Trcka, M. & Hensen, J. L. M. 2010. "Overview of HVAC system simulation", Automation in Construction, vol. 19, no. 2, pp. 93-99.

Overview of HVAC system simulation

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The paper gives an overview of heating, ventilation and air-conditioning (HVAC) system modeling and simulation. The categorization of tools for HVAC system design and analysis with respect to which problems they are meant to deal with is introduced. Each categorization is explained and example tools are given. Further, the paper summarizes current approaches used for modeling (i) HVAC components, (ii) HVAC control and (iii) HVAC systems in general. After giving an overview of solution techniques for HVAC system simulation, the paper provides suggestions on how one should select an HVAC modeling approach relative to the simulation objective at hand.

1. Introduction

Forty-year long development of building performance simulation (BPS) tools resulted in a wide range of currently available products [1,2]. These products range (complexity-wise) from spread-sheet tools to more advanced special-purpose simulation tools, and (integration-wise) from tools that handle a single aspect of the building design, to tools that integrate multiple aspects of the building design [3].

A brief historical overview BPS tools is given in [4]. First generation of BPS tools is based on simplified methods found in handbooks (calculations based on analytical formulations that embody many simplifying assumptions). Second generation tools are based on methods that assume simplified (still analytical) modeling of dynamics in buildings. Third generation tools use numerical methods and provide partial integration of different performance aspects of buildings, e.g. thermal energy, visual, and acoustical. The current fourth generation tools tend to be fully integrated with respect to different building performance aspects, with new developments concerned with intelligent knowledge-based user interfaces, application quality control and user training. The current tools can capture reality much better than earlier tools, but are more complex to use.

The number of currently available BPS tools, diversity of aspects taken into account in those tools and modeling approaches used by those tools makes writing a general overview of the field a difficult task. Thus, this paper is restricted to an overview of modeling and simulation developments in one of the more important subsystems in buildings: heating, ventilation and air-conditioning (HVAC) systems.

2. Tools for HVAC system design and analysis

Tools for HVAC design and analysis can be categorized with respect to the problems they are meant to deal with. Although these problems are not mutually exclusive, and some tools can handle several problems, they do tend to be investigated in isolation from each other. The categories are as follows.

Tools for pipe/duct sizing are system design tools that consider flow distribution and sizing of liquid/air distribution system (AFT Fathom, DOLPHIN, Duct Calculator, DUCTSIZE, Pipe-Flo, PYTHON, etc.).

Tools for equipment sizing and selection offer HVAC equipment sizing (Carrier HAP, Trane TRACE 700, EnergyPlus, etc.). Most sizing tools are based on standard procedures and algorithms established by e.g. American Society of Heating Refrigeration and Air-conditioning Engineers (ASHRAE), but many are proprietary software products distributed or sold by equipment manufacturers [5]. Digital catalogues that are provided by equipment manufacturers can be used to locate a suitable component model for the given design criteria. They can be further linked to the equipment sizing tools, e.g. Carrier's HAP tool can be linked to their chiller selection tool by importing performance data for the actual chiller.

Tools for energy performance analysis are designed to predict the annual energy consumption of an HVAC system. Based on a system of equations that define thermal performance of buildings and systems, and with given boundary conditions, operation strategy and controls, these tools perform (hourly or sub-hourly) simulations (Carrier HAP, Trane TRACE 700, DOE-2, eQUEST, EnergyPlus, ESP-r, IDA ICE, TRNSYS, HVACSIM+, VA114, SIMBAD, etc.). These tools are typically used to calculate and analyze the full-and part-load performances, to analyze system operation strategy, to compare different design alternatives, etc. [6–9].

Tools for system optimization are used in conjunction with tools for energy performance analysis. In multiple simulation runs, a set of parameters is optimized according to a given objective function. An example is the generic optimization tool GenOpt [10].

Toolsfor controlanalysisand controloptimization (see also Section 3.2). The level of HVAC system control modeling and simulation in the available tools varies:

- Controllers can be associated with high abstraction system models, such as in ESP-r.
- Controllers can be represented explicitly either -as models of supervisory control, such as in EnergyPlus, or -as simple models of local control, such as in ESP-r and TRNSYS.
- • More advanced representation of controllers, such as fuzzy logic, are available in e.g. MATLAB based tools (SIMBAD), Dymola and tools coupled to MATLAB (ESP-r [11], TRNSYS [12]). These tools are efficient for design and more comprehensive testing of controllers in a simulation setting [13], as well as for testing and validation of controller design in real time [14].

- Simulation tools for real-time performance optimization. Benefits of using simulation tools in the building operational stage are still insufficiently explored. Simulation tools could be used for:

- Commissioning diagnostics (initial commissioning): i.e. to verify the performance of the whole building, its subsystems and components [15];

- Monitoring diagnostics (continuous commissioning) and fault detection diagnostics: i.e. to detect, analyze, locate and/or predict problems with systems and equipment occurring during everyday operation [16–19];

- Emulating a building and its HVAC systems: i.e. simulating the response of a building and its HVAC systems to building energy management system (BEMS) commands. Emulators can also be used for control product development, training of BEMS operators, tuning of control equipment and imitating fault situations to see how the BEMS would cope [20];

- Simulation assisted control: i.e. to execute a simulation model (encapsulated within the BEMS) as part of the control task in order to evaluate several possible control scenarios and make a choice in terms of some relevant criteria [20].

The system simulation models that belong to this category are expected to predict system performance accurately. Thus, they need to be able to treat the departures from ideal behavior that occur in real systems and to realistically model controls and HVAC system dynamics. The tools for energy performance analysis can be used as tools for real-time optimization of system performance [21,22], but models of a building and its systems need to be well calibrated [23].In general, well calibrated first-principle models can be used [24], but simpler and precise empirical (e.g. neural network models) models can be used as well [16].

3. Modeling approaches

3.1. Modeling approaches for HVAC components

According to Zeigler [25], the majority of models in building and system performance simulation are:

- Continuous in state, as the range of model variables is represented by real numbers or intervals. However, some models assume a discrete set of values and are thus discrete state models.
- Discrete in time, as time is specified to proceed in discrete steps. If the model is continuous in state and discrete in time, it is then described by a (system of) difference equation(s).
- Deterministic. However, stochastic models are used as well, e.g. in predictive control applications [20].
- Time varying, since the rules of interaction are different at different times.
- Both steady state and dynamic.
- Forward, as they are used to predict the response of output variables based on a known structure and known parameters when subjected to input and forcing variables. Backward (data-driven) models[1] tend to be much simpler but are relevant only for cases when system-specific and accurate models of specific building components are required, e.g. for fault detection and diagnosis [16].

There is a distinction between primary and secondary HVAC system components. The former are sometimes referred to as plant, and the latter are referred to as system. A primary system converts fuel

and electricity and delivers heating and cooling to a building through secondary systems. Examples are: chillers, boiler, cooling towers, thermal storage systems, etc. Secondary systems include air-handling equipment, air distribution system and liquid distribution system between the primary system and the building interior.
In both primary and secondary systems there are two types of components: distribution components and heat and mass balance components. The distribution components are: pumps, fans, dampers, valves,ducts and pipes.Theyaffectthe energy flow in buildings by [26]:

- consuming electrical energy which drives pumps and fans, and
- transferring thermal energy to/from the working fluid in all distribution components.

The distribution component models should satisfy energy and mass balance equations. Most of the BPS tools model distribution components in a simplified way [26], which eliminates the need to calculate the pressure drop through distribution system at off-design conditions. In general, this approach is sufficiently accurate for studying temperatures in the system. For detailed analysis of e.g. fan/pump control loops and for answering questions related to the placement of the return/exhaust fan, type and size of dampers/pipes, flow and pressure balancing between the components is necessary [18].
The above heat and mass transfer components are usually described by fundamental engineering principles — first-principle

In data-driven models the input and the output variables are known and measured, and the objective is to determine the mathematical description and to estimate the system parameters.
models (if equations are derived from fundamental principles but require some empirical input these models are also referred to as quasi-first-principle models [27], e.g. most of the component models in [28] and [29]), or by empirically obtained equations, i.e. by using regression analysis of design data published by a manufacturer, or by simply specifying look-up tables. The former modeling approach is usually used for secondary system component descriptions, while for primary system components, due to their complexity, the latter approaches are more often used, but exceptions exist [29].

3.2. Modeling approaches for HVAC control

HVAC controllers can be divided into two categories as follows.
Local controllers are low-level controllers that allow HVAC systems to operate properly and to provide adequate services. Local controllers can be further subdivided into two groups [30]:

- Sequencing controllers define the order and conditions associated with switching equipment ON and OFF. Typical sequencing controllers in HVAC systems are chiller sequencing controller, cooling tower sequencing controller, pump sequencing controller, fan sequencing controller, etc.
- Process controllers adjust the control variables to meet the required set point in spite of disturbances and considering the system dynamic characteristics. The typical process controllers used in the HVAC field are P, PI, PID, ON/OFF, step controller, etc.

Supervisory controllers are high level controllers that allow complete consideration of the system level characteristics and interactions among all components and their associated variables. For example, a supervisory controller sets operation modes and sets points for local controllers.
From a modeling point of view, controllers are represented by equations that must be satisfied in every simulation step. The controllers direct the interaction between building and system as well as interactions between components within the system.
In reality, the closed-loop local-process control includes a sensor that samples a real-world (measurable) variable. The controller, based on the set point value and measured value, and according to the controller-specific control algorithm, calculates the control signal that feeds the real-world actuator. However, in the simulation tool the user can address variables that cannot be sensed or actuated in reality, as well as apply control algorithms that do not exist in reality. For example, a modeler can directly actuate the heat flux in a model where in reality this could only be done indirectly by changing a valve/damper position.
Furthermore, due to the accessibility of many variables not directly known in the real world, such as the zone cooling/heating load, in simulation the concept of “ideal” (local process) control becomes feasible. An “ideal” local-process controller means that the actuated variable will be adjusted to satisfy the set point requirements for the controlled variable, without specifying the explicit control algorithm and by numerically inverting the (forward) simulation models (from the required output calculate the input needed

to satisfy this).

Possibilities to simulate different (advanced) controllers in stateof-the-art BPS tools are limited. Some tools offer pre-defined control strategies (system-based simulation tools), some offer flexibility in specifying only supervisory controllers (EnergyPlus) and some even in specifying local controllers (TRNSYS, ESP-r). The domain-independent environments, such as MATLAB and Dymola, are efficient tools for designing and testing of controllers in a simulation setting, but lack the models of all other physical phenomena in buildings.

3.3. Modeling approaches for HVAC systems

Hensen [31] defines four categories of HVAC system representation in BPS tools, ranging from purely conceptual towards more explicit, as follows.

Pure conceptual system modeling approach represents the case where only room processes are considered, while all other processes in primary and secondary systems are idealized, with a possibility to impose a capacity limitation upon them. An example application is to use the predicted room cooling/heating peak loads to determine the required HVAC system size. Most state-of-the-art BPS tools can be used to model systems using this approach. Some, like ESP-r, introduce certain complexity by modeling conceptual systems — thermal zone interactions through control algorithms. Thus, even though the pure conceptual system model is used, system processes are not completely idealized. Their interaction with the building is more realistically modeled since their characteristics can be included in terms of aspects such as heat injection/extraction point, flux limit values, response time, and convective/radiant split. In [32] the authors state that this method of system simulation is often misunderstood and under-rated.

System-based modeling approach represents the case with pre-configured common system types, such as variable air volume system and constant-volume variable-temperature system. This modeling approach is implemented in DOE-2, eQUEST, Building Energy Analyzer, BLAST, DesignBuilder, HAP, etc. The user has flexibility in specifying capacities, system flow rates, efficiencies and off-design system component characteristics, but is restricted to the system configurations and control strategies that are pre-defined in the tool.

Component-based system modeling approach represents the case where a system is specified by (a) network(s) of interconnected component models. This approach is more flexible in terms of possible system configurations and control strategies compared to the previous approach.

Component-based multi-domain system modeling approach represents the case where component representation is further partitioned into multiple interrelated balance concepts, e.g. fluid flow, heat and electrical power balance concepts. Each balance concept is then solved simultaneously for the whole system. Thus, the overall system of equations is broken into smaller systems of equations. Different solvers, well adapted for the equation types in question, can be used for different problem partitions. It is also possible to easily remove partitions as a function of the problem at hand.

As an addition to the above four categories defined by Hensen [31], this paper lists a fifth category: the equation-based system modeling approach. This modeling approach represents the case where a system is represented by a basic modeling unit that is physically “smaller” than a component and that is in the form of an equation or a low-level physical process model. It has evolved from the need to improve the BPS tools that had been based on technology available in the early seventies [33]. Equation-based simulation tools are [34,35]:

- input–output free (all models are declarative in nature) as opposed to the traditional procedural,
- modular (supported by object-oriented programming languages),
- hierarchical (enable incremental modeling, i.e. models can consist of sub-models in multiple levels), which helps in managing the complexity of large systems,
- universal (model definition in a generic form, e.g. using NMF and Modelica).
- They provide separation of modeling the physics from numerical solution algorithms.
- They provide faster developments of simulation models, etc.

Examples of equation-based tools are:

SPARK (Simulation Problem Analysis and Research Kernel), formerly EKS/US and SPANK, is developed by the Lawrence Berkeley laboratory [36]. The primary goal of the EKS/US was improvement of the modeling and solution processes which resulted in SPARK. It is an object-oriented simulation environment, of which the fundamental object is an equation. EKS (Energy Kernel System) was researched in the UK [37]. The objective of the EKS/UK was to place tool development on a task-sharing basis in order to ensure integrity and extensibility of future systems. The primary goal of EKS/UK, i.e. to improve the tool development process, was later researched via primitive part modeling in the ESP-r simulation environment [34].

NMF (neutral model format) was designed to bring the power of differential algebraic equation (DAE)-based modeling to the building simulation community and yet be compatible with major BPS tools such as TRNSYS, IDA and SPARK. The basic objective of NMF is to provide a common format of model expression for a number of existing and emerging simulation tools, e.g. TRNSYS, HVACSIM+, IDA and SPARK [38].

IDA is one of a few equation-based efforts that have been pursued beyond the stage of prototyping [38]. The NMF initiative continues to live with IDA, since most of the IDA models are written in NMF, besides a few written in Modelica [33].

Modelica [39] is an ambitious modeling language that has shown potential to bring order to the fragmented world of DAE-based simulation. It draws on the collective experience of a large number of first generation languages. Since the first Modelica based tool, Dymola, appeared in 1999, several large industries such as Toyota, Ford, United Technologies, Caterpillar, ABB, Alstom, TetraPak, etc. have adopted it [38]. Efforts to develop building and HVAC system simulation models resulted in various Modelica libraries, such as ATPlus [40], UTRC Modelica library [41] and Building Informatics Environment [42].

SimScape [43] is a new development by MathWorks that extends Simulink with tools for modeling and simulating multi-domain physical systems, such as those with mechanical, hydraulic, and electrical components. SimScape can be used for a variety of automotive, aerospace, defense, and industrial-equipment applications. Together with other MatLab toolboxes, SimScape allows modeling of complex interactions in multi-domain physical systems. There appears to be no evidence yet of using SimScape in BPS.

Based on object-oriented programming approach, the above projects were aiming to introduce “modern concepts from computer science and software engineering in the BPS field to make available to developers basic software modules and supporting framework that could be used to construct new BPS software” [44]. But, as Sahlin et al.
[33] notes that nothing much has happened in recent years to “change the direction of fundamental reasoning”. The authors also state several factors that contributed to this apparent lack of progress, as follows:

- Some exploratory projects did not deliver as expected.
- Leading research groups have reverted back to existing solutions and “organic” evolution.
- Multi-domain simulation is being attempted by coupling of existing domain specific simulators (co-simulation).
- Driven by product model research, attention has shifted from new tool development to improved integration of existing modeling and simulation tools into the design process.

Sahlin [45] states that the primary cause of the lack of success is “unwillingness by BPS developers to learn other engineering fields”.It seems that the equation-based tool development has not shifted away attention from existing tools. Due to the difficulty in obtaining funding for work other than incremental improvements of BPS tools [46], many research teams continued to improve the integration of “traditional” simulation tools into the design process.

The major motive for the adoption of object-oriented software engineering approaches has been its support for modularity in modeling. However, a model for the simulation of a complex system, such as a building, in object-oriented languages is not trivial [47]. One of the main questions is to what the objects should correspond. Should they correspond to real-world entities, or to the equations associated with those entities. The lack of the agreement upon the above issue has resulted in a limited presence of object-oriented programming in the domain of BPS.

3.4. Solution techniques for HVAC system simulation models

The differences in solution techniques employed by different simulation tools are based on the distinction in the way the integrator is employed [48].
Simultaneous modular solution, where the various components are integrated simultaneously by a common integrator. In general, the tools that employ this solution technique use model equations that are based on first principles [48]. Each component is described with time-averaged discretized heat and/or mass conservation statements, which are combined to form a system matrix, and which are solved simultaneously for each simulation time step using either an implicit, explicit or mixed numerical scheme.

Independent modular solution, where each module is provided with individual integrator routines. In general, the tools that employ this solution technique use model equations that can be based on first principles but can also be empirical input/output correlations [48]. The component's modules encapsulate all information relevant to the component's simulation model setting and execution. Each component is executed sequentially and the system solver iterates until a convergent solution has been found.
Equation-based solution using formula manipulation, which has emerged in recent years with the developments of equation-based tools. Models composed with these tools cannot be executed directly. To be executed, a model needs to be transferred into a programming language that can be compiled. Tools employ different techniques to reduce the dimensionality of the linear and non-linear systems defined in the model in order to increase the execution efficiency of the compiled program. For example, in SPARK [49], mathematical graph algorithms are used for problem decomposition and reduction, greatly reducing solution time for wide classes of problems [50].

4. Integration of building and HVAC system models

The integration of building and HVAC system models is accomplished at different levels. The models can be (i) sequentially coupled (many duct/pipe sizing tools, BLAST, DOE-2, etc.) – without system model feedback to the building model or (ii) fully integrated (ESP-r, EnergyPlus, IDA ICE, TRNSYS, etc.) – allowing the system deficiencies to be taken into account when calculating the building thermal conditions. Levels of detail of both building and system models can vary from simple (e.g. the bin method and pure conceptual representation for system model) to complex (numerical model of physical processes).

5. Issues in selecting HVAC modeling approach

Different HVAC system modeling approaches demand different levels of user skills, different modeling resolutions and details, and different levels of user customization capability. Higher explicitness in system representation requires more knowledge about the system because of the increasing number of model parameters for system specification, often difficult to obtain as they are not supplied by manufacturers. In addition, for higher explicitness in system representation the computational requirements become more intensive and the analysis of the results more complicated.
Most design analyses do not require detailed system modeling and simulation as the energy consumption can be estimated by using simpler modeling approaches. The conceptual system representation shows its advantages (lower required user expertise, lesser input data, less intense computations, easier results analysis, etc.) when only load predictions are considered, and/or when energy saving options are investigated. However, for comparing HVAC system alternatives and evaluating different control strategies [18,51] detailed HVAC system models are required. In the system-based modeling approach, the speed of system alternatives evaluation is much higher than in the component based modeling approach, but the investigation of innovative technologies is limited.

Matching the applicabilities of system modeling approaches with the design questions at hand, the user can benefit from both ease of the former categories and flexibility of the latter ones. However, building a right model for a simulation task at hand is still more an art than an engineering discipline. This issue is highly relevant when there is no (measured) data which can be used for direct model accuracy evaluation. Thus, in this case the model adequacy for the particular simulation objective needs to be evaluated differently.

Building a right system model for a specific purpose is to require that the modeling validity and data validity match as far as possible the required validity [52]. The required validity is assessed only against those aspects of the real world that are of relevance for successful accomplishment of simulation objectives, represented by performance parameters.

Model complexity can be expressed in terms of scope (defined by a number of components in the model) and resolution (definedby a number of states per component in the model) of the model and interactions among components in the model. Abstraction is a general process and includes various simplification approaches with regards to system boundaries considered, number of modeled physical phenomena, the resolution of modeling of each considered phenomenon, etc. in increase in model complexity increases the cost of using the model. Thus, the model should be of the lowest complexity while preserving its validity for the intended simulation objectives. The required lowest model complexity depends on the simulation objective. Also, increasing the complexity, for different simulation objectives, has different implications for the value of the model to the user, as schematically shown in Fig. 1. For different simulation objectives the model cost exceeds the model value to the user at different model complexities. For some objectives the cost of the model will exceed its value even when the modeling complexity is low, and for some, the simulation objective can justify the use of more complex models. Moreover, the rate of change in the model value can be different for different simulation objectives at different complexities. On the one hand, a simple model can have a high value at low modeling complexity for some simulation objectives; this value might not be increased by increasing the complexity. On the other hand, a model has a value only above certain modeling complexity for some other simulation objectives, as illustrated in Fig. 1.

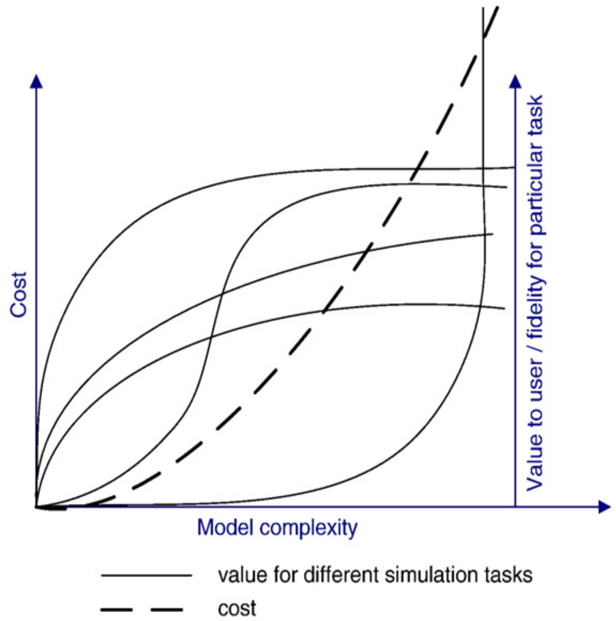

Fig.1.Cost and value to the user vs. complexity.

The potential techniques that can be used to ease selection of modeling complexity for a particular simulation objective can be described in following paragraphs (the use of the techniques has been reported previously [53,54]).

Definition of the minimum required modeling complexity can be accomplished by using the checklist rationale from [55] represented in Fig. 2.

The stakeholder defines the simulation objectives and the relevant performance indicators. Based on this information, the checklist framework can be used to identify the entities and variables to be used in the simulation and thus estimate the initial modeling complexity. The initial modeling complexity should be the lowest possible complexity that satisfies the simulation objectives in terms of performance indicators. The quantification of validity of the initial/ minimum required modeling complexity is achieved by specifying a range for error tolerance, as a model deviation of the real world.

The error in a verified model is the sum of: (i) abstraction error, (ii) input data error, and (iii) numerical errors. Here, only the former two are discussed while it is assumed that by decreasing the discretization step the numerical errors can be controlled. The first error is due to the modeling abstractions, i.e. using an incomplete model of a physical system, and the second is due to uncertainties in the parameters themselves. Sometimes the distinction between the two is not clear. Parameter uncertainty can be quantified and therefore the corresponding uncertainty of the model output as well. This uncertainty of the output is known as predictive uncertainty.

The modeling uncertainty is not easily quantifiable and therefore its influence can be considered as a modeling bias. As illustrated in Fig. 3, with the increase of modeling complexity the predictive uncertainty rises as there are more parameters to consider. On the other hand, the models approach reality and the bias decreases. The curve that defines predictive uncertainty depends on how much of

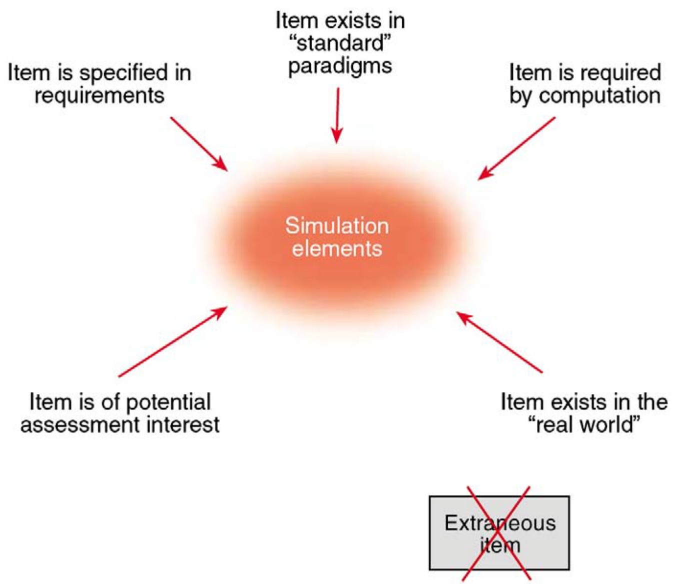

Fig. 2. Schematic representation of a checklist rationale [55]: 1. There must be a total tracking of items in the requirements to the conceptual model. 2. There should be a specific simulation element for every item (parameter, attribute, entity, task, state, etc.). 3. As far as possible, there should be "real world" counterparts for every simulation element. 4. The simulation elements should correspond to standard and widely accepted decomposition paradigms to facilitate acceptance of the conceptual model and effective interaction (including reuse of algorithms and other simulation components) with other simulation endeavors. 5. Simulation elements required for computational considerations that fail to meet any of the previously stated items should be used only when absolutely essential. 6. There should be no extraneous simulation elements.

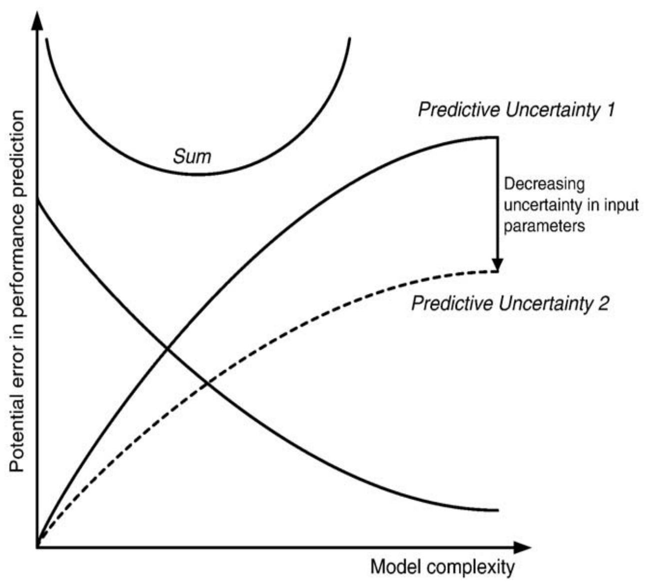

Fig.3.Model uncertainty vs. complexity.

system knowledge is available. If the modeled system is well known, the input parameters are less uncertain and the rate of increasing predictive uncertainty with model complexity is low. The modeling complexity for which the model error has its minimum will closely be related to the available system knowledge.

There is a certain modeling complexity after which the predictive uncertainty will be higher than the modeling bias. There is no sense in going beyond this complexity, as the overall error in the model uncertainty will not decrease. Hence, whether the required validity will be met by the model depends not only on the system modeling complexity, but also on the available system knowledge.

6. Conclusion

This paper presents a review of available tools for HVAC system design and analysis, modeling approaches and simulation techniques. The numerous available tools range from simple spread-sheet tools to more advanced simulation tools. Even though they cover a wide range of design and operational problems, there is still an enormous amount of work to be done in this area. We finish by identifying some requirements for further research and development:

- Buildings are complex systems of which the real performance usually deviates from the performance predicted in the design stage. Recent studies (e.g. [56] show that the difference between the predicted and real energy consumption can be up to 40%). For crude analysis, including the relative comparison of the design alternatives, this may not be a problem. However, to be able to correctly base design decisions on predictions, there is a need to understand where the above discrepancies come from and to include the uncertainties in the system model.
- In general, the ongoing research that deals with uncertainty and sensitivity analysis in building performance predictions does not take into account the modeling bias, but only the predictive uncertainty. In order to assess the validity (fidelity) of the model, both the modeling bias and predictive uncertainty need to be taken into account.
- The capability of most of the tools is limited to a set of predefined system configurations. To successfully continue the development of BPS tools to accelerate innovation of building technologies and thus help in mitigating climate change, the focus should be on supporting flexible modeling environments that allow to analyze building systems which are not yet covered in current BPS tools.

- Although some design (operational) problems immediately exclude the use of some tools, the user is still free to choose between a large number of available tools for a particular case. So far, there is no comprehensive guideline on how to make this choice relative to the required accuracy of the predictions based on the model. The above discussion regarding selection of the most appropriate modeling approach could be a first step towards such a guideline. More research is needed in this area.
- Simulation tools have been seen as promising tools for establishing the baseline (or baseband) performance prediction which can be used during building operation to monitor the performance and/or to detect and identify abnormalities in the system behavior. However, the research is still in its early phases.

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