BIM-BASED DECISION SUPPORT SYSTEM FOR THE MANAGEMENT OF LARGE BUILDING STOCKS

A. Carbonari[a], A. Corneli[a], G. Di Giuda[b], L. Ridolfi[a] and V. Villa[c]

[a]DICEA Department, Polytechnic University of Marche, Italy
[b]ABC Department, Polytechnic of Milan, Italy
[c]DISEG Department, Polytechnic of Turin, Italy
E-mail: alessandro.carbonari@staff.univpm.it, a.corneli@pm.univpm.it, giuseppe.digiuda@polimi.it, l.ridolfi@staff.univpm.it, valentina.villa@polito.it

Abstract –

While on the one hand the BIM methodology is an essential reference for the construction of new buildings, on the other hand it is receiving particular attention and interest also from owners of large building stocks who want to take advantage of the benefits of Building Information Modelling so as to have a coordinated system for the sharing of information and data.

This, especially in a process that concerns the management and maintenance of a large building stocks, involves the processing of uncertain information in BIM, particularly when dealing with existing buildings, due to the lack of and/or incomplete documentation, entailing a significant investment in terms of time and additional costs.

Therefore, to represent the reliability of existing building data, we suggest introducing a tool based on Bayesian Network that offers a valid decision support under conditions of uncertainty and is used to evaluate the compliance with the latest standard.

This paper presents a process to provide an integrated database defined by a minimum information level that can be used both to extrapolate and query specific information from a digital building model and populate the decision model in order to evaluate the performance parameters of existing buildings which is based on a Multicriteria decision making approach (AHP).

Keywords –

Building Information Modelling; building stock; data management; Bayesian networks; Multicriteria decision making

1 Introduction

In this work, attention has been given to the role played by public administrations in the management of large building stocks, focusing specifically on school buildings, the majority of which is outdated and lacks of compliance with current legislation.

The purpose of this paper is to propose a decision support model that can be used by public administrations, such as provinces and municipalities, which need to define the priorities of refurbishment actions among the school buildings they own.

This Decision Support System (DSS) concerns multiple regulatory areas in which evaluation is performed, namely Accessibility, Energy Efficiency and Acoustics. In addition, the DSS makes it possible to manage the uncertainties deriving from the scarce availability of necessary data on existing stock. The DSS was conceived so as to be able to obtain the necessary information directly from the Building Information Modelling (BIM) database. In addition, the decision support model includes a multi-criteria evaluation of performance indicators, each related to a determined regulatory area, with the aim of defining a final ranking of the schools assessed, in which the one with the lowest score shows the highest priority of intervention.

In conclusion, the aim of this paper is to develop a BIM-based Decision Support System for the assessment of building stocks which is able to perform the evaluation even in the case it has to manage uncertain or incomplete information. Our tool integrates networks that help evaluate the performance parameters of existing buildings, whose inputs can be retrieved from BIM models, and prioritise refurbishment actions through a multi-criteria assessment approach of some selected performance indicators.

2 Literature review

In many practical cases it is hardly possible to retrieve all the information about existing buildings through the query of the most relevant characteristics contained in a model in a reliable way. Even in the case of existing buildings for which extensive construction and operational documentation is available, some parameters might be uncertain or unknown.

Several research studies have been carried out to develop decision making systems to deal with the extensive and uncertain information characterising the existing stock. DSSs have been developed for a wide variety of engineering-related issues in the construction industry. For example, in [1] since the selection of curtain wall systems involves numerous technical, environmental and economic factors and impacts on all project stages from concept design and manufacture to installation and operation, a decision support system is proposed as a potential solution.

In [2] the authors presented the result of a research carried out with the purpose of establishing a multicriteria method for the assessment of architectural heritage to identify buildings with higher refurbishment priority. The author in [3] created and tested a multicriteria risk-based decision support model for investments in energy efficiency projects under uncertainty of building energy retrofits. In [4], a study was developed to provide systematic means for priority setting of maintenance activities in various hospital buildings as well as a Key Performance Indicator for building performance. Other researches focused on the choice of what information is needed to make models significant to maintenance and on handling uncertainty due to incomplete building documentation [5].

The above listed results are remarkable but do not deal with the compatibility between DSS and BIM models of existing buildings. Indeed, the modelling and conversion of captured data into semantic BIM objects, the updating of information in BIM and the handling of uncertain data, objects and relations in BIM, which are typical challenges in existing buildings [6], must be analysed.

Hence, this paper deals with the development of a BIM based decision support tool based on the use of Bayesian Networks (BNs) for the evaluation of building stock compliance with technical requirements and its ranking according to selected performance indicators.

BNs are an effective representation of knowledge uncertainty, because they provide the possibility of constructing an estimated probabilistic model, since not all information can be accessed. In addition, they make it possible to update the network inputs when new evidence is collected and updates results accordingly. BNs are composed of elementary parts (separate fragments) and recall their outputs in a larger network. They make it possible to reverse reasoning and can manage variables of different types (e.g. Boolean, numerical, interval or label nodes). BNs work with as many data as are available to give accurate results. Moreover, within each iteration, they learn more and refine their model to give updated results.

A great advantage of BNs is that they allow us to combine prior knowledge with new data even if they come from different sources. Once the model is compiled, we can get very quick results by using the already established conditional probability distribution tables.

Many organisations, especially in the public sector, own a large variety of buildings and other types of constructed facilities. These buildings need regular maintenance, as well as occasional renovation, rehabilitation or, perhaps, complete reconstruction [7]. Multicriteria decision making analysis arose to model complex problems like these [8]. Multiple criteria decision making (MCDM) is a generic term for all those methods that exist to help people make decisions according to their preferences in cases where there is more than one conflicting criterion to be taken into account [9]. Following a research throughout scientific literature, it was found that the majority of the methods used are based on AHP, ELECTRE and PROMOTHEE approach [10]. As outlined in [10], AHP can provide decision makers with a robust solution. The most important part of this method is that it puts decision makers' preference first and helps elect a method for their decision making in maintenance management without considering uncertainty rate and problem complexity.

For these reasons, the AHP methodology was applied according to what suggested by Saaty [11].

3 Modelling of school building stock

Although a detailed set of information about existing buildings would be necessary to carry out a reliable assessment of real estates, most of the buildings were built in the pre-digital age [12].

Some public administrations are developing preliminary BIM models of their stock, but they are willing to limit the complexity of these models within the lowest amount of information needed for management and maintenance purposes, in order to make that process affordable. For the reasons stated above, we selected two case studies of school buildings which are particularly complex. In the selected scenarios, there is a clear need to adapt the existing buildings to current legislation in terms of different aspects such as accessibility, energy performance, acoustic etc.

3.1 The case studies

In this paper two school buildings located in Melzo (Milan, Italy) were studied. The first one is the "Ungaretti" primary school, whose surface area measures 4528 m^2 and is arranged on four levels, one of which is the basement and the remaining three floors are above ground. The gymnasium is accommodated in a separate building, which communicates with the main one through two horizontal connections in the basement and one placed on the ground floor. The basement houses the canteen, the kitchen, laboratories, archives, refreshment areas and infirmary. On the ground floor there are classrooms and offices, while on the first floor there are just classrooms and on the second floor classrooms and auditoriums. The restrooms are distributed throughout the building and the gym.

The second case study is the “Mascagni” secondary school located in Melzo (Milan, Italy), which is as large as 5736 m^2 and is composed of three functional blocks. One block holds the classrooms and laboratories located over two floors above ground, the other two blocks hold the cafeteria/auditorium and the gymnasium.

3.2 BIM models

Developing BIM models of existing buildings implies, first of all, a thorough study of available documentation and then an accurate analysis of the real state of the buildings.

The next step involves the construction of three-dimensional BIM models of the buildings (developed through the Autodesk Revit™ platform) containing all the technical elements identified and the organisation of collected information. The models become the materialisation of the technical information related to the element or system they refer to. Each element of the models is “informed” of all parameters, specifications and characteristics of the real elements [13].

Nowadays, buildings information is often incomplete or obsolete, hence, during operation “an inordinate amount of time is spent locating and verifying specific facility and project information”. This is the case of the two BIM models of the two schools selected as case studies: the Ungaretti primary school (Fig. 1-a) and the Mascagni secondary school (Fig. 1-b).

Sometimes not all the information needed to perform a complete assessment is available in the BIM models.

a.

b.

Figure 1. BIM models of the case studies a) Ungaretti school b) Mascagni school.

4 Methodology

Owners of any large building stock, such as public administrations, usually have to manage a huge variety of buildings with a limited budget. For this reason, targeted refurbishing actions are needed to ensure that those buildings comply with the latest standards and public administrators have to make important decisions regarding what part of their stock should be refurbished first.

Hence, the work developed in this paper is made up of several parts (Fig.2):

- A BIM database of the building stock;
- A set of Bayesian Networks for the evaluation of stock compliance with technical requirements and its ranking according to performance indicators;
- An interface between the BIM database and the Bayesian Networks, which automatically picks out relevant inputs from BIM models and transfers them to BN;
- A multi-criteria decision system, which ranks buildings according to the BN outputs;
- A further set of BN that estimates the budget needed to improve the status of any building.

DSS tool based on BN will be shown with the aim of assessing what buildings must be refurbished first.

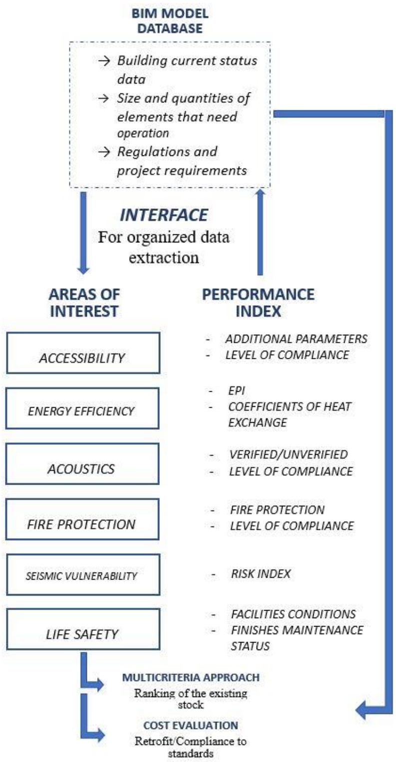


Figure 2. Schematic diagram of the structure of the decision support system.

4.1 Decision support system based on Bayesian Networks

A BN is a directed graph whose nodes are the uncertainty variables and whose edges are the casual or influential links between the variables. Associated with each node there is a set of conditional probability functions that model the uncertain relationship between the node and its parents [14]. Each variable may take two or more possible states of numerical (i.e. discrete), interval (i.e. subdivision into ranges), label or Boolean types. An arc from any set of n variables, called a_i, to another variable b denotes that the set a_i causes b and a_i are said to be the parents of b (b is evidently their child). The strength of those relationships is quantified by conditional probability tables (CPTs), where the probability of observing any state of the child variable is given with respect to all the combinations of its parents' states. In our example this probability is labelled $P(b|a_1, a_2, \dots, a_n)$, where any variable a_i is conditionally independent of any variable of the domain that is not its parent. Thus, we can obtain a conditional probability distribution over every domain, where the state of each variable can be determined by the knowledge of the state of only its parents, and the joint probability of a set of variables E can be computed by applying the "chain rule" [15]:

$$P(E) = P(E_1, E_2, \dots, E_n) = P(E_n|parents(E_n) \qquad (1)$$

That is: the joint probability of a set E_n of variables is equal to the conditional probability of the variable, given only its parents. Other relevant benefits are: the DAG provides a clear understanding of the qualitative relationships among variables; every node can be conditioned by new information (e.g. evidence about the features of a building in our case study); the same belief that updating is supported from consequences to causes, also known as diagnostic reasoning, and can be applied when the budget for renovation is limited and inference must be conducted from child nodes (e.g. cost of renovation) back to parent nodes (e.g. status of a building sub-system); finally, CPTs can describe the relationships among variables of different types (e.g. Boolean nodes, interval node, etc.), even within the same network.

Presently, every local administration performs separate evaluations of existing stock to decide where to focus the intervention first and there is no coordinated assessment at the national level on a proportional distribution of efforts. To that purpose, informed planning according to real priorities is needed, which means detecting any lack of compliance with respect to current legislation, in terms of comfort, energy performances, accessibility, seismic vulnerability, etc.

4.2 Multicriteria ranking

The methodologies for Multi-Criteria Analysis can be divided into two main groups: (i) Multi-Criteria Objectives Analysis (MCOA) and (ii) Multi-Criteria Attributes Analysis (MCAA). In the case of MCOA, the decisional process consists in the selection of the best solution within a group of infinite alternatives, implicitly defined by the problem boundaries. On the contrary, Multi-Criteria Attributes Analysis (MCAA) is a multidimensional evaluation method subset, whose final purpose is to locate the best strategy among a restricted number of alternatives, which are ranked according to their preferences [16]. MCAA can act as a support in the decision-making process [17], which leads through a systematic analysis of the solutions.

As a first step, the hierarchy is defined as follows: the top level is "stock value", the second is composed of all the areas of interest such as accessibility, energy efficiency, acoustics and others; instead, the third level is made up of the outputs from the BN "Level of Compliance" (LoC) node for Accessibility, "EPI" and "Heat Transfer Coefficient" nodes for Energy Efficiency and "Level of Compliance" (LoC) and "Compliance of acoustic requirements", as reported in Section 5. The second step consists in the pairwise comparison between the different areas of interest. As a result, the final ranking is inferred as a combination between the values obtained from the BN and the weights determined by means of the pairwise comparison [18].

4.3 Analysis of the minimum Information level

The next sub-sections show the necessary information to evaluate the level of compliance for the different regulatory areas, particularly the Accessibility Bayesian Network, the Energy Efficiency BN and the Acoustics BN.

4.3.1 Accessibility Bayesian Network

Italian legislation (D.M. 236/89) defines all the requirements and the related technical standards that are shown in the Accessibility Bayesian Network.

The output node 'Level of Compliance' is a child node of several parent nodes, each concerning a specific sub-area [19]-[20]:

- "Accesses": e.g. width, handle height, maximum opening force;
- "Doors": e.g. width, handle height, maximum opening force, maneuvering clearance;
- "Parking spaces": e.g. parking space width;
- "Lift": e.g. car elevator dimensions, car control keypad height;
- "Floors": e.g. floor frictional coefficient, floor joint

width, floor ridges, changes in level;
- “Stairways and Ramps”: e.g. handrails, tread and riser size, stair width, maximum slope;
- “Toilets”: e.g. water closet position, grab bar location and size, lavatory position;
- “Routes”: e.g. clear width of an accessible route, passing space interval;
- “Windows and balconies”: e.g. railings, maneuvering clearance, window opening force, handle height;
- “Facilities outlets”: e.g. facilities outlet height.

The ratio of verified technical prescriptions (e.g. at the building component level) was evaluated in order to fill in the conditional probability tables of all the ten aforementioned Boolean-type intermediate nodes (admitting “true” and “false” states only).

4.3.2 Energy Efficiency Bayesian Network

The whole Energy Efficiency Bayesian Network was derived from previous research on reduced-order models for thermal simulations of buildings [21]-[22].

With the purpose of learning the CPTs of the BN from data, the reduced-order model was repeatedly run to generate a database containing more than 100 records which was used as a dataset to estimate the CPTs, while casual dependencies were quantified by means of the EM-learning tool implemented in the Hugin^{TM} software program [23].

This network estimates two performance indicators:

- Heat Transfer Coefficient (HTC);
- Seasonal Energy Performance (SEPi).

In this case, the nodes represent the variables of the reduced-order model, while arcs were determined according to the casual relationship between the variables of the same reduced-order model.

4.3.3 Acoustic Bayesian Network

New and existing buildings must be characterised by specific noise insulation performance. The legislation (DPCM – 5 December 1997 “Determination of passive acoustic requirements of buildings”) defines all the requirements and concerns:

- Insulation from airborne noises between different real estate units;
- Insulation from external noise (façade insulation);
- Insulation from trampling noise;
- Insulation from the noise of systems;
- Reverberation time of classrooms and gyms.

For each type of noise, the DPCM indicates:

- The indicators to use;
- The threshold values to be met depending on the intended use of the building.

Acoustic BN is divided into two sub-networks, the first of an analytical nature, as it reflects the Sabine equation for the calculation of the reverberation time, the second for the control of the remaining parameters.

4.3.4 BIM semantic enrichment

BIM models must comply with a minimum information level to be able to automatically retrieve information from them and transfer it as inputs in the BN. The management of this information is an extremely important issue from two points of view:

- The kind of information to be entered and how/where to enter it;
- How to extract information from the model in order to be able to carry out successive processing.

After reading the legislation, the verification network was created by taking into account all the aspects that can be evaluated through available information from BIM models. Tools such as SQL and Dynamo, were used to manage data transfer in order to automate the minimum level of information transfer between the BIM models and the networks system.

For both schools, the necessary data were extracted from the respective BIM models related to each requirement of the Accessibility BN, Energy Efficiency BN and Acoustics BN. If the data are not present in the model, they must first be added, if known, and then extrapolated. In the absence of applications that automatically extrapolate information from the BIM model, information must be extrapolated manually.

Table 1 reports the necessary information (available in the model, not available but derived from the models and after post-processing information) for the Accessibility network, Energy Efficiency network and Acoustics network:

Table 1. Necessary information for the networks

Available	Not available	After post processing
Access door width, internal door width, door handle height, ramp width, stairs railing height, stair flight width, hand rail height, tread depth, window parapet height,	Opening doors force, path width and length, door space check, Internal setpoint T, number of floors, lift car depth and width, door clear span, lift platform length	Average transmittance of the opaque and transparent elements, useful floor area, S/V ratio, air-conditioned gross volume, average global irradiation, average external

balcony parapet height, thickness and material of the various constituent layers, intended use, wall type, wall thickness, floor type, layers, floor thickness, internal wall type, window thickness	and width, sink height, toilet lateral wall distance, wc hand rail height, wc nominal height, slope, opening window force, window handle height, balcony operating space, friction coefficient, threshold height	temperature, Ce, Cm, Rm, Rea, Rie, Cih, Irradiation, conduction, gains, Q_op, envelope, power, efficiency, gains_tot, infiltration, forced_ventil, Qh, Epi/EPe, reverberation time, Las_{max}, La_{eq}

5 Results and discussion

These networks were implemented on two schools case studies (Fig.3). For both schools, the necessary data were extracted from the respective BIM models.

a.

b.

c.

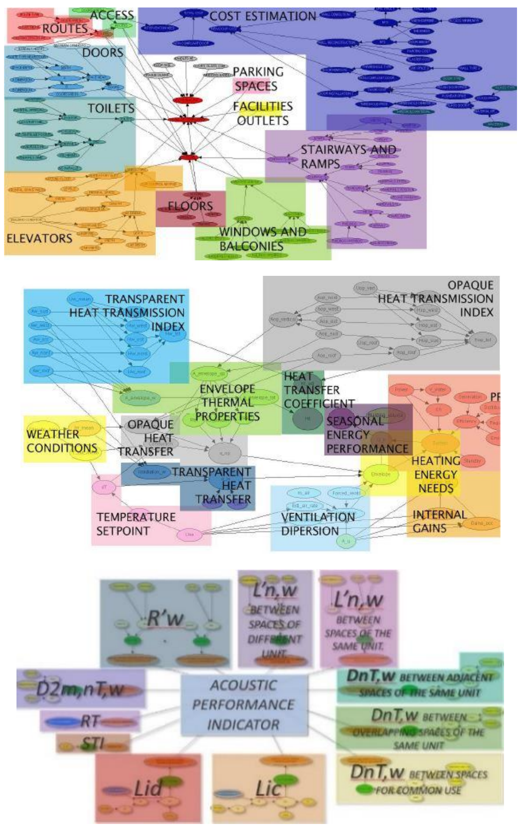


Figure 3. Accessibility Bayesian Network (a), Energy Efficiency BN (b) and Acoustic BN (c).

The Accessibility BN requires 62 inputs, the Energy Efficiency BN requires 32 inputs, while the Acoustics BN requires 30 inputs. Out of the 124 required inputs, 8 and 20 (respectively accessibility and acoustics) were directly available from the BIM model and 39 (regarding accessibility) were available because the BIM designer performed a customised modelling procedure. The remaining data were obtained through combined analyses of several parameters. As for acoustics, the compliance was checked room by room obtaining as output an acoustic performance index for each of them, an arithmetic average between the KPI obtained for each school was calculated.

In Table 2 the values of the BN output nodes are listed. The output “Level of Compliance” (in the second column) represents the ‘true’ percentage value of the node according to the information entered in the network. The other two columns represent the outputs of the Energy Efficiency BN. The rightmost column shows the percentage of ‘true’ of the “Level of Compliance” node of the Acoustics BN.

Table 2. BN outputs for the two cases studies

Case Study	Accessibility	Energy Efficiency		Acoustics
Output	LoC	HTC	EPi	LoC
Units	%	W/m^2K	KWh/m^3y	%
Ungaretti	54,9	2,39	47,04	49,44
Mascagni	55,73	2,55	45,87	55,41

After having obtained the values of the BN outputs nodes, a multi-criteria analysis was applied using the AHP approach for the classification of the two schools to evaluate them in the three regulatory areas.

As a first step, the hierarchy was structured where the first level (goal) is “Intervention Priority”; Accessibility, Energy Efficiency and Acoustics are on the second level (criteria); the third level (sub-criteria) includes the outputs of the nodes “Level of Compliance” for accessibility, “Level of Compliance” for acoustics and “SEPi” and “HTC” for energy efficiency; the fourth level (alternatives) includes the Ungaretti primary school and the Mascagni secondary school.

The second step consisted in the pairwise comparison between the different areas of interest and the different indicators within the same area (e.g. energy efficiency). As a result, the final ranking was inferred as a combination between the values obtained from BN and the weights (Table 3) determined by means of the pairwise comparison, as follows:

$$R = W_A * A + W_{EE} * EE + W_{KPI} * KPI \quad (2)$$

Where A is the "Level of Compliance" for the accessibility and KPI is the "Level of Compliance" for the acoustics reported in Table 2; W_A, W_{EE} and W_{KPI} are the weights (Table 3) and EE is computed as follows:

$$EE = W_1 * HTC + W_2 * SEPi \tag{3}$$

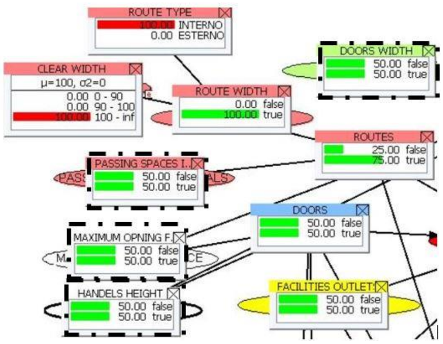
Table 3. Weight values

	W_A	W_{EE}	W_{KPI}	W_1	W_2
Weight values	0.63	0.26	0.11	0.17	0.83

As a result, Ungaretti was assigned {HTC, SEPi}={1, 0.975} and Mascagni was assigned {HTC, SEPi}={0.937, 1}. The application of Equations (2) and (3) to the cases of the two schools gave the following ranking results: R is equal to 0.66 in the case of "Ungaretti" school and 0.67 in the case of "Mascagni" school. Hence, Mascagni is ranked higher, the refurbishment should be prioritised for the Ungaretti school.

More remarkably, the use of Bayesian Networks allows us to draw attention to input nodes even in the case of uncertainty about the selected parameter in the BIM model, or in the case it is completely missing. For example, considering the Accessibility BN, when some information is not available, all the states of a node can be set at the same probability value (e.g. 50% false and 50% true in the case of a Boolean node). A hypothesis was made to show how the outputs can change (Fig.4) depending on the level of uncertainty of the inputs (e.g. door width and handle height) in the BN of the two school case studies, as Table 4 shows:

a.



b.

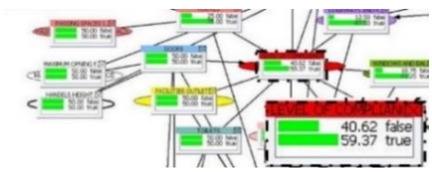


Figure 4. Accessibility Bayesian Network with a level of uncertainty (a) and related results (b).

Table 4. BN outputs of the two case studies with new inputs for Accessibility

Case Study	Accessibility	Energy Efficiency		Acoustics
Output	LoC	HTC	EPi	LoC
Units	%	$W/m^2 K$	KWh/m^3y	%
Ungaretti	59,37	2,39	47,04	49,44
Mascagni	60,21	2,55	45,87	55,41

Table 4 shows the new values of Level of Compliance of Accessibility. The application of Equations (2) and (3) to the cases of the two schools gave the following new ranking results: R is equal to 0.65 in the case of "Ungaretti school and 0.69 in the case of "Mascagni" school. Despite the changes made, the overall assessment remains always coherent, showing that the Ungaretti school is still the school that gets the minor score, so the first to require intervention.

6 Conclusion

To validate the Decision Support System proposed, an actual case project involving two existing schools in Melzo (Milan) was used. The system proposed incorporates 3D BIM models and Bayesian Networks that are capable of semi-automatically evaluating the level of compliance of existing buildings. BNs are a useful means to handle uncertainty due to the lack of some information about existing buildings, because they are capable of dealing with several types of variables and because inference propagation can be inverted. BNs can also consider multiple aspects linked to different regulatory areas simultaneously.

The whole decision support system includes a multi-criteria assessment of some performance indicators, each of them relative to a specific area of interest. The ranking of buildings was performed by means of the AHP approach. Considering the limited budget available to Public Administration, this makes it possible to carry out the evaluations of existing buildings with reduced time and costs.

This paper reported the application in terms of "Accessibility", "Energy Efficiency" and "Acoustics" networks, which were shown to give back reliable results, once interfaced with the BIM models of the case studies. In addition, the development of the BN and the detection of the necessary inputs through the interpretation of regulations give back the amount of information that must be provided by BIM models to perform those analyses.

The methodology detailed in this article can be extended to other regulatory areas such as seismic risk, safety and fire safety.

References

[1] Kassem M., Dawood N. and Mitchell D., A decision support system for the selection of curtain wall systems at the design development stage, *Construction Management and Economics*, 30:1039–1053, 2012.

[2] Vodopivec B., Žarnić R., Tamošaitiene J., Lazauskas M. and Šelih J., Renovation priority ranking by multi-criteria assessment of architectural heritage: the case of castles, *International journal of strategic property management*, 18:88-100, 2014.

[3] Hosseinian S., Choi K. and Bae J., IRIER: A Decision Support Model for Optimal Energy Retrofit Investments, *Journal of Construction Engineering and Management*, Vol.143 Iss.9, 2017.

[4] Shohet I.M., Building evaluation methodology for setting maintenance priorities in hospital buildings, *Construction Management and Economics*, 21:681-692, 2003.

[5] McArthur J.J., A building information management (BIM) framework and supporting case study for existing building operations, maintenance and sustainability, *Procedia Engineering*, 118:1104-1111, 2015.

[6] Volk R, Stengel J. and Schultmann F., Building Information Modeling (BIM) for existing buildings – Literature review and future needs, *Automation in Construction*, Vol.38:109-127, 2014.

[7] Rosenfeld Y. and Shohet I.M., Decision support model for semi-automated selection of renovation alternatives, *Automation in Construction*, 8:503-510, 1999.

[8] Jato-Espino D., Castillo-Lopez E., Rodriguez-Hernandez J. and Canteras-Jordana J.C., A review of application of multi-criteria decision-making methods in construction, *Automation in Construction*, 45:151-162, 2014.

[9] Løken E., Use of multicriteria decision analysis methods for energy planning problems, Renewable and Sustainable Energy Reviews 11:1584-1595, 2007.

[10] Sabaei D., A review of multi-criteria decision-making methods for enhanced maintenance delivery, *Procedia CIRP*, 37:30-35, 2015.

[11] Saaty T.L., How to make a decision: The Analytic Hierarchy Process, *European Journal of Operational Research*, 48:9-26, 1990.

[12] Carbonari G., Stravoravdis S. and Gausden C., Building Information Model Implementation for Existing Buildings for Facilities Management: a Framework and two Case Studies, *Building Information Modelling (BIM) in Design, Construction and Operations*, 149:395-406, 2015.

[13] Di Giuda G.M., Villa V. and Schievano M., BIM modeling of the existing school heritage for investment planning, *Conference ISTeA – Environmental sustainability, circular economy and building production*, 29-48, 2015.

[14] Neil M., Fenton N. and Nielson L., Building large-scale Bayesian networks, *The Knowledge Engineering Review*, Vol.15(3):257-284, 2000.

[15] Pearl J., Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference, 2nd ed., *Morgan Kaufmann Publishers*, California, 1998

[16] Salat S., Assessing cities: A new system of spatial indicators, *SB11 World Sustainable Building Conference*, 18-21, Helsinki, Finland, 2011.

[17] Balcomb J.D. and Curtner A., Multi-criteria decision-making process for buildings, *Energy Conversion Engineering Conference and Exhibit 2000, (IECEC)*, 35th Intersociety 1:528-535, 2000.

[18] Corneli A., Meschini S., Villa V., Di Giuda G.M., Carbonari A., Integrating BIM and Bayesian Networks to support the management of large building stock, *Re-shaping the construction industry*, 224-233, 2017.

[19] DECRETO MINISTERIALE 14 giugno 1989, n.236, Prescrizioni tecniche necessarie a garantire l'accessibilità, l'adattabilità e la visitabilità degli edifici privati e di edilizia residenziale pubblica sovvenzionata e agevolata, ai fini del superamento e dell'eliminazione delle barriere architettoniche, GU Serie Generale n.145 del 23-6-1989.

[20] Architectural Barriers Act (ABA) Standards, Adopted by Department of Defense, General Services Administration, *U.S. Postal Service*, 2015.

[21] Benedettelli M., Carbonari A., Naticchia B., Vaccarini M., Reduced-order Models for Supporting Energy Audits of Buildings, *33rd International Symposium on Automation & Robotics in Construction*, pp.563-571, 2016.

[22] Giretti M., Lemma M., Casals M., Macarulla M., Fuentes A., Jones R., Effective building modelling for energy performance contracting, *Building Simulation Applications*, Bolzano, 2017.

[23] Fayyad U.M., Piatetsky-Shapiro G., Smyth P. and Uthurusamy R., Advantages in Knowledge Discovery and Data Mining, *AAAI Press/The MIT Press*, Menlo Park, California, 1996.