RESEARCH ARTICLE

Development of intelligence analytic models for integrated building management systems (IBMS) in intelligent buildings

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With the availability of innumerable 'intelligent' building products and the dearth of inclusive evaluation tools, design teams are confronted with the quandary of choosing the apposite building control systems to suit the needs of a particular intelligent building project. The paucity of measures that represent the degree of system intelligence and indicate the desirable goal in intelligent building control systems design inhibits the consumers from comparing numerous products from the viewpoint of *intelligence*. This article is designed to develop a model for facilitating the system intelligence analysis for the integrated building management system (IBMS) in the intelligent building. To achieve these objectives, systematic research activities are conducted to first develop, test and refine the general conceptual model using consecutive surveys; then, to convert the developed conceptual framework to the practical model; and, finally, to evaluate the effectiveness of the practical model by means of expert validation. The findings of this study suggest that IBMS has a distinctive set of intelligence attributes and indicators. The research findings also indicate that operational benefits of the intelligent building exert a considerable degree of influence on the relative importance of intelligence indicators of the IBMS in the model. This research suggests a benchmark to measure the degree of intelligence of one control system candidate against another.

Keywords: integrated building management system; intelligent building; model; system intelligence

INTRODUCTION

There is little doubt that there has been widespread implementation of intelligent building technologies in many contemporary building developments. The desire for an effective and supportive environment within which an organization can reduce energy consumption, improve worker productivity, and promote maximum profitability for their own business has stimulated the growth of highly adaptable

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and responsive buildings (Clements-Croome, 2001a). Recent years have seen a variety of intelligent building control products developed and introduced to the market, designed to enhance building 'intelligence' performance and environmental sustainability, and to satisfy a variety of human needs. They are designed to provide environmental control, mobility, communications, facilities, fire protection and security in the intelligent building. With the availability of a myriad of so-called 'smart' or 'intelligent' building control systems over the last decade, the adjective 'intelligent' has been widely adopted to describe the intelligent property of the building control products. However, the perspectives and understandings of 'intelligence' are still so abstract and ambiguous that it leads to a concern about the abuse of the term 'intelligent' without making any effort to clarify what the 'intelligent' building control system should be (Schreiner, 2000).

Though the study of machine intelligence has been attempted in other closely related areas, such as in intelligent robots and machines (Park et al., 2001; Bien et al., 2002), there is a paucity of research that has investigated the system intelligence of intelligent building control systems and developed general analytic models. Previous intelligence evaluation models in intelligent building research are also limited to the assessment of the overall intelligence of the intelligent building, without examining the intelligence of the building control systems inherent in it. Therefore, it is important that the current imbalance towards the evaluation of the system intelligence of intelligent building control systems be redressed. The development of an effective formal method for determining what is in an 'intelligent' building control system or for measuring its performance provides the discipline of building control with a more formal definition and classification of what constitutes 'intelligence' of the building control systems. The developed intelligent measures can also be used to provide benchmarks for system performance, and to assist users and designers of systems to better understand the benefits of one control system versus another.

With the limitations and deficiencies of the current research in mind, the purpose of this research is to investigate and develop a list of intelligence indicators for an integrated building management system (IBMS) in commercial intelligent buildings (i.e. office buildings), and is conducted within the context of intelligent buildings in Hong Kong. The specific objectives of this research are to perform the following:

- develop a general conceptual model that incorporates 'suitable' intelligence attributes and indicators for evaluating and assessing the degree of intelligence of each of the key IBMS'
- test and refine the general conceptual model developed in (1) by testing the level of importance of the intelligence indicators
- develop a practical model of IBMS intelligence performance analysis
- validate and check the robustness of the practical model developed in (3).

The methodology of this research is set out and reported in five steps. First, a review of existing intelligent building literature was conducted to choose and determine the intelligence indicators, and to set up the general conceptual model for the system intelligence analysis. This conceptual model was then tested and refined by means of two consecutive questionnaire surveys – i.e. a general survey and a survey combining the analytic hierarchy process (AHP) and the analytic network process (ANP). Then, the refined conceptual model was transformed into a practical model in order to demonstrate its practicability for intelligence performance appraisal. Finally, the practical model was validated by experts in order to check its robustness and to examine whether it could simulate the decision of experienced intelligent building experts.

LITERATURE REVIEW

EXISTING BUILDING INTELLIGENCE ASSESSMENT METHODOLOGIES

For the past decade, building intelligence has been increasingly perceived by developers as a unique and important measure to reflect the specific performance and properties of intelligent buildings. The models of building intelligence evolve from early intelligent building performance evaluation studies and refine them. Examples of pioneer building intelligence rating methods include the Orbit 2.1 (Davis et al., 1985), post-occupancy evaluation (Preiser et al., 1988), building-in-use assessment methods (Dillon and Vischer, 1987), BREEAM (Baldwin et al., 1990), and environmental impact analysis (Rau and Wooten, 1980). However, these models delved more specifically into the environmental impacts and the evaluation of physical parameters. Boyd and Jankovic (1994) argue that these approaches insufficiently reflect the degree of intelligence of a building. In addition to these earlier studies, a number of studies have been developed within the last 15 years, for example, building IQ (Boyd and Jankovic, 1994); magnitude of systems integration (Arkin and Paciuk, 1995); and reframing and building the intelligent assessment index (Smith, 1999). Besides the works of these academics, a number of professional institutes (for example, AIIB, 2001, 2004; IBSK, 2002; CABA, 2004) have published their intelligent performance assessment tools and standards for intelligent buildings.

Given the above literature review, it can be seen that the majority of the past research in building intelligence has been limited to assessing the overall intelligent performance of buildings and classifying them into particular forms of simplified and generic indexes of intelligence (Wong et al., 2005). Little has been done on the assessment of the system intelligence of building control systems. As a plethora of intelligent components and products have been introduced and made available in the building markets over the last 20 years, the adjective 'intelligent' has been extensively applied to portray the smart properties of building system products. Manufacturers of intelligent technologies often claim their systems are more intelligent than others of their kind, but these assertions tend to be vague and unjustified (Bien et al., 2002). Considering the existing problems in the research as well as in practice, a new index that represents the degree of system intelligence and indicates the desirable goal in designing intelligent building control systems must be developed (Schreiner, 2000; Park et al., 2001). Therefore, the important issues are to investigate and determine how to measure system intelligence, and to determine the key intelligence indicators for assessing degrees of system intelligence of the building control systems in intelligent buildings.

A REVIEW OF EXISTING MACHINE INTELLIGENCE MEASUREMENT

While there is a dearth of research investigating the degree of intelligence of building control systems in intelligent building and construction literature, some closely related studies in machine intelligence measurement have been documented in engineering literature over the past decade (Bien et al., 1998, 2002; Szu, 2000; Park et al., 2001). For example, in the 1990s Saridis and his colleagues (Saridis, 1988; Valavanis and Saridis, 1992; Lima and Saridis, 1993, 1996) developed a series of analytical models to describe and control various functions of intelligent machines according to the 'principle' of increasing precision with decreasing intelligence. Zadeh (1994), in his discussion paper, identifies the key factor in making machine intelligence as the use of soft computing techniques to mimic the ability of the human mind, in effectively employing modes of reasoning which are approximate rather than exact. Despite these efforts, Antsaklis (2000) and Bien et al. (2002) criticize early studies in machine intelligence for being focused on developing a way to make a system or a machine more intelligent. Little attention is paid to the measurement and assessment of the degree of intelligence in existing systems or machines.

In recent years, a breakthrough has been recorded in machine system research. In an investigation of the intelligent characteristics of a controller, Zames (reported by Antsaklis, 2000) developed a machine intelligence quotient (MIQ) to measure the task performances that an intelligent controller can achieve compared to those achieved by a classical controller. While Zames's work was an important initial step in establishing the benchmark for machine intelligence measurement, Antsaklis (2000) argued that the challenge in the quotient development is related to the 'characterization of performance in unknown environments, learning, controller and task complexity, and associated tradeoffs'. On the other hand, Szu (2000) proposed a machine IQ measure of a logarithmic-like nonlinear but monotonic scale with up to 50% of the measurement based on the supervised learning capability. The work of Szu is interesting and innovative, but it is considered rather subjective in nature (Bien et al., 2002). Bien et al. (2002) argue that intelligence is an entity related to complex and unstructured phenomena, and is not a straightforward activity that can easily be measured. Based on the ontological and phenomenological points of view on intelligent machines, Bien et al. (1998, 2002) recently developed a revised MIQ. Details of the model of machine intelligence proposed by Bien et al., are discussed in the following section.

THE MACHINE INTELLIGENCE QUOTIENT (MIQ)

Bien's machine intelligence model (Bien et al., 2002) generally includes four key attributes of machine intelligence, which were identified from a vast review of intelligent control system literature. These four key intelligence attributes are:

- autonomy
- man–machine interaction
- controllability of complicated dynamics
- bio-inspired behaviour.

Autonomy refers to a machine's ability to perform self-operative functions (Bien et al., 2002). According to Liu et al. (2005), autonomy is generally considered as the condition or quality of being:

- autonomous and independent
- self-governing or having the right of self-government, self-determining and self-directing.

This implies that an intelligent system should be designed in a manner that as much as possible allows minimum human intervention during the execution of a task. Bien et al. (2002) argue that there are four key autonomous features or indicators of intelligent systems. These are:

1. self-calibration
2. self-diagnostics
3. fault-tolerance
4. self-tuning

A second key attribute of intelligent systems and machines is the level of man–machine interaction. This is related to the ability of an intelligent system to interface with operator and working staff, making the human users feel more comfortable and the system more user-friendly (Bien et al., 2002). Bien et al. (2002) suggest that the intelligent machine and system should possess a number of important man–machine features (or indicators): ergonomic design, emergence of artificial emotion, and human-like understanding or communication. In addition, Bien et al. (2002) argue that the third key attribute of intelligent machines or systems is their level of control over complicated dynamic systems. A system is considered 'intelligent' when it possesses the ability to perform interactive operative functions and is able to make a very complicated dynamic system well controlled. The last attribute of intelligent systems is the existence of bio-inspired behaviour in the system. According to Bien et al. (2002), this relates to the system's capability of showing bio-inspired behavioural traits, and the system's ability to interact with the building environment and the services provided. Bien et al. (2002) also point out that an intelligent system should exhibit a number of bio-inspired traits: biologically motivated behaviour, cognitive-based behaviour, and characteristics of neuroscience. The inclusion of the neuroscience in the investigation of system or machine intelligence provides better understanding of human and animal motor control mechanisms and related sensory systems (Bien et al., 2002). The model further posits that any intelligent system with the four identified intelligence attributes can generally lead to improved safety, enhanced reliability, higher efficiency and more economical maintenance. The model of machine intelligence is presented in Figure 1.

PROPOSED CONCEPTUAL FRAMEWORK FOR MEASURING SYSTEM INTELLIGENCE OF THE IBMS

In this research, the model of machine intelligence by Bien et al. (2002) is extended to investigate and evaluate the degree of system intelligence of the IBMS previously mentioned. However, the proposed model in this research differs somewhat from that suggested by Bien et al. (2002) in that the interrelationships between the intelligence attributes of the IBMS and the operational benefits of the intelligent building are taken into consideration. This is based on the argument that the adoption of intelligent technologies in buildings should not be limited to advances in technology, as the ability of installed intelligent control systems to enhance the goals or benefits of the clients and end-users are equally significant (Clements-Croome, 2001b; Smith, 2002). The model of Bien et al. is extended to consider the relationship between the degree of intelligence possessed by the intelligent building control system and the extent of the expected benefits/goals achieved (Wong et al., 2008a, b). In particular, investigating their relationships is

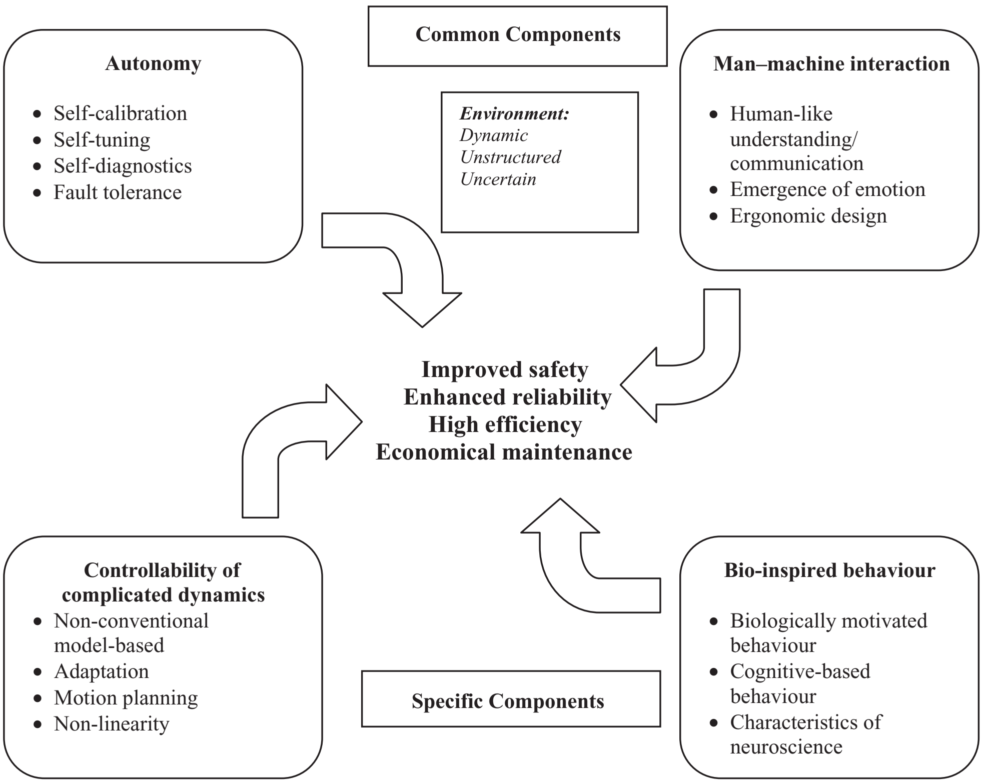

FIGURE 1 Taxonomy of key intelligence attributes in a general intelligent machine or system (Bien et al., 2002, p8)

based on the assumption that the intelligence attribute(s) of the IBMS will be most important in achieving the decision-maker's goal of improved operational benefits. In contrast, each intelligence attribute (i.e. autonomous features of the IBMS) might have a varied degree of importance in generating four identified operational benefits, which are improved operational effectiveness and energy efficiency, enhanced cost effectiveness, increased user comfort and productivity, and improved safety and reliability (Wong et al., 2008a, b). Figure 2 provides a general conceptual system intelligence framework for a typical intelligent building control system.

RESEARCH METHOD

In this study, two surveys including a simple rating method and a combination of analytic hierarchy process (AHP) and analytic network process (ANP) approaches are undertaken, to elicit and examine the 'suitable' intelligence indicators. A self-completion postal questionnaire using a simple rating method is employed first to test the criticality of the proposed intelligence

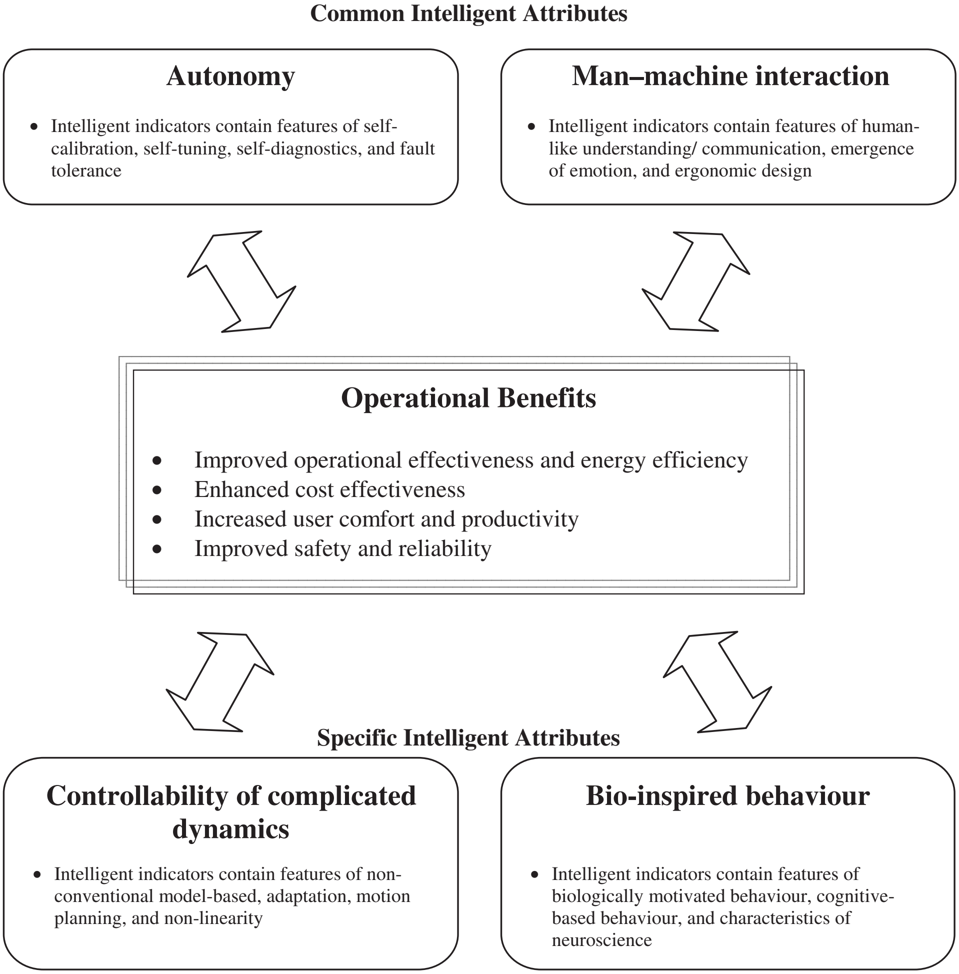

FIGURE 2 Conceptual framework of system intelligence of a general building control system in the intelligent building

indicators and to elicit groups of 'suitable' intelligence indicators for the IBMS. An AHP-ANP questionnaire was then employed to evaluate the comparability of each 'suitable' intelligence indicator, with the investigation of the interrelationships with operational benefits and intelligence attributes, in order to refine the system intelligence analytic model.

THE AHP AND ANP

AHP considers both qualitative and quantitative aspects of research and combines them into a single empirical inquiry (Cheng, 2001, p54). The AHP is able to adopt a qualitative method in building the decision hierarchy, and also uses a quantitative approach in data collection and analysis to test the attributes of the models by using a self-completed questionnaire. The AHP has the capability to combine various types of criteria in a multi-level decision structure to obtain a single score for each alternative, to rank the alternatives among the available multi-attribute approaches (Yurdakul, 2003, p365). ANP is an advanced version of AHP, which models a network structure that relaxes the hierarchical and unidirectional assumption in the AHP. The ANP can provide a more generalized model of multi-criteria decision-making that takes interdependent relationships into consideration (Cheng et al., 2005). Similar to AHP, ANP possesses the same qualitative (decision model development) and quantitative (decision model analysis) procedures to structure and analyse a decision problem. It can further consider quantitative steps to solve a network decision problem, and thus it is appropriate when the interdependencies between two components are investigated. Despite this, ANP is still a new method that is not well known to the operations research community and practitioners (Meade and Sarkis, 1999). So far the use of ANP in solving decision-making problems in construction and intelligent building research with illustrative examples has been very limited (for example, Cheng et al., 2005; Chen et al., 2006; Cheng and Li, 2007). As previously mentioned, the model of Bien et al. (2002) was further elaborated and extended to consider the interdependencies between the intelligence attributes of an intelligent building control system and the building's operational benefits. It is for these reasons that ANP is proposed for use as a method of analysis in this study.

The proposed ANP algorithm procedure was established based on the concept developed by Saaty (1996) and extended by Meade and Sarkis (1998) and Cheng et al. (2005). The algorithm procedures of the ANP primarily follow the AHP approach, except for the intrusion of interdependent relationships and the formation of a super-matrix. The four steps of the ANP method for prioritizing the intelligence measures for assessing the system intelligence of the IBMS were:

1. model construction and problem structuring
2. pair-wise comparison matrices between component/attribute levels and of independent component levels
3. checking the degree of consistency of the matrix
4. formation of the super-matrix.

MODEL VALIDATION BY EXPERTS

In this research, after the system intelligence analytic model is examined and refined, the developed model is then converted to a practical model that needs to be validated. According to Leeflang et al. (2000), model validation is an important procedure in the process of model development. This process implies assessing the quality or the success of the model. A review of construction literature revealed that one method of model validation involves a comparison of the output of the model with the solutions given by the experts (Nkado, 1992). Ling et al. (2003) tested their selection model for design consultants for design-and-build projects in Singapore by consulting a number of experts. Experts were presented with the statistically important attributes and asked whether these attributes represented all the factors that should be involved in evaluating consultants. The model's relative ranking of different consultants was compared with the experts' order of preference. Following this, the similarity between the scores given by the model and the experts was evaluated. In this study, the model validation design was based on the approach of Ling et al. (2003).

According to Ling et al. (2003), after obtaining the weights of variables, the examination of the practicability of the developed conceptual model requires the development of ratings of each candidate option on each of the variables and the formulation of an aggregation formula to sum up the weighted ratings. In this study, these two process steps are adopted to move the developed conceptual model to the practical model. In order to evaluate the candidate IBMS against each intelligence indicator in the model developed, the assessment methods and standard summated rating scales must first be set up for each of these intelligence indicators. Having established the assessment methods and rating scores for each intelligence indicator, the scores of intelligence indicators are then aggregated in order to produce one overall score for each candidate IBMS. To derive the weighted rating scores, the important weights of each intelligence indicator are multiplied by the ratings that the candidate IBMS obtains for the corresponding intelligence indicator.

To validate the practical model, the model's aggregate score must first be compared with the global scores given by the experts (Ling et al., 2003). In this research, each expert was asked to recall their past experience and was required to supply two examples of real control systems they had encountered. They were told to evaluate the nominated IBMS alternatives based on their expert judgement and on their global impression of them. Each proposed building system alternative was first ranked according to the experts' preferences for them. The experts were then requested to use the practical system intelligence analytic model to evaluate the nominated building system alternative. The results will compare the aggregate scores in both models and test whether they are consistent with the preferences of the experts for both parts.

The consistency between the model's aggregate scores and the experts' global scores are further tested and analysed by the statistical methods. The Pearson correlation coefficient (*r*) and the Spearman rank order correlation coefficient (*rho*) are employed to ascertain the strength and direction of the relationship between the scores of models and experts. If there is a high correlation between the two sets of scores, this means that the model is able to reflect the expert's preference.

DATA ANALYSIS AND RESULTS

RESULTS OF THE GENERAL SURVEY

The first general survey is designed to elicit the 'suitable' intelligence indicators for the IBMS. The list of proposed intelligence indicators was derived from an extensive review of intelligent building literature and trade publications, and expanded on with the advice of industry experts and practitioners. The posited intelligence indicators were developed and organized into four main intelligence attributes suggested by Bien et al. (2002) (i.e. *autonomy, controllability of complicated dynamics, man–machine interaction and bio-inspired behaviour*). A pilot study was first undertaken to test the suitability and comprehensibility of the questionnaire. In the main survey, a total of 157 questionnaires were sent out and distributed, and 44 usable replies were collected for the analysis, giving a net usable response rate of 28%.

In the questionnaire, participants were invited to give their opinions on the suitability of each of the proposed intelligence indicators on a five-point Likert-scale format (1=Not suitable; 2=Less suitable; 3=Suitable; 4=More suitable; and, 5=Most suitable). Likert scales facilitated the quantification of responses so that statistical analysis could be taken and differences between participants could be observed and generalized (Abdel-Kader and Dugdale, 2001). In this survey, the critical rating was fixed at scale '3' since ratings above '3' represent 'suitable', 'more suitable' and 'most suitable' according to the scale. This survey employed the mean score ratings and *t*-test analysis as the statistical techniques to elicit and analyse the 'suitable' intelligence indicators. Table 1 summarizes the results of the first general survey, a total of 16 critical selection criteria for the IBMS.

RESULTS OF THE AHP–ANP SURVEY

For a penetrating insight into the measurement of the degree of system intelligence in IBMS, a more meticulous investigation and prioritization of the 'suitable' intelligence indicators was needed by the intelligent building experts. The influence of the interdependent relationship between intelligence attributes of the IBMS and the operational benefits of intelligent buildings was taken into consideration. A combination of AHP and ANP methods was utilized to execute the prioritization of indicators. AHP was selected to perform the prioritization of the elements (i.e. intelligence indicators), while ANP was employed to take the above-mentioned interdependent relationships into consideration, resulting in the formation of a network-like structural framework.

The application of the AHP–ANP approaches first requires the construction of a hierarchical decision network for the decision problem which is to be evaluated. The conceptual analytical framework for the system intelligence for the IBMS is illustrated in Figure 3. At the top of the control hierarchy is the ultimate objective to achieve. In this case, the ultimate objective is to determine the overall degree of system intelligence of the IBMS. The top level is broken down into intelligence attributes (level 2) and their corresponding intelligence indicators (level 3). In order to investigate the interdependent relationships between intelligence attributes and operational benefits, another separate but related component, relating to the building's operational benefits, is depicted above the intelligence attributes in the decision model. Four operational benefits act as external variables and form network relationships with the four intelligence attributes in the analytical decision model.

Once the analytical model is developed, the matrices should be designed for pair-wise comparison. A total of nine experts participated in this survey. The AHP–ANP questionnaire in this survey was designed first to pair-wise compare the matrices of interdependent component levels and variables of intelligence attributes. ANP is established on the ratio scale measurement. Pair-wise comparisons of elements are undertaken

TABLE 1 A summary of system intelligence indicators for the IBMS

- Adaptive limiting control algorithm (AL)
- Self-diagnostic of operation deviations (SD)
- Year-round time schedule operation (YT)
- Ability to link multiple stand-alone building control systems from a variety of manufacturers (ALMS)
- Remote control via internet (RCI)
- Ability to connect multiple locations (ACML)
- Alarms and events statistics (AES)
- Control/monitor lighting time schedule/zoning (ML)
- Control and monitor heating, ventilation and air-conditioning (HVAC) equipment (MHVAC)
- Reports generation and output of statistical and trend profiling of controls and operations (RG)
- Ability to provide operational and analytical functions (APOAF)
- Single operation system/platform for multiple location supervision (SOS)
- Graphical representation and real-time interactive operation action icons (GR)
- Run continually with minimal human supervision (RC)
- Analyse operation function parameters (AOF)
- Provide adaptive control algorithms based on seasonal changes (PAC)

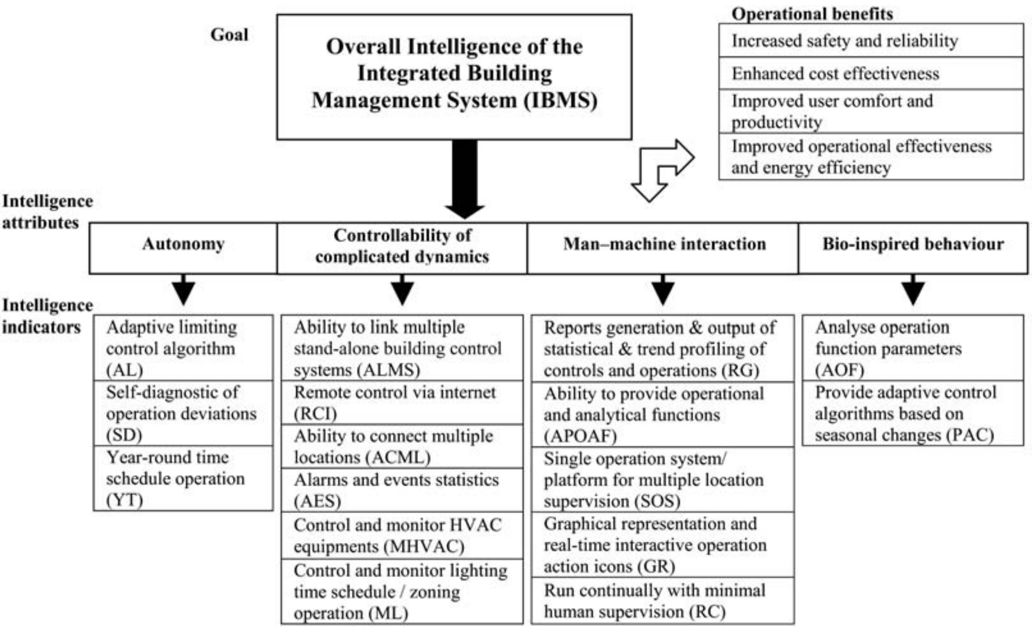

FIGURE 3 ANP decision model for the system intelligence measurement of the IBMS

to determine their relative importance or priority. The calculation of the relative importance of two compared elements was based on the nine-point priority scale of pair-wise judgement, which was developed by Saaty (1996).

In the study, the four intelligence attributes (level 2) of IBMS were rated pair-by-pair with respect to the decision problem (level 1). Then, the relative importance of the intelligence attributes (e.g. autonomy vs. man–machine interaction) with respect to a specific operational benefit of the intelligent building was investigated. A pair-wise comparison matrix was required for each of the operational benefits for calculation of impacts of each intelligence attribute. Then, four pair-wise comparison matrices were required to calculate the relative impacts of each operational benefit (i.e. enhanced cost effectiveness vs. improved operational effectiveness and energy efficiency) on a specific intelligence attribute. As a result, a total of eight pair-wise comparison matrices were required to describe the two-way relationship. Once the pair-wise comparisons were completed, the local priority was calculated. The relative importance of each intelligence indicator with respect to each of their corresponding intelligence attributes was investigated.

After applying this approach for all expert respondents, simple averaging of the weights was completed for final evaluation since it was assumed that the importance (i.e. knowledge, expertise and perceptions) of all experts was equal. In the case of any unequal allocations of importance, a weighted average is used (Sarkis and Sundarraj, 2002, p342). In this survey, all completed pair-wise comparisons by the respondents appeared to have acceptable consistency. After the calculation, the weighted priorities for each of the operational benefits were combined to form a matrix with four columns and four rows. The local priority weights (LPWs) for the relative importance of the benefits on the intelligence attributes were then investigated. As a result, the weighted priorities for each of intelligence attributes were combined to form a four-column, four-row matrix.

The next step involves the formation and analysis of the super-matrix. The super-matrix promotes a resolution of the effects of the interdependence that exists between the elements of the ANP model. This can be achieved by entering the local priority vectors (LPVs) in the super-matrix, which in turn provides the 'global' priority vectors (GPVs). In this study, if the same-level impacts are assumed not to be significant, then matrices A and B are required to combine to form the super-matrix. The super-matrix summarizes the eigenvectors associated with the four intelligence attributes with respect to the decision problems. It also includes the eigenvectors from the interdependent influences between the four intelligence attributes and four operational benefits. The final sub-step of the ANP calculation relates to the calculation of a limit super-matrix by the *Super Decisions*. The results of the average limiting super-matrix with the relative importance and final weights of each intelligence indicator of IBMS are summarized in Table 2.

The findings of the AHP-ANP survey suggested that, in the IBMS, the top three intelligence indicators – *'self-diagnostic of operation deviations'; 'adaptive limiting control algorithm';* and *'year-round time schedule performance'* – are all under the attribute of 'autonomy'. This indicates that an 'intelligent' IBMS should possess the capability of detecting the deviations in its operation and self-adjusting these problems.

TABLE 2 The final weights of intelligence indicators

Indicators	Weight (Ranking)
Integrated Building Management System (IBMS)	
Autonomy (AUT)	
Adaptive limiting control algorithm (AL)	0.1130 (2)*
Self-diagnostic of operation deviations (SD)	0.1143 (1)*
Year-round time schedule operation (YT)	0.1015 (3)*
Controllability of complicated dynamics (CCD)	
Ability to link multiple stand-alone building control systems from a variety of manufacturers (ALMS)	0.0427 (11)
Remote control via internet (RCI)	0.0258 (15)
Ability to connect multiple locations (ACML)	0.0334 (14)
Alarms and events statistics (AES)	0.0604 (8)
Control/monitor lighting time schedule/zoning (ML)	0.0520 (9)
Control and monitor HVAC equipments (MHVAC)	0.0623 (7)
Man–machine interaction (MMI)	
Reports generation and output of statistical and trend profiling of controls and operations (RG)	0.0243 (16)
Ability to provide operational and analytical functions (APOAF)	0.0339 (13)
Single operation system/platform for multiple location supervision (SOS)	0.0383 (12)
Graphical representation and real-time interactive operation action icons (GR)	0.0444 (10)
Run continually with minimal human supervision (RC)	0.0706 (6)
Bio-inspired behaviour (BIB)	
Analyse operation function parameters (AOF)	0.0854 (5)
Provide adaptive control algorithms based on seasonal changes (PAC)	0.0979 (4)

Note: * represents a higher weighting score between the ANP and AHP approaches.

APPLICATION OF THE MODEL

The first step for the transformation of the conceptual model to an applicable one was to identify and develop rating scales and assessment methods for each of the intelligence indicators. The rating scale was designed to facilitate the evaluation of the degree of intelligence of the IBMS. The summated rating scales, which ranged from 0 to 5, were adopted in this part of model construction. Eight rating methods were developed and verified by two industry experts who participated in the ANP survey. Table 3 maps these assessment methods to different intelligence indicators.

Having developed the assessment methods and scoring systems for the model, the next process step required for performing system intelligence analysis was to aggregate the scores to produce one overall score for the IBMS. The score for each intelligence indicator is obtained by multiplying the weights (*w*) of each intelligence indicator with the ratings (*r*) that each proposed

TABLE 3 The weight and scoring formula of different intelligence indicators

Intelligence attributes and indicators of the IBMS	Indicators' weight from ANP (w)	Options' rating by experts (r)	Score (w*r)
Integrated Building Management System (IBMS)			
Autonomy (AUT)			
Adaptive limiting control algorithm (AL)	0.0916	r_{IBMSA1}	$0.0916{*}r_{IBMSA1}$
Self-diagnostic of operation deviations (SD)	0.0926	r_{IBMSA2}	$0.0926{*}r_{IBMSA2}$
Year-round time schedule operation (YT)	0.0822	r_{IBMSA3}	$0.0822{*}r_{IBMSA3}$
Controllability of complicated dynamics (CCD)			
Ability to link multiple stand-alone building control systems from a variety of manufacturers (ALMS)	0.0464	r_{IBMSC1}	$0.0464{*}r_{IBMSC1}$
Remote control via internet (RCI)	0.0280	r_{IBMSC2}	$0.0280{*}r_{IBMSC2}$
Ability to connect multiple locations (ACML)	0.0363	r_{IBMSC3}	$0.0363{*}r_{IBMSC3}$
Alarms and events statistics (AES)	0.0657	r_{IBMSC4}	$0.0657{*}r_{IBMSC4}$
Control/monitor lighting time schedule/zoning (ML)	0.0565	r_{IBMSC5}	$0.0565{*}r_{IBMSC5}$
Control and monitor HVAC equipments (MHVAC)	0.0677	r_{IBMSC6}	$0.0677{*}r_{IBMSC6}$
Man–machine interaction (MMI)			
Reports generation and output of statistical and trend profiling of controls and operations (RG)	0.0276	r_{IBMSM1}	$0.0276{*}r_{IBMSM1}$
Ability to provide operational and analytical functions (APOAF)	0.0386	r_{IBMSM2}	$0.0386{*}r_{IBMSM2}$
Single operation system/platform for multiple location supervision (SOS)	0.0436	r_{IBMSM3}	$0.0436{*}r_{IBMSM3}$
Graphical representation and real-time interactive operation action icons (GR)	0.0505	r_{IBMSM4}	$0.0505{*}r_{IBMSM4}$
Run continually with minimal human supervision (RC)	0.0803	r_{IBMSM5}	$0.0803{*}r_{IBMSM5}$
Bio-inspired behaviour (BIB)			
Analyse operation function parameters (AOF)	0.0896	r_{IBMSB1}	$0.0896{*}r_{IBMSB1}$
Provide adaptive control algorithms based on seasonal changes (PAC)	0.1028	r_{IBMSB2}	$0.1028{*}r_{IBMSB2}$

building system obtained for the corresponding indicators. All individual scores of the intelligence indicators under the same building control system are then summed to produce an aggregate system intelligence score. In this case, the mathematical expression for the aggregate system intelligence score, ($Score_{SI}$), is given as follows:

$$Score_{SI} = (\Sigma w_{II1} \times r_{II1}) + (\Sigma w_{II2} \times r_{II3}) + (\Sigma w_{II3} \times r_{II3}) \ldots + (\Sigma w_{IIn} \times r_{IIn}) \quad (1)$$

where, $w_{II1}, w_{II2}, w_{II3} \ldots w_{IIn}$ represent the weights of the intelligence indicators; and, $r_{II1}, r_{II2}, r_{II3} \ldots r_{IIn}$ represent the rating given to the IBMS option for the intelligence indicators.

To demonstrate the computation of the system intelligence score ($Score_{SI}$), two real IBMS candidates were selected to demonstrate their assessment procedures and application. The brand names were all fictitious and the product information was undisclosed to prevent any commercial conflicts. The first IBMS alternative, System C, is developed by a European manufacturer and contains unique features of peer-to-peer operation with a flexible and remote alarm management system. The second IBMS alternative, System D, is produced by a US manufacturer with similar system features to System C. A score from 0 to 5 was assigned to each intelligence indicator. Table 4 summarizes the judgements of the experts on the intelligent performance of Systems C and D. In this example, although the aggregate system intelligence score ($Score_{SI}$) of man–machine interaction (MMI) was higher in System D, System C had higher aggregate scores in another two intelligence attributes: autonomy (AUT) and controllability for complicated dynamics (CCD). Finally, the demonstration results indicated that System C (3.8351) had a higher aggregate system intelligence score than System D (3.6333). The results can also be graphically depicted and illustrated in the form of radar diagram plots as in Figure 4.

TABLE 4 Aggregate system intelligence score ($Score_{SI}$) of two IBMS candidates

Intelligence indicators (Attribute group)	Indicator's weight (ANP)	IBMS system C		IBMS system D	
		Score	Weight	Score	Weight
AL (AUT)	0.0916	4	0.3664	3	0.2748
SD (AUT)	0.0926	4	0.3704	4	0.3704
YT (AUT)	0.0822	4	0.3288	3	0.2466
ALMS (CCD)	0.0464	4	0.1856	4	0.1856
RCI (CCD)	0.028	5	0.1400	4	0.1120
ACML (CCD)	0.0363	4	0.1452	4	0.1452
AES (CCD)	0.0657	5	0.3285	3	0.1971
MHVAC (CCD)	0.0677	4	0.2708	4	0.2708
ML (CCD)	0.0565	4	0.2260	3	0.1695
RG (MMI)	0.0276	3	0.0828	5	0.1380
APOAF (MMI)	0.0386	3	0.1158	4	0.1544
SOS (MMI)	0.0436	4	0.1744	5	0.2180
GR (MMI)	0.0505	4	0.2020	5	0.2525
RC (MMI)	0.0803	4	0.3212	4	0.3212
AOF (BIB)	0.0896	3	0.2688	3	0.2688
PAC (BIB)	0.1028	3	0.3084	3	0.3084
	Weighted mean ($Score_{SI}$) =		3.8351		3.6333

Note: Intelligence indicators weights were normalized. The indicators were rated based on a scale of 0–5 based on their existence and level of functions/services. Maximum system intelligence score ($Score_{SI}$) = 5.0000.

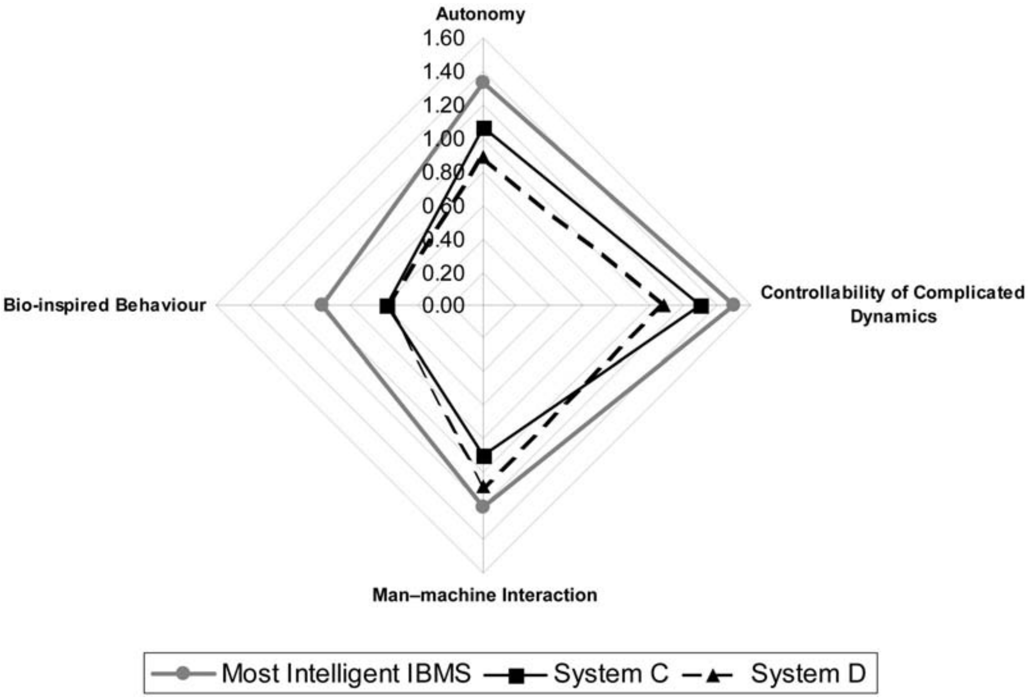

FIGURE 4 Radar diagram plot of the system intelligence score ($Score_{SI}$) of the proposed IBMS options

MODEL VALIDATION

To validate the system intelligence analytic models, another five intelligent building experts were used. The relative rankings of the different alternatives of IBMS were first compared with the order of preference from the experts. The study verified how similar the experts' and models' scores were.

To obtain information from the experts about their opinions and judgements on the system intelligence of the candidate IBMS, a model validation questionnaire was designed. Individual structured interviews were set up to provide guidance for the completion of the questionnaire. Each expert was invited to supply and nominate for IBMS two candidates that they had come across and were most familiar with in their past experience of intelligent building design and development. Then, the experts were invited to indicate a preference for each pair of IBMS they nominated. A score from 0 to 10 (where 0–4 represent 'poor'; 5 represents 'average'; 6 and 7 represent 'good'; 8 represents 'very good'; and 9 and 10 represent 'excellent') were again assigned for each alternative based on their overall intelligent performance or degree of intelligence. Then, the experts were invited to evaluate the same set of alternatives by using the system intelligent analytic model as described in Table 3. A weighting score between 0 (extremely poor) and 5 (excellent) based on the assessment methods were assigned to reflect the degree of each of the nominated building control system candidates in fulfilling each intelligence indicator. Table 5 summarizes the experts' global preference scores and models' aggregate scores of each candidate IBMS. The results indicate that 80% (i.e. four out of five) of the models' aggregate scores reflect the preferences of the experts.

After the comparison of the rankings, the model's aggregate scores (column 3 of Table 5) were further correlated with the expert global scores (column 4 of Table 5). Table 6 summarizes

TABLE 5 Summary of experts' global system intelligence scores and models' aggregate system intelligence score

Expert reference	Proposed system options	Models' aggregate scores (Ranking of scores)	Experts' global score (Ranking of scores)
MVEX1	MVEX1-IBMS1	4.2074 (1)	8 (1)
	MVEX1-IBMS2	3.7100 (2)	7 (2)
MVEX2	MVEX2-IBMS1	3.6098 (2)	6 (2)
	MVEX2-IBMS2	3.9534 (1)	7 (1)
MVEX3	MVEX3-IBMS1	3.7852 (1)	8 (1)
	MVEX3-IBMS2	3.4866 (2)	7 (2)
MVEX4	MVEX4-IBMS1	4.0176 (1)	9 (1)
	MVEX4-IBMS2	3.6403 (2)	7 (2)
MVEX5	MVEX5-IBMS1	4.0575 (2)	9 *
	MVEX5-IBMS2	4.2664 (1)	9 *

Note: * Same score was assigned by the expert on the overall ability or performance of the control system.

the results of the Pearson correlation coefficient (*r*) and Spearman's *rho* between the models' aggregated scores and the experts' global scores for each IBMS. The analysis results indicate a high correlation between all experts' scores and the scores generated by the models with respect to the degree of intelligence. The value of Spearman's *rho* is 0.820, while the value of Pearson's *r* is 0.771 (Table 6). This implies a 'very strong' relationship between the experts' and models' system intelligence scores of the IBMS in general (de Vaus, 2002).

LIMITATIONS AND RECOMMENDATIONS

This study has set down the foundation for a meticulous examination of the IBMS in system intelligence analysis, including the development of conceptual frameworks and practical models. However, this research was deliberately limited to an investigation of seven of the most general building control systems in commercial intelligent buildings (i.e. offices). As the uses and requirements of building control systems depend on the building type (for example, office building, residential tower, shopping mall, hospital on airport building) and their ultimate usage. (Ancevic, 1997), this implies that the intelligence indicators identified in this research might not be generalized to all types of intelligent buildings. This study has also focused on the practices of system intelligence assessment of intelligent building control systems among experts and professionals in the context of Hong Kong.

The research methodology adopted in this research also imposed its own limitation. First, the size of the sample in this research was limited. Since the intelligent building industry is new and developing, a large sample of professionals was not available. Only a very limited number of experts could be identified for the surveys.

TABLE 6 Summary of correlation coefficient results between the scores of system intelligence by the experts and models

Building control system	Correlation coefficient	
	Pearson's *r*	Spearman's *rho*
Integrated Building Management System (IBMS)	0.771*	0.820*

Note: * Correlation is significant at the 0.01 level (2-tailed).

Numerous possibilities are suggested for extending and elaborating upon the research undertaken. First, the current dearth of research in the area of intelligence appraisal for intelligent building control systems means that there is considerable scope for undertaking further studies. Research methodology employed in this study can be used as a basis for model development work. Further research could be undertaken by refining the models or developing similar models in related areas. Empirical work similar to this study could be extended and further developed in other countries, for other building control systems, or in other types of intelligent building. Some new variables may be added into the model. A larger sample would help to improve the extent to which these models represent human decision-making processes. Future study should also include the building occupants as part of the survey sample because they are the end-users of the intelligent building. The application of software and group decision support systems, on the other hand, can minimize the difficulties in implementing this technique. To conclude, as intelligent building technologies evolve and develop into the foreseeable future, system intelligence analysis of building control systems will continue to be seen as an area of interest to explore and investigate.

CONCLUSION

This article presents the development of indicators, and develops analytical decision models for appraising system intelligence of the IBMS. The study started with a review of the current research in intelligent building appraisal, and emphasized the current research deficiencies and practical problems. The literature review in this article argued that there is a demonstrable need to develop a list of 'suitable' intelligent attributes and indicators because there has been a lack of satisfactory consensus for characterizing the system 'intelligence' of the building systems in the intelligent building. A general survey was first undertaken to elicit a group of suitable indicators for use in assessing the system intelligence of the IBMS. Then, analytic network process (ANP) was applied to the development of the analytical model for intelligence evaluation because the ANP method enables all significant intelligent indicators to be taken into account in the analysis. This suggests that not only should the values be considered, but also the interrelationship between the intelligent attributes (i.e. autonomy; controllability of complicated dynamics; man–machine interaction; and bio-inspired behaviour) and the operational goals/benefits (i.e. enhanced cost effectiveness; improved operational effectiveness and energy efficiency; improved user comfort and productivity; and increased safety and reliability) of the IBMS. The findings of the AHP–ANP survey suggested that *'self-diagnostic of operation deviations', 'adaptive limiting control algorithm',* and *'year-round time schedule performance'* are the three most important intelligence indicators of the IBMS. These indicators are all under the attribute of 'autonomy'. This indicates that an 'intelligent' IBMS should possess the capability of detecting the deviations in its operation and self-adjusting these problems. Overall, the findings suggested that ANP is a robust approach if the decision model is significantly influenced by interdependent relationships.

This study has helped to build a better understanding of what intelligent features or properties are needed for the optimum building control system (i.e. IBMS). With the establishment of applicable models, a system intelligence score ($Score_{SI}$) can be calculated for the proposed control system alternatives, providing a basis for comparison and ranking so that rational decisions may be made. The system of evaluation suggested in this research is one approach along the pathway towards a true generic platform. The models are intended to structure the decision-maker's mind by providing a systematic prioritization of alternative options, so as to lessen the dependence on human expertise and judgement. From a commercial perspective, the establishment of aggregate system intelligence scores provides a way that allows developers or design teams to value building control system products using the index to reveal their intelligence superiority.

Furthermore, it provides a benchmark to measure the degree of intelligence of one control system candidate against another. Building control system consumers are also provided with an alternative approach to compare and contrast several building control system products from the viewpoint of intelligence (Meystel and Messina, 2000; Schreiner, 2000). The proposed evaluation model would also help clients and stakeholders to consider a wide range of intelligence attributes and indicators before committing to a particular choice of system alternative, or to assess any existing building's intelligence in fulfilling the users' or owners' expectations. The system intelligence analytic approach developed in this study can be considered as a reference for existing buildings as well as future developments, to systematically analyse the intelligence performance of a particular building system (i.e. IBMS) which adds value to the modern building. In terms of research methodology, this study demonstrated the application of ANP as an approach to quantify the system intelligence of smart building systems.

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