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A decision support system for the multicriteria analysis of existing stock

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Abstract

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, to preserve the stock and also keep it in good condition. As a result, most public administrators have to make important decisions regarding what part of their stock should be refurbished first.
In this paper a new methodology regarding an objective assessment of the quality of large building stock is suggested, as it could help prioritize refurbishment actions. The methodology is based on a decision support system, that is capable of semi-automatically evaluating the compliance of existing buildings with a set of rules by means of the application of Bayesian Networks. The main findings of this research led to the identification of relevant parameters to be used for that assessment; the re-use of those parameters to build a multi-criteria analysis tool; the identification of criteria and requirements to interface this decision tool with BIM models of the stock under consideration. A rough estimation of costs needed to refurbish those buildings that are not compliant, in order to include budget concerns, will be dealt with in the next research step. Finally, a preliminary application of the decision support system to evaluate two Italian school buildings – selected as case studies - will be reported.

Keywords: Multi-criteria analysis, Bayesian networks, decision networks, building stock, BIM

Nomenclature

E_n	Random variable	W_i	Weight of area of interest/index
R	Ranking value	HTC	Heat transfer coefficient
A	True value of 'level of compliance' index	SEP	Seasonal energy performance

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1. Introduction

One of the most important responsibilities of Public Building Administrations is the prioritization of refurbishment actions on large building stock, for example schools. The majority of public buildings are outdated and informed planning, according to real priorities, means detecting any lack of compliance with respect to current legislation, in terms of comfort, energy performances, accessibility, seismic vulnerability, etc. While sticking to large building stock, the aim of this research work is to develop a decision support tool based on a Bayesian Network that can extract relevant information directly from a BIM database of the building stock and evaluate the compliance of the stock to some pre-determined technical requirements.

The decision support system was developed so as to be compliant with two BIM-based models of two schools located in Melzo (Milan), which are used for Facility Management (FM) and which acted as test cases in this research work. The whole decision support system includes a multi-criteria assessment of some performance indicators, each of them relative to a specific area of interest. Finally, the system was arranged so as to be expandable with the additional feature of estimating the budget needed to improve the status of non-compliant buildings, which will be implemented in the next research step and is expected to lead towards a cost-benefit analysis of potential scenarios.

To sum up, this tool was conceived as a tool to support a methodology for Public Administrations that have to schedule three-year plans of Public Works in advance within budget and quality constraints, while expeditiously evaluating benefits from technical improvements. In fact, the standard current methodology usually requires, as a first step, a preliminary survey on the state of the art of buildings through the creation of a repository, possibly a BIM repository, where all the information is accommodated in a structured database. Then, a second tailored survey is expected to complete the information framework and help the assessment phase. The accomplishment of these two steps, however, requires huge time and cost efforts, which can barely be afforded when strict budget constraints are posed, hence strategic management for the efficient selection of actions should be preferred. For this reason, the decision support tool reported in this paper would be functional for supporting informed choices in several situations, e.g. for the execution of new school buildings, the renovation of existing properties, small maintenance interventions, diagnostic investigations, securing and retrofitting existing buildings.

2. Scientific background

Decisions for building maintenance require integration of various types of information and knowledge created by different members of teams involved in design and construction [1]. A gradual and incremental approach towards the use of BIM has been experienced over the last decade within the construction industry as a way to increase productivity and collaboration [2]. In 2012 attention was drawn to the crucial role of BIM in this phase of building life, stating that the initial costs of inserting BIM systems into the processes are justified only if meant to support operation and maintenance [1]. Although the need for BIM in Facility Management (FM) has been acknowledged by researchers and practitioners, BIM is still not being effectively utilized in this phase, even if refurbishment activities are often carried out [3]. Also, it was highlighted that some studies on “BIM in Building Refurbishment and Maintenance” are focused on applications at an FM level, whereas just a few studies are related to BIM applications in either maintenance or refurbishment. Some other research focused on the choice of what information is needed in order to make models significant to maintenance, and on handling uncertainty due to incomplete building documentation [4]. Since BIM is becoming a project standard, FM is expected to be based on information related to the BIM model database. In addition, FM managers could use this knowledge to evaluate the quality of buildings and to rank refurbishment priorities, provided that the decision issue among the several involved parameters has been solved. Hence, this paper deals with the development of a decision support tool based on the use of Bayesian Networks to evaluate the performance parameters of existing buildings, whose inputs are retrieved from BIM models, which may not be fully detailed but just limited to the level of available information about the existing stock [5]. The results from this evaluation are used as inputs for multi-criteria evaluation of the quality of the analyzed stock. Finally, this paper contributes to the definition of the minimum level of information that must be included in BIM models in order to support performance evaluation.

3. Decision support framework

3.1. Overview

Owners and public owners of large stocks~~,~~ that are constrained by limited budget availability must face the big challenge of creating a priority list of their buildings needing refurbishment that is based on the real status of each facility and on the available budget. Hence, the work developed in this paper is thought of as being part of a wider decision support system that is made up of several parts (Fig. 1):

- A BIM database of the building stock;
- A set of Bayesian Networks for evaluating stock compliance to technical requirements, and which are ranked by performance indicators and split into five groups: Accessibility, Energy Efficiency, Life Safety, Fire Protection, Seismic Vulnerability;
- An interface between the BIM database and the Bayesian Networks, which automatically finds those inputs in BIM models that are required to perform inferences in the BN;
- Another set of Bayesian Networks that estimates the budget needed to improve the status of any building, just in case it does not comply with minimum requirements, from the present status to the minimum compliance level; if buildings are compliant, the estimated costs will be null;
- A multi-criteria decision system, which ranks buildings according to the BN outputs.

The performance indicators represent the output nodes of the first set of BN. The indexes regarding Accessibility and Fire Protection qualitatively estimate the level of fulfillment to minimum requirements. The remaining ones, regarding Energy Efficiency, Seismic Vulnerability and Safety, were designed so as to provide users with quantitative and measurable levels of performance.

In this paper, the BN relative to Accessibility and Energy Efficiency, which are the subjects of sub-Sections 4.1 and 4.2, respectively, will be reported in detail.

The Accessibility Bayesian Network includes three qualitative performance indicators:

- “Level of compliance” (A), which is represented by a labelled node and identifies how far the building is from the minimum compliance level, whose range is between 0 and 100%, the latter being verified just in case the “Regulation obeyed” is true, and which is an input to the multi-criteria decision;
- “Additional parameters”, which is represented by a labelled node, and estimates how many non-mandatory requirements, if any, are fulfilled by the building beyond the mandatory ones.

The outputs of the Energy Efficiency Bayesian Network are given by two quantitative performance indicators:

- “Heat transfer coefficient” (HTC), which is represented by an interval node, and estimates the average heat transfer coefficient of the building according to the standard EN13790;
- “Seasonal energy performance” (SEP), which is represented by an interval node, and estimates the annual energy required for conditioning over a whole year per unit area~~,~~ according to the EN13790 standard.

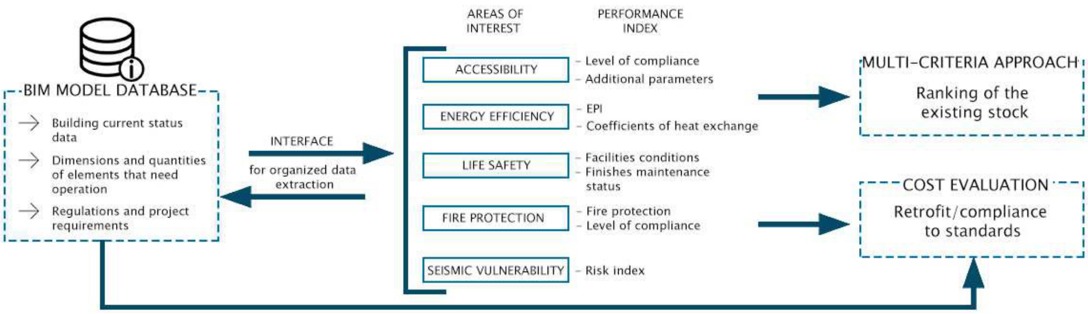

Fig. 1. Schematic diagram of the main parts of the decision support system.

3.2. Bayesian Networks

Bayesian Networks (also called belief Bayesian Networks or causal probabilistic networks) have been dominating the field of reasoning under uncertainty, thanks to their ability to deal with incomplete or uncertain information [6]. Bayesian Networks are always made of a graphical model and an underlying conditional probability distribution. The graphical model is represented by a direct acyclic graph (DAG), whose nodes represent random variables that are linked by arcs, corresponding to causal relationships among the previous nodes. 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 is said to be the parents of *b* (*b* is evidently their child). The strength of those relationships are 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 it would be labelled $P(b|a_1, a_2, \ldots, a_n)$, 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" [7]:

$$P(E) = P(E_1, E_2, .., E_n) = P(E_n \mid parents(E_n)) \tag{1}$$

That is: the joint probability of a set E_n of variables is equal to the conditional probability of that variable given only its parents. Therefore the complete specification of any joint probability distribution does not necessarily require an absurdly huge database. This is the first of a series of benefits provided by the use of BNs for the application reported in this paper. 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), hence the inference (also called belief updating) is performed via a flow of information through the network, and the most likely state of a set of "query" nodes (e.g. the indicators in our case study) can be computed; the same belief updating is supported from consequences to causes, also known as diagnostic reasoning, and it 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 in the Accessibility BN and interval nodes in the Energy Performance BN), even within the same network.

3.3. Multi-criteria analysis

Multi-criteria analysis is in contrast with standard analyses based on the ratio between costs and benefits. Instead, the multi-criteria approach hides in criteria the risk of an excessive subjectivity by evaluators: the choice of some criteria instead of others might cause an overestimation or an underestimation of some effects [8]. Multi-criteria analysis represents a series of techniques, the scope of which is to consider several features that are in some way related to different aspects of the problems under analysis, with the final objective of bringing to the surface different points of view on the analyzed object. 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; hence, the purpose is to create the best alternative, taking into account the objective to be reached. 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 [9]. In this case, the project mission must always be kept in mind, hence the problem is located on the choice, instead of on the creation, of the solution. MCAA cannot be thought of as an algorithm, which would automatically give the desired solution, rather it can act as a support in the decision making process [10], which leads through a systematic analysis of the solutions.

In the development process, all objectives, criteria and alternatives must be defined. MCAA is usually structured on six points:

- Definition of the evaluation matrix, which is the analytic instrument that represents the value added to each alternative and is based on pre-determined criteria;
- Dominance analysis to eliminate any alternatives which prove to be dominated from the decisional process, i.e. having worse performances, if compared to the others. In this way, the evaluation matrix eliminates dominated solutions and the analysis continues based on the residual choices;
- Normalization of the evaluation matrix, which makes qualitative and quantitative data homogeneous and operable. This process elaborates the data in the evaluation matrix, converting them into dimensionless values through logical and mathematical functions;
- Appointing the weight associated to each criteria, which makes it possible to define the relevance order among all criteria and sub-criteria, hence the priority matrix is created. The most popular techniques used to develop criteria are: direct appointment, paired comparison, Delphi method and single order technique. All these methods require managing approximation, due to the non-experimental nature of scores;
- The techniques used to set up the organization of options can be divided into (a) those ones which provide equal points, and (b) those others which give differential points. In the first category the main techniques used are *maximin* e *maximax*; in the second one we can identify MAUT or AHP for example, which diverge as for the method used in the evaluation of preferences and the formalization used in their representation and elaboration;
- Sensitivity analysis is needed for checking the robustness of solutions. It consists in a sensitivity analysis of the priority scale with respect to variations in the model. Sensitivity analysis has the scope of dealing with uncertainty problems gathered from the chosen method, from pre-determined criteria and sub-criteria, and from the corresponding weights. The importance of this check is due to its role as the only way for the decision–maker to better understand the relation between results and appointed points.

4. System development

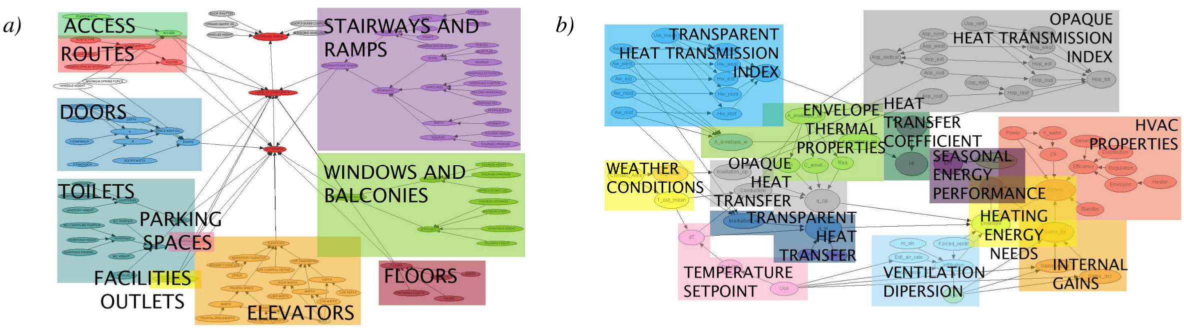

Fig. 2. Accessibility Bayesian Network (a) and Energy Efficiency Bayesian Network (b).

4.1. Accessibility

The Accessibility Bayesian Network mirrors requirements posed by Italian legislation (D.M. 236/89) and related technical standards (Fig. 2-a). The output node ‘Level of compliance’ (ref. subsection 3.1) is a child node of several parent nodes, each concerning a specific sub-area [11, 12]:

- “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.
- “Elevators”: 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.

Conditional probability tables of all the ten aforementioned Boolean-type intermediate nodes (admitting “true” and “false” states only) were dependent on the ratio of verified technical prescriptions (e.g. at the building component level), which were represented by their parent node.

4.2. Energy efficiency

The Energy efficiency Bayesian Network estimated two performance indicators:

- Heat transfer coefficient (ref. sub-section 3.1)
- Seasonal energy performance (ref. sub-section 3.1)

The whole network was inferred by previous research on reduced-order models for thermal simulations of buildings [13,14]. The nodes in the Energy Efficiency Bayesian Network represent the variables of the reduced-order model, while arcs were determined according to the causal relationships between the variables of the same reduced-order model (Fig. 2-b). In order to learn 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, and causal dependencies were quantified by means of the EM-learning tool implemented in the Hugin™ software programme [15].

4.3. Implementation of the decision tool for a case study

Both networks were tested on two case studies: the first is the “Ungaretti” primary school in Melzo (MI) with a surface area of 4528 m^2. The classrooms, laboratories, toilets and cafeteria are located over three floors above ground, while the gym is in a separate building. The second case study is the “Mascagni” secondary school in Melzo (MI) with a surface area of 5736 m^2, which is formed of three functional blocks. One block holds the classrooms and laboratories located over two floors above ground, the other blocks hold the cafeteria/auditorium and the gymnasium. Both schools are made of a reinforced concrete bearing structure (Fig. 3.a). The Accessibility Bayesian Network requires 62 inputs (Fig. 3.b), while the Energy Efficiency Bayesian Network requires 32 inputs (Fig. 3.c). As the BIM decision tool interface is not yet available, the inputs were retrieved manually from the BIM models. Out of the 94 required inputs, 8 (about accessibility) were directly available from the BIM model; 39 (about accessibility) were unavailable (no evidence put in the corresponding node) but some suggestions can be provided to designers in order to do so; in the remaining cases, the user had to analyze combined parameters in order to work out

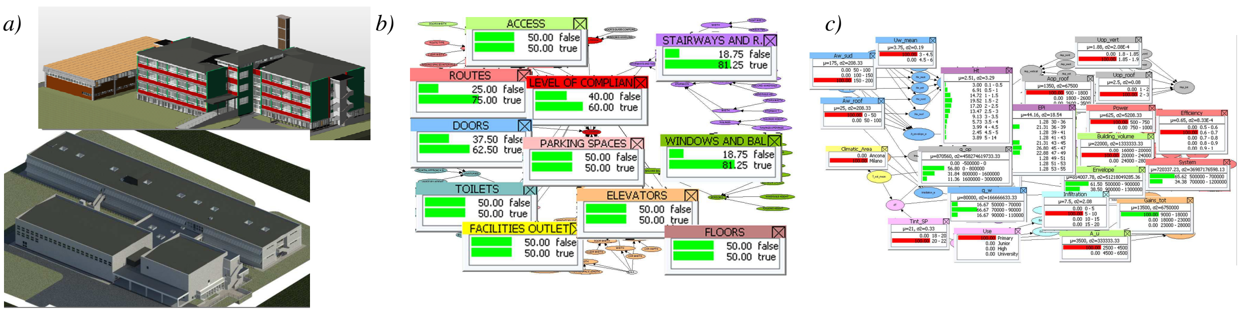

Fig. 3. BIM models of the cases studies (a); the output of the Accessibility (b) and Energy Efficiency BN (c) for the case of the Ungaretti school.

the required inputs. The resulting output estimates are shown in Tab. 1. The probability inferences on the Accessibility Bayesian Network output nodes are shown in the columns from 'Access' to 'Level of compliance', and as all these columns represent Boolean nodes, the probability of being true for the first 10 nodes directly affects the 'true' percentage value of the 'Level of compliance' node. The outputs of the Energy Efficiency Bayesian Network are reported in the two remaining columns, and, as they are represented by Interval nodes, they show a quantitative assessment of performances based on the provided inputs.

Table 1. BN outputs for the two cases studies.

Case Study	Access	Doors	Parking Spaces	Elevators	Floors	Stairways and Ramps	Toilets	Routes	Windows and Balconies	Facility outlets	Level of compliance	HTC	SEP
Units	%	%	%	%	%	%	%	%	%	%	%	W/m^2K	kWh/ym^2
School Ungaretti	50	62.5	50	50	50	81.3	50	75	81.3	50	60	2.43	45.29
School Mascagni	16.7	37.5	50	50	50	67.2	50	75	75	50	52.1	3.43	45.79

It can be seen that the two rightmost columns are in very good agreement with detailed energy simulations performed on the buildings [16, 17], hence the Energy Efficiency Bayesian Network gives accurate inferences.

Finally, the AHP decision approach was applied to the two case studies, according to the procedure suggested by Saaty [18]. Computations were implemented by means of an Excel™ spreadsheet. As a first step, the hierarchy was defined as follows: the top level is "stock value", the second is composed of all the areas of interest such as accessibility, energy efficiency and the others; instead, the third level is made up of the outputs from the BN "Level of compliance" node for Accessibility, and the "EPI" and "Heat transfer coefficient" nodes for Energy Efficiency. The second step consists in the pairwise comparison between the different areas of interest displayed in Tab. 2 and the different indicators within the same area (e.g. energy efficiency) displayed in Tab. 3. 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, as follows:

$$R = W_A * A + W_{EE} * EE \tag{2}$$

Table 2. Areas of interest pairwise comparison.

	Accessibility	En. Efficiency	Weight
Accessibility	1	5	0.83 (W_A)
En. Efficiency	0.2	1	0.17 (W_{EE})
	λ=2.98	CI=0.976	

Table 3. Energy efficiency indicators pairwise comparison.

	HTC	SEP	Weight
HTC	1	0.2	0.17 (W_1)
SEP	5	1	0.83 (W_2)
	λ=2.98	CI=0.976	

Where A is the "Level of compliance" reported in Tab.1, WA and WEE the weights from Tab.2, EE is computed as follows:

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

Both HTC and SEP were normalized according to their best values, being the lowest in both cases, which are listed in Tab.1. As a result Ungaretti was assigned {HTC, SEP}={1,1} and Mascagni was assigned {HTC, SEP}={0.71,0.99} . The application of Eqs. (2) and (3) to the cases of the two schools, where the weights are shown in Tabs. 2 and 3, provides the following results: R is equal to 0.67 in the case of "Ungaretti" school and 0.59 in the case of "Mascagni "school. Hence Ungaretti is ranked higher and refurbishment should be prioritized for the Mascagni school.

5. Conclusions

The decision support system reported in this paper is meant to help owners of large building stocks in managing a huge number and variety of buildings, taking into consideration a lot of aspects related to different technical issues, such as accessibility, energy efficiency, life safety, fire protection and seismic vulnerability. The technical parameters were assessed by means of Bayesian Networks for several reasons, among which because they can handle uncertainty that can be due to the lack of some information about the buildings under evaluation, and because they are capable of dealing with several types of variable. The ranking of buildings was performed by means of the AHP approach. In the application reported in this paper, the networks regarding "Accessibility" and "Energy Efficiency" were evaluated, and they were shown to give back reliable results once interfaced to the BIM models of the case studies. The inputs of the Bayesian Networks give back the amount of information that must be provided by BIM models in order to perform those analyses. In addition, once an intelligent interface between BNS and BIM has been developed, they can run automatically and work out a lot of analyses with reasonable effort, constituting a powerful decision support system.

6. References

[1] I. Motawa, A. Almarshad, A knowledge-based BIM system for building maintenance, Automation in Construction 29 (2013)173-182.
[2] Z. Alwan, BIM performance framework for the maintenance and refurbishment of housing stock, Structural Survey, Vol. 34 Iss 3 (2016) 242-255.
[3] D. Ilter, E. Ergen, BIM for building refurbishment and maintenance: current status and research directions, Structural Survey, Vol. 33 Iss 3 (2015) 228-256
[4] J. J. McArthur, A building information management (BIM) framework and supporting case study for existing building operations, maintenance and sustainability, Procedia Engineering 118 (2015) 1104-1111
[5] P. A. P. Ramirez, I. B. Utne, Bayesian network for decision making on ageing facilities, in: European Safety and Reliability Conference, ESREL, Troyes, 2011, pp. 80-88.
[6] K.B. Korb, A.E. Nicholson, Bayesian Arificial Intelligence, Chapman & Hall/CRC Edition, 2004.
[7] J. Pearl, Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference, 2nd ed., Morgan Kaufmann Publishers, San Mateo, California, 1998.
[8] J.R. Canada, W.G. Sullivan, Economic and Multi-attribute Evaluation of Advanced Manufacturing Systems, Prentice Hall, Englewood Cliffs, 1989.
[9] S. Salat, Assessing cities: A new system of spatial indicators, SB11, World Sustainable building Conference, 18-21 ottobre, Helsinki, Finland, 2011.
[10] J. D. Balcomb, A. Curtner, Multi-criteria decision-making process for buildings, Energy Conversion Engineering Conference and Exhibit 2000, (IECEC) 35th Intersociety, vol.1, pp. 528-535, 2000.
[11] DECRETO MINISTERIALE 14 giugno 1989, n. 236, Prescrizioni tecniche necessarie a garantire l'accessibilita', l'adattabilita' e la visitabilita' 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 - Suppl. Ordinario n. 47).
[12] Architectural Barriers Act (ABA) Standards, Adopted by Department of Defense, General Services Administration, U.S. Postal Service, 2015.
[13] M. Benedettelli, A. Carbonari, B. Naticchia, M. Vaccarini, Reduced-order Models for Supporting Energy Audits of Buildings, in: 33rd International Symposium on Automation & Robotics in Construction, Auburn, 2016, pp. 563-571.
[14] M. Giretti, M. Lemma, M. Casals, M. Macarulla, A. Fuentes, R. Jones, Effective building modelling for energy performance contracting, in: Building Simulation Applications, Bolzano, 2017.
[15] U. M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, R. Uthurusamy, Advantages in Knowledge Discovery and Data Mining, AAAI Press / The MIT Press, Menlo Park-California, 1996.
[16] G.M. Di Giuda, V. Villa, F. Paleari, M. Schievano, BIM modeling of the existing school heritage for investement planning, Conference ISTeA – Enviromental sustenability, circular economy and building production (2015) 29-48.
[17] G.M. Di Giuda, V. Villa, F. Paleari, From BIM to BEM for the management of the existing school buildings, Conference ISTeA – Rethinking the digital construction industry (2016) 19-28.
[18] T. L. Saaty, How to make a decision: The Analytic Hierarchy Process, European Journal of Operational Research 48 (1990) 9-26.