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Intelligent Heating System: Simulation in NetLogo

Jiri Kazda and Kamila Stekerova
Faculty of Informatics and Management, University of Hradec Kralove,
Rokitanskeho 62, 50003 Hradec Kralove, Czech Republic

Abstract: We propose an agent-based model of smart home with intelligent heating system, i.e., a kind of computational laboratory for experimenting with smart solutions and ambient technologies. The model consists of four components simulating behavior of inhabitants, weather changes impacting the use of the heating system, heat transfer of the building, three control logics of the heating system which are non-intelligent thermostatic system, learning home a predictive system operating with the room occupancy matrices and attentive home-an adaptive predictive system which builds its own representation of the presence of individuals in rooms. The model is used to evaluate different scenarios of living in smart home with respect to two measures (user discomfort, heating costs). The model was implemented in NetLogo with IODA extension.

Key words: Agent-based model, heat transfer, NetLogo, simulation, smart home, components

INTRODUCTION

Smart technologies are designed to make our lives more comfortable and cost-effective by automating routine tasks. In case of several users of multiple technologies at the same place and time, it may be hard to anticipate all consequences. The agent-based simulation is a natural way how to represent practical scenario of application of smart technologies and their adoption: humans as well as smart devices can be represented by autonomous agents with their individual needs, requirements and possibilities, all of them surrounded by the environment which has got its features and processes. Moreover, simulations can be used to persuade potential users about the benefits of smart technologies.

Our intention is to show how the agent-based simulation provide insight into the practical use of smart home with intelligent heating system. Within our model, it is possible to explore combinations of parameters and scenarios to run the model and to collect data on interactions of people, environment and smart technology.

The main objective of the model is to optimize settings of the heating system with respect to two metrics (user comfort, cost), i.e., to identify those settings that maximize comfort of users and minimize heating costs.

Smart homes: The term smart home describes home that is managed by information technologies and is able to communicate with the world outside. Various researcher introduced similar terms such as computer home, electronic house, intelligent home, interactive home, home informatics or intelligent building (Vales, 2008).

According to the level of integration of smart technologies, 5 hierarchical classes of smart homes are recognised (Wilensky and Logo, 1999):

- Homes which contain standalone intelligent objects,
- Homes which contain intelligent, communicating objects
- Connected homes with internal or external networks and optional remote control
- Learning (adaptive) homes which accumulate data to anticipate user's needs
- Attentive homes constantly registering activities and locations of people and objects

The intelligent solutions are typically implemented into heating system, air conditioning, ventilation, blinds, water heating, lighting or operating appliances (Kubera *et al.*, 2011). According to the level of automation (Harper, 2003) classifies:

- Manual control of functions
- Remote control of functions
- Fully automatic functions based on settings such as of time zones
- Fully automatic functions reflecting current presence of users

Corresponding Author: Jiri Kazda, Faculty of Informatics and Management, University of Hradec Kralove, Rokitanskeho 62, 50003 Hradec Kralove, Czech Republic

Smart homes platforms with different level of automation are provided, e.g. by Loxone, iNELS smart home solutions, control4 or Haidy, most of them are connected homes (Kazda, 2016). Adaptive and attentive smart homes are at the stage of research project (GIT., 2017; Silva *et al.*, 2012; Warriach, 2013).

MATERIALS AND METHODS

Model: Our model is used for simulating family life in smart house of five rooms (Fig. 1 for a floor plan) with optional predictive heating system. The house is used either by young couple (needing home office and home gym) or by family with 2 children (having their bedrooms).

Several scenarios are defined, each of them specifies the sequences of daily routines and habits of individuals living in the house with corresponding presence of people in rooms which impacts on the need to manage the heating system effectively. Scenarios are represented by decision trees and matrices, unique for each user and day of week and are loaded from external files. The room occupancy is defined by matrices which are input for the prediction mechanism of the heating system. The core of the simulation is the periodical evaluating of presence and thermal comfort of individuals in room.

Two energy classes of the building are taken into account (building 1-standard (Table 1) building 2-low-energy (Table 2)). The house is expected to be situated in the Czech Republic with its typical weather. The temperature curves for the day and night were used for specification of course of the heating season.

The simulation of 7 months long heating season is divided into 75,600 time steps (ticks) one step represents 4 min long interval (i.e., 1 day takes 360 ticks). The length of the interval corresponds to the regular check of comfort of users in rooms and relevant update of settings of the heating system. The simulation process consists of three parts: simulation of user's activities, weather simulation and simulation of the heating system including the heat transfer of the building.

The world outside is specified by the weather state which changes every day (each 360th tick) main features are temperature and sunlight intensity which are given by the annual curves. The sunrise time, minimum and maximum temperature are taken into account.

Four types of days are specified (Sunny-S, Partly Cloudy-P, Cloudy-C, Rainy-R, Table 3) sunrise time, minimum and maximum temperature are defined. The transition between types of days are implemented through Markov chains (Fig. 2). Our weather simulation provides synthetic data that fit well real data (Fig. 3) Kazda, 2016).

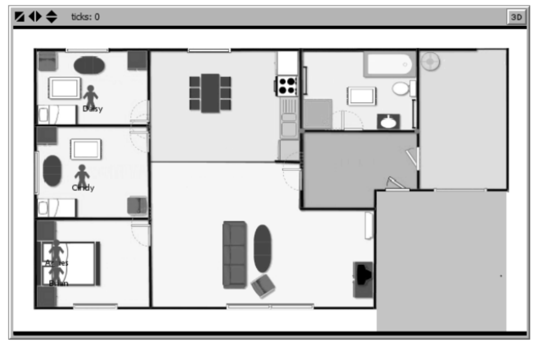

Fig. 1: Model visualization with floor plan

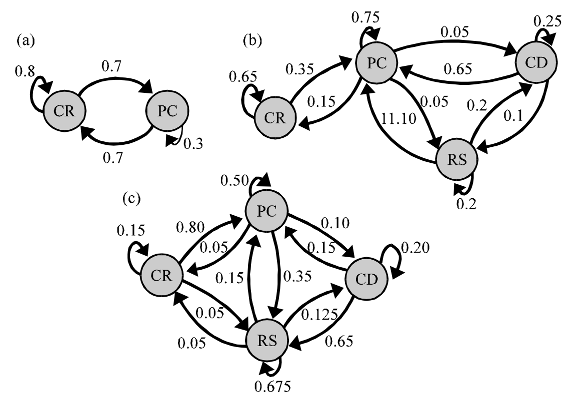

Fig. 2: Probabilities of transitions for sunny, partly cloudy and cloudy days

Table 1: Parameters of the standard building

Room	Area (m^2)	Heat loss (W)	Heat power	tCost (kW)
Living room	29	1030	1.90	1.909
Kitchen	20	645	1.86	1.733
Bedroom 1	12	263	3.42	1.178
Bedroom 2	12	258	3.49	1.156
Bedroom 3	10	240	2.81	1.290
Bathroom	10	230	3.91	1.236

Table 2: Parameters of the low-energy building

iWho	Area (m^2)	Heat loss (W)	Heat power	tCost (kW)
Living room	29	2795	0.78	2.250
Kitchen	20	1755	0.68	2.048
Bedroom 1	12	715	1.51	1.390
Bedroom 2	12	700	1.54	1.361
Bedroom 3	10	655	1.26	1.529
Bathroom	10	630	1.67	1.470

Table 3: Frequency of days in month

Months	S	P	C	R
Jan.	3.2	6.2	10.6	10.0
Feb.	5.0	9.8	7.2	8.0
Mar.	11.6	9.0	1.4	8.0
Apr.	11.4	13.6	2.0	3.0
May	12.8	9.6	2.6	5.0
Jun.	14.2	11.0	1.8	3.0
Jul.	14.8	12.6	0.6	2.0
Aug.	12.6	13.8	1.1	2.5
Sep.	11.4	11.4	2.2	5.0
Oct.	7.8	12.6	1.6	8.0
Nov.	3.6	7.8	7.6	11.0
Dec.	3.0	5.0	10.0	12.0

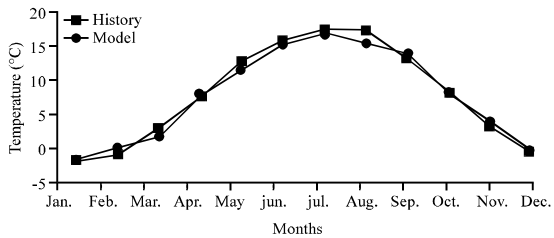

Fig. 3: Average temperature-historical records vs. weather simulation

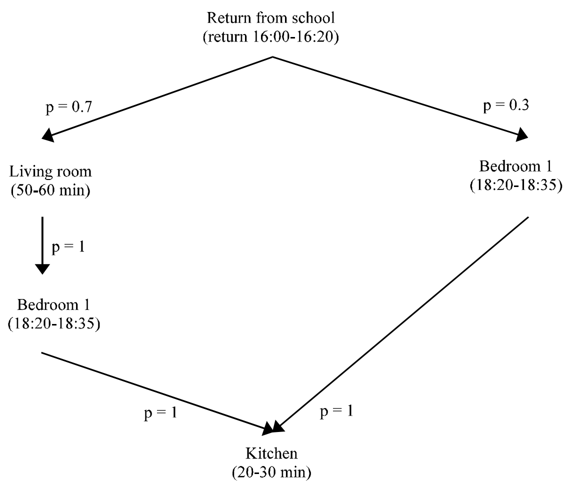

Fig. 4: Example of sequence of activities of user

The schedules of activities (e.g., sleeping, washing, eating or being out) of each user are represented by decision trees, unique for each day of week with probabilities of transitions from one activity to another (Fig. 4). The activities of users are bounded to certain rooms and take certain time including the specification of preferred temperature (Gann *et al*., 1999).

Sample scenario for the family of four with agents Agnes, Brian, Cindy, Daisy describes the activities of two adults and two students. Parents get up very soon, children a bit later. They all return home in late afternoon, children spend most of their time in bedrooms while mother works in the kitchen, all of them meet together in the living room etc. In case of irregularities in schedules (such as the child with flu staying at home for few days) manual setting of the smart home functions is expected.

Each room has got its attributes including the total area, total heat loss, heat power coefficient, heat consumption per hour, sunlight index, duration of sunlight during the day (Table 4 and 5).

The heating system responds to presence of users (current or expected soon) in rooms. If two people share the room, the optimum temperature is the mean of values preferred by individuals. Three control logics of the heating system are implemented, non-intelligent system operates with time intervals with predefined temperature for each room during the day, the initial settings match daily routines of inhabitants, learning home builds on presence of users which is defined by room occupancy matrices, runtime data is collected and used to refine predictions, attentive home enhances the learning home by generating maps of behavior/movement of users.

Table 4: Action of the agents, interface elements: user and thier activities, rooms and temperatures

Name	State	Rooms	Change
Agnes	Eating/cooking	Kitchen	274
Brian	Relaxing	Living room	325
Cindy	Studying	Bedroom 2	277
Daisy	Studying	Badroom 3	271

Table 5: Temperatures of the rooms

Room	Temperature	Goal
Living room	22.82	21
Kitchen	20.95	21
Bedroom 1	18.0	18
Bedroom 2	22.07	22
Bedroom 3	22.1	22
Bathroom	23.98	24

Within the simulation, it is possible to select the season of the year and the length of the learning period (number of days) for training of the predictive system. Key parameters are:

Sensitivity value: The minimum average room occupancy for switching the heating system.

Minutes on/off: The prediction takes into account the expectation of at least one incoming person during the next hour.

Smart cooling on/off: Setting of the adaptive cooling of the room (the temperature does not fall below the limit). Two measures are defined:

- User discomfort (unhappiness)-temperature preferences are defined for each user and room, preferences are compared with current temperature in the room
- Heating costs (energy)-maximum heating costs per hour are defined for each room

RESULTS AND DISCUSSION

Experiments were run to learn more about the efficient setting of the predictive heating system with respect to different configurations of the model (standard and low-energy building, family of four, control logic 1-3) and both measures (unhappiness, energy). The simulation started with the autumn season, 14 training days were used.

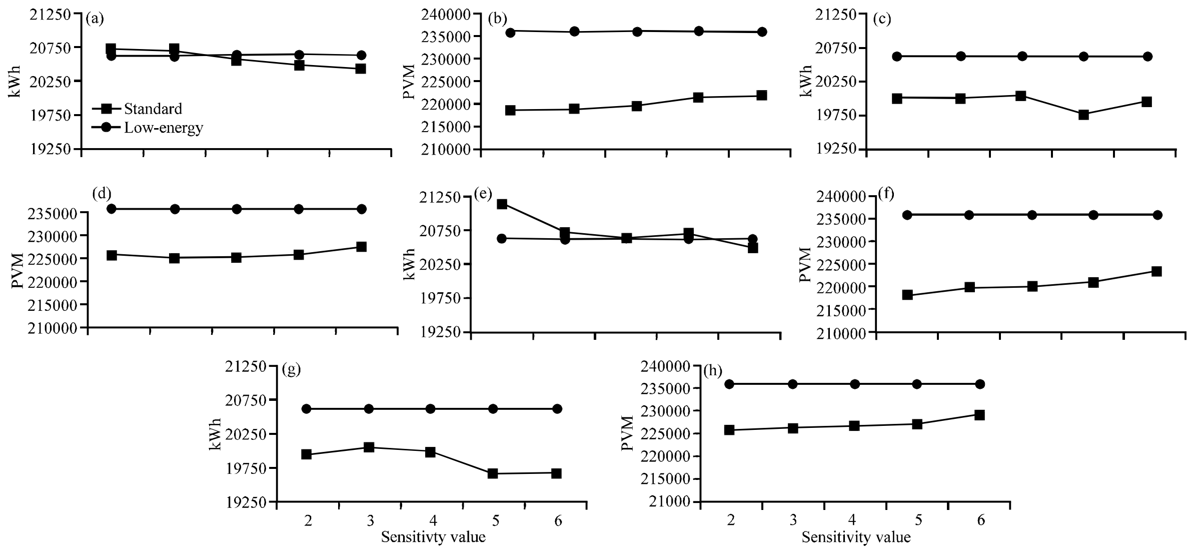

Fig. 5: Results-standard building, learning home: a) Energy: Minutes on, smart cooling on; b) Unhappiness: Minutes on, smart cooling on; c) Energy: Minutes on, smartcooling off; d) Unhappiness: Minutes on, smart cooling off; e) Energy: Minutes off, smart cooling on; f) Inhappiness: Minutes off, smart cooling on; g) Energy: Minutes off, smart cooling off and h) Unhappiness: Minutes off, smart cooling off

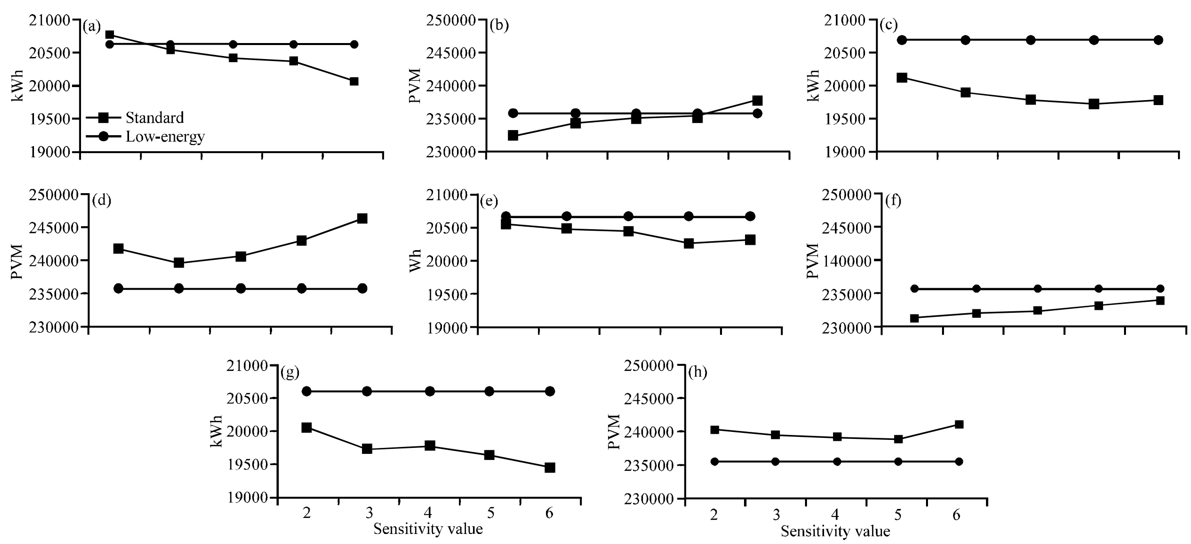

Fig. 6: Results-standard building, attentive home: a) Energy: Minutes on, smart cooling on; b) Unhappiness: Minutes on, smart cooling on; c) Energy: Minutes on, smartcooling off; d) Unhappiness: Minutes on, smart cooling off; e) Energy: Minutes off, smart cooling on; f) Inhappiness: Minutes off, smart cooling on; g) Energy: Minutes off, smart cooling off and h) Unhappiness: Minutes off, smart cooling off

Main outputs are the plot of energy consumption and the plot of discomfort of users for each combination of sensitivity value, minutes and smart cooling parameters.

In case of standard building and learning home logic (Fig. 5) it is always possible to determine sensitivity value which will reduce heating costs and/or increase user comfort. The best results are achieved with off-value of smart cooling and higher values of sensitivity. In this case the household reduces heating costs by up to 5% while increases thermal comfort also about 5%.

In case of the+same standard building with attentive home logic (Fig. 6) it is likely to achieve similar savings as a learning house but at the cost of a slight deterioration of comfort (around 1%).

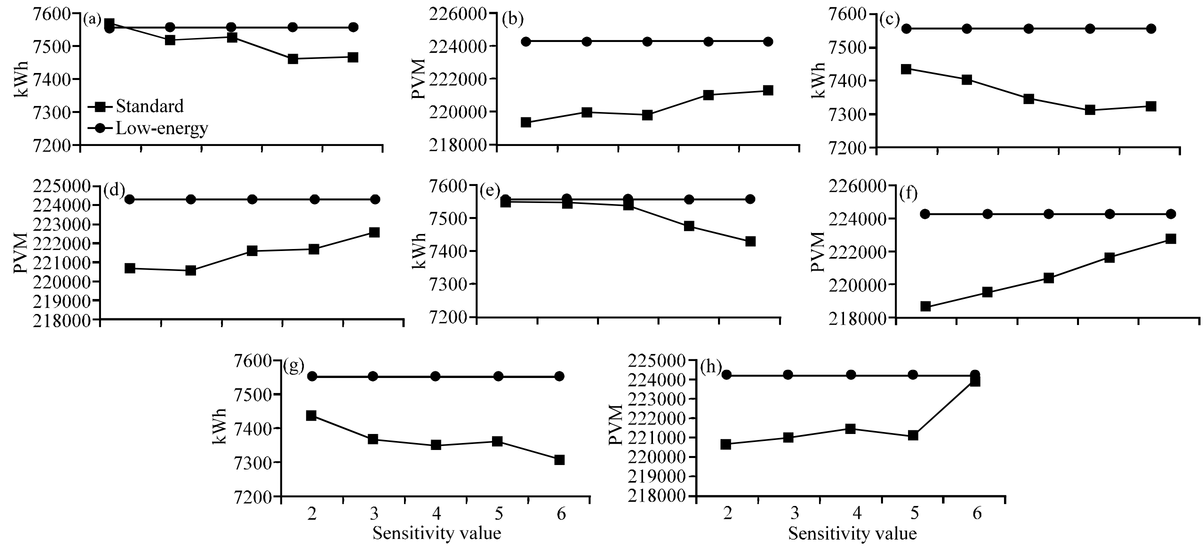

Fig. 7: Results-low-energy building, learning home: a) Energy: Minutes on, smart cooling on; b) Unhappiness: Minutes on, smart cooling on; c) Energy: Minutes on, smartcooling off; d) Unhappiness: Minutes on, smart cooling off; e) Energy: Minutes off, smart cooling on; f) Inhappiness: Minutes off, smart cooling on; g) Energy: Minutes off, smart cooling off and h) Unhappiness: Minutes off, smart cooling off

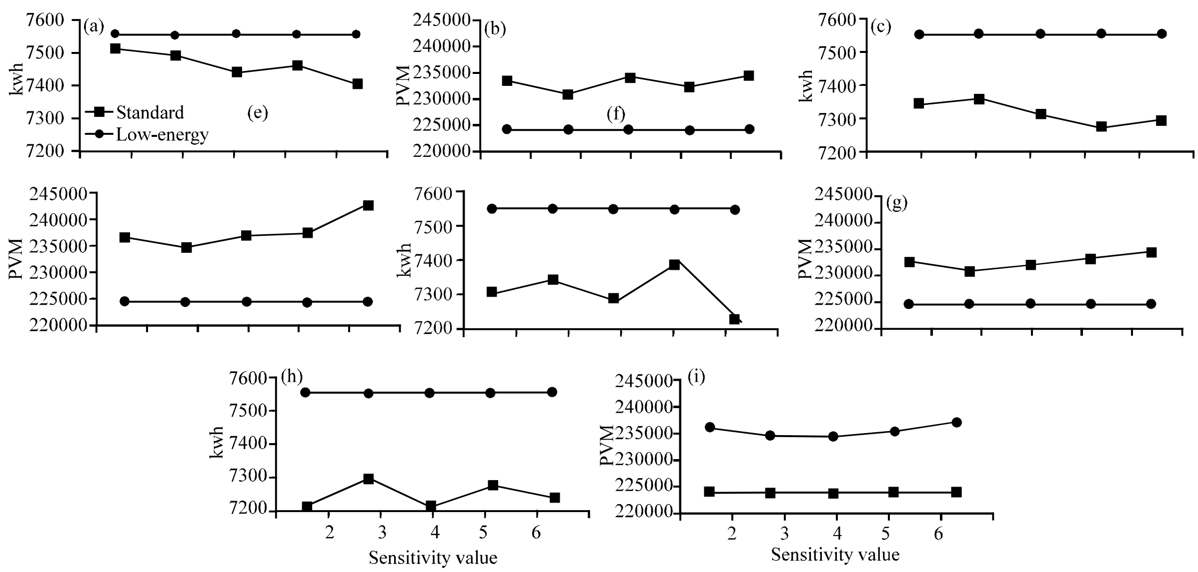

Fig. 8: Results-low-energy building, attentive home: a) Energy: Minutes on, smart cooling on; b) Unhappiness: Minutes on, smart cooling on; c) Energy: Minutes on, smartcooling off; d) Unhappiness: Minutes on, smart cooling off; e) Energy: Minutes off, smart cooling on; f) Inhappiness: Minutes off, smart cooling on; g) Energy: Minutes off, smart cooling off and h) Unhappiness: Minutes off, smart cooling off

In case of low-energy building and learning home Fig. 7 the best option is to choose the highest value of sensitivity. For off value of smart cooling, independently on values of minutes, the best achievable saving is around 3.5 %. However, the parameter minutes impacts the level of comfort.

The attentive home is not the best option (Fig. 8). The total satisfaction of users is lower than in case of learning home. The reason is that the attentive home tries to achieve optimum temperature for each individual and cannot deal with unexpected incomers in rooms. Analogically, experiments were run for the family of two, results are presented by Kazda (2016).

CONCLUSION

Our NetLogo Model shows how the agent-based simulations help to get insight into practical issues of implementation of smart technologies in everyday life. The model provides three control logics of the heating system and can be used as a computational laboratory for experimenting with parameters of the intelligent heating system. The input data files can be modified easily, so, parameters of the building, its location and users can be varied.

In calculation of the thermal stability of the room, the accumulation of the heat and the gradual cooling of the heating system were neglected. If the more precise modelling of the course of the temperature is required, corresponding parameters and formulas can be added to the model.

Similarly, the model can be enhanced in other dimensions of its components (scenarios of behavior of users, more complex environmental processes, multiple interacting smart technologies). Here we can mention that according the Gartner special report (Jones, 2014) more than 500 smart devices would be used in typical family home by 2022.

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