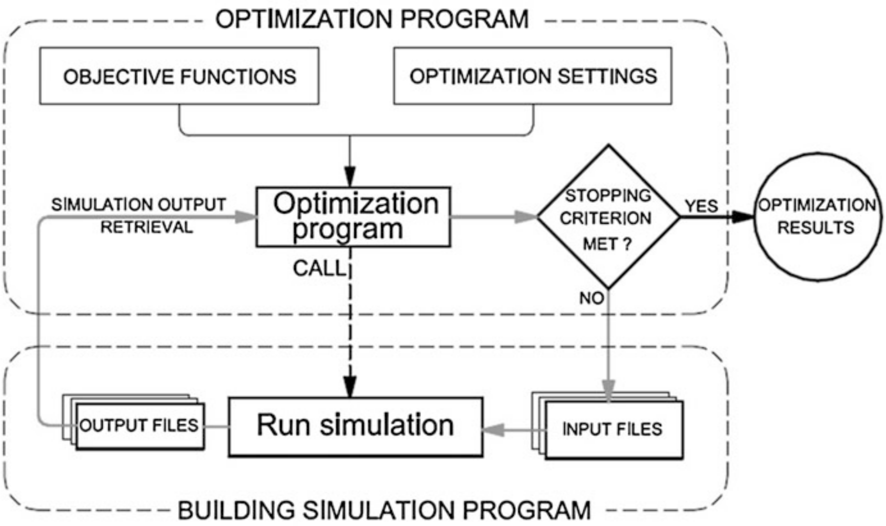

Fig. 3 Interface between an optimization program and a generic BPS program (Reproduced from Ref. [81])

(possibly hundreds) of simulations are required to be run for each optimization that assumes different technical/financial scenarios.

Regarding the computational cost of simulation-based optimizations, powerful and parallel computing can speed up such optimizations, but there is still a need to avoid unnecessary detailed models, not only to speed up the optimizations further but also to increase the probability of success. In fact, design and/or operation options often contain candidate solutions that can cause the simulation to fail particularly if detailed modeling is used in a scenario which degrades the effectiveness of the simulation-based optimization search [80].

Building optimization tools, such as GENE_ARCH (Caldas 2006), BEopt [82], Opt-E-Plus, jEPlus + EA [101], DesignBuilder optimization [102], and MultiOpt2, support decision-making in early design stages. For instance, while BEopt adopts the encapsulating concept by using two simulation engines, DOE2 [83] for calculating the heating, cooling, lighting, and appliances' energy use and TRNSYS [84] for calculating the DHW energy savings by solar thermal collectors as well as for calculating the annual electrical energy production from a grid-tied PV system [82], it does allow holistic optimization. The optimization approach adopted by BEopt firstly searches all energy-saving options (wall type, ceiling type, window glass type, HVAC type, etc.) for the most cost-effective building design, then holds the building design constant, and increases the PV capacity to reach the net zero-energy balance [85]. Decomposing holistic, black-box building energy models into discrete components can increase the computational efficiency of large-scale building analysis [74]. However, it could lead toward less accurate results. As design/operation parameters have different level of interactions [86], it is technically difficult to perform automatically time-efficient simultaneous optimization of the building envelope, HVAC and RES, where many simulation/calculation engines are employed for evaluating the integrated building and systems' performance. Hamdy and Sirén [81] introduce a novel multi-aid optimization scheme (MAOS) that is schematized in Fig. 4.

MAOS manages different tools (dynamic simulation engines, simplified models, and optimization algorithms) for avoiding time-consuming simulations and unhelpful evaluations. When possible, simplified models based on the post-processing of pre-simulated results are used instead of running computationally expensive simulations so as to reduce the computational cost of optimizations. A hybrid double-check optimization scheme is used to avoid unhelpful evaluations toward optimal solution, while a close-to-optimal solution is guaranteed. The MOAS approach adopts the encapsulating concept (presented in the previous section), but it has not been implemented automatically, while holistic optimization is already implemented for considering multivariate interactions between possible design/operation options and financial/technical assumptions. MAOS can be considered a practical tool to increase investor confidence and trust in investments toward green buildings (e.g., nZEBs) by providing a comprehensive analysis according to a greatly reduced time scale (particularly by applying post-processing for addressing a large number of economic scenarios). However, as the scheme conducts separate optimization run for each addressed scenario, it would require high computational power if large technical/occupant scenarios need to be investigated.

Challenge No. 8: Expanding the BPS Potential Through Building Information Modeling

Building information modeling (BIM) is a process used to model and manage the digital representation of a building over its entire life cycle [87]. According to the US General Services Administration [88], the use of BIM-based BPS provides several benefits including (i) more accurate and complete energy performance analysis in early design stages, (ii) improved life-cycle cost analysis, and (iii) more opportunities for monitoring actual building performance during operation. The emergence of BIM in the building industry has allowed for increased collaboration among building design and construction project members. For instance, creating a building energy model (BEM) for conducting building performance simulation (BPS) is a time-consuming process that requires data collection, often leading to uncertainty [6]. Building information modeling (BIM) in conjunction with building energy modeling (BEM) seeks to make this process seamless throughout the design process [89]. The IEA EBC Annex 60 was established to focus on the use of building information modeling (BIM) as a basis for building performance simulation. The Annex 60 project [90] introduced an open framework for automated building performance model generation from a BIM data source. The project outcomes include open-source software tools and a Model View Definition (MVD) for IFC to BPS information exchange with Modelica.

Two major challenges must be considered when developing a semiautomated data exchange process between BIM and BPS [90]:

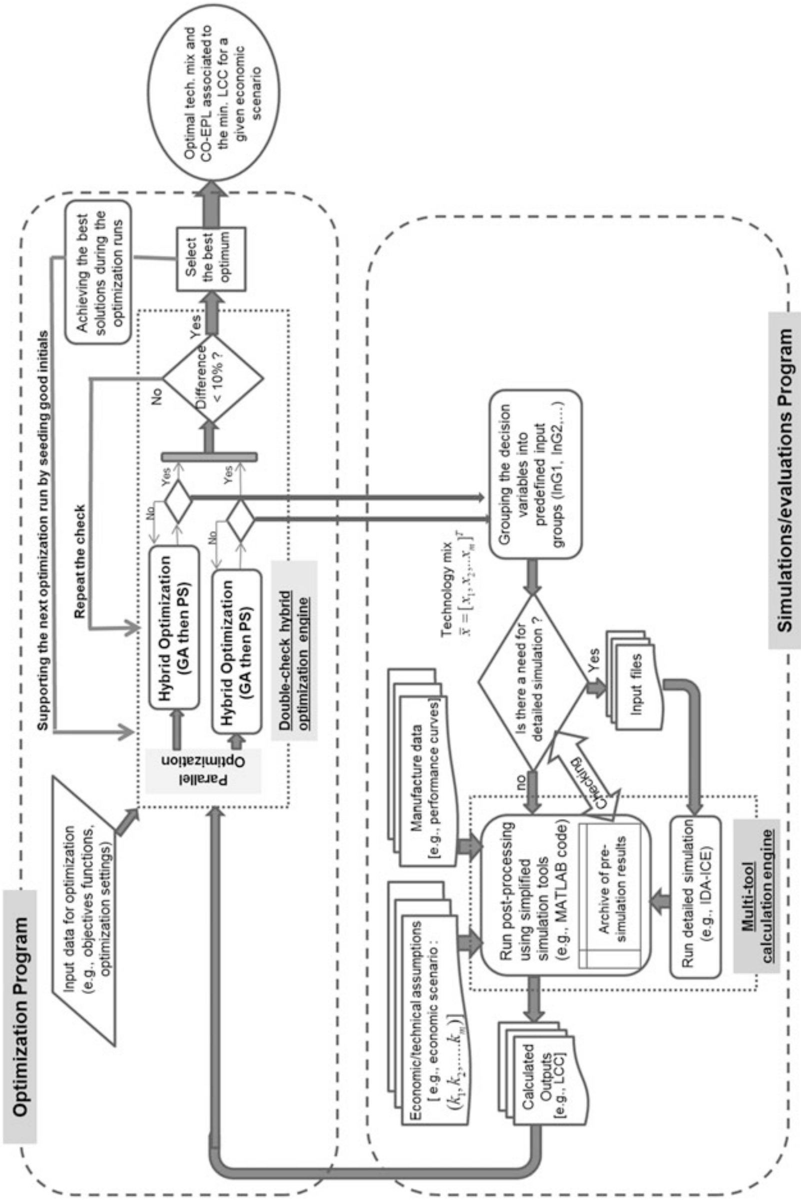

Fig. 4 Structure of the multi-aid optimization scheme (Reproduced from Ref. [81])

- Mapping data from BIM platform to BPS tool needs to consider different aspects including building geometry and HVAC components [91]. This requires expert knowledge of both BIM and BPS, which are quite different domains, in order to define consistent mapping rules.
- Preparation of a building energy model for running BPS is not only a matter of data conversion, but it also requires sufficient initial boundary conditions, consistent system models, and reliable parameter sets at the system level. In addition, flexible interfaces that allow the user's knowledge and additional information to be added in an easy-to-use manner are required.

Challenge No. 9: Visualization and Communication Skills of BPS Tools

While hundreds of tools are available on the market to assist engineers and consultants in domain-specific technical sizing and computations, only a few tools are oriented toward the holistic needs of architects [33], who in many cases are more directly related to clients than engineers and consultants. "No single BPS tool is entirely adequate to assist the architect's decision-making process. One of the major limitations is the poor communication and visualization of the output results" [92]. Over the last decades, a large number of energy-saving measures (ESMs) and renewable energy sources (RESs) have entered the construction market of green buildings. This dramatically increased the complexity of finding optimal solutions (i.e., combination of ESMs and RESs) toward integrated green building design. More time, experience, and effort became required to explore all possible combinations of available design options (i.e., traditional and innovative ESMs and RESs). A literature review made by Baba et al. [93] showed that few BPS tools support the early architectural design process; input quality affects accuracy, while output needs careful expert interpretation. Baba et al. [93] recommended that the BPS tool developers should realize that to develop architect-friendly tools, decisions are broad at the early design stages, and there is minimal concern for detail. The BPS tools should allow the description and simulation of building in fewer minutes without requiring an extensive training on the part of architects. The results from such output should be in a form that can be understood even by non-experts and be able to give architects a quick and accurate output with minimum input. This is because, at the early design stage, the focus is mainly on the estimation of the differences between different design alternatives; hence, calculations and all simulations should be ideally performed quickly and effectively.

Challenge No. 10: Selection of a Suitable BPS Tool

This is often what a neophyte modeler may think is the first challenge in modeling and simulation of a building, but, on the basis of previous sections, it emerges that the selection of an appropriate BPS tool is not a trivial task and requires guidance, particularly for architects, engineers, and contractors with limited background in building physics and energy simulation. According to Bambardekar and Poerschke [94], architects prefer using intuition and rule of thumb approaches rather than using BPS. Attia et al. [4] indicate a wide gap between architect and engineer priorities for selecting BPS tool.

Several papers focus on selecting existing BPS tools to be used in particular building life-cycle phases [34, 92, 95]. Specifically, Reeves et al. [34] developed a guideline that evaluates the BPS tools based on six criteria: interoperability, usability, available inputs, and available outputs as well as speed and accuracy. The study concludes that the existing PBS tools present a wide range of capabilities and applications, but the selection of a BPS tool depends on how the user intends to apply the tool and how the tool is incorporated into the design, construction, and facility management workflows. For example, Green Building Studio may be a more appropriate selection for users requiring a faster output for comparing numerous design iterations related to building specifications. But, IES VE was selected as the most appropriate BPS software when all the studied criteria were weighted evenly [34]. However, Weytjens et al. [92] found that none of available BPS tool is entirely adequate for architect's use, despite recent developments. One of the major limitations of current tools can be attributed to the poor communication and visualization of the calculation output, which do not assist the architect's decision-making process. When the usability and applicability are chosen as criteria of evaluating the existing BPS tool, Attia et al. [33] found that it is difficult for architects to integrate existing BPS tools into the design of green building; none of the existing tools is applicable to investigate different possibility for achieving green building like zero-energy buildings. This is concluded by Attia et al. [33], although many BPS tools are able to make simultaneous performance assessments of all issues fundamental to building design (i.e., shape, envelope, glazing, HVAC systems, controls, daylight and electric lighting, indoor air quality, thermal and visual comfort, energy uses, etc.). This reveals that the existing BPS tools have a limited capability to design green buildings with an advanced technology mix.

Conclusions and Future Directions

The exploitation of green buildings, as a feasible sustainable solution, needs for innovation that has to involve all the phases of a building life cycle, from the concept development of a building inserted into a given urban environment to the sustainable end-of-life disposal, passing through its performance estimation. The ultimate aim of BPS is to support such innovation by providing a high integrity representation of the dynamic, connected, and nonlinear physical processes that govern the disparate performance aspects and dictate the overall acceptability of buildings and their related energy supply systems.

The integration of BPS into the design, construction, and operation and maintenance of green buildings has become more crucial than ever before [34, 92, 96]. Indeed, the principal stakeholders of the building process – including architects, engineers, contractors, and facility managers – are appreciating the potentialities of BPS but are still facing many challenges related to the use of and interaction with BPS (e.g., the ten aforementioned ones). Moreover, research that is oriented to computationally support the design and operation of sustainable built environments, like green buildings, tends to be fragmented, and "It is essential that a more holistic approach should be developed to better understand the relationship between urban, building, building systems, and material" [97].

The holistic approach requires extending the capabilities of the available BPS tools by coupling them with building information modeling (BIM), multi-objective optimization algorithms, and other advanced analysis techniques, for example, multi-criteria decision-making and sensitivity analysis. However, it needs to be mentioned that this coupling could lead to additional modeling errors, simulation failures, and misleading optimization. To reduce such problems, one strategy is to use a sophisticated single BPS-based tool as it is proposed by the Chartered Institution of Building Service Engineers (CIBSE).

Moreover, visualization and communication of simulation output, which are intuitively interpretable from architects and are able to convince clients, are still required. "The present challenge is to ensure that BPS tools evolve to adequately represent the built environment and its myriad supply technologies in terms of their performance, impact and cost. Attaining multi-functional tools, and embedding these within the design process, is a non-trivial task" [98]. This challenge is being addressed by the International Building Performance Simulation Association that provides a forum for researchers, tool developers, and practitioners to review modeling methods, share evaluation outcomes, influence technical developments, address standardization needs, and share application best practice.

As seen above, BPS has become not only a building performance design support tool but also a planning tool for micro-grid, urban energy management and Internet energy services. Moreover, BPS portends a future that can deliver a virtual reality to its users. This will require the replacement of present-day output constructs with features that will support experiential appraisals. In the Internet-of-things (IoT) era, where *big data* is available, BPS can help mapping observations to suggested action as a part of the analytics applied to collect and analyze data. The big data can also play a significant role in bridging the gap between BPS-derived predictions and IoT-gathered observations. This will enhance the trust in BPS and should give a boost to the development of more BPS-assisted applications in the near future.

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