TOWARDS A GUIDELINE FOR SELECTING THE APPROPRIATE ABSTRACTION LEVEL FOR BUILDING SYSTEMS SIMULATION

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ABSTRACT

Each modeler meets a challenging task of abstracting the relevant physical behavior of the system to be modeled. What physical phenomena are important for the particular simulation task and what models to use are the questions that need to be answered every time when performing a simulation task. This paper initiates a concept of a guideline that will guide a modeler in selecting the appropriate level of heating, ventilation and air conditioning (HVAC) system modeling abstraction. We introduce the concept of conceptual modeling and fidelity and present possible solutions for measuring the suitability of modeling abstraction level for a particular simulation task. The paper concludes with a simple worked out example that is used to demonstrate the proposed checking criteria.

INTRODUCTION

There is no such thing as a correct model for a physical system. Systems can be modeled in variety of ways, and different design analysis can require different models of the same system. Choosing the system model for a specific purpose is still more an art then an engineering discipline [Forbus 1996, Moody 2005].

This paper focuses on developing a guideline for selecting an appropriate modeling abstraction level for HVAC system related simulation queries. To accomplish this we follow Ockham's Razor, a principle proposed by William of Ockham in the fourteenth century: “Pluralitas non est ponenda sine necessitate”, which translates as “Given two equally predictive theories (models), choose the simpler”. In other words, we aim on answering the question: what is the minimum required complexity of a model that will produce results within the required tolerances of aspects of interest.

In [1995], Hensen distinguishes four levels of abstraction for system modeling and simulation in building performance simulation (BPS). He points out that the level of abstraction primarily depends on simulation objectives. However, limited data availability may influence the modeling abstraction level selection. So far, there are few procedures that will guide a modeler in making decisions about which abstraction level to use for a particular problem at hand. An effort from previous research [Djunaedy et al. 2003], shows an attempt to define a decision-making method for selecting the appropriate tool for building airflow simulation.

This paper introduces related research in other fields and discusses their potential use in the field of building system simulation.

CONCEPTUAL MODELING

A conceptual model describes how the model developer intends an implementation to satisfy its requirements. It is the primary mechanism for transforming simulation requirements (simulation objective, query about real world systems’ (in some papers, real world system, or system to be simulated is called simuland or scenario) behavior) into specifications that will guide simulation development and implementation. In other words, it is a collection of information about assumptions, relationships and data, which describes a modeler’s concept about the real world. Figure 1 shows how and where the conceptual modeling phase takes place within the overall modeling and simulation process.

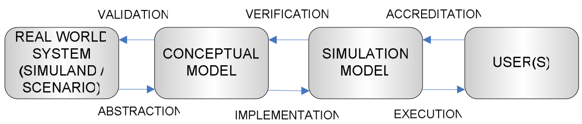

Figure 1 Modeling abstraction in the simulation process [Frantz 1995]

It is the abstraction of reality that distinguishes the real world system from a conceptual model of that system for a particular task. Implementation of the conceptual model is a simulation model. The simulation model is software specific, while the conceptual model should be software independent. This also reinforces that a model should be problem- not software-led.

Defining the modeling and simulation process as in Figure 1, clearly defines where the validation and verification processes take place. Validation will ensure that the right model is used, and the other way.

The verification process is needed to check whether the conceptual model is implemented correctly.

There are in general four steps in conceptual model development [DMSO 2000a] and [Pace 2000]:

1. collecting authoritative information for the simulation domain;
2. identifying processes and entities that are to be represented in the simulation for it to accomplish its objectives. Making decisions about level of detail and aggregation;
3. making decisions about the level of accuracy, precision and resolution of entities identified in step two;
4. establishing relationships between entities (from step two and three) to take into account all constraints and boundary conditions imposed by the simulation context.

Pace [2000] stated: "Simulation fidelity is a function of both the scope and representation in a simulation (step two) and the quality of entity and process representation (step three)." It can be concluded that the second and third steps are of great importance for validity of the conceptual model.

As mentioned before, it is the abstraction that distinguishes a real world system from its conceptual model and having a good overview of abstraction techniques is very important to understand the formulation of conceptual model.

MODEL ABSTRACTION TECHNIQUES

Frantz in [1995] categorizes these into three broad approaches:

1. model boundary modification that involves changing the exogenous variables of the model – model scope;

2. model behavior modification that involves the changes to the internal components of the system model in terms of eliminating transition through system states which distinction is irrelevant to the simulation requirement – model quality;

3. model form modification that involves changes in input-output relations of the component model itself.

The taxonomy can be used to map different conceptual models for a real world system into a three-dimensional space with coordinates defined to represent each abstraction category (boundary, behavior and form abstraction). From such a model structure the modeler would select the simplest model, based on the chosen criteria (see conceptual modeling frameworks) that sufficiently approximate real system behavior.

HVAC component models range from very simple (lookup table) to very complex (detailed numeric model) and it is not an easy task to define their distribution in the abstraction space. It is also very difficult to define the most appropriate level of modeling abstraction, i.e. to define coordinates in the three-dimension space that would determine what components to include in the particular model for the particular modeling task.

CONCEPTUAL MODELING FRAMEWORKS – LITERATURE REVIEW

In every phase of modeling and simulation development, the unique measure of "goodness" is called fidelity [DMSO 2000b]. It describes how "well" or closely the model represents the real system (or perception of the real system) to be simulated (scenario or simuland). However, it is very difficult to define the real system, as much about it is unknown. Therefore, the (perception of) real world is abstracted to a **referent –** a confined body of knowledge about the thing being simulated (Figure 2). The fidelity can be defined as [Gross 1999]: the extent to which the model reproduces the referent, along one or more aspects of interest, such as: accuracy, scope, resolution, level of detail, etc.

There are three basic categories for describing fidelity: short, shorthand, and long. Short descriptions are qualitative in nature and expressed in terms of: "high", "medium", or "low" [DMSO 2000b]. Long descriptions quantify fidelity aspects in terms of scope and quality.

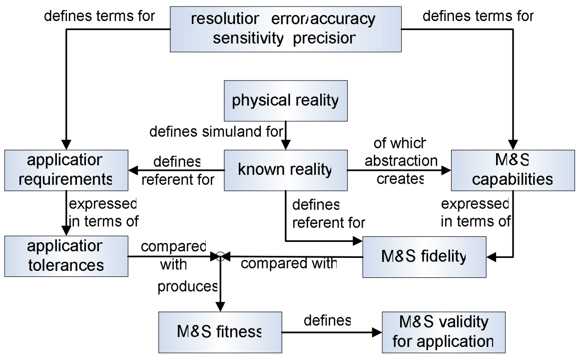

Figure 2: Conceptual model fidelity framework [DMSO 2000b]

Here, we address two major styles of frameworks: frameworks with checklist style and frameworks that employ some sort of metrics to judge the conceptual model for a specific purpose.

1. Fidelity frameworks with checklist rationale

Checklist rationale guides the selection of simulation elements for inclusion into a model. Pace in [2000], states that although modeling is essentially an art rather than scientific method, there are some rational processes that can be applied for conceptual model development. He made a sort of checklist that consists of six points that relate to *conceptual model decomposition*:

1. there should be a specific simulation element for every item explicitly specified in requirements (query);
2. there should be a specific simulation element for every item for potential performance assessment related to the purpose of the simulation;
3. as far as possible there should be a real world counterpart for every simulation element;
4. if possible, simulation elements should correspond to widely accepted decomposition paradigms;
5. simulation elements that do not meet any of the previous points but are required for computational considerations should be used as little as possible;
6. there should be no extraneous simulation element, i.e. an element that does not meet any of the previous points as this is not in agreement with Ockham's Razor.

Falkenhainer and Forbus [1991] use a similar approach to define the entities to include in simulation. Rickel in and Porter [1997] define a list of *eleven adequacy constraints*. Another, more domain specific checklist based framework is found in [Gross 1999] – *fitness for purpose*, where based on the specified measurement of performances (MOPs), the physical system is decomposed and influential entities' aspects and tasks are recognized and modeled in more detail.

The checklist-based frameworks are sort of guidelines that a modeler should follow while constructing a conceptual model. However, it is still more or less up to the modeler to decide what entities and with what level of detail to be incorporated into the model.

2. Fidelity frameworks with computation of fidelity metrics

Building a right model for a task at hand is to require that the *present fidelity* in the model matches as far as possible the *required fidelity* [DMSO 2000b]. These are characterized in terms of fidelity aspects (accuracy, precision, resolution) and needs to be quantified. The required fidelity is expressed in terms of tolerances, while the available fidelity can be measured. Comparing those, one can assess model fitness for purpose. Djunaedy in [2003] presents a decision-making criterion for finding a right model for a specific task that employs this kind of fidelity checks. The required tolerances and/or some threshold value are compared with sensitivity analysis results of the model. If comparison shows that the sensitivity of the variable (parameter) of interest falls within the required tolerance, the abstraction level of the model is said to satisfy and further model refinements are not necessary. However, if the model shows discrepancies with requirements, a less abstract modes shall be used.

Cascading accuracy, sources of uncertainty and fidelity differential frameworks [Gross 1999] attempt to use some sort of metrics for fidelity checking. One assumes that the errors and uncertainties introduced with the model are known in advance. The other directly compares the outcome of the model to the expected output, which is considered known. They all advice to use of a very broad range of techniques: from simple enumeration of factors via the use of expert opinion to the standard statistical techniques. The following section gives an overview of available techniques that might be used for this purpose.

MEASUREMENTS OF MODEL ACCURACY

Accuracy is an aspect of fidelity. There are techniques that enable model accuracy judgments. Here, we list some of the techniques that follow top-down approach, meaning that the fitness of the known model is estimated without considering higher resolution models.

Sensitivity analysis (SA)

There are many ways of performing sensitivity analysis. The main purpose of its use is to investigate how a change in models will affect its resulting predicted behavior over time and identifies the most influential inputs. In [Hamby 1994] more then a dozen SA methods are reviewed. Lomas and Eppel [1992] suggested three SA methods for use in building performance simulation programs, such as: differential, Monte Carlo and stochastic sensitivity analysis. De Wit [2001] and Macdonald [2002] investigated the importance of many input parameters in building simulation model predictions. In our case, the sensitivity analysis of input parameters that are recognized as simplifications between the models of different abstraction levels should be quantified. This approach is used by Djunaedy [2003], where extreme values are assigned to selected parameters and the uncertainty of examined outputs is evaluated. The author varied two parameters independently. However, in the case of HVAC simulation, the choice and number of variables varies with model abstraction level and is model specific, as will be shown in "worked out example".

Discrepancy driven refinement

Discrepancy driven refinement, on the other side deals with refining the model. So, it is a top-down approach. The approach starts with a simple model and retracts assumptions until model's fidelity reaches required level. It requires a great understanding of the models themselves. Also, stepping through the range of available components it might not always be clear what dimension or attribute of complexity is added when incorporating a "more complex" model. Enabling the use of this technique for our needs will require a detailed structuring of available models in the domain with specifying their differences along several axes of abstraction.

Bounding abstraction

Assume that we have two models [Weld 1992]: Q and P where Q is less abstracted model then P; and that the query looks like inequality represented as: Y<X. If the simpler model P, underestimates X, and/or overestimates Y and if the inequality is true for this model it must be true also for model Q. However, if the inequality is false, the model Q should be used to evaluate whether the reasoning from the simpler model is valid. However, the modeler that uses this technique has to determine whether variables in the query are over- or underestimated in the simpler model. If knowledge about over- or underestimation is available, the use of this technique is top-down: from simple towards more complex models.

Djunaedy in [2003], implicitly assumes that with assigning the value of a certain input parameter of the simplified model within an extreme range will assure that the simplified model over- or underestimates results compared to the less abstract model. However, this is not always true as will be demonstrated in the "worked out example" section. The implementation of this method is also limited to queries of the type X<Y.

Perturbation theory – norm-based sensitivity estimates

Matrix perturbation theory offers an analytic approach for sensitivity estimates calculation. It assumes that the system is represented in a matrix form. Perturbations are introduced to matrix coefficients and a bound of the solution vector is calculated [Stewart and Sun 1990]. The method is limited to solvers that hold system representation in matrix form and may overestimate the bounds. Thus it is not suitable for decisions that are as "strict" as ours in model abstraction checking.

Order of magnitude reasoning (OoM)

Raiman [1991] and Nayak and Joskowicz [1996] use order of magnitude reasoning. Knowing the relationships, estimation of the order of magnitude of a quality can be made and compared with the allowed order of magnitude. If the estimated OoM is below/above allowed OoM then a more detail model for that quality must be sought.

There is not an ideal model abstraction level checking procedure that will satisfy requirements of every level of HVAC model abstraction. A system model boundary (scope) and minimal granulation can be initially anticipated following the points in the checklists. To verify the sufficiency of chosen abstraction level some of the quantitative methods should be used. A specification with bounding abstraction can be applied whenever the model complexity and the nature of a simulation task allow. If not, differential sensitivity analysis on simplified variables would be the next step. The illustration of these steps is presented in "worked out example" section.

WORKED OUT EXAMPLES

The abstraction regarding the scope and aggregation of the models was tested in two examples below. The abstraction in the context of components models form is not considered. The metrics for model form abstraction checking are still to be researched.

Example 1

The first example concerns the modeling abstraction for a cooling system supplying a thermal zone with the query (simulation objective): *Assuming that the cooling capacity is 3kW; would the number of thermal zone overheating degree hours (above 25^{o}C) exceed the value of 150?*

We start from a conceptual checklist framework and try to define the conceptual model that satisfies the query. We consider all six points defined by Pace [2000]. We grasp that at least a model of the thermal zone and a model of a cooling source of capacity 3kW need to be included. Simulation needs to be performed at least on hourly basis. The results from the simulation (86 overheating degree hours) are shown as the first bar on Figure 3. However, the available cooling capacity can be lower due to heating losses in the system, thermal mass of the system, control strategy that fails to respond to the zone demand etc. All this information is hidden from the model and can be estimated through the uncertainty of the "bounding abstraction". To guarantee that this modeling abstraction level is appropriate for the objective, underestimates (simplification) of boundary abstractions (see section on measurements of model accuracy) are used. If the query again proves to be true, the complexity of the model for this task is consider adequate.

The second simulation with available cooling capacity of 2.9kW (3% underestimate) is performed. The results (125 overheating degree hours) are shown as the second bar on the Figure 3.

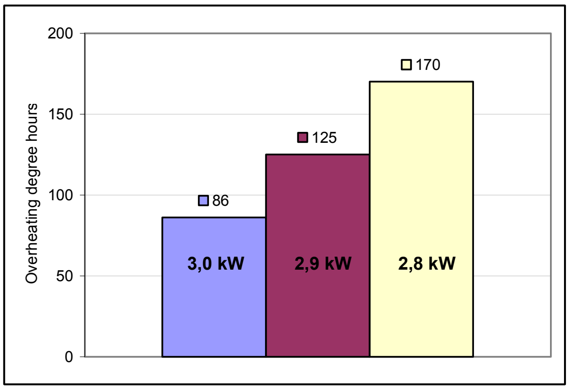

Figure 3 Fidelity check – underestimates of boundary abstraction technique

From the results we conclude that the model sufficiently accurate represent system's behavior. However, if we judge the uncertainty of cooling capacity to be higher (6.5%) then values of overheating degree hours are above the required limit (170dh) and the next model in complexity scale should be used to more accurately model the cooling system, as the results of the simpler are model cannot be trusted.

Example 2

The second example tackles the query: *Check whether a radiator with a nominal capacity of 6kW will at any time meet the heating demand of the target building, if the inlet water temperature linearly follows the changes in the outside temperature.*

Again, we go through all guidance points [Pace 2000] and we conclude that at least a radiator model with explicitly defined inlet water temperature and building component should be modeled and that the selected models should account algorithms for both heating demand and source capacity calculations.

In this case, the use of metrics based on simplification with bounding abstractions for checking whether the model could be even simpler – modeled on the highest abstraction level (conceptual model in context defined in [Hensen 1995] without explicit modeling of input water temperature) is limited by the scenario itself. If we underestimate the capacity of the heat source (the only system information for this level of modeling abstraction) the inequality: "demand" < "available capacity", if valid, only applies for nominal conditions and does not give sufficient information, since the "available capacity" will decline with possibly higher rate then the "demand" with changes in outside temperature.

To check whether the estimated model abstraction, with regards to model scope is sufficient, the differential sensitivity analysis or bounding abstraction can be employed to the parameters that define inlet water temperature. We assumed that the inlet water temperature is set according to the exterior temperature with water law: $T_{w\_inlet}=-a*T_{ext}+b$. The parameters *a* and *b* were "pessimistically" bounded with perturbation by 10% their original values. The number of hours when the zone temperature falls below 20^{o}C, with highlighting the hours below 19^{o}C is shown on Figure 4.

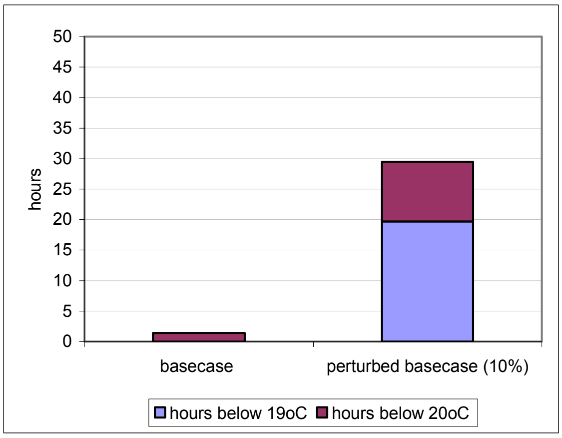

Figure 4 Fidelity check – underestimates of boundary abstraction technique

The pessimistic boundary abstractions show the worst-case scenario in regards to simplified parameters combination. If one is satisfied with the estimated bounds, he/she will not have to proceed to the lower model abstraction level. In opposite the other more detail model of the system is sought.

CONCLUSIONS

The concept of the conceptual modeling was introduced and a range of possible techniques that might be employed to construct conceptual models was defined. The simple worked out examples show how to use the chosen techniques and highlight the potential benefits of using a decision making tool for choosing the right modeling abstraction level for a given task. The bounding abstractions have a great prospective as a tool for model accuracy checking, but are also limited in their applicability to the query formulation.

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