ISSN 1392–124X (print), ISSN 2335–884X (online) INFORMATION TECHNOLOGY AND CONTROL, 2015, T. 44, Nr. 3

Statistical Evaluation of Four Technologies used for Intelectualization of a Smart Home Environment

Agne Paulauskaite-Taraseviciene, Nerijus Morkevicius, Vaidas Jukavicius, Raimundas Jasinevicius, Vytautas Petrauskas, Vygintas Kazanavicius

Centre of Real Time Computer Systems, Kaunas University of Technology, Studentu st. 50-214c, LT-51424, Kaunas, Lithuania

crossref http://dx.doi.org/10.5755/j01.itc.44.3.11965

Abstract. This paper addresses the issues of decision-making methods and their usage capabilities for intelligent control based on the habits of home residents. Learning from the behaviour of the resident is essential for the system to adapt and provide intelligent control based on behavioural habits. However, even deeply ingrained habits are subject to change over time. Therefore, an intelligent system has to respond to a changing and diverse environment. Various decision-making methods have the potential of a number of benefits in providing intelligent control for smart home systems. In this paper, concurrent decision-making methods, including Artificial Neural Networks, Fuzzy Logic, Linear Programing and Bayesian technique, are employed with proposed algorithms in order to provide control based on the habits of residents. These approaches are tested and compared in experimental scenarios for intelligent lightning control with the constant and changing habits of the residents.

Keywords: intelligent control, behavioural patterns, habits, re-training.

1. Introduction

The distinction between intellectualized and non-intellectualized home environments is usually based on certain system properties, such as autonomy, self-awareness, proactivity and others. The resident is undoubtedly one of the most important elements of this environment, and the real challenge of intellectics usually resides in modeling his activities. Following and learning from the behaviour of the resident is very important in order to acquire information on his habits, generate expected decisions automatically and create an intelligent control system based on behavioural patterns. The main goal of such systems is to anticipate the periodic actions of the user and help him in daily routines [21]. Smart home systems that are able to meet the goal of personalized comfort could improve the quality of living, particularly for older people or people with disabilities [8],[19]. It is obvious that intelligent and user-friendly systems are concerned primarily with the control of home devices according to the behavioural patterns of the residents [20]. Energy consumption, maximum effectiveness and green home strategies are secondary [6]. Another important matter that must be taken into account is the change in individual habits over time. Therefore, an intelligent system has to be flexible and prompt in responding to the changing and diverse environment. Some provided solutions are based on undergoing a new training process every time the resident confirms that his wishes have changed [34]. Making decisions after the resident was questioned is not the best solution for two reasons. First of all, the resident himself cannot always identify the changes in his or her behaviour because sometimes habits change slowly, inconsistently, or take place only in specific situations. Secondly, an intelligent and unobtrusive control system should be able to adapt automatically and make right decisions in the changing environment without asking questions with requests to approve resident's behaviour. The development of such system according to all of the aforementioned objectives leads to the incorporation of methods that are able to learn habits of the residents and adapt quickly to the changing environment.

The purpose of this paper is to explore the applicability of different methods – Fuzzy Logic (FL), Artificial Neural Networks (ANN), Bayesian and Linear Programing (LP) for intelligent control systems according to the behavioural patterns of residents, as well as to investigate the learning capabilities in various conditions, including stable, changing and a new environment.

2. Behaviour-based intelligent control system

The structure of the proposed intelligent control system for the control of smart home devices (actuators) is depicted in Fig. 1. There are two main parts in this structure: the intelligent environment and decision making system.

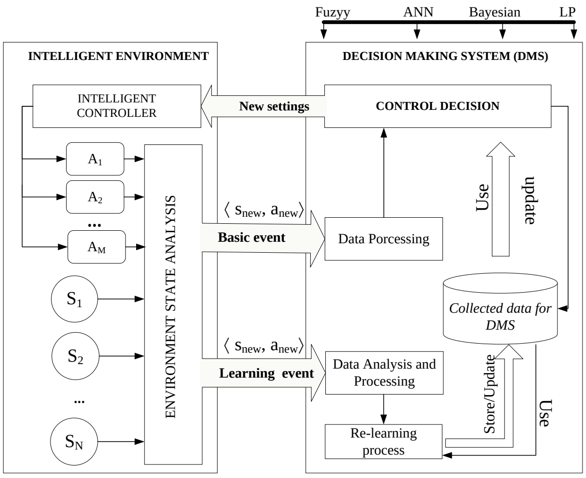

Figure 1. Structure of the Intelligent Control System

The intelligent environment collects information from all sensors in the surrounding environment. This information is used by the decision-making system that calculates corresponding control decisions and forwards them to the intelligent environment. According to these decisions, the intelligent environment adjusts the settings of particular actuator states.

All available features in the intelligent environment are obtained from N installed sensors $S_1, S_2, .., S_N$, $i = 1, 2, \ldots, N$. Sensors detect the presence of the residents, track their coordinates and record the states of home electric devices. If the state of a particular sensor is denoted as s_i, then the states of all sensors compose the vector $\mathbf{s} = (s_1, s_2, \ldots, s_N)$. All controllable devices are represented by M actuators A_j, $j = 1, 2, \ldots, M$. Each actuator A_j enables the control of particular intelligent equipment by modifying its state a_j. The states of all actuators compose the vector $\mathbf{a} = (a_1, a_2, \ldots, a_M)$.

The intelligent system provides automatic control according to the behaviour of the resident. The expectations are denoted as E_k, $k = 1, 2, \ldots, L$. Each value of the expectation e_k is expressed as an expected state of a particular sensor or an actuator. Values of all the expectations compose the vector $\mathbf{e} = (e_1, e_2, \ldots, e_L)$. The triplet of these vectors $\langle \mathbf{s}, \mathbf{a}, \mathbf{e} \rangle$ fully describes a particular situation in the intelligent environment.

The decision-making system operates in the following way: external events received from the intelligent environment are categorized into two types – *basic* events and *learning* events. This constitutes the information on the current state of the environment (as a pair of vectors $\langle \mathbf{s}_t, \mathbf{a}_t \rangle$).

A Basic event is generated whenever a state in the environment is changed (e.g. changes in the coordinates of the resident, values of light/ temperature/windows, etc.) and a new control decision is required. In response to this event, the decision control system has to make a decision regarding the adjustments of particular actuators to meet the predicted expectations of the residents.

A Learning event is the feedback of the resident generated when the resident is unsatisfied with the decision made by the control system. This dissatisfaction is expressed by adjusting the actuators manually. In response to this event, the control system records the present situation into the data storage and re-trains itself to act accordingly if a similar (or the same) situation is encountered in the future.

3. Decision-making systems

Methods capable of suggesting control decisions based on the behaviour of residents should be involved in a decision-making system. The correlation of this behaviour with control actions can be specified in several ways: 1) recognition and classification, 2) defining to a set of rules, and 3) operation according to some prescribed tendencies. Four methods that meet the aforementioned criteria best are examined below. These four methods are: Fuzzy logic, ANN, Bayes and LP. Their strengths and weaknesses in dealing with the objective task are highlighted as well. Challenges of providing intelligent control using these classical approaches, required functionality and proposed modifications are described in the following sections of this paper.

3.1. Fuzzy-based decision-making system

The advantages of fuzzy logic are based on practical implications of the research community: fuzzy systems are fairly comprehensible and considerably easy to design. A lot of attention is devoted to developing fuzzy-based systems for the prediction of the behaviour of residents and the recognition of their activities [17],[26]. Most of the investigations conclude that experiments verify the feasibility of fuzzy systems for solving tasks related to a home environment, as well as the accuracy of the obtained results. However, these methods usually follow the development process of classical fuzzy systems: a set of rules is created and membership functions are defined by an expert. This process might become undesirably complex and time-consuming as the number of rules is subject to the specifics of certain applications. The whole process could be made easier if rules were created automatically and their number was minimized.

The fuzzy decision-making system built according to a typical Mamdani fuzzy controller structure is presented in this paper. However, new algorithms for the hierarchical fuzzy training, retraining, and self-training are included as well. Training algorithms based on fuzzy logic use top-down hierarchical analysis of home situations under consideration to deal with the curse of increasing number of rules. The viability and efficiency of the proposed refinements were tested and simulated in a specialized virtual modelling system [16].

A fuzzy decision-making algorithm is depicted in Fig. 2. All events and situations are collected and stored in a database. The trapezoidal terms used to describe fuzzy input variables should be defined properly. Having in mind the necessity to simplify and unify the implementation of outputs, only five terms ("On", "Off", "Decrease", "Increase" and do nothing "N") are included for each output value of an actuator. For example, temperature control can be linked to outputs "Decrease", "Increase" and "N; garage gates – to "On" and "Off"; control of lighting – to all five outputs, depending on the type of lamps used in the smart house setting. A concrete output value is obtained as a result of CoG (Center of Gravity) defuzzification.

The first thing to be done once an event is received by the system is to define whether it is a basic event or a learning event. If it is a basic event, the algorithm selects the necessary information, processes it and prepares the fuzzy system for the fuzzification process.

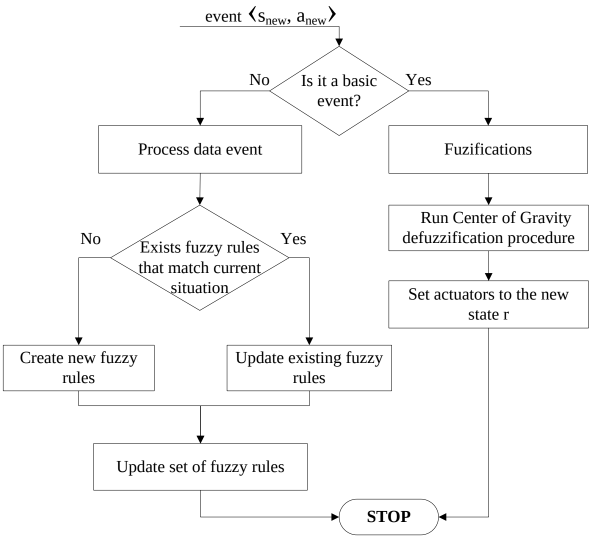

Figure 2. Fuzzy Decision-Making Algorithm for Behaviour-Based Intelligent Control

The actuators are controlled according to the calculation results (output values). The algorithm for actuator setting to a new state *r* is depicted in Fig. 3.

The value change in each of the actuators is determined during the "Make decision" process. In the case of an adjustable actuator, the process goes as follows: if the output value is -10, the actuator is decreased by 10 units. If the output value is 5, the actuator is increased by 5. If the output value is 0, the position of the actuator does not change. In the case of an actuator with On/Off control, its current status and the one calculated by fuzzy is checked to see if it matches. If it does not, the position of the actuator is changed to the one calculated by fuzzy.

In the case of a learning event, the algorithm chooses the necessary information and prepares it for self-learning. The terms are determined and then used to identify the fuzzy rules that define the current situation. A process of creating new rules is included into the algorithm and is triggered if no rules can be detected. The algorithm of creating new rules is used both in self-training and re-training stages. In the case of a learning event, actuators do not need to be adjusted because such event is generated when the resident adjusts one of the actuators himself.

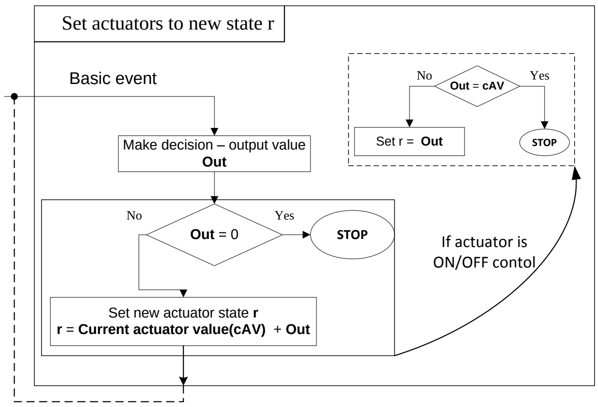

Figure 3. Fuzzy Algorithm for Setting the Actuators to a New State

3.2. Decision-making system based on ANN

In order to avoid the necessity of expert knowledge and to determine data dependencies automatically, the application of ANN may be beneficial. Depending on the problem, different adaptations of ANN algorithms can be used. Most of researches aim to provide intelligent control through the learning of statistical data. In the case of real time control, ANNs are capable of solving problems by implementing online learning strategies that include the incremental learning [7] or network retraining when new data are received [3]. Online learning deals with large amounts of data that are needed for further network learning, causing data storage to increase constantly. Several theories have been proposed to validate the learning optimization decisions for finding the best network solutions and eliminating low-quality solutions [24]. However, the attainment of high accuracy results is time-consuming and may not be suitable for behaviour-based intelligent control. Other researchers try to predict data tendencies, but ANN prediction algorithms for human behaviour do not always provide expected accuracy [10], [25].

In this paper, an ANN decision-making system is developed using a Back-propagation neural network with a data replacement algorithm detailed below. To improve the efficiency of the ANN learning process and to avoid unlimited increase of data sets, limitations on data storage have been applied. If the data array is full and a new data entry arrives, one of the data entries can be selected and replaced with the new one according to predefined rules. The old entry can be selected and replaced by the ANN that has the smallest learning error (SLE algorithm). Another way is to replace the old entries randomly (RD algorithm) [27]. It should be taken into account that some of the actions may be accidental and some changes are temporary. Replacing data entries one by one allows the network to adapt gradually and leads to a less crude decision-making.

In regard to data replacement, an algorithm based on data similarity threshold (TB) was developed for efficient training/retraining of ANNs. The point of this method is to ensure that a new data entry d_{new} replaces an old data entry d_i , which is the most similar to the input part but has a different output part. A different output condition helps to avoid a cycle of the same entry selection and replacement. Here we are dealing with another question: how to determine the difference between outputs? The situation is clear when we have actuators with *On/Off* control. But if the controlled actuators have values, specific deviation limits that describe possible variations for each controlling level should be included. For example, the outputs of the adjustable actuators are considered distinct if the difference between their values is more than a predefined threshold value *Oth.* By analogy, similarity of inputs can be defined using a threshold value *Ith* between the components of inputs. If there are no data entries similar to the new entry, the second replacement algorithm should be involved. Experiment results show that the smallest learning error algorithm (SLE) is more accurate than the random selection algorithm (RD). Therefore, the SLE algorithm is chosen as a complimentary method for data selection and replacement in the proposed threshold-based algorithm.

In order to verify the validity of the proposed algorithm for lighting control, several experiments were carried out. Three algorithms RD, SLE, TB embedded in separate neural networks were tested for comparison in a simulation environment for intelligent light control *BiaSim*. Experiments have been performed over two cases where constant and changing lighting control habits are specified. Obtained results have shown the superiority of the proposed algorithm TB in situations with changing habits of the resident, because the TB algorithm adapts quite quickly to the changes and at the same time provides correct decisions in the unchanged lighting zones [2].

ANN decision-making algorithm for behaviour-based intelligent control is depicted in Fig. 4. The algorithm selects and normalizes relevant data from the vectors $\langle \mathbf{s}_{new}, \mathbf{a}_{new} \rangle$ and forms a data entry d_{new} . Then, the corresponding ANN is run using the values from d^i_{new} as inputs. The results that provide parameters (predicted by ANN) for new actuators are assigned to the variable *r*. Once the adjustments are made, two possible outcomes may arise: if the resident is satisfied with the new situation – he leaves all actuators as they are. On the other hand, if the resident disagrees with the decision, he can manually adjust the position of the actuators, and in such way inform the control system about his expectations. In the latter case, a learning event is generated by the environment and the system must respond by triggering a re-training process.

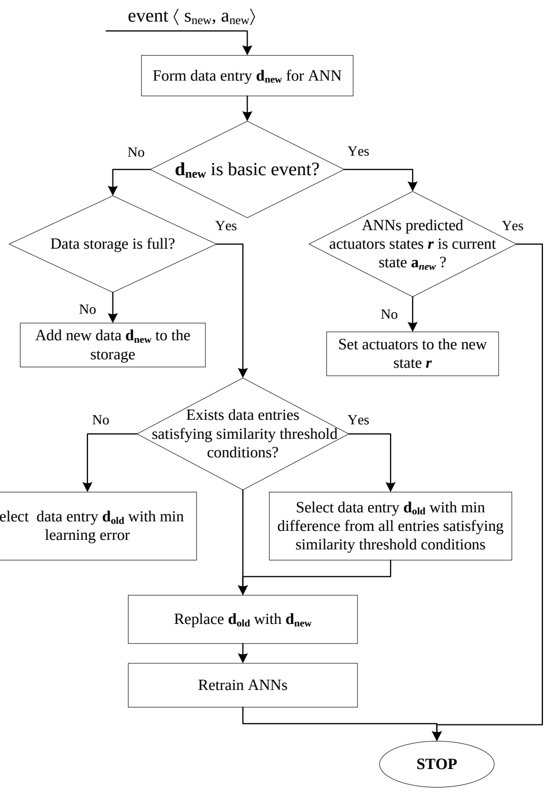

Figure 4. ANN Decision-Making Algorithm for Behaviour-Based Intelligent Control

3.3. Decision-making system based on Linear Programming

The approach to apply the augmenting sequence of linear programing tasks to solve the problems of system intellectualization is quite new and challenging because LP is more often used for the optimization of control decisions [30] and not for their intellectualization. The main purpose of LP-based smart home systems is usually twofold: to meet user‘s preferences and to assure energy efficiency. These are formulated as an optimization problem for the control algorithms based on linear programming. However, the achievement of such goals is a complicated task, especially when residents have different preferences, and when these preferences change over time [28]. In order to provide control based on behavioural patterns, the standard LP needs to be improved by adding certain functionalities, like classification of situations, evaluation of events similarity and selection of events with the highest degree of similarity.

The methodology proposed in this paper is based on formation of LP tasks that include the procedures for retraining and creation of linear problems. These procedures allow to form patterns of similar situations that help classify new unknown situations [1]. The decisions are made according to their correspondence to a certain pattern. In addition, this methodology allows to solve problems of learning situations even when the resident, because of the complexity of situations and the abundance of parameters, is no longer sure if the situation is good, comfortable, poor or even intolerable. The description of the proposed decision-making system based on LP is presented below.

Usually, similar situations must trigger the same action that depends on the habits of the resident. If the control environment of an actuator has multiple actions defined as $r = 1, 2, \ldots, p, \ldots, P$, then the patterns of situations that trigger corresponding actions must be described (P is the number for all available actions and p is a certain action). In this case, a situation is described by the features obtained from available sensors, as well as from the expectations of the resident. These features of a particular situation c are expressed as the states of all sensors $\mathbf{s}_c$. Better reasoning results are usually achieved when features of situations are not only normalized but centered as well [23], [22]. Therefore, vector $\mathbf{s}_c$ is normalized and centered obtaining vector $\mathbf{s}_c^o$. Resident's expectation values $\mathbf{e}_c$ are expressed as particular actions for each controlled actuator. All available information on the situation and the specific action p is denoted as $\mathbf{s}_c^{op}$. If there are several situations that are similar to the action p, they form a p-th class of situations. Now, the main task is to determine the significance of the feature of the pattern of each situation of the p-th class for a particular actuator and to present them in a vector form denoted as the pattern of the generalized situation $\mathbf{w}_{jp} = (w_{jp1}, w_{jp2}, \ldots, w_{jpi}, \ldots, w_{jpN})$. The corresponding linear programming problem can be solved if it is formulated in the following way.

The number of linear programming problems formed for each actuator A_j corresponds to the number of different actions (different classes of situations) related to that actuator and performed by the resident. Considering a random representative of the p-th class of situations, the requirement is to find such $\mathbf{w}_{jp}$, so that the measure of certainty degree $\Phi_{jp}\left(\mathbf{w}_{jp}, \mathbf{s}_l^{op}\right)$ that belongs to the pattern p of the selected situation l would be maximum:

$$\Phi_{jp}\left(\mathbf{w}_{jp}, \mathbf{s}_l^{op}\right) = \mathbf{w}_{jp} \cdot \left(\mathbf{s}_l^{op}\right)^T = \sum_{i=1}^{N} w_{jpi} \cdot s_{li}^{op} \to \max , \quad (1)$$

and it must be reached under the following constraints:

$$\mathbf{w}_{jp} \cdot \left(\mathbf{s}_c^{op}\right)^T \ge \gamma \cdot \mathbf{w}_{jp} \cdot \left(\mathbf{s}_l^{op}\right)^T, \quad \forall c \ne l , \quad (2)$$

$$\mathbf{w}_{jp} \cdot \left(\mathbf{s}_c^{or}\right)^T \le \kappa \cdot \mathbf{w}_{jp} \cdot \left(\mathbf{s}_l^{op}\right)^T, \quad \forall r \ne p , \gamma > \kappa . \quad (3)$$

It is recommended [31] that the optimal values of the real numbers be selected from the interval [0-1]. Concrete values of these coefficients depend on the expert's knowledge or choice. Investigation of the problem described above shows that the problem belongs to the class of linear programing problems where inequalities need additional constraints:

$$0 \le w_{jpi} \le B , \quad (4)$$

where B is any practically convenient real number. A solution for the p-th pattern of situations consists of the obtained value for $\max \Phi_{jp}\left(\mathbf{w}_{jp}, \mathbf{s}_l^{op}\right) = \Phi_{jp\max}$ and the generalized pattern of situations for class p $\mathbf{w}_{jp} = \left(w_{jp1}, w_{jp2}, \ldots, w_{jpi}, \ldots, w_{jpN}\right)$.

This procedure for each actuator A_j must be repeated for all classes of situation patterns. In this way, a set of P solutions will be obtained. The procedure of situation recognition must be performed considering the necessity to assure the proportionality condition. This condition is fulfilled using verbal definitions that denote the similarity of situations, thus guaranteeing the same numerical degree of certainty for the qualitative evaluation of these situations:

$$z_1 \Phi_{j1\max} = \cdots = z_p \Phi_{jp\max} = \cdots = z_P \Phi_{jP\max} = Z , \quad (5)$$

where Z and z_p are real numbers.

This solution enables to construct a situation recognition instrument capable of assigning any unknown situation to one of the possible patterns and to perform a corresponding environmental action. Then, the unknown situation $\mathbf{s}_c^o$ arises, the decision that action p should be performed is usually made according to the maximum value of the degree VD_{jp}:

$$VD_{jp} = \mathbf{w}_{jp} \cdot \left(\mathbf{s}_c^o\right)^T \cdot z_p, \quad \forall p . \quad (6)$$

An LP decision-making algorithm is presented in Fig. 5.

The main steps involve the formation of the objective function and constraints for each possible action using all previously known situations and performed actions that are saved in a database. Then,

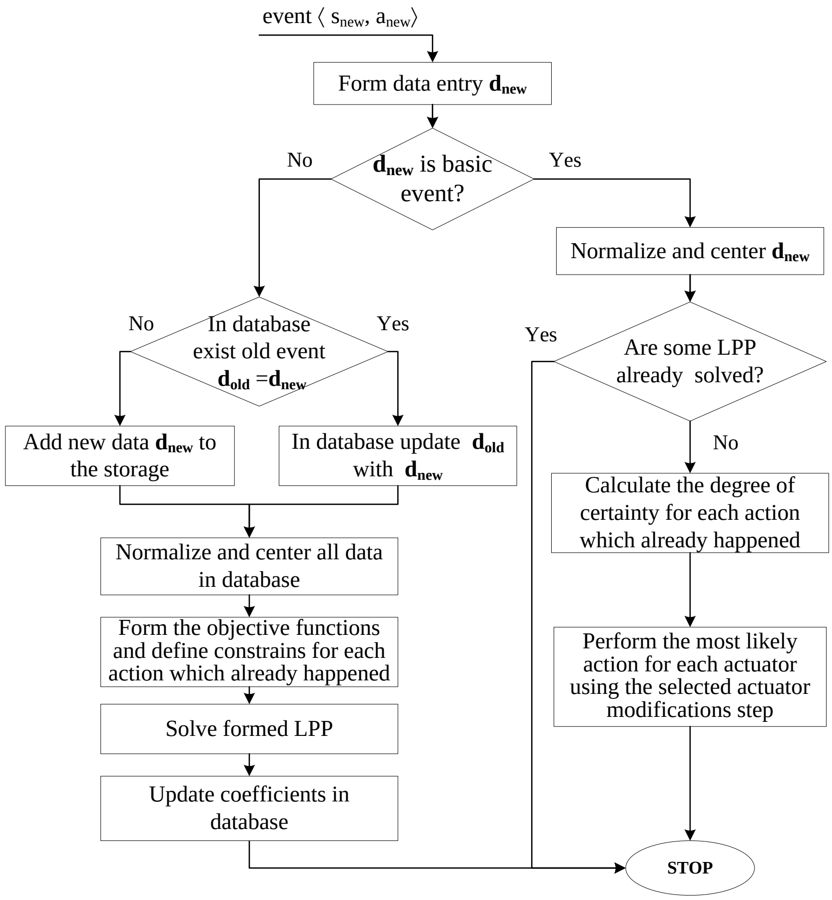

Figure 5. LP Decision-Making Algorithm for a Behaviour-Based Intelligent Control

the formed LP problems (LPPs) are solved, the obtained coefficients (selected by an expert) are used to calculate the degree of certainty for each action by multiplying them by normalized and centred values of the features. According to the calculated degrees, the control system performs an action with the largest degree of certainty. When an action with the largest degree of certainty is "Do nothing", then the control system waits for the resident to interact and update the situation database. Otherwise, the control system modifies the value of the actuator and then waits for the environment to react.

When the algorithm is applied for more than one actuator, LP problems are formed and all calculations and decisions are performed for each actuator separately.

3.4. Bayesian-based decision-making system

In order to provide control by using evaluated probabilities, the Bayesian inference procedure and the Bayesian networks can be employed. Currently, these two are being broadly used for various control applications, including modelling of human interactions [18], tracking and recognizing user's activities [12],[29],[32] recognition of environment and making decisions by forecasting user's activities [15]. However, it can be a challenge to collect a considerable amount of information on resident's activities for the purpose of constructing an activity model or to define the Bayesian network structure. Moreover, when dealing with a dynamic environment, the activity model or the structure of the Bayesian network must be adapted to the properties of a changing environment. Some of the approaches that deal with the construction and adaptation of the structure of the Bayesian network [14], [34] achieve accuracy that barely exceeds 50%-70%. These approaches also highlight important problems related to the changes of resident's habits. The idea that the resident should confirm his steady or changing habits to the system is a poor approach in general because the user acts in the environment automatically and does not realize whether his actions refer to changing habits or not. Moreover, the user can perform some actions accidently, or change his habits for a short period of time. To evaluate the dynamics of changes and the significance level of the resident actions by applying the Bayesian method is not an easy task, because when the general inference procedure is applied, all events have the same priority in terms of significance. In order to solve this problem, the inference procedure was modified by including the possibility to evaluate the dynamics of change in the wishes of residents and make control decisions according to that. The proposed Bayesian inference

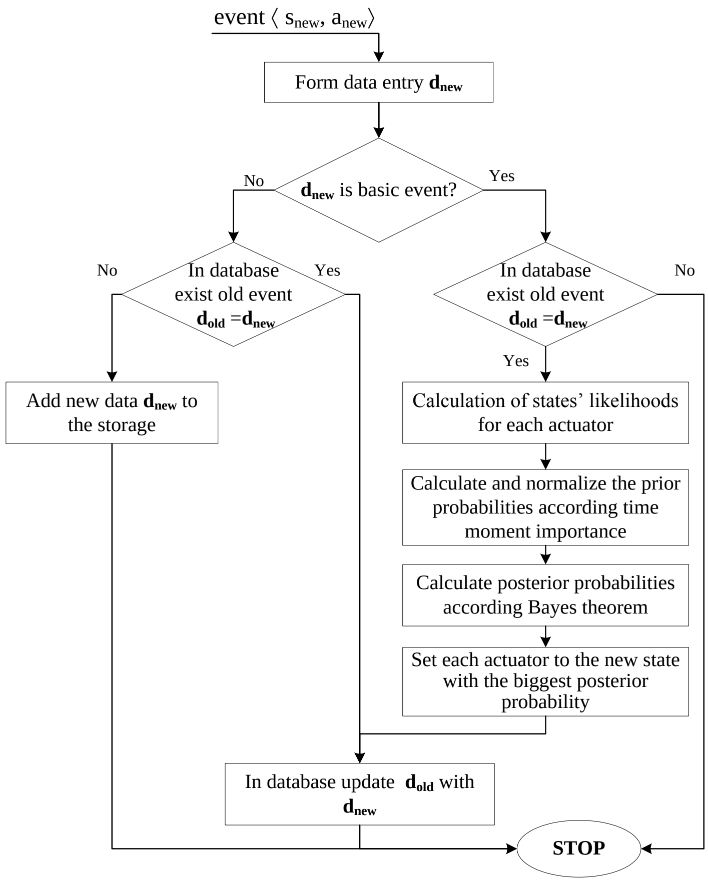

Figure 6. The Bayesian Decision-Making Algorithm for the Behaviour-Based Intelligent Control

procedure includes the calculation of prior probabilities by taking into account the coefficients of significance of past moments of time. The coefficients are chosen according to the habits of each resident. This allows for the decision-making system to adapt successfully to individual habits. The Bayesian decision-making algorithm is presented in Fig. 6.

Assuming that resident's expectations are expressed as actuator states for each actuator A_j, these expectations are described as follows:

$$\mathbf{e}_{cj} = \mathbf{a}_{cj} = (a_{cj}^{t-1}, a_{cj}^{t-2}, \ldots, a_{cj}^{t-T}) . \quad (7)$$

Some of these actuator states are usually the same. Therefore, different actuator states are defined as follows:

$$\mathbf{a}_{cj}^{d} = (a_{cj1}^{d}, \ldots, a_{cjl}^{d} \ldots, a_{cjD}^{d}) , \quad (8)$$

where D is the number of different actuator states.

The decision on the state to which each actuator A_j should be set when a certain situation c occurs, is made by calculating Bayesian probabilities. Generally, decisions are made by the following steps:

Step 1: When the history of the previous states is known, the likelihood $P(\mathbf{a}_{cj} | a_{cjl}^{d})$ can be calculated, and a particular state of the actuator A_j should be set to a_{cjl}^{d}:

$$P(\mathbf{a}_{cj} | a_{cjl}^{d}) = \frac{n_{cjl}}{T} , \quad (9)$$

where n_{cjl} is a number of l-th actuator state recurrence.

Step 2: When calculating probabilities, not only the decisions made previously need to be taken into account, but also moments of time when those decisions were made in analogous past situations. Usually, the behaviour of the resident in the near past is more important than the one in the distant past. In this case, the prior probabilities are calculated according to the importance of a time moment, which is defined as a weight vector $\mathbf{w} = (w^{t-1}, w^{t-2}, \ldots, w^{t-T})$. These weights are set according to the understanding of the resident on the impact of his wishes in each time moment that influences the final decision. The sum of all weights should be equal to 1:

$$\sum_{m=1}^{T} w^{t-m} = 1 . \quad (10)$$

Prior probabilities $P(a_{cjl}^{d})$ are calculated as follows:

$$P(a_{cjl}^{d}) = \sum P(\mathbf{a}_{cj} \left| a_{cjl}^{d}\right.) \cdot w^{t-m}, \quad \forall m, a_{cjl}^{d} = a_{cj}^{t-m}, \quad (11)$$

Step 3: Calculated prior probabilities are normalized:

$$P^{norm}(a_{cjl}^{d}) = \frac{P(a_{cjl}^{d})}{\sum_{l=1}^{D} P(a_{cjl}^{d})}, \quad (12)$$

Step 4: And, finally, the posterior probabilities are calculated according to the Bayesian formula:

$$P(a_{cjl}^{d} \left| \mathbf{a}_{cj}\right.) = \frac{P^{norm}(a_{cjl}^{d}) \cdot P(\mathbf{a}_{cj} \left| a_{cjl}^{d}\right.)}{\sum_{l=1}^{D} P^{norm}(a_{cjl}^{d}) \cdot P(\mathbf{a}_{cj} \left| a_{cjl}^{d}\right.)}. \quad (13)$$

The decision on the state of an actuator is made according to the largest posterior probability.

4. Example case. Lighting control system based on the habits of the resident

In order to explore and compare the four decision-making methods presented in this paper, an example case of intelligent lighting control under resident's behaviour patterns have been selected. The majority of academic or commercial systems aim to modernize lighting control by minimizing energy consumption [33],[9]. In general, such control systems aim to maintain a balance between energy saving and the visual or psychological comfort of users [4], [5]. However, when residential homes are concerned, individual comfort plays a more important role than energy costs. The system should be able to observe the actions of the residents, collect and evaluate data, learn to predict the expectations of the residents in various situations, and adjust the lighting of the environment according to these predictions.

Table 1. Predefined Values of Sensors According to Lighting Preferences

		Sensors	
Lighting	ID zone	S1, lx	S2, lx
A	L1	220-260	-
	L2	-	220-260
B	L1	320-360	-
	L2	-	320-360
C	neutral	background lighting	
D	L1-L2	160-180	160-180

A structural model of experimental environment for intelligent lighting control is presented in Fig. 7. The environment is composed of the following elements: intelligent sensors $IS_1 - IS_4$ capable of identifying the residents (ID_1 and ID_2) and tracking their position in the room; lighting conditions near the tables T_1 and T_2 are recorded using light sensors S_1 and S_2. Dimmable luminaires L_1 and L_2 are capable of reporting their status to the control system.

The lighting zones specified in the experimental environment define the positions of residents and the values of particular sensors. Five different zones are distinguished. Predefined values of the sensors for possible lighting preferences in each zone are provided in Table 1.

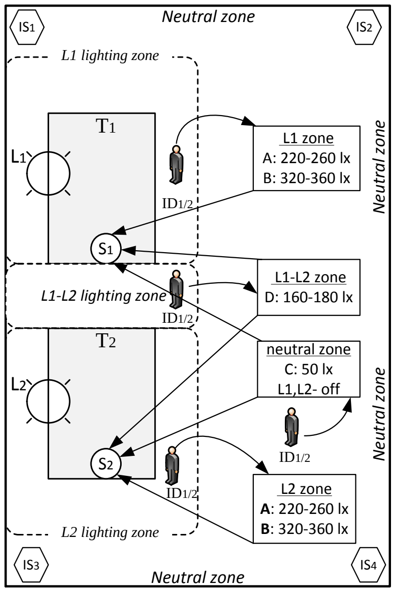

Figure 7. An experimental environment for intelligent lighting control according the behaviour of resident ID_1

5. Experiments

Scenario 1 was created to determine the accuracy of the decision-making methods that were trained in advance according to the wishes of the residents. The results gathered in 50 lx background lighting environment are given in Fig. 8. Experiment results show that the ANN, FL and Bayesian methods that were trained according to pre-gathered statistical data can control the lighting very accurately. LP errors occur because of very similar situations with a different output that makes complicated the creation of exact patterns.

ANN decision-making is highly dependent on weight values and the neuron threshold value. If a network underwent a learning process with more data on lighting A, usually more than one data entry with output B is required in order to achieve expected decision. In the case of the Bayesian method, the re-training process can take place with the first change in resident's preferences. This is due to the fact that the Bayesian method can be configured so the decision will be completely dependent on the last action performed by the resident. FL gathers "event history" so the re-training process can take place after a set number of resident's actions. As determined by the scenario, fuzzy re-trains with the first change in resident's preferences. A very small 3 lx error is

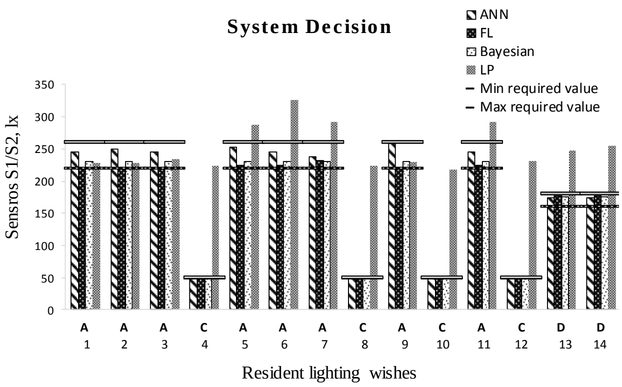

Figure 8. Control Decisions with Constant Resident Habits

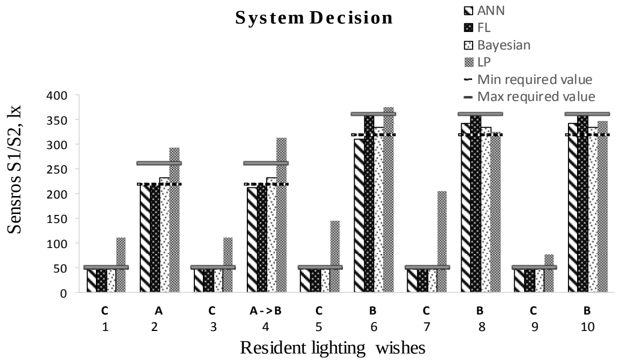

Figure 9. ANN, FL, Bayesian and LP Control Decisions with a 1 Step Adaptation to the New Habits of the Resident

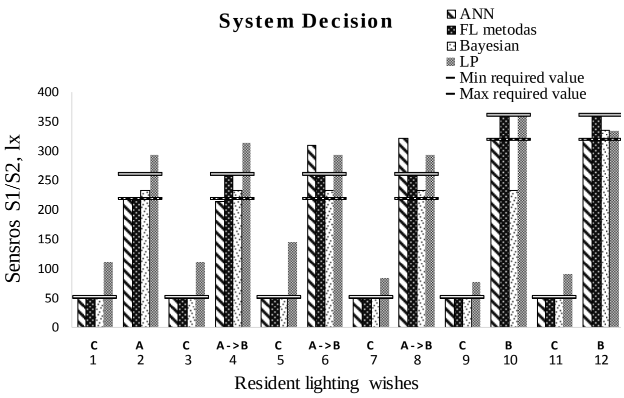

Figure 10. Control Decisions with a 3 Step Adaptation to the New Habits of the Resident

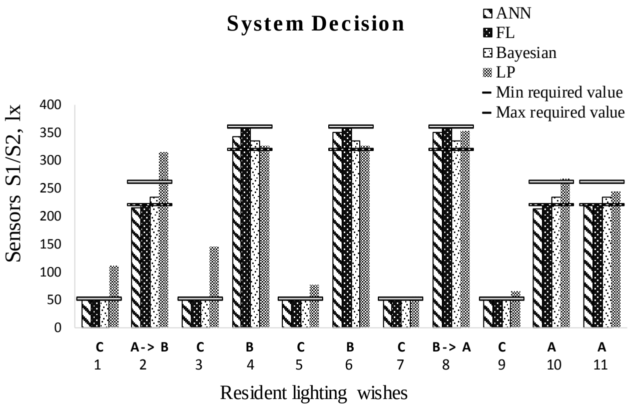

Figure 11. Control Decisions with a 1 Step Adaptation to the New and Old Habits of the Resident

produced due to the manner in which the lighting is controlled. Control is performed in whole actuator levels, and a fuzzy decision is produced in real numbers. Errors appear when those numbers are rounded to whole numbers (or a zero).

Experimentation results for a system that was required to adapt in three steps are shown in Fig. 10. In this case, the system is required to adapt slowly and to respond to changes gradually. The results show that ANN begin the adaptation process to the new situation with the first change and produce an "intermediary" decision that delivers a lighting intensity between lighting A and lighting B. The Bayesian method can define the coefficients of significance in such a way so the re-training process takes place in three steps. However, it does not produce intermediary decisions as seen in the case of ANN. Both in the cases of Fuzzy and LP, the system can be configured so the re-training will take place in the third try. Errors in LP occur under the same reasons that were mentioned in the previous case.

Scenario 3 was created to assess how the methods react to a new, short-term wishes of the resident, and how fast (as fast as possible) they can adapt when the resident returns to his previous habits. A new, temporary wish B was introduced in step two. The resident returns to his previous lighting preferences A in step eight (Fig. 11).

The experimental results show that the methods applied can adapt more quickly and make control decisions according to the latest wishes of the resident, if it is required.

Scenario 4 was created to examine the ability of the methods to respond to situations in which the resident starts acting inconsistently by changing his lighting preferences from A to B and vice versa (Fig. 12).

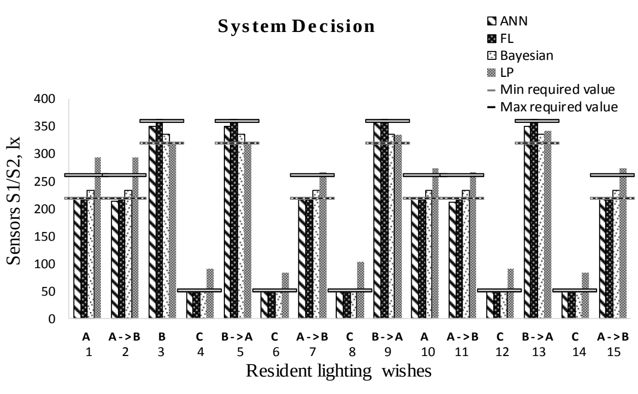

Figure 12. Control Decisions with 1 Step Adaptation to Repetitive Changes of Habits

Scenario 5 was created to assess the ability of the methods to learn when data on the wishes of the residents are yet to be obtained. Here, the methods are in their initial learning stage. In the case of this scenario, it is assumed that the resident knows exactly what he wants.

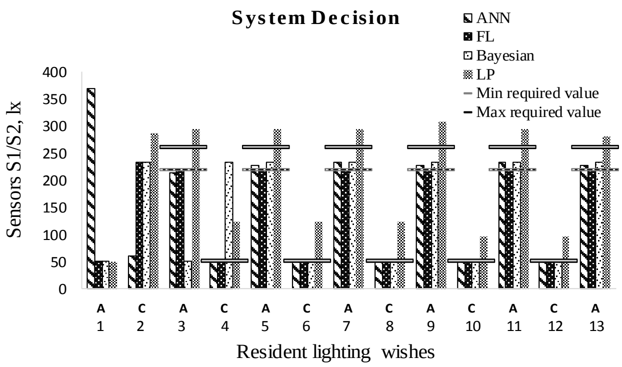

Figure 13. Control Decisions in the Initial Learning Process

Experiment results (Fig. 13) show that compared to other scenarios, LP produces more significant errors. This is because the method has an insufficient amount of data in the initial stage, so it delivers lighting that is brighter than requested. However, the number of errors decreases gradually with the collection of data.

6. Conclusion remarks

Four methods (ANN, FL, Bayesian and LP) with improved algorithms were applied in order to create an intelligent control system based on both stable and changing habits of the resident. Modifications proposed in this paper allow to achieve better accuracy and adaptation results in various environmental situations.

Experimental results gathered from the simulated scenarios have shown that control based on ANN is adaptive and it is a perfect fit for a user who is inconsistent with his choices. Based on the results, the efficacy of the included TB algorithm is proven, especially in situations where adaptation to a changing environment is required. The transition to new control decisions is made gradually and the system usually provides intermediary decisions. However, a user who is certain that every change is significant and needs the system to react to the changing environment quickly, a system based on FL or Bayesian methods should be chosen that can produce more “crude” but speedy decisions.

Fuzzy logic is most effective in those learning situations where the co-dependence of the environment and the situations that arise in it can be easily understood. All decision changes in the system require a creation of new rules or a modification of the old ones. The merit of this approach is that it allowed to minimize the number of rules. This reduction can be seen in all scenarios because the same number of variables and terms are used in all of them. When hierarchy was used, the rules generated altogether – 2500 – were reduced to 520 (4.8 times).

The Bayesian method with the inclusion of the inference procedure has the ability to adapt to changing habits; it can perform re-training procedures according to past events; it can revert to previous settings quickly by interpreting the dynamics of habit change; ability to ignore random and/or infrequent wishes of the user.

Decisions based on LP are useful in situations with a relatively high amount of data and features to be processed, and every situation defined by sensor data can be assessed in advance. LP is not very effective in terms of system re-training because the system needs to formulate and solve vague LP tasks in real time. It needs to redefine all of the formed tasks by changing the situations that are similar to the one that undergoes the re-training process. This, in turn, leads to faulty algorithm operation because it is unable to create correct situation patterns.

References

[1] **A. Dmuchovskis, R. Jasinevicius, V. Jukavicius, E. Kazanavicius, L. Kizauskiene, A. Liutkevicius.** Solution of the Augmenting Sequence of Linear Programming Problems as a Tool for the Intellectual Home Environment’s Self-Training. *Information Technology and Control*, Vol. 44, No. 2, 2015, 221–233.

[2] **A. Paulauskaite-Taraseviciene, N. Morkevicius, A. Janaviciute, A. Liutkevicius, A. Vrubliauskas, E. Kazanavicius**. The Usage of Artificial Neural Networks for Intelligent Lighting Control Based on Resident’s Behavioural Pattern. *Elektronika ir Elektrotechnika.* Vol. 21, No. 2, 2015, 72–79.

[3] **A. D. Doulamis, N. D. Doulamis, S. D. Kollias**. On-Line Retrainable Neural Networks: Improving the Performance of Neural Networks in Image Analysis Problems. *IEEE Transactions on neural networks,* Vol. 11, No. 1, 2000, 137–155.

[4] **A. D. Galasiu, J. A. Veitch**. Occupant preferences and satisfaction with the luminous environment and control systems in daylit offices: a literature review. *Energy and Buildings*, Vol. 38, No. 7, 2006, 728–742.

[5] **A. E. Mad, M. Boubekeur, G. Provan, C. Ryan, K. N. Brown**. Intelligent Hybrid Control Model for Lighting Systems Using Constraint-Based Optimisation. *In: 5th International Workshop, Advances in Intelligent and Soft Computing*, Vol. 73, 2010, pp. 249–259.

[6] **B. Thomas, D. Cook.** CARL: Activity-aware automation for energy efficiency. In: *ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 2014, pp. 939–946

[7] **B. Perez-Sanchez, O. Fontenla-Romero, B. Guijarro-Berdinas.** An incremental learning method for neural networks in adaptive environments. *In: The International Joint Conference on Neural Networks (IJCNN)*, 2010, pp. 1–8.

[8] **C. Doukas, I. Maglogiannis.** Advanced patient or elder fall detection based on movement and sound

data. *In: Proceedings of the Second International Conference on Pervasive Computing Technologies for Healthcare*, 2008, pp. 103–107.

[9] **C. Carrillo, E. D. Dorado, J. Cidras, A. B. Pregal, P. Falcon, A. Fernandez, A. A. Sanchez.** Lighting control system based on digital camera for energy saving in shop windows. *Energy and Buildings* 59, 2013, pp. 143–151.

[10] **C. Chen, B. Das, D. Cook.** Energy prediction using resident's activity. In: Proceedings of the International Workshop on Knowledge Discovery from Sensor Data (KDD workshop), 2010.

[11] **C. Igel, M. Hüsken.** Improving the Rprop Learning Algorithm. *In: H. Bothe and R. Rojas, eds.: Second International Symposium on Neural Computation*, ICSC Academic Press, 2000, pp. 115–121.

[12] **D. Wilson, C. Atkeson.** Simultaneous Tracking & Activity Recognition (STAR) Using Many Anonymous, Binary Sensors. *In: Third International Conference, PERVASIVE*, 2005, pp. 62–79.

[13] **D. N. Monekosso, P. Remagnino.** Behavior analysis for assisted living. *IEEE Transactions on Automation Science and Engineering*, Vol. 7, No. 4, 2010, pp. 879–886.

[14] **E. Nazerfard, D. J. Cook.** Bayesian Networks Structure Learning for Activity Prediction in Smart Homes. *In: Eighth International Conference on Intellegent Environments*, 2012, pp. 50–56.

[15] **H. Miki, A. Kojima, K. Kise.** Environment Recognition Based on Human Actions Using Probability Networks. In: *Second International Conference on Future Generation Communication and Networking*, 2008, pp. 441–446.

[16] **J. Dovydaitis, R. Jasinevicius, V. Petrauskas, A. Vrubliauskas.** Training, Retraining, and Self-training Procedures for the Fuzzy Logic-Based Intellectualization of IoT&S Environments *International Journal of Fuzzy Systems*, Vol. 17, No. 2, 2015, 133–143.

[17] **M. Ros, M. Delgado, A. Vila, H. Hagras, A. Bilgin.** A fuzzy logic approach for learning daily human activities in an Ambient Intelligent Environment. In: *IEEE International Conference on Fuzzy Systems*, 2012, pp. 1–8.

[18] **N. M. Oliver, B. Rosario, A. P. Pentland.** A Bayesian Computer Vision System for Modeling Human Interactions. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 22, No. 8, 2000, 831–843.

[19] **N. K. Suryadevara, S. C. Mukhopadhyay, R. K. Rayudu, Y. M Huang.** Sensor data fusion to determine wellness of an elderly in intelligent home monitoring environment. In*: Conference on Instrumentation and Measurement Technology (I2MTC)*, 2012, pp. 947 – 952.

[20] **P. Rashidi, D. J. Cook.** Keeping the resident in the loop: adapting the smart home to the user. *IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans*, 2009, Vol. 39, No. 5, 949–959.

[21] **P. Rashidi, D. J. Cook, L. B. Holder, M. Schmitter-Edgecombe.** Discovering activities to recognize and track in a smart environment. *IEEE Trans. Knowl. Data Eng*., Vol. 23, No. 4, 2011, 527–539.

[22] **R. Jasinevicius, V. Petrauskas.** Fuzzy expert maps: the new approach. In: *WCCI 2008 Proceedings: IEEE World Congress on Computational Intelligence*, 2008, pp. 1511–1517.

[23] **R. Jasinevicius.** Parallel Space-Time Computing Structures. *Mokslas*, Vilnius, 1988, (in Russian).

[24] **R. Marti, A. El-Fallahi.** Multilayer Neural Networks: An Experimental Evaluation of On-Line Training Methods. *Computers & Operations Research*, Vol. 31, Issue 9, 2004, pp. 1491–1513.

[25] **R. P. Singh, P. X. Gao, D. J. Lizotte.** On Hourly Home Peak Load Prediction. In*: Smart Grid Communications Conference*, 2012, pp. 163–168.

[26] **S. Y. Chiang, Y. C. Kan, Y. C. Tu, H. C. Lin.** Activity recognition by fuzzy logic system in wireless sensor network for physical therapy. *Intelligent Decision Technologies*, 2012, pp. 191–200,

[27] **T. Mikluscak, M. Gregor, A. Janota.** Using Neural Networks for Route and Destination Prediction in Intelligent Transport Systems. *Communications in Computer and Information Science*, Vol. 329, 2012, 380–387.

[28] **V. Singhvi, A. Krause, C. Guestrin, J. H. Garrett, H. S. Matthews.** Intelligent light control using sensor networks. In*: Proceedings of the 3rd international conference on embedded networked sensor systems*, 2005, pp. 218–229.

[29] **Y. H. Chen, C. H. Lu, K. C. Hsu, L. C. Fu, Y. J. Yeh, L. C. Kuo.** Preference Model Assisted Activity Recognition Learning in a Smart Home Environment. *In: The 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, October 11-15, 2009, pp. 4657–4662.

[30] **Y. Ming, Y. Yuan.** A Multi-attribute Reverse Auction Decision Making Model Based on Linear Programming. *Systems Engineering Procedia* 2012, Vol. 4, pp. 372–378.

[31] **Y. R. Fan, G. H. Huang, Y. P. Li.** Robust interval linear programming for environmental decision making under uncertainty. *Engineering Optimization*, 2012, Vol. 44, No. 11, 1321–1336.

[32] **Z. H. Lin, L. C. Fu.** Multi-user Preference Model and Service Provision in a Smart Home Environment. *In: IEEE Conference on Automation Science and Engineering*, 2007, pp. 759–764.

[33] **Z. Wang, Y. K. Tan.** Illumination control of LED systems based on neural network model and energy optimization algorithm. *Energy and Buildings*, Vol. 62, 2013, 514–521.

[34] **Z. Y. Chen, C. L. Wu, L. C. Fu.** Using Semi-Supervised Learning to Build Bayesian Network for Personal Preference Modeling in Home Environment. In*: IEEE International Conference on Systems, Man, and Cybernetics*, 2006, pp. 3816–3821.

Received April 2015.