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Past, present and future mathematical models forbuildings

FOCUS ON INTELLIGENT BUILDINGS (PART 1)

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This is the first of two articles presenting a detailed review of the historical evolution of mathematical models applied in the development of building technology, including conventional buildings and intelligent buildings. After presenting the technical differences between conventional and intelligent buildings, this article reviews the existing mathematical models, the abstract levels of these models, and their links to the literature for intelligent buildings. The advantages and limitations of the applied mathematical models are identified and the models are classified in terms of their application range and goal. We then describe how the early mathematical models, mainly physical models applied to conventional buildings, have faced new challenges for the design and management of intelligent buildings and led to the use of models which offer more flexibility to better cope with various uncertainties. In contrast with the early modelling techniques, model approaches adopted in neural networks, expert systems, fuzzy logic and genetic models provide a promising method to accommodate these complications as intelligent buildings now need integrated technologies which involve solving complex, multi-objective and integrated decision problems.

Keywords: buildings; intelligent buildings; mathematical modelling

INTRODUCTION

Mathematical modelling has been used for decades to help building scientists design, construct and operate buildings. In the development of technologies in the building industry, one of the most cited models is the heat conduction equation by Joseph Fourier published in 1822 (e.g. Lu et al., 2005a–c; Lu and Tervola, 2005). Building researchers have applied and extended the heat conduction equation to more complicated models for detailed thermal analysis of energy demands, passive design, environmental comfort and the response of control, especially since the energy crisis in 1973 (Mitalas and Stephenson, 1967; Stephenson and Mitalas, 1971). Other extension models have a similar partial differential equation basis describing underlying mechanisms, for instanceenergy and mass transport (Ben and Perre, 1988; Pedersen, 1992; Hartwig and Kurt, 1997; Haupl et al., 1997; Lu, 2002). Even more detailed and complicated models include the Navier- Stokes equations which describe the flow of fluids for air flow, temperature and contaminant distributions (Tsou, 2001). Various numerical techniques such as finite element method, finite difference method, boundary element method and computational fluid dynamics (CFD) are employed to handle these equations (Press et al., 1992).

Validating these models requires experimental data which can be difficult and expensive to obtain. Moreover, these models can be computationally intensive. This partly reflects the limitations of the early models but the situation is changing as computational power has increased several fold. New mathematical models are being developed that incorporate the early models to solve the large set of equations and to formalize the reasoning about uncertain knowledge in buildings. It is now possible that intelligent buildings can not only offer better control over various automotive features, but also have learning and adaptation abilities. We are facing a new era of an increasing demand for intelligent buildings worldwide.

It should be recognized that the development of intelligent buildings from conventional buildings is a continuous improvement process. No universal definition of intelligent buildings has been accepted, since the definition is still evolving, and there is no clear-cut difference between conventional and intelligent buildings. The definition was first brought out in the late 1970s when buildings were equipped with IT (Caffrey, 1998). It is now commonly acknowledged that an intelligent building should also be able to learn from its occupants and the environment and adjust its performance (Clements-Croome, 1997). Nevertheless, it can be loosely defined as a building integrated with information processing capabilities and intelligence, at each stage of its life – from design and construction through to lifetime management and use. Intelligent buildings have to be sustainable in terms of energy, water and pollution; provide healthy environmental conditions; optimize whole-life value and be responsive to the needs of occupants and organizations. This demands the measurement and analysis of objective and subjective data. Today, embedded technologies are being developed to link the building and its systems more closely to the occupants. The decision-making chain is complex and involves many stakeholders and each decision contains multi-variables. Traditionally this process is generally simplified to a linear dynamic model but in reality a non-linear dynamic approach is needed.

In this review we present a broad classification of mathematical models and approaches applied to developing intelligent buildings, but without the complex mathematical details. The review begins by examining technical differences between conventional and intelligent buildings. It proceeds to describe goals, expectations and application areas of some important mathematical models and then discusses the extent to which it is reasonable to expect these mathematical models to provide proper simulations. Ultimately it explores the gap between mathematical models applied to conventional and intelligent buildings.

In order to gain a better understanding of mathematical models to support the development of intelligent buildings, and to provide a basis for future work, the article provides a brief review of mathematical models applied in conventional buildings, but with a focus on mathematical approaches in intelligent buildings. The strengths and limitations of the applied mathematical models are discussed and new directions for future work are then explored. As an illustration, the feasibility of semiotics theory applied to intelligent buildings is demonstrated conceptually with the building's control system model. Moreover, the review is meant to be representative and attempts to cover all the promising mathematical methods that can be applied in the intelligent buildings field. The mathematical abstract level of the applied models is detailed and integrated with the most recently published literature; review papers are used wherever possible. Finally, by focusing on an example of intelligent buildings systems and the models that have been developed for such systems, we show how mathematical models have played an important part in integrating various control and management systems to maximize technical performance for intelligent buildings. This study tries to uncover new and potential evidence for other mathematical models which may be appropriate.

MATHEMATICAL MODELS FOR DEVELOPING INTELLIGENT BUILDINGS FROM CONVENTIONAL BUILDINGS…

Mathematical models address, first, the question of which components of the building system should be modelled and then the kind of equation that is used to represent the dynamics of each component. Up to now, many modelling approaches have been available and the techniques have become quite mature. However, only two extreme modelling approaches can be generalized.

The first one, called *physical models*,[1] builds up models entirely based on universal laws, physical laws and principles. The second approach, called *empirical models*,[2] constructs models entirely based on experiments or data. Pure physical or empirical models have both advantages and disadvantages (Estrada-Flores et al., 2006). Very often a combination of both models is adopted to compensate for their deficiencies as individual approaches. The final models are known as *semi-physical* or *grey box models*.

In physical models, partial differential equations governing mass, momentum, and energy transport describe the system components, for example, Navier-Stokes equations with CFD approaches. CFD models have been extensively used in many building applications such as ventilation (Gratia and De Herde, 2007; Norton et al., 2007), thermal comfort (Somarathne et al., 2005), indoor air quality (Guo, 2002), fire and smoke security (Lo et al., 2002; Delemont and Martin, 2007), and many others (Bartak et al., 2002; Stamou and Katsiris, 2006). CFD models are usually studied at steady state due to the difficulty, for example, in solving thermal interactions across the boundaries and its heavy computation load, especially for a building system with large-scale components and control processes with distributed parameters, interactions and multivariables. In fact, a balance between model complexity and the desired accuracy should always be a major consideration of any model. The selection of the modelling approach often determines the outcomes of this complexity and accuracy trade-off.

Therefore, dynamic, state-space and more simplified algebraic models are often adopted instead, which generally provide a less detailed assessment but take into account time-dependant internal and external environmental conditions. These can be entirely physical models with some simplified assumptions. For example, by assuming fully mixed, thermal conditions the thermal dynamics can be expressed as lumped capacity models written as differential equations (Tashtoush et al., 2005). Models combining physical and empirical approaches are also common (Nielsen and Henrik Madsen, 2006). This is advantageous since the physical knowledge reduces the model space, whereby the validity of the statistical methods is better preserved.

Although these models, say physical models for simplicity, were originally developed to simulate conventional buildings, we believe that they can also succeed to varying degrees in modelling intelligent buildings (see CFD application in intelligent buildings, Malkawi and Srinivasan, 2005). Given the fact that the difference between conventional and intelligent buildings is only a matter of how advanced building systems are, we try to explore the major discrepancies of mathematical models between conventional and intelligent buildings.

…TO INTELLIGENT BUILDINGS

The most difficult part of reviewing mathematical models for intelligent buildings is that of defining what it is meant by intelligent buildings compared with conventional buildings. Indeed, there is no general agreement on definitions for intelligent machines or human behaviours. The Turing test is one of the earliest proposals for a test of a machine's intelligence capability described in Professor Alan Turing's paper 'Computing machinery and intelligence' in 1950. The test involves two persons as well as a 'tested' computer. Using the terminal, a person communicates with both computer and another person. When the person is unable to tell who is who, then the machine is said to pass the test. The Turing test clearly emphasizes that the machine's intelligent behaviour should be similar to human behaviour. Ill-definition, uncertainty and multiple objectives are primary characteristics of human decision-making processes in contrast to a machine's behaviour. Pure physical approaches and so-called physical models as applied to conventional buildings cannot model human behaviour-based systems.[3] Mathematical modelling approaches which have uncertainty and flexibility characteristics, such as neural networks, expert systems, fuzzy logic and statistical models, offer much better ways of representing human behaviour. Recent advancements in artificial intelligence are making it possible to integrate buildings' learning and adaptation capabilities into these uncertainty mathematical models (Hong et al., 2000). Note that, here, we viewed intelligent buildings as machine-based systems and generalized their modelling paradigm.

Let us focus on intelligent buildings research to try and pinpoint more suitable mathematical models. According to Carlini (1988a, b), Arkin and Paciuk (1997) and Wong et al. (2005), a major technical difference between conventional and intelligent buildings is that intelligent building technologies are characterized by a hierarchical presentation of system integration. Most intelligent buildings comprise three levels of system integration. The top level deals with the provision of various features of *building operation* and *communication management*. The middle level is performed by the *building management systems* which control, supervise and coordinate the building's relevant subsystems. These subsystems comprise the bottom level. Intelligent buildings allow interaction and integration among the subsystems. The subsystems are services systems typically including heating, ventilation and air-conditioning (HVAC), lighting, transportation, security and *communication systems. The middle level's control systems can vary from traditional hard- wired relay-logic ones for conventional buildings to computer-controlled microelectromechanical systems for intelligent buildings. The middle and bottom levels also characterize the performances of conventional buildings. Figure 1 illustrates the hierarchical levels of buildings in relation to corresponding mathematical models.*

The authors of this article argue that the most important difference between intelligent buildings and conventional buildings is that intelligent buildings have the ability to integrate their service systems to learn and adjust their performance appropriately; this is an essential feature of any 'intelligent' system (Kasabov, 1998).4 The integration and learning capabilities are performed using frameworks5 which can be quite complex since they include consideration of not only information flow, timing and non-deterministic human behaviour, but also integration of various problem-solving methodologies in order that the building can learn from its occupants and environment and adjust its performance (Power and Bahri, 2005). In controlling such complex systems, which include subjective responses and non- deterministic aspects of human behaviour, we need uncertainty models such as neural network, fuzzy logic and genetic algorithm models.

Consider wider applications such as, intelligent manufacturing. This can be broken down into two major areas based on its level of application, namely strategic and tactical intelligent manufacturing. The two areas are linked hierarchically through a semantic network (Byrd and Hauser, 1991; Gholamian and Ghomi, 2007). An illustration of such a breakdown structure for intelligent buildings has been demonstrated by Chen et al. (2006) and Clements-Croome et al. (2003). Gholamian and Ghomi (2007) reviewed basic and important mathematical models called frames, covering manufacturing aspects such that each frame informs applications of intelligent systems in various aspects. These frames are essentially uncertainty models, such as neural networks, expert systems, fuzzy logic and genetic algorithm models.

Last, from the technology and investment point of view, efficiency assessment and investment considerations are needed in order to increase the number of buildings incorporating intelligent building concepts. Clearly, costs and benefits have to be identified and generalized before the evaluation with any type of method. Many authors have attempted to use various approaches, though simplified and deterministic mostly, to identify and classify various costs associated with intelligent buildings, but now emphasize whole life value (Clements-Croome et al., 2007). The identified costs and values range from technological factors to management factors and many others (Flax, 1991). In the investment evaluation area, a plethora of evaluation techniques have been developed to investigate and evaluate the economic desirability of intelligent buildings (Wong et al., 2005). These techniques, in a similar fashion to those applied in cost identification and classification, are based on the 'time-cost-money' principle which clearly involves uncertainty. A general review of this topic has been reported by Wong et al. (2005). In this report, uncertainty mathematical models such as fuzzy logic, analytic hierarchy process (AHP), multi-criteria decision-making method etc. have been recommended, though few applications of these methods have been found yet. AHP has been used for self-assessment of productivity (Li, 1998).

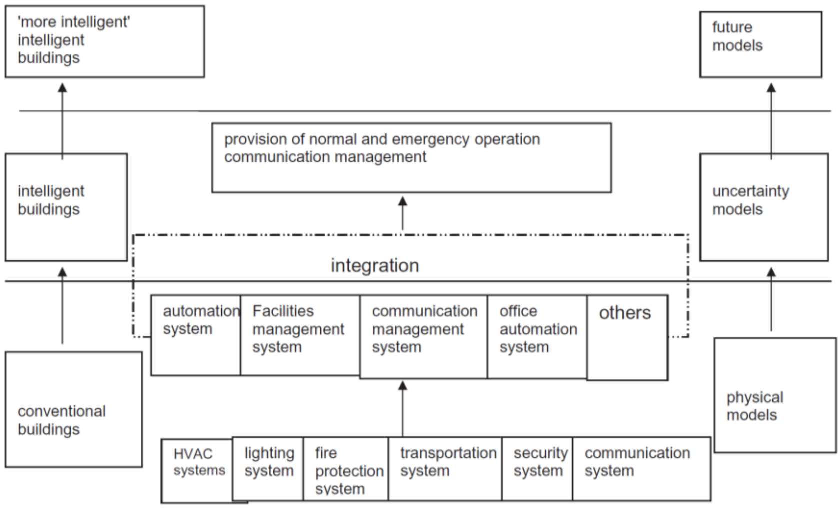


FIGURE 1 Hierarchical levels of buildings in relation to corresponding mathematical models; historical evolution of building technologies and applied mathematical models

TABLE 1 Classification of mathematical approaches applied in intelligent buildings

Conceptual models	**Probability-based models**
Simple analytical approach	AHP/ANP
	Bayesian inference
	Petri nets
Analytical models	**Knowledge-based models**
Linear dynamic approach	Neural networks
Non-linear dynamic approach	Expert systems
	Fuzzy logic
	Genetic algorithm

MATHEMATICAL APPROACHES

Having identified and proved the suitability of uncertainty models in intelligent buildings modelling from different viewpoints (building development, intelligent building research, intelligent manufacturing, intelligent building investment), a summary of general mathematical models is presented in this section. The literature of uncertainty models applied to intelligent buildings is rich. A variety of approaches has been proposed to handle different forms or degrees of uncertainty. By choosing to detail at an abstract level, four model classes can be generalized: *conceptual* models, *analytical* models, *probability- based* models and *knowledge-based* models as presented in Table 1. The proposed classification is certainly not exhaustive, and the first two categories have been extensively used for modelling conventional buildings. Nevertheless, each model category will be discussed in detail and the most relevant literature cited.

CONCEPTUAL MODELS

A conceptual model illustrates multiple factors and their possible relationships for analysing the main factor effect. The concept of *'main factor'* is used to embrace any uncertainties. The main factor therefore is a function of other factors. In simple case studies, such function can be explicitly defined and is often a simplified, deterministic and algebraic formula.

Wong and Li (2006) proposed a conceptual model for the selection of an appropriate combination of building systems and components for a particular intelligent building project, based on a questionnaire. They first determined the key attributes affecting the selection of the building systems and components based on a literature review. A structured questionnaire was then constructed which required the respondents to rate the influence of the predetermined attributes based on their judgement and experience. A statistical 'significance test' was employed to identify the rank of these attributions, which led to the final conceptual model.

In assessing intelligent building performance based on the degree of systems integration, Arkin and Paciuk (1997) proposed a simple index, *magnitude of* system integration (MSI), to evaluate and compare systems' integration.

In evaluating investment performance of intelligent buildings, many models for life-cycle cost analysis and cost–benefit analysis are based on the conceptual model of *net present value method* (Akalu, 2001).

ANALYTICAL MODELS

The analytical approach generally involves detailed mathematical models. Model equations can be based on first principles preferably, dynamic, linear, state-space, non-linear and statistically empirical equations. Perhaps the most important models are dynamic models, as building researchers are not simply interested in the steady states of building performance, but also in the mechanisms of change that lead from one state to the next.

Linear dynamic models

Many building systems can be modelled with linear dynamic models (LBNL, 1982; Solar Energy Laboratory, 2000; Crawley et al., 2001; Strand et al., 2001). Model parameter estimation, termed *modal analysis,* is the common approach to performing linear modelling. Model equations are in the form of model parameters which can describe the behaviours of a system for various inputs and outputs. The linear superposition principle is the cornerstone which is well developed for linear systems. Using this principle, various theories and methods for dynamics and system identification have been developed such as *eigensystem realization method* (Stephenson and Mitalas, 1971; Hittle and Bishop, 1983); *state-space method* (Jiang, 1982); *time-domain method* (Davies, 1997) and *frequency-domain method* (Wang and Chen, 2003) to cite a few.

The application of linear dynamic models in intelligent building studies includes, for example, Ng and Xu's work (2007), which investigated control of a building complex for an intelligent building, consisting of a main building and a podium structure, by using variable friction dampers for mitigating seismic responses.

Non-linear dynamic models

Non-linear dynamic models have been used extensively in simulating building services systems (Bourdouxhe et al., 1998; Pasgianos et al., 2003; Jin et al., 2006; Stables and Taylor, 2006). Apart from the service systems, we frequently need to model human behaviour and performance for intelligent buildings in order to understand and improve human performance in building settings. Human behaviour results from the interaction of people's generic, physiological and psychological attributes with the environment. Human behaviour is unpredictable and should always be coupled with environment events. Complicated behaviour cannot be modelled using linear dynamic models. In addition, non-linear dynamic models can account for marked individual differences in response to different environmental factors. This is because the equations that describe the system are sensitive to the initial starting behaviour conditions. For two slightly different initial sets, their states may quickly diverge (Howe and Lewis, 2005). *Chaos* can result.

Other modelling studies on intelligent buildings include, for example, building life-cycle cost analysis. Both initial construction expenses and lifetime costs need to be appropriately addressed. The lifetime costs include those due to business utilization, operation, maintenance, repair, damage and/or failure consequences, and also impact on business such as improved productivity (Clements-Croome et al., 2007). Aleatory and epistemic uncertainties should also be considered in probabilistic performance evaluation of the structures (Cornell et al., 2002). These uncertainties refer to the record-to-record variability and the lack of sufficient knowledge in emergent events. The system stability can be altered such that some states become less preferred and less reliable, while others become more stable and dominant. *'Phase transition'* is often used to characterize such phenomenon. Bifurcation can be encountered.

These features clearly exhibit non-linear behaviours which will be addressed briefly later in this section. Indeed, non-linearity is generic in nature and linearity is only an exception. However, the main reason why often-linear behaviour is taken for granted is that non-linear dynamical systems are far less established than linear systems. The basic linear superposition which is applied to linear systems and forms the basis of model parameter estimation is no longer valid for non-linear systems. Complicated phenomena can be found in non-linear systems such as jumps, limit cycles, bifurcations and chaos of a highly individualistic nature (Kerschen et al., 2006).

The traditional linearization approach of analysing non-linear systems is based on the assumptions of weak non-linearities, but these may lead to erroneous results (Kerschen et al., 2006). Therefore, identification of non-linear systems is of vital importance. The identification approaches can be classified as *linearization, time-domain methods, frequency-domain methods, modal methods, time-frequency analysis, black-box modelling and structural model updating*. Once non-linear behaviour has been detected, model parameters can be estimated using optimization tools such as *linear programming, non-linear programming* and *dynamic programming*.

Using time-domain methods, Ríos-Moreno et al. (2007) identified non-linear behaviours of indoor temperature variations for intelligent buildings. They then compared two time-series models: linear autoregressive models with external input (ARX) and autoregressive moving average models with external input (ARMAX) for forecast purposes. Outside air temperature, global solar radiation flux, outside air relative humidity and air velocity were used as the input variables. The result showed that the ARX models gave a better prediction.

PROBABILITY-BASED MODELS

Probability-based approaches are often used to represent uncertainty and deal with multicriteria decisions. The AHP, its generic form *analytic network process* (ANP) and *Bayesian analysis* are commonly applied in studying intelligent buildings.

AHP/ANP

AHP, developed by Saaty (1980) and Yager (1979), is used to derive ratio scales from both discrete and continuous paired comparison in multilevel hierarchical structures. It is a method employed to integrate perceptions and purposes into an overall synthesis. Box 1 summarizes the steps followed in the AHP and ANP approaches (Saaty, 1996; Cheng and Li, 2004, 2005; Yurdakul, 2007). Bayesian inference

Bayesian analysis is an iterative process of integrating accumulating knowledge in order to best judge a future event based on a series of prior situations. It provides updating information in the form of possibilities using Bayes' theorem, a statement in probabilities relating causes to outcomes, as shown in Box 2. It has broad application in a multitude of scientific, technological and policy settings.

BOX 1 A brief summary of the AHP/ANP model

1. Developing the structure of the model.*
2. Conducting pair-wise comparisons on the clusters and sub-clusters.
3. Calculating elements and consistency ratio of matrices.**

* The objective of the model is further decomposed into clusters and sub-clusters. AHP is restricted to hierarchical. ANP is a network structure where the hierarchical restriction can be relaxed.

** ANP has specific steps for generating the global priorities for elements; see references.

BOX 2 Bayes' theorem

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)}$$

$P(A|B)$ is the probability of event A, given the occurrence of a second event B with unconditional probability $P(B)$. $P(A \mathscr{I} B)$ is the joint occurrence probability.

Petri nets

One useful mathematical model applied in intelligent systems is Petri nets and after this there has been a number of extensions. Petri nets consist of places, transitions, and arcs that connect them, and are very useful for modelling discrete dynamic systems. Petri nets are a promising tool for analysing systems that are characterized as being concurrent, synchronous, distributed, parallel, non-deterministic, and/ or stochastic. These features are particularly important in building services systems. With Petri nets, it is possible to set up state equations, algebraic equations, and other mathematical models governing the behaviour of systems.

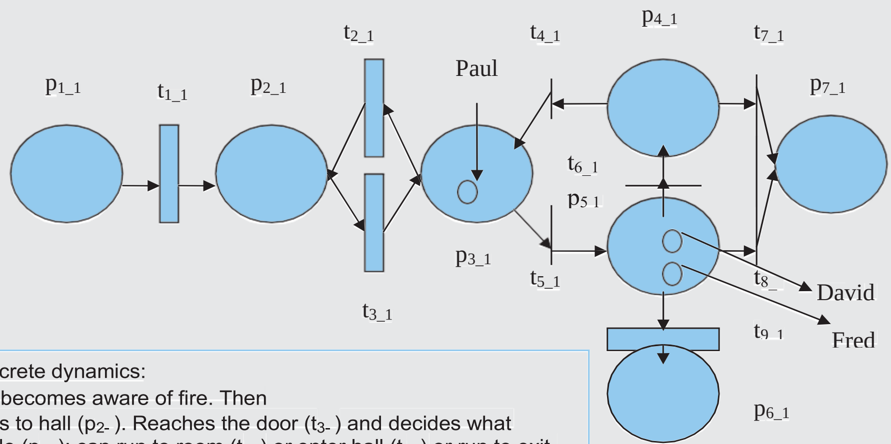
Box 3 presents an example of the Petri netsdescribing the discrete dynamics of the class. This class models the behaviour of a personescaping from a hall (Villani et al., 2006).

Villani et al. (2006) analysed control strategies for fire safety systems of intelligent buildings. The components of whole fire safety systems presented different dynamic natures, such as continuous and discrete dynamics, and therefore a hybrid-modelling model was applied. A Petri nets model was used to describe the discrete dynamic components.

Chen et al. (2006) adopted the ANP model to evaluate lifetime energy efficiency of intelligent buildings. Based on literature and a conceptual model of intelligent building evaluation and renovation, the authors started with an energy-time consumption index and chose its approximated gradient, presented as a simple index function, as a sub-cluster. Its clustered index, called the *key performance indicator*, was rated through the ANP approach. Su et al. (2005) discussed Petri nets-based supervisory control theory in discrete event systems. Such a system is a type of dynamical system created along with the development of computer science, communication networks and sensor technology. The system has been widely used in intelligent buildings.

Makarenko and Durrant-Whyte (2006) proposed an active sensor network which combines decentralized information fusion and decision-making into a unified flexible framework using a Bayesian approach. Such a framework is suitable for sensing information applicable to intelligent buildings.

BOX 3 An illustration of the discrete dynamics model of class (Villani et al., 2006)



Discrete dynamics:
t_{1-} becomes aware of fire. Then
runs to hall (p_{2-}). Reaches the door (t_{3-}) and decides what
to do (p_{3-}): can run to room (t_{2-}) or enter hall (t_{5-}) or run to exit
(p_{5-1}). If enters the hall, may change direction (t_{6-}) and run back to
the room (p_{4-1}). While in the hall, the person may die (t_{7-} or t_{8-}) or
reach exit (t_{9-}). Currently Paul is at the entrance of the hall, David
and Fred are running to the exit.

KNOWLEDGE-BASED MODELS

Since knowledge-based models are uncertainty models which are often applied for intelligent decision support and control, they are suitable for modelling the increased complexity in intelligent building systems and therefore are being extensively applied in such fields. Further details, including model complications, will be discussed in the following subsections.

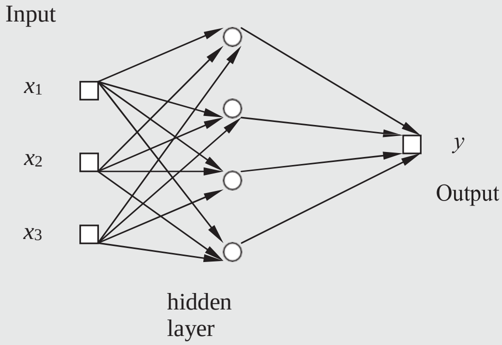
Neural networks

Motivated by the structure of the human brain, neural networks are composed of simple elements, so-called neurons, operating in parallel. These elements are quite similar to brain neurons, which can process massive amounts of information in parallel. Neural networks are largely determined by the connections between elements, and their structure has to be determined from external stimulus data (Cheng and Titterington, 1994).

Box 4 illustrates a simple example of neural networks with three inputs, one hidden layer of neurons containing four nodes and one output. Such neural networks system can be considered as a system connecting inputs and outputs in a possible linear or non-linear way through hidden layers. In Box 4, arrows indicate the direction of each relation.

The neural network approach has been widely used in pattern recognition applications. The goal of neural networks is to adjust weights by training examples to perform a particular task. Mathematically, this particular task often means minimizing a cost function which measures how close predicted values are to target values. However, the required number of training examples is often combinatorially large meaning combinatorial complexity of learning requirements. This complication, known as *'the curse of dimensionality'*, was first identified in pattern recognition research in 1960 (Bellman, 1961).

BOX 4 An illustration of a neural network model



Let weight w_{ij} connect between input x_i and neuron in the hidden layer through activation function g. Similarly, weight w'_j connects between neuron and output y through activation functions f and g. Then,

$$y = f(\sum_j w'_j \, g(\sum_i w_{ij} x_i))$$

Expert systems

An expert system collects human expertise and transfers it to a computer for decision-making. The computer-stored knowledge can be called on by users for advice. The computer can make inferences and arrive at a specific conclusion. Hence an expert system acts as an expert consultant and provides powerful and flexible means for obtaining solutions to a variety of problems that cannot be dealt with by other traditional approaches.

A rule-based expert system was first introduced in 1970 (Winston, 1984) to solve the problem of combinatorial complexity of learning requirements in neural networks. The idea behind the system was that the rules could capture knowledge without learning (Perlovsky, 2006). A rule-based expert system contains information such as IF-THEN. However, with the number of rules growing, such a system suffers from combinatorial complexity of rules.

Other types of expert systems, called knowledge-based systems, began in the 1980s (Perlovsky, 2006) and combined advantages of rules with learning adaptation to target the problem of combinatorial complexity of rules in rule-based expert systems. The learning adaptation is accomplished by fitting model parameters, which requires selecting data subsets corresponding to various models. The number of subsets can be combinatorially large. The systems have combinatorial complexity in the computation processes.

Fuzzy logic

In parallel research, fuzzy logic was introduced in the 1960s and presents the process of making decisions by simulating human reasoning, characterized by uncertainty and imprecision (Zadeh, 1965). The approach is useful because process description is not always a matter of black and white, true or false like classical Boolean logic. Therefore, fuzzy logic provides a simple way to arrive at a conclusion based on vague, ambiguous and imprecise data. Take an example: the rule $A \Rightarrow B$. If A is not observed nothing can be inferred in classic logic. However, if 'nearly A' is observed, a conclusion can be drawn (and precisely constructed), which can be expressed as 'nearly B' in fuzzy logic. The idea can be used to monitor systems what would be difficult or impossible to model with classical logic ideas. In fuzzy logic, an element can belong partially to several subsets using a membership function as illustrated schematically with a simple example in Box 5.

One of the classical uses of fuzzy logic is the design of fuzzy rules which can be interpreted from linguistic rules like temperature 'low', 'medium' and 'high'. Fuzzy logic systems treat the imprecision of inputs and outputs by defining them with fuzzy memberships and sets. Fuzzy logic encounters a problem of degree of fuzziness. If too much fuzziness is specified, the solution does not achieve a good accuracy; if too little, it becomes formal logic. Therefore, it is difficult and time-consuming to determine the correct set of rules and membership functions for a complex system; fine-tuning a fuzzy solution can be time-consuming too. This presents a combinatorial complexity problem.

To resolve these weaknesses, expert systems, neural networks and genetic algorithms are often combined to learn the best membership functions through training algorithms, as demonstrated by Mendel and John (2002).

BOX 5 An illustration of definition and properties of a membership function

Definition

set X : $x \in X$; membership function $\mu_A(x)$: $X \rightarrow [0,1]$

- fuzzy set A is defined by $\mu_A(x)$ which takes values in the interval of [0,1].
- for x, if $\mu_A(x) = 1$ then x fully belongs to A.
- for x, if $\mu_A(x) = 0$ then x does not belong to A.
- of course the intermediate cases interest us.

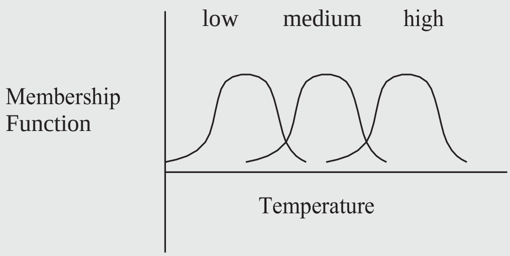
Properties

The general properties of classical sets can also be extended to fuzzy sets, e.g. for fuzzy sets A and B

$$\mu_{A \cup B} = \min\{\mu_A(x), \mu_B(x)\}$$

$$\mu_{A \cap B} = \max\{\mu_A(x), \mu_B(x)\}$$

$$\mu_{\bar{A}} = 1 - \mu_A(x)$$



Genetic algorithm

A genetic algorithm, belonging to evolutionary computation, is a method for solving optimization problems originally inspired by biological evolution (Goldberg, 1989). A genetic algorithm encodes a potential solution to a specific problem to a chromosome-like structure and applies recombination operators to these structures in order to preserve critical information. A genetic algorithm starts with an initial population and then selects parents to produce the next generation using specific rules. Three main rules are shown in Box 6. Over successive generations, the population evolves towards an optimal solution. A large number of iterations may be needed for a genetic algorithm to develop an optimal solution which is again a combinatorial complexity problem.

Intelligent buildings provide a wide range of expert system applications. La Roche and Milne (2004) developed a microcomputer-controlled thermostat as an intelligent component for intelligent buildings based on simple rule-based decisions. Such controllers can manage air flow according to cooling needs in a building and the resources in the environment. Sacks et al. (2000) studied knowledge-based models for the structural design of buildings. They created *intelligent parametric templates* within an automatic building system. The template was applicable for rectangular plane building types. Liu et al. (2004) developed a domain name system (DNS) intelligent management system using a knowledge-based system and ontological engineering technologies which can both be extended to intelligent buildings applications.

Moreover, combinations of two or more knowledge-based approaches are common, especially when applying fuzzy logic models. Tani et al. (1998) developed an optimal adaptive and predictive control system and its digital simulations for a five-degree-of-freedom system subjected to earthquake loading for intelligent buildings. Prediction of earthquake input and structural identification were performed by using neural networks and a genetic algorithm. Optimization was carried out by means of maximizing decision using fuzzy logic approaches.

Rafael Alcalá et al. (2005) proposed intelligent HVAC control for intelligent buildings by using weighted linguistic fuzzy rules in combination with genetic algorithms for a rule selection process. Lo et al. (2007) did similar work for automatically detecting faults on HVAC systems. Sierra et al. (2006) proposed an intelligent system architecture based on neural networks, expert systems and agent technologies to improve the performance of intelligent buildings.

The central computer, containing a database for information and the expert system for decision- making, carried out monitoring, visualizing and recording parameters while local controllers performed regulation throughout the building. The information about relevant occupancy and setting conditions, as well as the final values of environmental variables, was used to train a multi-layer neural network, the outcomes of which would provide environmental setting values in the case of absence of occupants or of preference information.

BOX 6 A brief summary of the genetic algorithm approach

- Select individuals that contribute directly to the population at the next generation (selection).
- Combine two parents to form children for the next generation (cross-over).
- Make random change to parents to form children (mutation).

CONCLUSION

This article has reviewed the historical evolution of mathematical models applied in the development of building technology, including conventional buildings and intelligent buildings. *Physical models* (or semi-physical models) have played an important role in understanding mechanisms of buildings and generating and testing hypotheses. They are widely applied in conventional building controls. *Knowledge-based uncertainty models* are a plausible approach to modelling intelligent building systems which have poor definition, uncertainty and multiple objectives – characteristics similar to human decision-making processes.

In the next issue, Part 2 of this article will discuss some models and show the advantages of approaches such as semiotics and chaos before drawing up a final set of conclusions.

NOTES

1. The models are also known as ‘mechanistic’, ‘phenomenological’ and ‘first principle’ models.
2. The models are also known as ‘black box’, ‘statistical’ or ‘input and output’ models.
3. Recent development of physical theories has great potential in modelling human behaviours by classical physics mechanism, see Perlovsky (2006).
4. According to the latest trends in the field, intelligence in building systems tends to be distributed (So, 1999).
5. Sometimes called model architectures, module architectures or system architectures. It can be considered as one type of mathematical conceptual model, which is discussed in Part 2.

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