Decision Support Tool for Multi-Criteria Analyses of the Quality of Large Building Stock

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Abstract –

The management of any large building stock with limited resources poses a problem of prioritization of refurbishment actions. Also, available technical information about the building stock is often incomplete and the process of standardization and updating is expensive and time consuming. Some public owners are developing preliminary BIM models of their stock, but they are willing to limit the complexity of the models within the lowest amount of information required for management and maintenance, so as to make that process affordable. Indeed, administrations are challenged by their duty relative to planning regular maintenance and operation of buildings, because of the legislation in force, which requires monitoring of their facilities.

For the reasons stated above, this paper presents a decision support tool that can help prioritize refurbishment actions on large building assets. To this purpose, many requirements must be jointly considered in this examination, each requirement being assessed by means of one or several indicators. Then the indicators are compared one another, according to a multi-criteria approach, that weighs the several criteria and rank the assets. In order to deal with the extensive and uncertain information that must be managed in this process, indicators are estimated by means of Bayesian Networks. This tool is used first to assess the technical indicators and rank the assets, while marking any facilities not complying with regulations. Then, additional Bayesian Networks are in charge of estimating the budget needed to upgrade non-compliant facilities with minimum legislation requirements. The outcomes of this research can be used even to assess the level of detail of the information that must be included in BIM models of the stock, in fact acting as guidelines for their development. Finally, the application of the decision tool on a real test case will be presented.

Keywords –

Decision support system; BIM; Bayesian Networks; Multi-Criteria; building stock

1 Introduction

The majority of public buildings are outdated. As a consequence, Public Building Administrations are in charge of the prioritization of refurbishment actions on the large building stock they manage, including schools.

Presently, every local administration performs separate evaluations of the existing stock deciding 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 is needed, according to real priorities, which 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 Bayesian Networks, which 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. In addition, the system included one Bayesian Network in charge of estimating the budget needed to improve the status of non-compliant buildings towards a new state where they are compliant with minimum legislation requirements. This piece of information is necessary to perform cost- benefit analyses.

To sum up, this tool was conceived as a tool to support a methodology for Public Administrations that have to schedule three-years 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 available 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 Literature Review

The development of guidelines and standard methodologies to speed up the process of maintaining and rehabilitating huge stock of buildings is not new. Even the Japanese government started a strong action towards rehabilitation of social housing in the 1970s, that was aimed at optimizing the overall approach [1]. That methodology consisted in a quick and systematic survey of the degradation stage, according to several technical requirements, and in the next merging of those indicators into a unique index assessing the overall quality of buildings. Indeed, decisions for building maintenance require integration of various types of information – which is sometimes incomplete - and knowledge created by different members of teams involved in design and construction [2]. This issue should consider that a gradual and incremental approach towards the use of BIM has been experienced over the last decade within the construction industry [3]. In 2012 attention was drawn to the crucial role of BIM in this phase of building life operation, stating that the initial costs of inserting BIM systems into the processes are justified only if it is meant to support operation and maintenance [2]. Although the need for BIM in Facility Management (FM) has been acknowledged by researchers and practitioners, BIM is still not being effectively exploited in this phase, even if refurbishment activities are often carried out [4]. 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 [5]. 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 have the opportunity to 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 any existing stock [6,7]. The results from this evaluation are used as inputs for multi-criteria evaluation of the quality of the analyzed stock. Finally, another set of Bayesian Networks are used to evaluate the refurbishment cost of those buildings that do not comply with minimum legislation requirements.

3 Description of the Decision Support System

3.1 Overview

Any large building stock requires a targeted and accurate management in order to comply with the latest standard and maintain a good level of conservation through maintenance. In addition, the hardest challenge that owners and public owners of a large stock have to deal with is the limitations in terms of budget. This leads to the need for a priority list of the buildings needing refurbishment that is based on the real status of each facility. Also, by means of preliminary analyses of potential refurbishment actions related to the building type and construction techniques, what refurbishment actions are affordable referring to the available budget can be inferred. 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 (in terms

of Accessibility, Energy Efficiency, Life Safety, Fire Protection, Seismic Vulnerability) and for ranking it 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 into BN;
- A multi-criteria decision system, which ranks buildings according to the BN outputs;
- 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, until it complies with minimum legislation requirements; when existing buildings are compliant, the estimated cost will be null.

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

In this paper, the Bayesian Networks relative to Accessibility, Energy Efficiency and Cost Estimation, which are the subjects of sub-Sections 4.1, 4.2 and 4.3, respectively, will be reported in detail. The outputs of the Energy Efficiency Bayesian Network are two quantitative performance indicators (both in accordance with EN13790):

- "Heat transfer coefficient" (HTC), which is represented by an interval node, and estimates the average heat transfer coefficient of the building;
- "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.

The Accessibility Bayesian Network includes two 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" node is true, and which is an input to the multi-criteria decision tool;
- "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.

As far as the Accessibility Bayesian Network is concerned, it is linked to another fragment of Bayesian Network, which estimates the "Total cost" for renovation. This fragment evaluates the total amount of retrofitting cost, due to the presence of non-compliant entrance doors width, as reported in sub-Section 4.3.

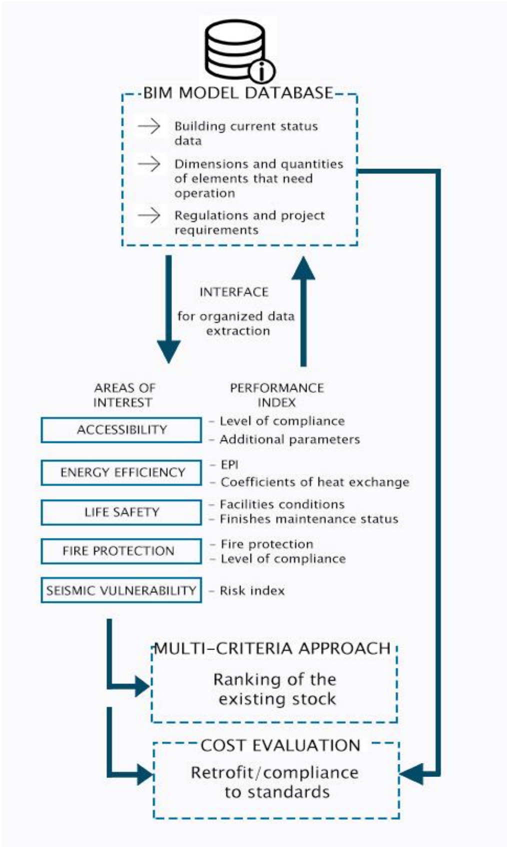

Figure 1. Schematic diagram of the structure of the decision support system.

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 [8]. Bayesian Networks are always made of two components. The first component is the graphical model, which 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 second component is represented by a set of conditional probability tables

(CPTs), whose values define the strength of relationships among nodes, where the probability of observing any state of the child e_n variable is given with respect to all the combinations of its parents' states: that is $P(e_n|e_1, e_2, \ldots, e_{n-1})$, where any variable e_i is conditionally independent of any variable of the domain that is not its parent. Thus, 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" [9]:

$$P(E) = P(E_1, E_2, .., E_{n-1}, E_n) = P(E_n \mid parents(E_n)) \cdot P\left(parents\left(E_n\right)\right) \quad (1)$$

where $E_1, \ldots E_{n-1}$ are the parents of E_n. 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 Bayesian Networks 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 upon 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, thanks to the application of the Bayes Theorem. This feature is critical in our application because it can be applied when the budget for renovation is strictly limited and inference must be conducted from child nodes – such as "admissible cost of renovation"- back to parent nodes – such as the "affordable technology options" for refurbishing.

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, hence sets of information from different sources can be merged into one comprehensive network.

3.3 Ranking of the quality of building stock

The Bayesian models reported in the next Section 4 provide users with two indicators for evaluating the quality of any building: on one hand, the technical indicator that is the result of a multi-criteria approach; on the other hand, the cost that must be afforded to make the building compliant with minimum legislation requirements.

The Multi-criteria approach includes the subjectivity by evaluators through the choice of some criteria instead of others [10], hence it can be customized to the specific needs dictated by several owners. In fact, the Multi-criteria approach 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. 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 [11]. MCAA can act as a support in the decision making process [12], which leads through a systematic analysis of the solutions. It is usually structured on six points:

(i) 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;
(ii) 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;
(iii) Normalization of the evaluation matrix, which makes qualitative and quantitative data homogeneous and operable;
(iv) Appointing the weight associated to each of the criteria, which makes it possible to define the relevance order among all criteria and sub-criteria, hence the priority matrix is created;
(v) Among the techniques used to set up the organization of options, we cite the AHP, which was used in our case study.

The AHP methodology was applied according to what suggested by Saaty [13]. 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, as reported in sub-Sections 4.1 and 4.2. 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, as follows:

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

where:

$$EE = W_1*HTC + W_2*SEP \quad (3)$$

Again, A is the output of the Accessibility BN (sub-Section 4.1); EE is the combination of the outputs of the Energy Efficiency BN (sub-Section 4.2) and W_A, W_{EE}, W_1 and W_2 are the weights worked out according to the AHP approach.

The estimation of refurbishment costs reported in sub-Section 4.3 was conducted according to three steps. As a first step, a list of activities necessary to refurbish non-compliant buildings differentiated on the basis of the several possible types of refurbishment actions was produced. Then, the DAG of the network was developed, which includes both the estimation of quantities (some nodes will be read straight from the BIM model while other nodes from the rest of the BN) and the estimation of unit costs, according to the framework suggested by the official list of unit costs of the Province of Milan (Italy). Finally, CPTs of Bayesian Networks were built from unit costs of the Province of Milan and from the knowledge of the range inside which every numerical node was expected to fall.

Both the Multi-criteria approach and the cost estimation 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 gymnasium is in a separate building.

a)

b)

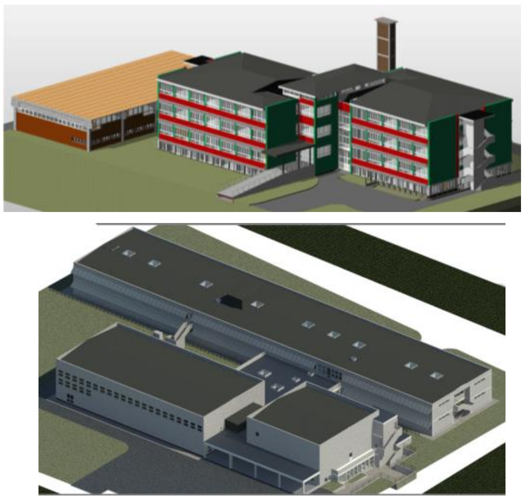

Figure 2. BIM models of the cases studies a) Ungaretti school b) Mascagni school

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 two blocks hold the cafeteria/auditorium and the gymnasium. Both schools are made of a reinforced concrete bearing structure (Fig. 2).

4 System development and testing

a)

b)

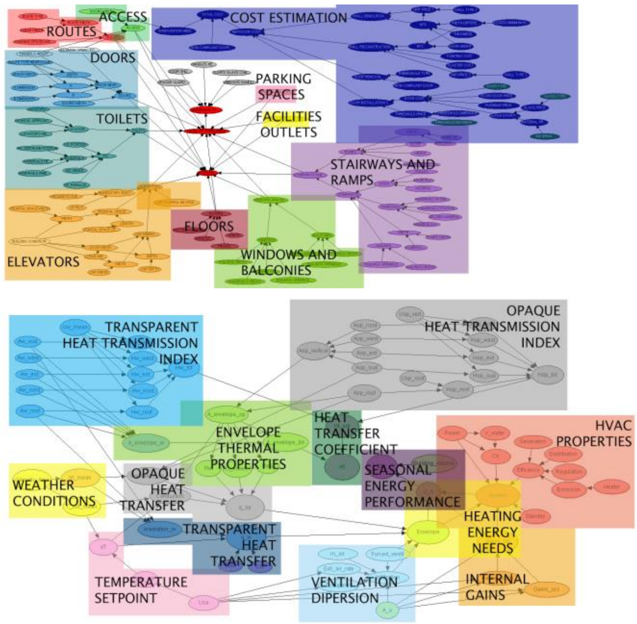

Figure 3. Accessibility Bayesian Network (a) and Energy Efficiency Bayesian Network (b).

4.1 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 (Fig. 3-a). 'Level of compliance' (ref. subsection 3.1) is the output node that sums up the current situation of the building. It is a child node of several parent nodes, each regarding the different building components [14, 15]:

- "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.

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

4.2 Energy Efficiency Bayesian Network

The whole Energy efficiency Bayesian Network was derived from previous research on reduced-order models for thermal simulations of buildings [16,17]. 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™ software program [18]. This network estimates two performance indicators:

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

In this case, the nodes 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. 3-b).

4.3 Cost estimation Bayesian Network

The first fragment of Bayesian Network for cost estimation reported in this sub-section is directly linked to the Accessibility BN. It is in charge of estimating the cost to be incurred in, so as to renovate those access doors that the in the corresponding input node of the Accessibility BN was instantiated as not compliant with minimum legislation requirements. The adoption of Bayesian models allowed to manage uncertain information about inputs, if any, and to reverse inference updating from constrained final budget (i.e. child nodes) back to inputs, or parent nodes (e.g. technology and geometric preferences).

The total cost is dependent on three nodes: the first one is the cost for complete refurbishment of one door only; the second one is the number of doors needing refurbishment, and the last one acts as a counter-check that current access doors really need refurbishment (when in "false" state). When this last node is "true" the cost of one door refurbishment is set to "zero".

In turn, the cost to renovate one access door is made of four tasks, which add up in terms of related costs:

- door removal, that depends on the type of door;
- demolition of a portion of wall, so as to enlarge the door space, related to the amount of partition to be demolished and wall technology;
- rebuilding of the interface between wall and new door, that is computed from the quantity and technology of wall, plaster and painting;
- installation of the new door and its accessories, which is given by the cost of the new threshold, and the cost of the new door (depending on type and material).

The latter part of the cost network is the only one that involves a choice by the user, that affects total cost. Indeed, the green nodes depicted on Fig. 4 are those nodes where owners are asked to choose among different options. These options entail the threshold material, but thickness is set as equal to the former one, the door type (i.e. flush or with glass) and material (i.e. metal or plastic). All the remaining information required by the network as inputs, including the type, size of the existing door, thickness and features of the wall, the number of access doors that do not comply with regulations, are extracted straight from the BIM model of the building. In the current version of the BN, pre-determined features, not included in the list of options, are "one leaf door" and "presence of a push-bar". The nodes dealing with costs were set as either Interval nodes or Numbered nodes. The Interval type was used when cost depends on the amount of material put in place, and when interval values were more expressive than many numbered states (e.g. "new door cost"). In case costs did not depend on quantities, the corresponding nodes were of Numbered type.

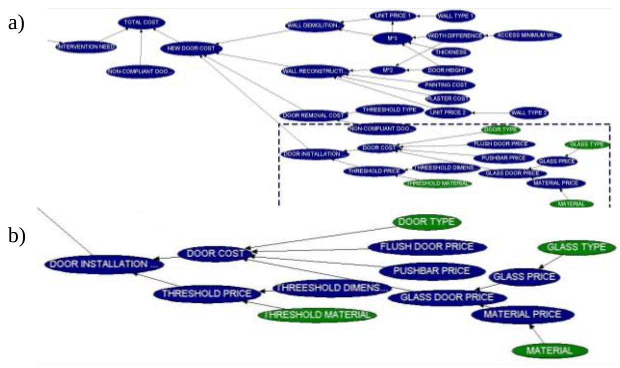

Figure 4. Cost estimation BN (a), which is a part of the Accessibility BN (Ref.Fig.3a), and zoom of the decisional nodes, marked in part a of the figure (b).

4.4 Implementation for a real case-study and results

The indices calculation requires 62 pieces of information as inputs for the Accessibility BN and 32 for the Energy Efficiency BN (Fig.3). These data came from the BIM models of the two schools and they have been detected manually as the tool interface is not available, yet. Among the 94 required input data, eight, concerning Accessibility, are always found in attributes of the BIM model, thirty-nine, still concerning Accessibility, can be found provided that the BIM designer performs a customized modelling procedure (e.g. adding attributes to user made families of BIM objects). The remaining data were obtained through combined analyses of several parameters. In Tab.1 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 two-rightmost columns represent the output of the Energy Efficiency BN. They show a quantitative assessment of performance based on the provided inputs and they are in very good agreement with detailed energy simulations performed on the buildings in past research steps [19,20].

Table 1 BN outputs for the two cases studies.

	W_A	W_{EE}	W_1	W_2
Weight value	0.83	0.17	0.17	0.83

In order to define a refurbishment priority through the Saaty AHP decision approach, a feasibility of the pairwise comparisons was preliminary tested, according to the procedure detailed in sub-Section 3.3. More specifically, the expertise of the research team was used to define every weight and a datasheet was set up so as to seamlessly correlate the output nodes of the BN with the priority index resulting from the AHP. The resulting weights are shown in Tab.2.

Table 2 Weights values from pairwise comparison

Case Study	**A**	**HTC**	**SEP**
Units	*%*	W/m^2K	KWh/ym^2
Ungaretti School	60	2.43	45.29
Mascagni School	52.1	3.43	45.79

After normalizing HTC and SEP according to their best values, being in both cases “Ungaretti” as the lowest ones, the Ungaretti array was re-allocated as {HTC, SEP}={1, 1} and Mascagni was allocated as {HTC, SEP}={0.71, 0.99}. Then, applying Eqs. (2) and (3) to the values shown in Tab. 1, after the aforementioned normalization with the weights listed in Tab.2, the final ranking is the following:

- Ungaretti, R=0.67;
- Mascagni, R=0.59.

As a result, Mascagni school is the one with the lowest ranking and is the building that should be refurbished first. Once the requirement indices of the non-compliant schools were estimated, an estimation of costs relative to renovation actions can be performed, by means of the cost estimation BN (ref. sub-section 3.3).

As the Mascagni school is the one ranked at the top place in the priority list (hence, at the bottom in the quality ranking), the cost estimation BN has been tested on this model, specifically about the renovation of access doors. Thirteen data were required as input information by the cost estimation BN fragment. Among them, seven were retrieved manually from the BIM model, two depend on a variable that was not included in the model and the remaining four are features that must be set by the user according to requirements and budget.

a)

b)

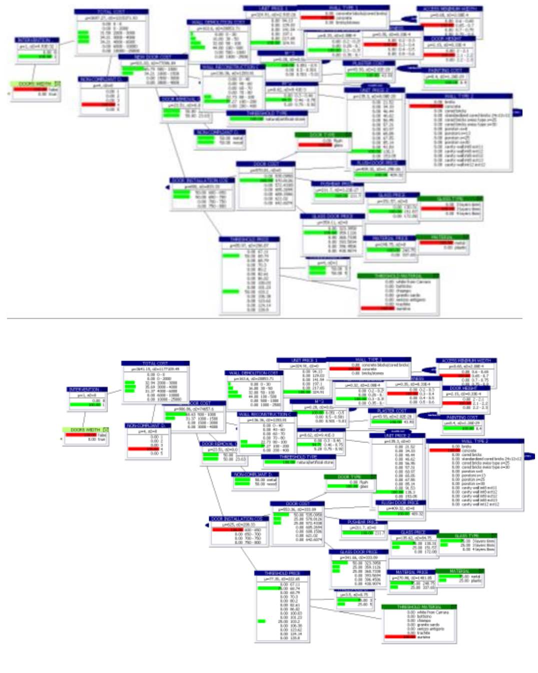

Figure 5. Inference for cost estimation (a) and backward reasoning for cost inversion (b).

For the purpose of this simulation, a metal framed and glazed new door, with triple glass stratification (8mm each) was inserted as input. This selection led to an estimated of cost, whose range spread over the “€2000-3000” interval (p=31.58%) , the “€3000-4000” interval (p=34.22%) and "€4000-6000" interval (p=34.20%), mean=€3697.00 like in Fig. 5-a.

In addition, the inversion rule was tested for this network: the user can constrain the output node at the available budget, and the network will suggest what renovation actions should be put in place.

As shown in Fig. 5-b, when the last aforementioned nodes are left free to vary, and the intermediate node "New door cost" is fixed at the "€600-650" interval (which can be due to the need for budget restriction), the network suggests that the best technology to be adopted is a glazed door, triple layer glass (6mm each) and metal frame. The expected total cost in €3641.00.

5 Conclusions and future work

The decision support system reported in this paper is meant to help the managers of large building stock taking into consideration different technical issues, such as accessibility, energy efficiency, life safety, fire protection and seismic vulnerability. The assessment of technical parameters was done by means of Bayesian Networks that are useful means to handle uncertainty that can be due to the lack of some information about the buildings under evaluation, because they are capable of dealing with several types of variables and because inference propagation can be inverted. 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 they are interfaced with 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. Finally, once an intelligent interface working as a network management module between BN and BIM database is developed, they can run automatically and work out a lot of analyses with reasonable efforts, hence they can constitute a powerful decision support system. The system will need to be completed with all areas of interest shown above and regarding to cost networks, these will have to be implemented with all possible refurbishment scenarios by studying in depth the technologies that best fit the different type of buildings using also expert opinion to evaluate the reliability of the final analysis.

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