Intelligent Elevators in a Smart Building

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***Abstract*—Smart Cities including Smart Buildings are a fascinating fast developing research area. The present work describes an intelligent elevator, integrated in the context of a smart building. A Bayesian network approach was designed to drive decision actions of an elevator, according to the information that is provided by fuzzy rules and by cameras with image recognition software. The aim was to build a decision engine capable to control the elevators actions, in way that improves user's satisfaction. Both sensitivity analysis and evaluation study of the implemented model, according to several scenarios, are presented. The final algorithm proved to exhibit the desired behavior, in 95% case of the scenarios tested.**

Keywords—Smart buildings; smart houses; elevator; Bayesian networks; intelligent decision making

I. Introduction

Our planet is entering a new epoch, where Internet-of-Things (IoT), and Artificial Intelligence (AI) will play a tremendous role in meeting the really big challenges. To tackle these challenges, to facilitate a constant sustainable urban development, and to improve the life level of citizens, it is necessary to have a multi-disciplinary approach. Urban performance nowadays highly depends on the availability and quality of knowledge communication and social infrastructure. Taking into consideration this fact, the idea of the "smart city" has been created to highlight the important role of Information and Communication Technologies (ICTs) in the competitiveness of a city. The smart city is an urban sustainable development based on human and social capital, cultural and natural resources, sources of knowledge like business information, communication services, and energy and environmental technologies.

The growing advancement in ICTs technologies is remarkable in the recent years, and intelligent systems are now very hot research area. Particularly, smart house applications are a new and attractive approach that can integrate automation systems and IoT and provide more comfortable conditions to users. Based on the analysis of a large amount of data from monitoring environmental conditions or physical statuses of users and using automated decision making system, smart houses can merge mobility and furnish more eligible service to residents. Existing works and current technologies are lack of effective capacity to handle complex logic, which raises uncertainty level in the system. Uncertainty always appears in the real occurrences of a phenomenon, to which the system must respond. Therefore, the main challenge in smart house research area is to develop a suitable expert system able to take into account the high level of uncertainty.

One interesting problem in the context of a smart house is the construction of an intelligent lifting system. Elevator system in smart houses is supposed to be "smart" too. The decision making in such lifting systems is a complicated procedure, which includes a lot of uncertainty. To tackle this uncertainty an intelligent automated expert system, that operates in a cost effective manner with minimal interruption of customer loads, should be invented.

This research area is still at the emerging stage. Nevertheless, first articles in intelligent building systems were written in the 90s. Alani [1] in 1995 proposed a good starting point for the improvement of expert systems to dispatch elevators using the counting of people in front of the elevator door on each floor. One year later So and Liu in [2] authored an overall review of existing at that moment advanced elevator technologies and concluded that artificial intelligence in every transportation system inside every building is not too overstated. A multi-objective elevator supervisory-control system [3] was developed later, which is supported by an individual floor-situation control, based on genetic algorithm that simulates biological evolution. The presented here solution provides a much more controlled algorithm by the designer, since Bayesian networks are more appropriate method for designing decisions.

For the purpose of this proposal, a smart house is assumed which is equipped with surveillance cameras on each floor, which constantly capture and record everything. These cameras should be established in the front of elevators on each floor, and using modern Computer Vision tools, will report the number of people waiting for an elevator. Using these data, an intelligent decision-making system could be constructed.

In this paper, a Bayesian Network approach is proposed to construct an intelligent elevator system [1]-[3]. The constraint-based technique Bayesian Networks is a well-known method, which came from Probability Theory. Bayesian Networks (BNs) is one of the most effective theoretical models for uncertainty inference and knowledge expression. Bayesian Networks found their application in various areas in science and industry. Subjective Probability theory is the core of BNs, which allows them to make causal inference, explaining inference, and diagnostic inference. Furthermore, Causal Bayesian Networks provide a convenient framework for reasoning about causality between random variables. Therefore, they are very suitable for problems with lots of uncertainty. Considering this fact, an expert system of an elevator based on fuzzy rules and BNs was developed, that exhibits a very convenient and efficient decision-making mechanism.

The present work describes a part of the whole expert system which is under implementation. It presents a decision network that provides front-end decision making capabilities about the upward functioning of elevators with the aim to serve better users. The improvement concerns the larger number of transferred persons within less waiting times for serving. The aim of this research paper was twofold. First, an effective way was proposed for integrating in BNs, fuzzy if-then rules. Second, a reasonable modeling with a workable and solvable topology was presented regarding the integration of all nodes into the network.

Rest of this paper is organized as follows. In the next section the literature and related work done on this topic i.e. presented. Then the relevant basics of Bayesian Networks are shown. Evaluation follows the implemented solutions. Finally, conclusions and a discussion about advantages and disadvantages of the method are given.

II. Related Work

A summary of recent significant works in smart buildings that are supported by decision making using artificial intelligence techniques, are described below:

A good review [4] appeared in 2002, which concerns projects that apply AI planning and multi-agent systems to elevator control problems. This publication, besides overview of projects, described the motivations behind the continuous interests in AI by smart elevator systems industry. It was also mentioned, that leading elevator companies installed AI techniques not only for improvement of transportation capacity of conventional elevator systems, but also to revolutionize the interaction and service between elevators and its passengers. Another approach to the multi-objective optimization problem was applied and described in [5]. The same year Eleview [6] was proposed, which is a remote intelligent elevator monitoring system that implements an adaptive transmission and recovery mechanism to enhance the quality of real-time video to detect humans' abnormal or criminal activities inside the elevator.

All early works in intelligent elevators described the high need of artificial intelligent based approaches in this industry. The algorithms should be fast, convenient and fit user's desires. AI industry includes itself many techniques such as machine learning, deep learning, computer vision, neural networks. All of these methods were applied to different industry problems, including smart buildings. An intelligent elevator detecting system based on neural network was proposed in [7], which can continuously collect and store the running data of elevators, and provide referential data to the inspectors. It utilizes a best wavelet packet basis and is able to correctly diagnose the jerk fault. Another AI approach is a Markovian model, which is a stochastic model used to simulate randomly changing systems, whose future states depend only on current states. Such model was applied to smart buildings for different time periods in one day for predicting electricity consumption [8]. Another machine learning approach was a robust locally weighted regression with adaptive bandwidth. This kernel based method was applied for personalized thermal comfort prediction for use in smart control for building automation [9]. Data mining methods aimed at predicting the electrical energy demand of air conditioning system were described with reference to a real-time control in smart buildings [10].

Image classification is another area of machine learning, which is very promising in smart elevator systems. Feature coding is a fundamental step in bag-of-words based model for image classification and have drawn increasing attention in recent works. Feature coding for image classification based on saliency detection with fuzzy reasoning and its application in elevator videos were studied in [11]. Recently, a novel two-stage Energy Management System (EMS) that is suitable for small-scale grid-connected electrical systems, such as smart homes and buildings, was developed [12].

The implementation of smart buildings and elevators has many complex problems not easily solved with conventional methods. In previous paragraphs information was given concerning how Artificial Intelligence techniques such as Artificial Neural Networks, Fuzzy Logic and Genetic Algorithms were used to deal with these problems. However, since always there is a high level of uncertainty, uncertain reasoning is a key feature to include in a successful model. To tackle this issue, BNs are used, which is one of the most effective theory models in the uncertainty level representation field and for explaining the outcome of stochastic processes. BNs were applied to smart buildings in various ways. In [13], spatial temperature distribution in smart buildings is accurately estimated by combining temperature modeling from few sensor measurements and Bayesian model framework. Another virtual temperature measurement for smart buildings via Bayesian fusion model is done in [14], where the key idea is to combine the prior knowledge on temperature statistics with sensor measurements and then using maximum-a-posteriori estimation, to predict spatial temperature distribution. In [15], intelligent data analytics, using Bayesian Regularized Neural Networks, is applied to build energy efficient smart buildings.

One of the first applications of expert system to elevator group-supervisory control was studied by Tsuji in 1989 [16]. Then in early 1990 expert systems for elevators were presented in [17]. One year later Bedard first time proposed a knowledge-based approach to overall configuration of multistory office buildings [18]. The same year elevator scheduling system using blackboard architecture was introduced [19]. Fuzzy Logic has been proved a valuable alternative when evaluating a large amount of criteria in a flexible manner. One of the first dispatching algorithms employing fuzzy approaches to develop expert rules for elevators was studied in [20]. Numerous works concern supervisory control for elevator group using fuzzy expert systems. These expert systems address riding time [21], and travelling time [22]. A related study of elevator group-control expert system based on traffic-flow mode recognition was done in [23].

The presented solution compared with the works mentioned in the previous paragraphs has a crucial difference. It does not try to predict future events with machine learning techniques. It utilizes the existing experience of experts in the form of fuzzy rules and encapsulates dynamic information from image recognition software connected with online cameras. All this integration is achieved with the help of the mathematical framework of BN graphs which is the only consistent method to drive appropriate decisions of any type. Due to this key difference, the behavior of the system is very stable and appropriate. Thus, it is expected that the proposed simple but not naïve solution will be commercially implement in near future

III. Bayesian Networks

Since Thomas Bayes developed Bayes' theorem in the 18th century subjective probabilities had a major effect on statistical inferences. When one event causes another event, the probability of a cause is inferred by the Bayes theorem.

If A and B are the occurrences of two events the Bayes rule is defined as:

$$P(A|B) = \frac{P(B|A)*P(A)}{P(B)} \quad (1)$$

Our belief about the event A, given that we get information about the event B, is updated using Bayes theorem. $P(A)$ is called the *prior* probability, $P(A|B)$ is called the *posterior* probability of A given B and $P(B|A)$ is the *likelihood* .

The Bayesian network is a graphical model without any cycles, where nodes represent random variables. There are connection arrows that represent causality and probabilistic dependencies between random variables. Briefly, BN is a probabilistic graphical model that restricts the graph so that it is directed and acyclic.

In the above example the link is from A to B, so B is called a *child* of A and A is called a *parent* of B. Each node in BN can have more than one parents and children.

The structure of BNs follows the Markov Property which states that all direct dependencies in the system are explicitly shown via links. The absence of a link denotes independence between two nodes.

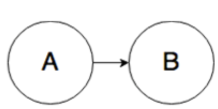

Fig. 1. Example of BN.

TABLE I. CPT of the Node B Given the Node A (Assuming Two States)

A		S_{A1}	S_{A2}
B	S_{B1}	$P(B = S_{B1}|A = S_{A1})$	$P(B = S_{B1}|A = S_{A2})$
	S_{B2}	$P(B = S_{B2}|A = S_{A1})$	$P(B = S_{B2}|A = S_{A2})$

After specifying the structure of BN, quantified relations between nodes should be specified. Each node of the network is annotated with conditional probability table (CPT) that quantifies the probabilistic relation the parent nodes have on the children nodes. CPT is constructed in the way that:

- Each row contains the conditional probability of each node value for each possible combination of values of its parent nodes.
- Sum of elements on each row must equal to 1.
- If a node has no parents, then it has one row.

For example, the case of a network with two nodes A and B, as shown in Fig. 1, each with two states, S_{A1}, S_{A2}, S_{B1}, S_{B2} is shown in Table 1.

Extending the metaphor of structural relations between nodes, if there is a directed chain of nodes, a node is called *ancestor* of another node if it appears earlier in the chain, whereas a node is called *descendant* of another node if it comes later in the chain.

The fundamental rule probability theory states that

$$P(X_1 \; and \; X_2) = P(X_1)P(X_2|X_1) \quad (2)$$

Iterative use of this rule leads to the property:

If $U = \{X_1, \ldots, X_n\}$ then

$$P(U) = P(X_n|X_1, \ldots X_{n-1})P(X_{n-1}|X_1, \ldots X_{n-2}) \ldots P(X_2|X_1)P(X_1) \quad (3)$$

This equation is called general chain rule. Chain rule for BN over $U = \{X_1, \ldots, X_n\}$ looks like:

$$P(U) = \prod_{i=1}^{n} P(A_i|parents(A_i)) \quad (4)$$

To decide for any pair of variables in a BN whether they are independent given evidence, d-separation is introduced (see Fig. 2).

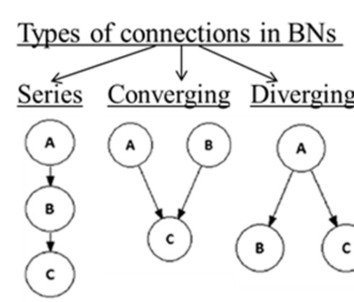

Fig. 2. Basic types of influences of informational nodes in a BN.

Two distinct variables in BN are d-separated if for all paths between them, there is an intermediate variable V such:

- the connection is serial or diverging, and V is instantiated, or
- the connection is converging, and neither V or any of V's descendants have received evidence.

In a BN with evidence e entered, if A and B are d-separated, then

$$P(A|B,e) = P(A|e) \tag{5}$$

and for a BN over the universe U we get:

$$P(A|e) = \frac{\sum_{U\setminus\{A\}} P(U,e)}{P(e)} \tag{6}$$

To build a BN different types of variables are used. Variables that represent a statement that is under question are called *hypothesis variables*. Variables that can be observed are called *information variables*. Variables introduced for a special purposes are called *mediating variables*.

The most skeptic part of BNs is the question of where the numbers come from. The acquisition of numbers (conditional probabilities) uses some modeling tricks. For example:

- *Noisy-or*

If binary B has binary parents $A_1, \dots, A_n$ and independent inhibitors Q_i with probability q_i inhibit the fact that $A_i = y$ causes $B = y$, then:

$$P(B|A_1, \dots, A_n) = \prod_{q_j \in Y} q_j \tag{7}$$

- *Divorcing*

If B has parents $A_1, \dots, A_n$ which can be partitioned into the sets $c_1, \dots, c_m$ in the way that if a_1^* and a_2^* from $(A_1, \dots, A_i)$ are in the same set c_j and $P(B|a_1^*, A_{i+1}, \dots, A_n) = P(B|a_2^*, A_{i+1}, \dots, A_n)$, then by inserting a intermediate variable C(child of A, parent of B) with states $c_1, \dots, c_m$,variables $A_1, \dots, A_i$ could be divorced from $A_{i+1}, \dots, A_n$.

A. More Complex BN

Example of calculating probabilities using *variable elimination* in a more complex BN is described below:

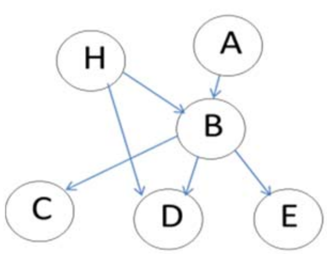

Fig. 3. A Bayesian network with one hypothesis and five informational nodes.

In this example, (see Fig. 3), the Bayesian Network universe U consists of variables A, B, C, D, E, H. Hypothesis is H, and the evidence $e = \{D = d\}$. It is useful to calculate $P(H,e) = P(H,d)$. According to the chain rule for BNs:

$$P(U,e) = P(A,B,C,d,E,H) == P(A)P(H)P(B|A,H)P(d|B,H)P(C|B)P(E|B) \tag{8}$$

To calculate $P(H,d)$, variables A, B, C, E should be marginalized out of $P(U,e)$. To start with E,

$$P(A,B,C,d,H) = \sum_E P(U,e) = \sum_E P(A,B,C,d,E,H) = P(A)P(H)P(B|A,H)P(d|B,H)P(C|B) \sum_E P(E|B) \tag{9}$$

Since only B affects E, $\sum_E P(E|B) = 1$. The same procedure is done with C, resulting:

$$P(A,B,d,H) = P(A)P(H)P(B|A,H)P(d|B,H) \tag{10}$$

Next, marginalize A out:

$$P(B,d,H) = P(H)P(d|B,H) \sum_A P(A)P(B|A,H) \tag{11}$$

Two tables $P(A)$ and $P(B|A,H)$are multiplied and A is marginalized out resulting to the table $T_0(B,H)$. Lastly, B is marginalized out:

$$P(H,e) = P(H) \sum_B P(d|B,H)T_0(B,H) \tag{12}$$

Multiplying two tables $P(d|B,H)$ and $T_0(B,H)$ and marginalizing B out results to the table $T(H,d)$. Thus

$$P(H,e) = P(H)T(H,d) \tag{13}$$

B. Addvantages of BN

Some of the useful advantages of using BNs are:

- BNs are natural effective methodology to handle incomplete data with missing values.
- BNs enable one to look at the problem in a wide spectrum by introducing causal relationships.
- BNs integrate the expert knowledge and experimental data by combining probabilistic and causal semantics.
- BNs graphical representation allows one to understand model complexity in a single view.
- BNs are capable to quantify low probability events, thus they can estimate likelihood of critical events.
- BN is an effective tool to avoid over fitting of data [24].
- BNs are easily combined with decision analytic tools to aid management [25].

IV. Modeling Intelligent Elevator Decisions

The decision model was developed initially for a five floors building, see Fig. 4. The evaluation and testing concerns this particular pilot BN. It is obvious that in future a more general algorithm will be implemented and tested concerning an elevator for N number of floors. The goal is to develop an efficient algorithm for elevators working in skyscrapers.

In this model the information than can be available by monitoring cameras in buildings is utilized. Cameras monitoring in each floor the entrance of elevators will provide an uncertain estimate of the number of people waiting to use the elevator.

States for the set of people waiting the elevator in one floor are: none (0), few (1-2), many (3or more). These states are reported every 30 seconds in the form of updating evidence coming from monitoring cameras. An image recognition software will provide information about the number of people waiting to call the elevator associated with a level of certainty. For example for 3th floor: 3 persons with certainty 70% or 2 persons with certainty 20%. The uncertainty is due to occasionally poor lighting or to walking persons etc.

The fuzzy Rules from experts (upward direction) that determine the CPT are:

- If floor 1 is in state “many” go to floor 1 (no matter other states of floors).
- If floor 1 is in state few go to the floor with state “many” except if this floor is the 4th. If there are a lot of floors in state “many” give equal priority to each one of them.
- If floor 1 is in state few go to the floor 1 if all other floors are in the state few or none.
- If floor 1 is in none position then go to the floor in state few or many. If there are a lot of floors with “few” or independently a lot with “many” assign the same priority to each of them.
- If all floors are in state “none” go to floor 1.
- If floor 2 is in state “many” go to floor 2 no matter the state of other floors is, except if floor 1 is in state many.
- If floor 2 is in state “few” go to the floor with state “many” if there is such a floor. If there are a lot of floors with “many” assign the same priority to each of them.
- If floor 2 is in state few go to the floor 2 if all other floors (except 1) are in the state few or none.
- If floor 2 is in state “none” go to the floor with state “many” or “few”. If there are a lot of floors with “few” or independently a lot of “many” assign the same priority to each of them.

There are similar rules for floors 3 and 4. There are no rules for floor 5 because the evaluation of the algorithm for the upward direction is described in this paper.

Now, another piece of information that has to be included in the model, concerns the proximity of the cabinet to the caller. This is an important factor to the final decision. The monitor camera (and not the elevator control unit) will also provide the information how long people are waiting in a particular floor in order to enter the elevator. The reason why this information is provided by the camera is that maybe the user or users suddenly decided to use the stairs or to enter into the cabinet that goes to the opposite direction. In this case the time is reset for this particular floor.

For this waiting time factor again there are fuzzy rules obtained after discussion with technicians and experts of this domain. The states of the prior nodes “Time Floor n” are “short” time, “moderate” time, and “long” time. The indicative list (not compete) of fuzzy rues “for upward direction” are:

- If floor 1 is in state “long then no matter the state of other floors give priority to floor 1.
- If floor 1is in state moderate give priority to floor 1 except if there are floors with state “long”. If there are a lot of floors with state “long” assign equal priorities to each of them.
- If floor 1 is in state “short” give priority to floor 1 except if there are floors with state “moderate” or “long”. If there are a lot of floors with state moderate or independently “long” assign equal priorities to each of them.
- If floor 2 is in state “long” then no matter the time state of other floors give priority to floor 2 with the exception of floor 1.
- If floor 2 is in state “moderate” give priority to floor 2 except of “moderate “floor 1 and except case where there are floors with state “long”. If there are a lot of floors with state “long” assign equal priorities to each of them.
- If floor 2 is in state “short” give priority to floor 2 except of short floor1 and except if there are floors with state moderate or long accordingly. If there are a lot of floors with state moderate or independently “long” assign equal priorities to each of them.

Similar rules exist for the case of the rest of the floors. The fifth floor does not interact.

Finally, the third critical information that will be utilized in the present design model is the factor of waiting time. If there are people in one floor that are waiting for a lot of time then the algorithm should give higher priority to them. The third factor can be represented with just a determining informational node without parents. The reason is that there is availability of only the piece of information, concerning in which floor the cabinet is. There are no fuzzy rules for this issue and there is no uncertainty. The system can assign the probability one to each of the five floors which are states of this proximity node.

In summary there are three determining variables that influence the utility node, see Fig. 4. The Utility node attributes utility values in cardinal scale to the states of the decision node. The states of the decision node are GoFloor 1, GoFloor 2, …, GoFloor 4. The designer of this elevator decision making is now responsible to develop a strategy for the overall utility in order to assign the correct weight/utility to the various combinations of states of the three determining nodes. This requires a two or three stages evaluation scheme in order to correct wrong weights that lead to unreasonable decision i.e. we want to avoid the elevator going more often to some floors without any particular reason but due to wrong weights.

In the presented design, mutually exclusive actions C_i with i = 1,…,n and three determining variable H^a with possible states H_j with j = 2,…,m (a hypothesis that drives the decision) are used. Another characteristic of this design is that we work with non-intervening actions, or in other words, actions implying that their state does not have any correlation with *P(H)*.

Finally, in order to set the values of a utility table that determines for each action C_i and each state H_j a number that expresses the utility $U(C_i, H_j)$ that is gained. Then, the expected utility for taking actions will be

$$EU(C_i) = \sum_{a=1}^{3} \sum_j U(C_i, H_j^a) P(H_j^a) \qquad (14)$$

The preferred decision is associated with the action that gives the maximal expected utility MEU

$$MEU(C) = \max_i EU(C_i) \qquad (15)$$

This proposed topology has the advantage that one can increase the detail of the information regarding the prior nodes without changing the topology and without making very complicated the utility table see (14), (15).

The fuzzy rules that are implemented in the BN are of the general form:

1) "If the floor 1 is the state A and the floor 2 in the state B and the floor 3 in the state C … then give more priority to floor X (much less, less, more, much more) preferable" .

2) For the time priority: "If the floor 1 is in state A and floor 2 is in B and ….then the time priority of floor X is (much less, less, equally, more, much more) strong".

In order to translate these fuzzy rules into probabilities through the defuzzification process we have to define first the membership function in use. For the purposes of the present paper triangle shaped memership functions were used.

Based now, on the defined membership functions, linguistic values contained in the rules are transferred to numerical values in order to fill the conditional probability tables, through the defuzzification approach of fuzzy logic.

V. Evaluation

Regarding the evaluation, a test was considered with 35 decision- making scenarios, which were derived from a randomly selected set of all possible combinations of all information nodes in all states. The final selected set of 35 scenarios was not completely created randomly. Some scenarios that were generated randomly were disregarded either as trivial or as quite the same as previously determined scenarios.

These 35 different scenarios that were characterized by different set of evidences resulted to a list of decisions that afterwards was compared with the list of 35 "gold" decisions reported by our experts.

The evaluation was performed for three rounds. In the first round 67% of the decisions were in agreement with the gold list. For these problematic cases, we retuned appropriately the probabilities in the CPTS and the weights in the utility table. After rerunning 35 scenarios a significant increase, 86% of the agreement with the gold list, was observed. A new careful retuning of the relevant probabilities and weights resulted finally to an agreement equal to 94% in the third evaluation.

Furthermore, as part of the evaluation procedure, another test regarding the sensitivity of the BN to some crucial informational nodes was performed. The analysis started selecting randomly 30 cases. For each of these cases different combinations of evidences were updated. A special build in function of the GeNIe tool (http://genie.sis.pitt.edu) was utilized. The inclusion of an additional indexing variable that points various values for probabilities in question, is considered in the context of the sensitivity analysis methodology. GeNIe calculates the impact of these values on the results. Thus, it was possible to check how sensitive is the final decision to the value of the various prior or posterior probabilities. In the given BN the crucial nodes are the parent nodes which admit also updates.

The whole analysis, which is a time consuming task, reveals that the final decision is more sensitive to certain floors. This result is not surprising since for example first and second floors are more influential due to the strategy emerged from the fuzzy rules. However, the final driven decisions for the cases based on these symptoms were fare.

Finally, for completeness, it is worth mentioning that there is also another type of sensitivity analysis. The sensitivity of the output if the membership functions in use, were modified. However, it is expected not to receive significant information from this study.

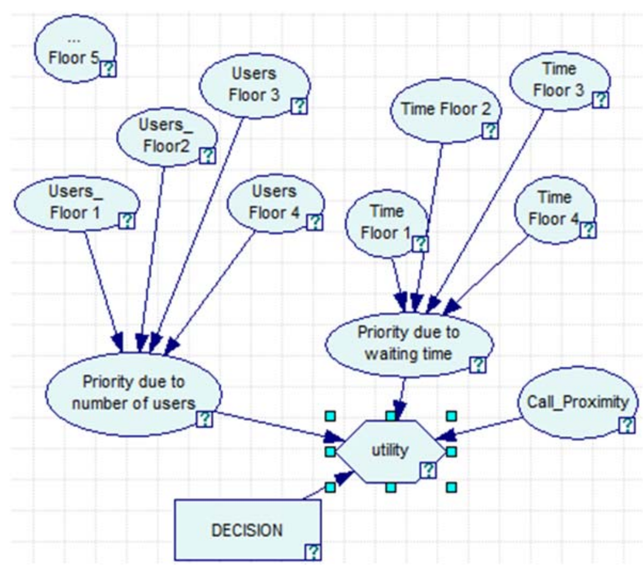

Fig. 4. The Bayesian network for the upward direction.

VI. CONCLUSIONS

In summary, the followed procedure in the presented design of the intelligent system starts from elevator experts. They have provided pieces of knowledge in the form of fuzzy rules. The decision system was tuned to provide actions based on these fuzzy rules and the information coming from the monitoring cameras.

After construction of Bayesian network using the Genie tool, a number of 35 scenarios for testing have been used in order to update the network with new evidences. The decision reasoning of the system was evaluated and resulted to retune some probabilities in the CPTs and some weights in the utility table in order to eliminate false responses. However even in this first pilot study a non-negligible improvement in the number of served successfully users was measured. The final model exhibits a very high percentage of 94% successful intelligent decisions. The most important feature of the proposed solution is the fact that it cannot have unpredictable behavior like the one commonly appeared from solutions based on prediction techniques of machine learning algorithms. Therefore, it is a reliable system ready to be commercialized.

This work suggests also a method for modeling decisions, which has several advantages: 1) BNs provide a graphical scheme for encapsulating information; 2) certain and uncertain knowledge can also be incorporated and fully explored; 3) nodes represent dynamic information coming from cameras and static information provided by experts; 4) the designer can adjust differently decision policies and strategies; 5) decisions are not statically soft coded into the implemented algorithm; this means that the BNs comprise a high level description of the decision strategy which could be modified, customized and re-used; and 6) if during evaluation, new rules have to be built in, the designer is able to either simply re-assign the various conditional probabilities or alter the topology of the network.

A list of disadvantages is: 1) the designer needs to know the Bayesian reasoning; 2) the designer must test the BN for sensitivity. The latter is for checking if the changes of the various probabilities have the appropriate impact on the utilities driven decision. This is not as difficult task as it sounds since for most of the scenarios only a small part of the network is involved.

Important and novel practices that have been followed are: 1) experts have not been used for the probability assignments but only for specifying the fuzzy rules 2) fuzzy rules have been translated to probabilities according to a de-fuzzification process, followed by a three stages re-evaluation scheme 3) there are only three determining nodes that affect the utility node.

Future work will be focused to integrate and evaluate this approach in both upward and downward direction and develop a more general algorithm for the transformation of fuzzy rules to subjective probabilities [26]. The described system implicitly provides energy saving too. An interesting extension would be to include the energy saving criterion explicitly into the BN [27]. It would be also useful to develop intelligent decision system of other type of elevators i.e. large buildings with more than one elevator. In upcoming work, more tests and trials have to be made for model validation [27], [28].

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