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BAYESIAN NETWORKS FOR PROGNOSING AND MANAGING THE PROPERLY USE OF THERMOSTATIC VALVES

Camelia GAVRILA[1], Rodica FRUNZULICA[2], Roxana PATRASCU [3]

In this paper, we describe an application of Bayesian networks in the prognoses of the properly utilization of thermostatic valves, by using the SamIam program. The application was validated based on the data obtained by measures in the District Heating System of Bucharest. Thermostatic valves transformed heating systems into efficient technical facilities, able to properly react to any internal and external disturbing factors. The diagnoses concerning the properly use of thermostatic valves represent the original contribution of the research team. At the end of the paper it will be illustrated practical applications of the theoretical knowledge discussed throughout the article in a number of case studies which present several problems related to the thermostatic valves.

Keywords: Bayesian networks, prognoses and management, properly use of thermostatic valves.

1. Introduction

A thermostatic valve is a self-acting automatic valve. The valve is controlled by an expanding element and gradually opens or closes. It reacts depending on the difference between the temperature set point and the indoor temperature.

Thermostatic valves have transformed heating systems into efficient technical facilities able to properly react to any internal and external disturbing factors. In the same time it is important to facilitate their efficient operation, both under constant and variable operational conditions. Such an approach requires a complex system, to estimate its interconnections with the environment, the consumer behaviour and to carry out a system analysis [1][2][3].

[1] Prof., Department of Thermal-Hydraulic Systems and Atmosphere Protection, Technical University of Civil Engineering of Bucharest, Faculty of Building Services and Equipment, Bucharest, Romania, e-mail: cgavrila2003@yahoo.com

[2] Prof., Department of Thermal-Hydraulic Systems and Atmosphere Protection, Technical University of Civil Engineering of Bucharest, Faculty of Building Services and Equipment, Bucharest, Romania

[3] Reader, Depart. of Energy Production and Use, Faculty of Power Engineering, University POLITECHNICA, Bucharest, Romania, e-mail: op3003@yahoo.com

Bayesian networks are recognized as a convenient tool for modelling processes of engineering sciences reasoning and allow modelling causality. The connection between causation and determination was studied by Spohn [4], and was later investigated with special focus on Bayesian networks in Pearl[5]. Bayesian networks have a long history in statistics, and can be traced back at least to the work in Minsky [6]. In the first half of the 1980s they were introduced to the field of expert systems by the works of Pearl [7] and Spiegelhalter and Knill-Jones [8]. Causal or inference networks are used in a number of areas to represent patterns of influence among variables. They consist of connected causal relations. Generally, causality can be seen as any natural ordering in which knowledge of an event influences opinion concerning another event. This influence can be logical, physical, temporal, or simply conceptual. The concept of causality is the key concept in our paper. Bayesian networks [5][7] with their associated methods are suitable for capturing and analyzing uncertainty. They are present in several domains, such as medical diagnosis [8][9], map learning [10], language understanding [11][12][13], vision [14], heuristic search [15] etc. Bayesian networks are also highly developed in the areas of engineering sciences. The study in this paper is applicable to prognoses and management of the properly use of thermostatic valves.

After this short introduction we will introduce the theoretic background. In the third section of the paper we will discuss our results. The paper ends with conclusions.

2. Bayesian Networks

Bayesian networks are DAGs (directed acyclic graphs), [6], in which the nodes represent variables, the arcs signify the existence of direct causal influences between the linked variables and the strengths of these influences are expressed by forward conditional probabilities.

Definition: A DAG *D* is said to be an *I-map* of a dependency model *M* if every d-separation condition displayed in *D* corresponds to a valid conditional independence relationship in *M*, i.e., if for every three disjoint sets of vertices *X*, *Y*, and *Z* we have

$$< X \mid Z \mid Y >_D \Rightarrow I(X, Z, Y)_M \quad . \tag{1}$$

A DAG is a *minimal I-map* of *M* if none of its arrows can be deleted without destroying its *I-mapness.*

Definition: Given a probability distribution *P* on a set of variables *U*, a DAG $D = (U, \vec{E})$ is called a *Bayesian network* of *P iff D* is a minimal *I-map* of *P*.

We now address the task of constructing a Bayesian network for any given distribution *P*.

Definition: Let M be a dependency model defined on a set $U=\{X_1,X_2,...,X_n\}$ of elements, and let d be an ordering $(X_1,X_2,...,X_i,...)$ of the elements of U. The *boundary strata* of M relative to d is an ordered set of subsets of U, $(B_1,B_2,...,B_i,...)$, such that each B_i is a Markov boundary of X_i with respect to the set $U_{(i)}=\{X_1,X_2,...,X_{i-1}\}$, i.e., B_i is a minimal set satisfying $B_i \subseteq U_{(i)}$ and $I(X_i,B_i,U_{(i)}-B_i)$. The DAG created by designating each B_i as parents of vertex X_i is called a *boundary DAG* of M relative to d.

Theorem 1: Let X, Y, and Z be three disjoint subsets of variables from U. If $I(X,Z,Y)$ stands for the relation "X is independent of Y, given Z" in some probabilisyic model P, then I must satisfy the following four independent conditions:

- Symmetry:

$$I(X,Z,Y) \Leftrightarrow I(Y,Z,X) \tag{a}$$

- Decomposition:

$$I(X,Z,Y \cup W) \Rightarrow I(X,Z,Y) \,\&\, I(X,Z,W) \tag{b}$$

- Weak Union:

$$I(X,Z,Y \cup W) \Rightarrow I(X,Z \cup W,Y) \tag{c}$$

- Contraction:

$$I(X,Z,Y) \,\&\, I(X,Z \cup Y,W) \Rightarrow I(X,Z,Y \cup W) \tag{d}$$

If P is strictly positive, then a fifth condition holds:

- Intersection:

$$I(X,Z \cup W,Y) \,\&\, I(X,Z \cup Y,W) \Rightarrow I(X,Z,Y \cup W) \tag{e}$$

Theorem 2: Let M be any semi-graphoid (i.e., any dependency model satisfying the axioms of eqs.(a) through (d)). If D is a boundary DAG of M relative to any ordering d, then D is a minimal I-map of M.

Theorem 2 is the key to constructing and testing Bayesian networks, as will be shown via three corollaries.

Corollary 1: Given a probability distribution $P(x_1,x_2,...,x_n)$ and any ordering d of the variables, the DAG created by designating as parents of X_i any minimal set Π_{X_i} of predecessors satisfying

$$P(x_i \mid \Pi_{X_i}) = P(x_i \mid x_1,...,x_{i-1}),\ \Pi_{X_i} \subseteq \{X_1,X_2,...,X_{i-1}\} \tag{2}$$

is a Bayesian network of P. If P is strictly positive, then all of the parent sets are unique and the Bayesian network is unique (given d).

Although the structure of a Bayesian network depends strongly on the node ordering used in constructing it, each network nevertheless is an I-map of the underlying distribution P. This means that all conditional independencies portrayed in the network (via *d*-separation) are valid in *P* and hence are independent of the construction ordering.

Corollary 2: Given a *DAG* *D* and a probability distribution P, a necessary and sufficient condition for *D* to be a Bayesian network of *P* is that each variable *X* be conditionally independent of all its non-descendants, given its parents Π_X, and that no proper subset of Π_X satisfy this condition.

The "necessary" part holds because every parent set Π_X *d*-separates *X* from all its non-descendants. The "sufficient" part holds because *X*'s independence of its entire non-descendents means *X* is also independent of its predecessors in a particular ordering *d*.

Corollary 3: If a Bayesian network *D* is constructed by the boundary-strata method in some ordering *d*, then any ordering *d'* consistent with the direction of arrows in *D* will give rise to the same network topology.

Corollary 3 follows from Corollary 2, which ensures that set Π_{X_i} will satisfy Eq. (2) in any new ordering as long as the new set of $X_i's$ predecessors does not contain any of $X_i's$ old descendants. Thus, once the network is constructed, the original order can be forgotten; only the partial ordering displayed in the network matters.

Structuring The Network

Let any joint distribution $P(x_1,x_2,...,x_n)$ and an ordering *d* on the variables in *U*. We start by choosing X_1 as a root and assign to it the marginal probability $P(x_1)$ dictated by $P(x_1,x_2,...,x_n)$. Next, we form a node to represent X_2; if X_2 is dependent on X_1, a link from X_1 to X_2 is established and quantified by $P(x_2 \mid x_1)$. Otherwise, we leave X_1 and X_2 unconnected and assign the prior probability $P(x_2)$ to node X_2. At the *i*-th stage, we form the node X_i, draw a group of directed links to X_i from a parent set Π_{X_i}, and quantify this group of links by the conditional probability $P(x_i \mid \Pi_{X_i})$. The result is a directed acyclic graph that represents many of the independencies embedded in $P(x_1,x_2,...,x_n)$, i.e., all the independencies that follow logically from the definitions of the parent sets.

Conversely, the conditional probabilities $P(x_i \mid \Pi_{X_i})$ on the links of the *DAG* should contain all the information necessary for reconstructing the original distribution function. We get the product

$$P(x_1, x_2, ..., x_n) = P(x_n \mid x_{n-1}, ..., x_1) P(x_{n-1} \mid x_{n-2}, ..., x_1) \cdots P(x_3 \mid x_2, x_1) P(x_2 \mid x_1) P(x_1) = \prod_{i} P(x_i \mid \Pi_{X_i}) \quad (3)$$

The parents of X_i are those variables judged to be *direct causes* of X_i or to have *direct influence* on X_i. An important feature of the network representation is that it permits people to express directly the fundamental, qualitative relationships of direct influence; the network augments these with derived relationships of *indirect influence* and preserves them, even if the numerical assignments are just sloppy estimates. The addition to the network of any new node *Y* requires that the knowledge provider identify a set Π_Y of variables that bear directly on *Y*, assess the strength of this relationship, and make no commitment regarding the effect of *Y* on variables outside Π_Y.

QUANTIFYING THE LINKS

Suppose we are given a *DAG D* in which the arrows pointing to each node X_i emanate from a set Π_{X_i} of parent nodes judged to have direct influence on X_i. To specify consistently the strengths of these influences, one need only assess the conditional probabilities $P(x_i \mid \Pi_{X_i})$ by some functions $F_i(x_i, \Pi_{X_i})$ and make sure these assessments satisfy

$$\sum_{x_i} F_i(x_i, \Pi_{X_i}) = 1 \quad (4)$$

where $0 \le F_i(x_i, \Pi_{X_i}) \le 1$ and the summation ranges over the domain of X_i. This specification is complete and consistent because the product form

$$P_a(x_1, x_2, ..., x_n) = \prod_{i} F_i(x_i, \Pi_{X_i}) \quad (5)$$

constitutes a joint probability distribution that supports the assessed quantities. In other words, if we compute the conditional probabilities $P_a(x_i \mid \Pi_{X_i})$ dictated by $P_a(x_1, ..., x_n)$, the original assessment $F_i(x_i, \Pi_{X_i})$ will be recovered:

$$P_a(x_i \mid \Pi_{X_i}) = \frac{P_a(x_i, \Pi_{X_i})}{P_a(\Pi_{X_i})} = \frac{\sum_{x_j \notin (x_i \cup \Pi_{X_i})} P_a(x_1, ..., x_n)}{\sum_{x_j \notin \Pi_{X_i}} P_a(x_1, ..., x_n)} = F_i(x_i, \Pi_{X_i}). \quad (6)$$

Moreover, all the independencies dictated by the choices of Π_{X_i} are embodied in P_a.

*DAG*s constructed by this method will be called *Bayesian belief networks* or *causal networks* interchangeably, the former emphasizing the judgmental origin and probabilistic nature of the quantifiers and the latter reflecting the directionality of the links.

3. Discussion and Results

There are 3 important factors involved in order to obtain thermal comfort and efficiency in heating systems where thermostatic valves are present [17].

The first factor is **factor A**: *the required indoor temperature.* Every person has his own metabolism. Depending on the desired comfort, the consumer has the possibility to adjust the thermostatic valve on a set-point temperature. This temperature varies usually between 15^0C and 26^0C for occupied rooms or under 15^0C for unoccupied ones. Most people agree the interval between 18^0C and 24^0C, outside these limits the temperatures are unusual or exception from a normal metabolism. Human health and ability to work depend on the microclimate in the room to a great extent. Such dependence influences the person's budget, the budget of a household, and in the end the budget of a state.

A second important is **factor B**: *heat consumer "discipline" of thermostatic valve utilization.* A thermostatic valve responds to changes of indoor temperature. However, the temperature field in the room is irregular, particularly in the upper and lower zones. Therefore, thermostatic valves must be located in such positions where they would take up an average value of the air temperature [18]. Usually, in residential buildings, the radiators are placed under the windows in order to heat the infiltrated outdoor air. Thermostatic valves gauge the temperature of a room using the air directly around them so it's imperative to ensure that they are not covered by curtains, furniture, other material or put near heat sources. They need an uninhibited passage of air flow to allow them to effectively "read" the temperature of the room. Not all consumers realize that their behaviour influences a lot the comfort and especially energy saving. An open window and a thermostatic valves set to the first set-point temperature are not compatible.

The third **factor C** refers to*: "free heat sources" share.* Thermostatic valves allow the achievement of the correct temperature in each room individually. They compensate a possible radiator over sizing and reduce heat output when other sources of heating (sun radiation, lamps, occupants etc. denominated as "free heat sources") compensate a part of the heat losses. In this respect, thermostatic valves provide the user with more flexibility, improve the comfort and save energy. During the heating season, mostly in the transition time (October-November and March-April), solar radiation is very important and sometime covers entirely the heat losses of the rooms. This type of free source has the most significant influence. At the outdoor medium temperature, sun radiation covers only a small part of heat-losses.

Depending on the factors A, B and C, a certain *"good or wrong manner"* in thermostatic valves utilization is incriminated (**factor D** in Bayesian network). For different reasons, many consumers are not using the thermostatic valves in an appropriate manner.

The **factor E** refers to: *insulation degree of the buildings.* The refurbishment of the buildings has been a real preoccupation only in the last 5-10 years. Many of ancient buildings have important heat-losses and the thermal resistance of their envelope is wick. Saving energy means to take several measures having more or less influence in energy consumption. In Romania only a few buildings are rehabilitated, but most of them need to be refurbished. At this time, the residential sector is very heterogeneous from insulation point of view, but the heat sources supply with no discrimination all the buildings. The measures regarding insulation are much related with the measure of implementation of thermostatic valves. Sometimes, in the rehabilitated buildings, the heat surfaces of the terminal unit remain unchanged and they provide too much heat comparing with the real heat demand of the rooms.

In order to apply the Bayesian method and taking into consideration the factors as they were presented before, a case study for Bucharest (Romania) is evaluated. The data has been obtained by measures done at the District Heating System of Bucharest. The collected data made possible the construction of the Bayesian network and provide the probability of the node states. A proper construction of a Bayesian network and the links between the nodes can provide information on how to intervene to obtain the best in relation to the different causes of the properly use of thermostatic valves. The aim of Bayesian networks is to make predictions on the quantification of uncertainty subject to certain assumptions and to what it is obvious. The Bayesian network in figures 1 and 2 was made with the free software SamIam [19] that allows the association of conditional probabilities to nodes in the graphical representation, in terms of the nodes that are in relationships of dependence.

SamIam (Sensitivity Analysis Modeling Inference and More) program was developed by the Automated Reasoning Group at UCLA to provide a graphical interface for manipulating probabilistic networks on Windows, Linux, or Mac OS. It is a new tool for modeling and reasoning with Bayesian Networks, it is developed in JAVA and includes a GUI for editing Bayesian networks which can read files in the HUGIN and Genie formats. SamIam supports several versions of junction tree inference, including the HUGIN and Shenoy-Shafer architectures.

Among the unique features of SamIam are:

- A full implementation of the algorithm of Recursive Conditioning (RC) which allows one to perform time-space tradeoffs;
- A sensitivity analysis engine which can suggest minimal changes to network parameters based on query constraints;
- An exact algorithm for computing MAP based on systematic search.

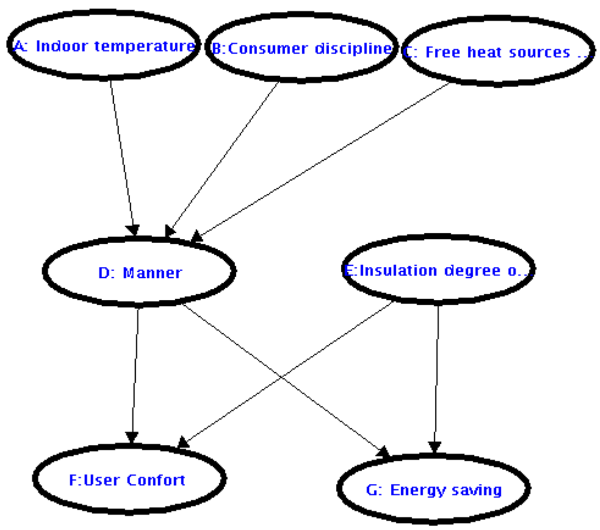

Fig. 1. Bayesian Network for the management of the properly use of thermostatic valves.

To estimate the probability of the network nodes we used real data corresponding to the main components of the properly use of thermostatic valves in conjunction with discussions with professionals, members of the Faculty of Building Services (Technical University of Civil Engineering Bucharest). Parameters and factors influencing the relations between variables are quantified and put in tables to quantify probabilities.

The actual data was processed in order to transform it in standard data for the system. Also, a large number of variables were necessary to synthesize data. The main purpose of reasoning of the Bayesian networks is to recalculate the probabilities of the associated variables, when considering new events, and to exploit the assumptions of independence of the variables to make the calculations more efficient; see Fig. 2.

Fig. 2 shows that utilization of the thermostatic valves, in Bucharest, is in 54% of the cases appropriate. It can be concluded from the analysis of Figures 2 and 3 that the utilization of the thermostatic valves is influenced the most by the required indoor temperature. Therefore, to obtain a corresponding 100% “user comfort –factor F” the values of the “appropriate” state of the “Manner-factor D” variable need to increase from 54% to 72%.

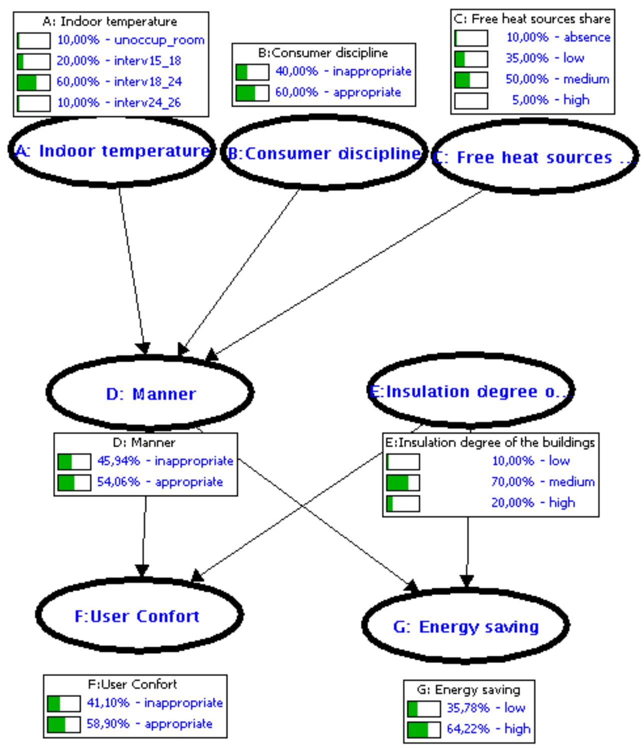

Fig. 2. Quantification of probability tables.

Thus, realizing a sensitivity analysis of the network, Figure 3, and considering the variable user comfort as 100%, relevant evidence is apparent that this occurs with a probability 0.83.

To get a corresponding 100% “Energy saves-factor G”, the values of the “appropriate” state of the “Manner-factor D” variable need to increase from 54% to 68% and the values of the “high” state of the “Insulation degree of the buildings” variable need to increase from 20% to 28%.

Realizing a sensitivity analysis of the network, Fig. 4, and considering the variable energy saving as 100%, relevant evidence is apparent that this occurs with a probability 0.89.

To get a corresponding 100% “Energy saving-factor G” and 100% “User Comfort-factor F”, the values of the “appropriate” state of the “Manner-factor D” variable need to increase from 54% to 80% and the values of the “high” state of the “Insulation degree of the buildings –factor E” variable need to increase from 20% to 33%.

Realizing a sensitivity analysis of the network, Fig., and considering the variables “Energy saves” and “User comfort” as 100%, relevant evidence is apparent that this occurs with a probability 0.74.

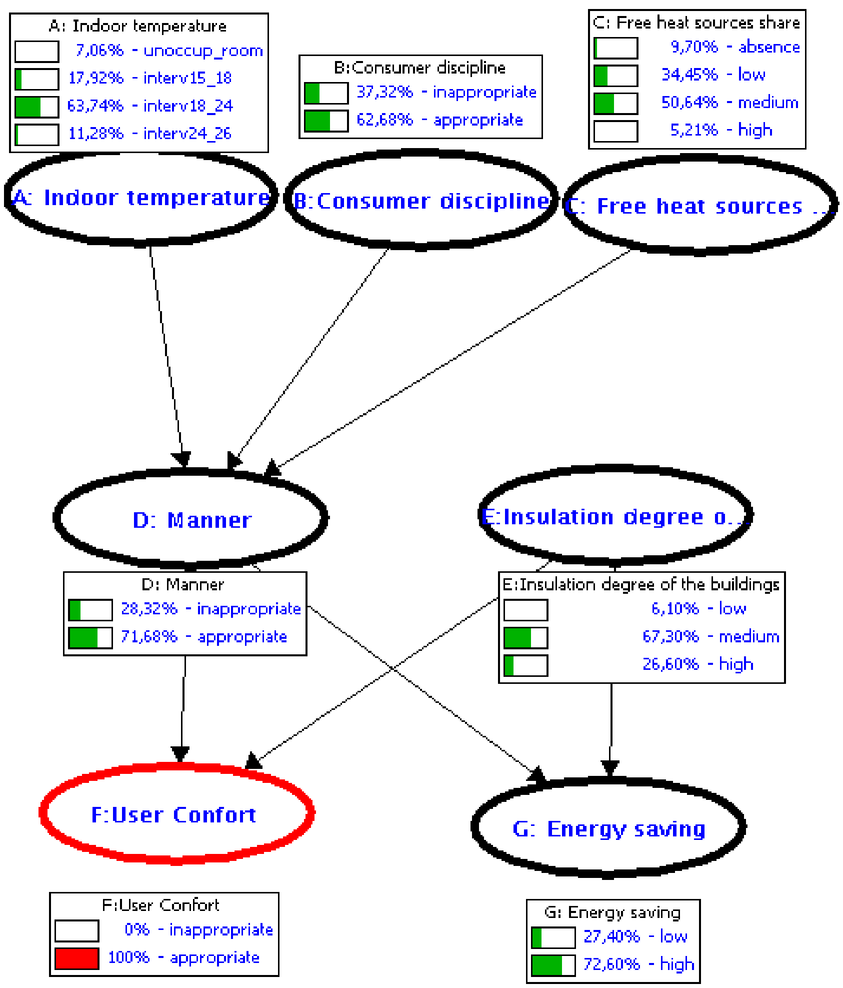

Fig.3. Network sensitivity analysis for the User Comfort.

Using the Kolmogorov's statistical test of agreement, we compared actual data with the same type of data resulting from our calculations. The materiality of 0.89 we checked the correctness of the algorithm, assuming that new construction method is efficient and correct. The considered model validation was performed comparing the results with actual data and the model performance can be expressed by positive real rate sensitivity analysis, considered the given network.

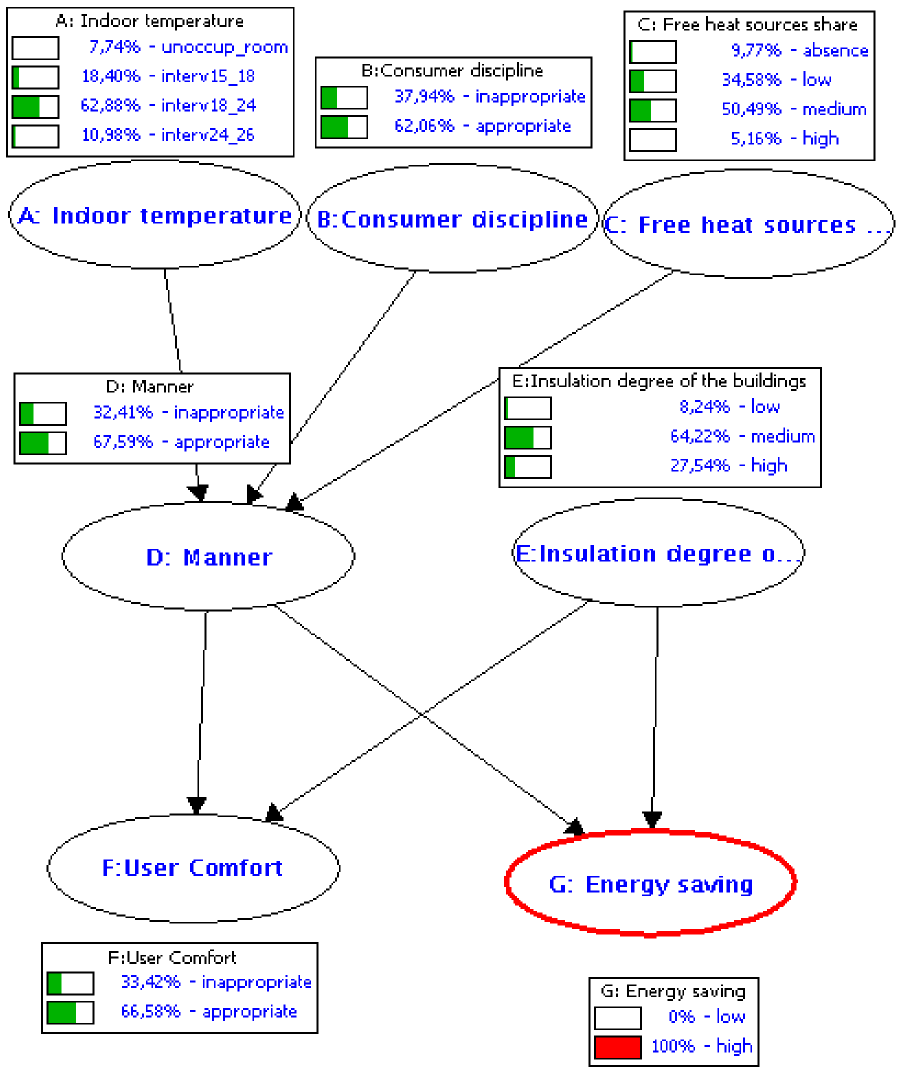

Fig. 4. Network sensitivity analysis for the Energy saving.

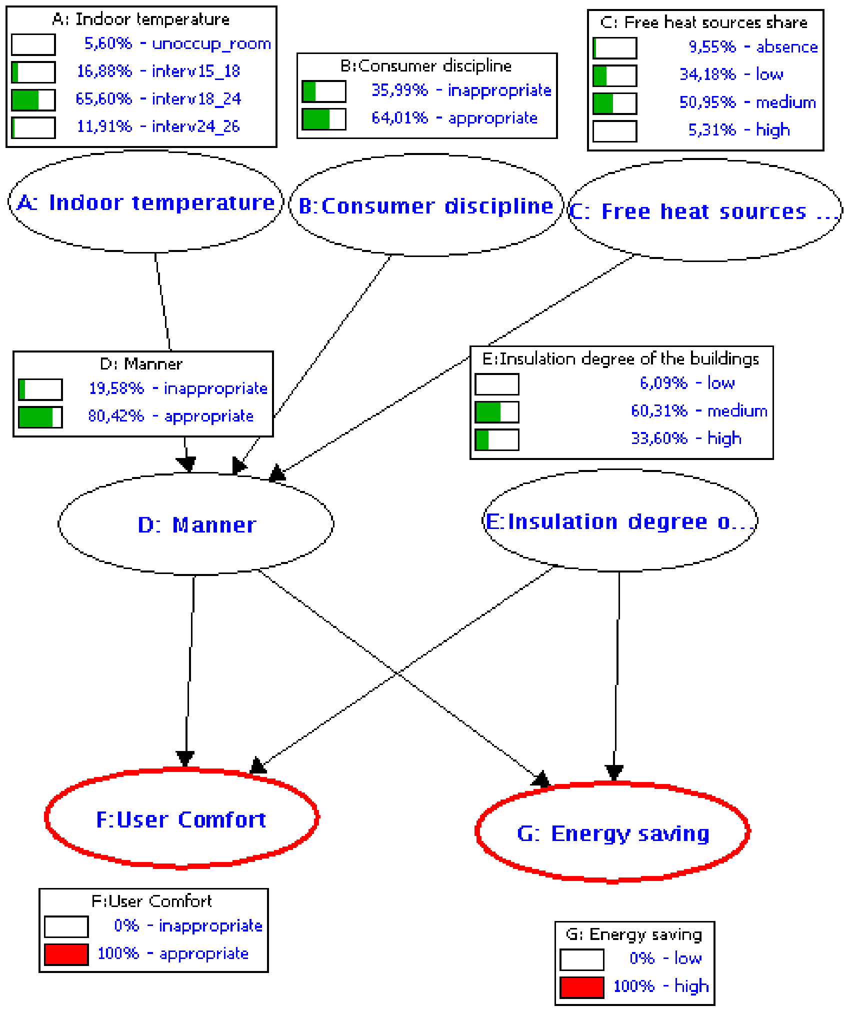

Fig. 5. Network sensitivity analysis.

4. Conclusion

The Bayesian network was applied aiming the results of thermostatic valves utilization for a better comfort of the consumers as the first target and second the thermal energy economy. The probabilities for the factors A, B, C and E are related to the real situation in Bucharest. If these factors are easier to predict, the D factor is sure very important for the obtained results. Many real situations demonstrated that more than 40% of consumers are not using correctly the thermostatic valves. In fact, applying the Bayesian network the result demonstrated that a better comfort is obtained if the consumers are more aware of their manner to act on thermostatic valves. The factors A to C are important, but they do not have a drastic influence on the comfort [20].

The important advantage of the Bayesian networks is obtained by applying the rules found in the theory of probability to propagate the probabilities of uncertain events in the Bayesian record. One important aspect is that Bayesian networks are direct representations of information, and no process of reasoning. Thus, arcs represent direct causal connections and not streams of information during reasoning (such as rule-based systems or neural networks). Reasoning processes can work Bayesian networks through information dissemination in any direction. Assumption of independence between variables is useful for obtaining knowledge simplification (reducing the number of parameters required to specify the distribution of ability) and to simplify the complexity of inference.

The Bayesian network proposed interactive decision-making theoretical systems to monitor the properly use of thermostatic valves by predicting the likely outcome and selecting the appropriate decision.

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