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Development of Matlab-TRNSYS co-simulator for applying predictive strategy planning models on residential house HVAC system

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ABSTRACT

Building energy simulators such as TRNSYS, EnergyPlus, and Esp-r offer an excellent opportunity for detailed design of house thermal model and its Heating, Ventilating, and Air Conditioning (HVAC) system and provide very accurate simulation results useful for performance analysis and optimization process. In contrast, these energy simulators do not include sub-models of advanced devices/strategies for control of HVAC system operation and suffer from poor control mechanism. In addition to lack of an advance controller, they inherently offer no mechanism for estimating the future state of their process models based on forecast weather dataset. Hence, no predictive controller can be designed and implemented within these simulators. This paper discusses the development of a Matlab-TRNSYS co-simulator in order to control/manage a TRNSYS program, which was previously developed and calibrated based on the characteristics of a real case study house, with an advanced predictive controller. This co-simulator investigates the effectiveness of different predictive strategy planning models, including Load Shifting (LSH), Smart Dual Fuel Switching System (SDFSS), and LSHSDFSS, as the integration of fuel switching and load shifting strategy planning models on 24 h ahead energy cost saving of the case study house HVAC system. Simulation results of different consecutive sample days indicate that SDFSS could bring significant energy cost saving. However, LSH and LSHSDFSS effectiveness is sensitive to the outdoor temperature.

1. Introduction

A high percentage of urban dwellings consists of residential houses (RHs). Hence, RHs can play significant roles in managing the network energy system. In order to investigate the effect of RHs on network energy system, different kinds of research have been previously conducted. For example, Mathew et al. [1] developed an internet-based distributed system utilizing distributed load shifting strategy to manage the community energy system. Liu and colleagues developed a constrained demand-side management system considering peak-to-average ratio and consumers' preferences in optimization routine for managing the energy systems of different residential houses [2]. Radhakrishnan and Selvan used load scheduling technique along with decentralization of power generation in various residential buildings to manage the network energy system [3]. In addition to their extensiveness, residential houses inherently have the potential for storing thermal energy, therefore, they present a great opportunity for managing/controlling electricity demand during peak hours utilizing various control techniques including advanced control system design [4] and (economic) model predictive control [5,6]. Furthermore, RHs energy systems can take advantage of various Strategy Planning Models (SPMs) to decrease the demand and particularly the energy cost at the user demand side. Naidu and Craig [7] present a chronological overview of the advanced SPMs implemented on heating, ventilating, and air conditioning (HVAC) and refrigeration systems. Weiss investigates an adaptive neuro energy management SPM in order to decrease the building energy cost [8]. Platt and colleagues used demand response experiments in two large office buildings [9]. Srinivas and Ning evaluated different demand response programs in order to analyze the benefits of applied SPMs [10].

Management and control of RHs energy systems have been extensively researched. For instance, García-Domingo designed a building integrated PV system to analyze the electrical energy balance of the house [11]. Keshtkar et al. [12] used smart wireless sensors in a residential house in order to reduce the electrical load. Onda et al. [13] utilized the storage system of the smart electric vehicle for shifting the house peak load to off-peak hours. Boehm [14] examined various approaches, including energy-conserving

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Nomenclature

ASH	Archetype sustainable houses
AHU	Air handling unit
ASHP	Air source heat pump
BCS	Best case scenario
CMC	Canadian meteorological center
COP	Coefficient of performance
DEC	Daily electricity cost
DFC	Daily fuel cost
DHW	Domestic hot water
DSO	Distribution system operators
HRDPS	High resolution deterministic prediction system
HVAC	Heating, ventilating, and air conditioning
LEED	Leadership in energy and environmental design
LSH	Load shifting
LSHSDFSS	Load shifting and smart dual fuel switching system
OEB	Ontario energy board
RH	Residential house
SDFSS	Smart dual fuel switching system
SPM	Strategy planning model
TOU	Time-of-use
TRCA	Toronto and region conservation authority

design and the use of photovoltaic arrays, to reduce the peak electrical demand in residences. Castillo-Cagigal et al. [15] examined the use of a semi-distributed demand-side management system to improve the house self-consumption capability. Fernandes et al. [16] developed a dynamic load management model for enhancing the participation of house in demand response events. Beizaee and colleagues [17] used zonal space heating controls to decrease the house demand. Naspolini et al. [18] investigated the benefits of solar water heating in house energy demand. Chassin et al. [19] examined the cost, comfort and energy impacts of a discrete-time controller in a residential house HVAC system. Li et al. [20] developed a dynamic zone modeling in order to reduce the HVAC system electricity cost. Nielsen and Drivsholm [21] developed a system in which ventilation was controlled by an intelligent demand controller. Among previous research, the ones that concentrate on residential HVAC load [17–21] are most useful and efficient since HVAC systems consume a significant portion of the total energy used in households. According to the Annual Energy Outlook published by the U.S. Energy Information Administration [4], HVAC systems consume more than 40% of the overall energy in residential houses resulting in higher operating costs and environmental pollution according to the Annual Energy Outlook published by the U.S. Energy Information Administration [4]. Over the past decade, numerous strategy planning and energy conservation methods/approaches have been developed to address the planning issues related to managing RHs and their HVAC systems energy demand and associated cost. For example, Ma and colleagues [5] showed that HVAC system energy cost can be reduced using thermal storage in building mass. Candanedo and Athienitis [6] examined the effect of floor heating mass on reducing the energy cost. In this study, the impacts of passive solar gains on managing the HVAC system energy demand, were considered. Temperature reset during unoccupied hours [7,8], night setback, precooling during off-peak period and set-point change during peak hours [9,10], optimum start and stop times [22], ventilation control [23,24] and economizer cycle control [25] are some of the SPMs implemented on HVAC system in order to decrease its energy demand and associated cost.

Many of the previous studies utilized house energy simulators such as TRNSYS [26], EnergyPlus [27,28], Mathcad [29], and Esp-r [30,31]. These energy simulators offer an excellent opportunity for detailed design and modeling of the house and its HVAC system and provide very accurate results useful for performance analysis and optimization process. In contrast, these simulators do not include sub-models of advanced devices/strategies for controlling the HVAC system operation and suffer from poor control mechanism. As a result, only simple conventional (on/off) controllers were employed in order to control and manage the house and its HVAC system performance. Due to the large thermal inertia of the conditioned zone and dynamic disturbances, the on/off controller cannot accurately regulate the zone temperature resulting in thermal discomfort for the occupants and higher energy costs [4,32]. In addition to the lack of advanced controllers, these energy simulators use operational/historical weather dataset (provided in a library file) for simulating the house's energy system. Hence, they inherently offer no mechanism for estimating the future state of their process models based on the forecast weather dataset. In the advanced predictive controller, a model of the system (building and its HVAC system) and the forecast weather conditions are used to determine the best set of control operations [4,32]. Hence, no predictive controller can be designed and run within such building energy simulators.

Therefore, in order to control the process models of such software with advanced and/or predictive controllers, a software/tool with advanced process control mechanism (i.e. Matlab) should be integrated/linked into these building energy simulators. This study discusses the development of a Matlab-TRNSYS co-simulator in order to control/manage the TRNSYS program with an advanced predictive controller. To design an advanced controller, three novel predictive strategy planning models (SPMs) including Smart Dual Fuel Switching System (SDFSS), Load Shifting (LSH) and LSHSDFSS as the combination of SDFSS and LSH-SPM models are developed in this study using Matlab program. To implement these predictive SPMs on the TRNSYS model, Matlab and TRNSYS programs are linked together to found a Matlab-TRNSYS co-simulator. The TRNSYS (TRNSYS 16) model utilized in this study has been previously developed and calibrated based on the characteristics/specifications of a real case study house (Archetype House A) [41]. In this study, the advantage of the developed co-simulator is examined by investigating the effectiveness of each SPM on HVAC system energy cost saving for the next 24 h horizon time. In this method of control, the future state of the system is predicted based on the forecast weather dataset, the system model, and control vector signals (generated as the model output) which drive the system towards the desired state. This co-simulator, which acts as a smart grid-friendly controller, also has the potential to be utilized as a test bed for implementing various SPMs previously developed for reducing the energy cost of HVAC systems.

This article consists of four sections. In Section 2, different formats of forecast weather dataset are described. The process model and the different strategy planning models are then described in detail as well. The simulation result as well as the effect of each SPM on the demand and energy cost of the case study house HVAC system are discussed in Section 3. The study is concluded in Section 4.

2. Model description

2.1. Historical and forecast weather information

Weather conditions play a significant role in house energy system simulation. As a result, getting access to accurate weather

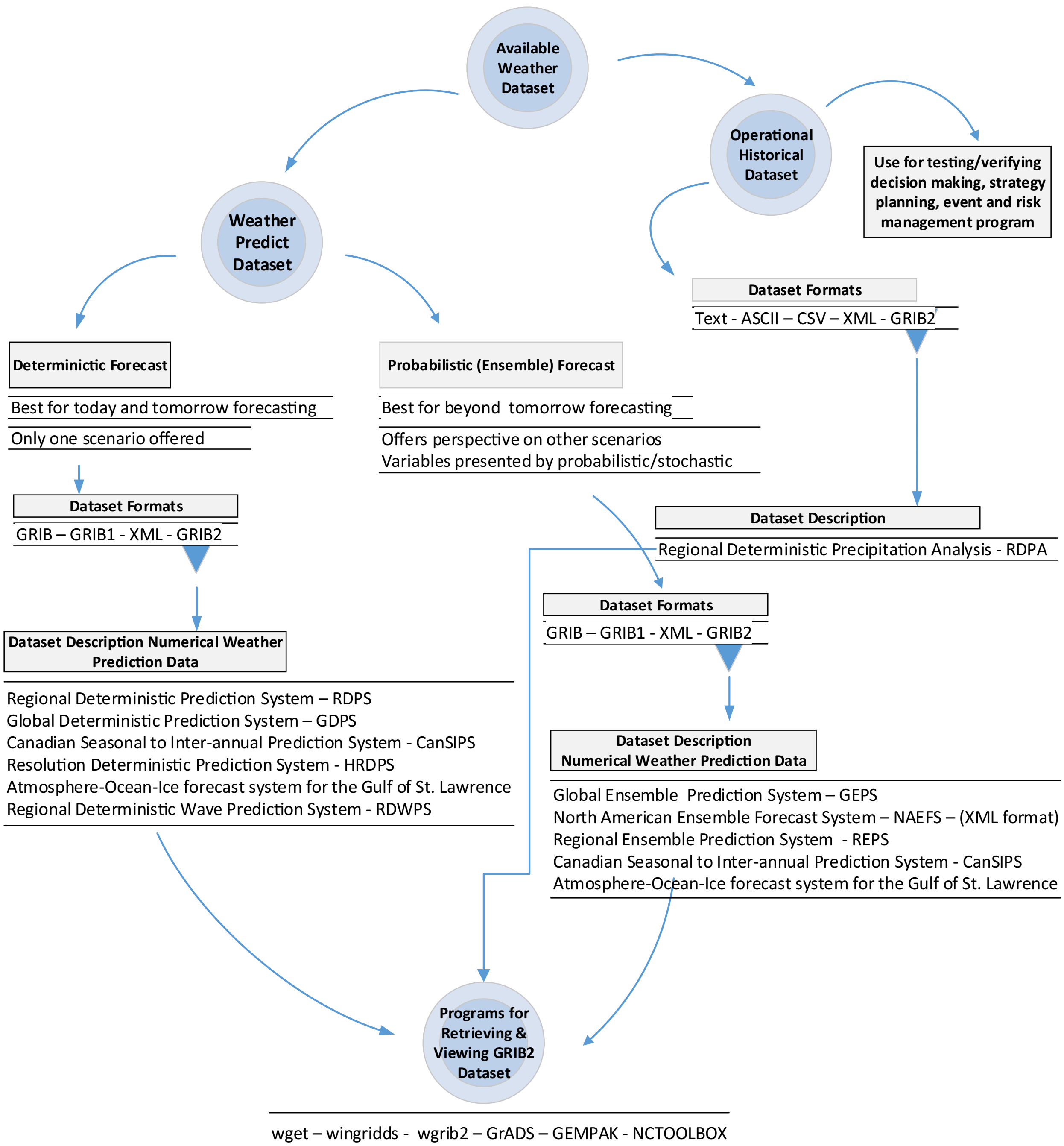


Fig. 1. The overall view of various available weather datasets.

forecast data is vital for simulating the house energy system. Canadian Meteorological Center (CMC) forecasts weather four times a day to ensure the predicted data are highly accurate. In addition, there is a wide range of historical weather dataset on different online sources [33] that could be used for testing and verifying the decision making or strategy planning models [34,35]. Fig. 1 provides an overall view of various available weather data used for different purposes. Deterministic and probabilistic are two separate methods used for generating predicted data. Each method has its own advantages. The deterministic forecast is based on the result of one or two predictive model(s). The data predicted using this method is highly accurate and is usually used for short-term control process [34,35].

The probabilistic forecast is the result of a group (sometimes as many as 21) of models producing a range of forecast data. An ensemble of different models generates a dataset with an appropriate range of values. This method is suitable for planning long-term control process [34,35].

The actual historical and weather forecast datasets are presented in different formats. Operational weather data is usually presented in spreadsheet (CSV), XML, ASCII (text) and GRIB2 formats [36,37]. However, GRIB2 is the most common format used for presenting the forecast dataset.

To be usable in TRNSYS and Matlab, GRIB2 data format should be retrieved into a standard numerical format. To this end, two software have been used in this project. The first one is “wget” [38] which is a command-line program designed for retrieving files using HTTP, HTTPS, and FTP protocols. The second one is “NCToolbox” [39], a Matlab toolbox designed for working with the datasets generated as the output of GRIB2 retrieving programs [34].

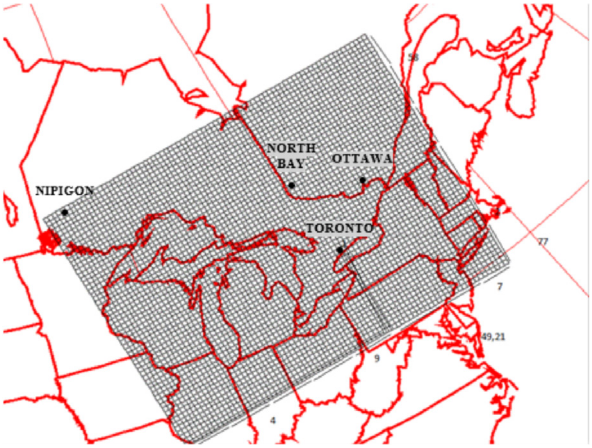


Fig. 2. The grid format of the GRIB2 data—Eastern Ontario.

Based on the nature of the project which requires accurate short-term prediction, high resolution deterministic prediction system (HRDPS) with bandage 2.5 km was selected from CMC website as the forecast dataset. In order to collect this information from the database, wget was installed on a computer and a system command was called from Matlab to collect the necessary data using wget [34,35]. This process downloaded 24 h' worth of weather forecast data onto the system that needed to be further processed and filtered so that only the temperature data for the next 24 h (as the most important parameter with the greatest impact on the house energy system) is remained. The information that was downloaded off the HRDPS source created a 2.5 km by 2.5 km grid across Eastern Ontario and contained the weather information for each element of the grid. Fig. 2 illustrates the described grid format of the GRIB2 data. In order to process the data, the coordination of the grid element from which the weather forecast is collected must be determined. In this study, the TRNSYS program models thermal energy of House A [40,41] located at Kortright Centre for Conservation in Vaughan, Ontario. Therefore, the grid element of (210, 490), corresponding to the location of the house, was selected for data collection.

In order to create an interface between Matlab and the collected GRIB2 data, the NCToolbox was installed, and the ncgeodataset function was used to present all the data stored in each of the 24 downloaded files as a multidimensional matrix. This matrix was filtered to include only the weather forecast information for each hour and then was stored into a single two-dimensional array.

2.2. *Estimation of 24 h-ahead HVAC system electrical demand based on weather forecast dataset*

2.2.1. *House description*

The twin Archetype Sustainable Houses (ASH) located at the Kortright Centre for Conservation in Vaughan have been constructed by the Toronto and Region Conservation Authority (TRCA) [40–42]. These twin-houses demonstrate sustainable housing technologies through experimentation and research and are among the first Canadian projects to achieve a Leadership in Energy and Environmental Design (LEED) for Homes Platinum Certification [40]. House A uses a two-stage variable capacity air-source heat pump and a natural gas mini boiler for space heating and cooling and domestic hot water (DHW) heating, and was selected for testing different strategy planning models in this project. This house has an air-tight building envelope according to the standards of ASHRAE 90.1 [40–42].

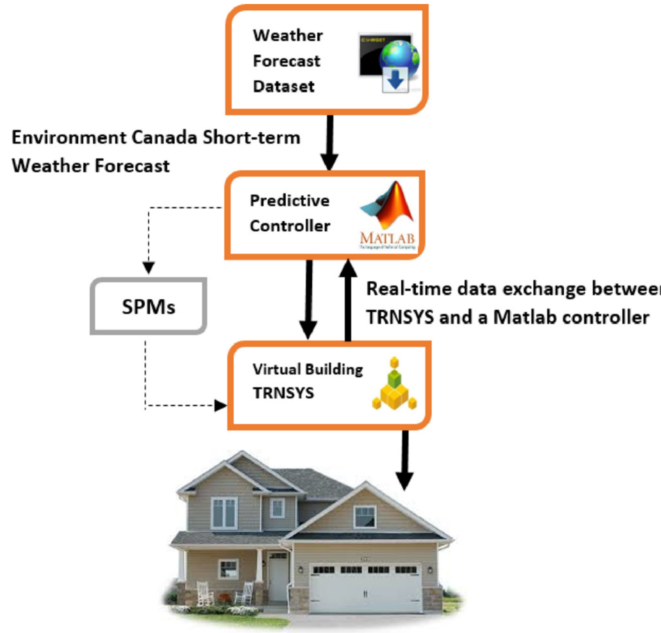


Fig. 3. Framework of the house energy simulation system.

2.2.2. *TRNSYS model*

TRNSYS is a transient system energy modeling software designed to solve complex energy system problems [41,49]. The House A TRNSYS model, developed by Safa et al. [41], is used in this project. According to a study on various building energy modeling programs [34–48], TRNSYS is reasonably robust when it comes to HVAC system modeling.

2.2.3. *Methodology*

Different sub-programs with various operational mechanisms are run to achieve the project's objectives. The study starts with downloading and processing of forecast weather data and continues with running the House A TRNSYS model with weather forecast data, implementing strategy planning models on TRNSYS system by generating operational command matrix, and lastly post-processing the generated data.

Fig. 3 illustrates the framework of the house energy simulation system consisting of three different but complementary programs. Wget runs first, downloading short-term weather forecast dataset from the CMC website. The second program is Matlab, which controls the operational process and links other programs in order to transfer the data. The third program is TRNSYS, which is used for simulating the house and its energy systems.

To achieve the project goals, each sub-program should be run at a particular time to generate the inputs for the next program. To control and manage this sequence, a master director program is required to drive each process on time. In this project, Matlab plays this role by handling the process, linking different programs as well as storing the data or calling the required data.

Fig. 4 depicts the overall process in a simple flowchart. As Fig. 4 shows, all retrieved weather forecast data are initially recorded with Matlab on an Excel lookup table. The lookup table is the only method used for importing external data into the TRNSYS program. In the next step, TRNSYS program is called by Matlab to read the weather forecast data from Excel file lookup table and perform House A energy simulation for the next 24 h. Then, all generated data including the hourly thermal demand of House A and air source heat pump (ASHP) electric demand are registered into another Excel file which will be used for post processing.

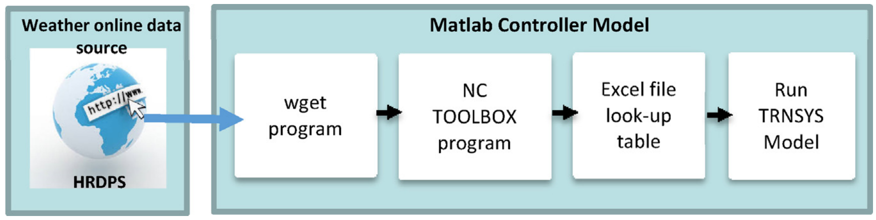
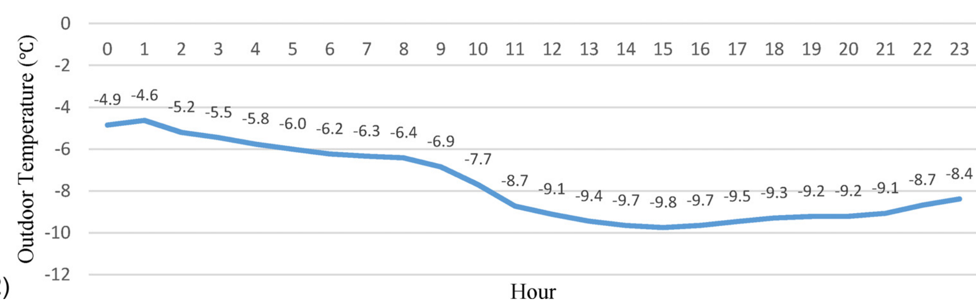


Fig. 4. Framework of Matlab Controller Program.

First 6 Hours	0	1	2	3	4	5
Command Signals	1 0 0 1 0 0 1 0 0 1 0 0	1 1 1 1 1 0 1 0 0 1 0 0	1 1 0 1 0 1 0 1 0 1 0 1	0 1 0 1 0 1 0 1 0 1 0 1	0 1 0 1 0 1 0 1 0 1 0 1	0 1 0 1 0 1 0 1 0 1 0 1
Second 6 Hours	**6**	**7**	**8**	**9**	**10**	**11**
Command Signals	0 1 0 1 0 1 0 1 0 1 0 1	0 1 0 1 0 1 0 1 0 1 0 1	0 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0
Third 6 Hours	**12**	**13**	**14**	**15**	**16**	**17**
Command Signals	1 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0
Fourth 6 Hours	**18**	**19**	**20**	**21**	**22**	**23**
Command Signals	1 1 0 1 0 1 0 1 1 0 1 0	1 0 1 1 0 1 0 1 0 1 0 1	1 0 1 0 1 0 1 1 0 1 0 1	0 0 0 0 1 0 1 0 1 1 0 1	0 0 0 1 0 1 0 1 0 1 0 1	0 0 0 0 1 0 1 0 1 0 1 0

(1)



(2)

Fig. 5. (1), Operational command matrix generated with Matlab program after using weather forecast data. (2), Outdoor temperature on Jan 4th, 2015 based on forecast weather dataset.

The operational command matrix generated by Matlab predictive controller is written to the Excel file in a lookup table. This lookup table is then read by TRNSYS in order to control the ASHP operation. This control mechanism, which acts as a thermostat module in TRNSYS program, is used to take care of lower and upper comfort level temperatures. Based on the ASHRAE Standard [45], the indoor temperature during the occupied period of the heating season should be kept between 20 °C and 24 °C for thermal comfort. In this project, to ensure the ASHRAE Standard, when the zone (1 st floor) temperature is lower than the minimum permitted temperature (20 °C), a trigger command ("1" signal) is sent to the ASHP to turn it on. When the zone temperature is higher than the maximum permitted temperature (24 °C, command "0" is sent to the ASHP to turn it off. This command mechanism is used for implementing different strategy planning models presented in the next section.

2.2.4. Process time step

Initially, all simulations were performed based on one-hour time step. However, the results were not very accurate since the events taking place during a given hour could not be monitored/processed by the control algorithm. After a few trials, we found that this problem can be avoided using 5-min time step. Although with 5-min time step it would take longer to simulate the model, the operation of the HVAC system would be controlled and monitored more accurately and the data would be measured more precisely. With 5-min time step, TRNSYS model is run twelve times per hour (289 times per day) to generate the result. Fig. 5(1) shows the operational command matrix generated after implementing weather forecast data illustrated in Fig. 5(2). Fig. 6 illustrates the same operational command matrix as a graph generated with TRNSYS program.

In this project, 22 °C is considered as the initial zone temperature. Fig. 7 shows the zone temperature curve during the 24 h simulation time. As the figure shows, the zone temperature started at 22 °C and fluctuated around 20.7 °C, the temperature selected as the heating set point temperature during the 24 h by the TRNSYS model developers. This set point has been set in the lookup table as the heating set point temperature before implementing any SPM. The essential goal of this project is to design a grid-friendly house by using different strategy planning models in order to shift the load to off-peak hours and minimize the HVAC system's daily energy cost. In this section the electricity consumed by ASHP is considered the only fuel consumed by the HVAC system.

2.2.5. Electricity prices

Distribution System Operators (DSOs) apply rates that penalize energy use during peak hours via demand charges and/or time of use (TOU) rates. Fig. 8 shows the price of electricity in Ontario since November 1st, 2014 for winter and summer. The electricity prices used in this project are 11.70 ¢/kWh, 15.40 ¢/kWh and 18.00 ¢/kWh for off-peak, mid-peak and peak hours, respectively. These prices are estimated using the Ontario Energy Board (OEB) TOU electricity prices [50].

2.3. HVAC system energy cost reduction with smart dual fuel switching system strategy planning model (SDFSS-SPM)

The test house, House A, has a natural gas mini boiler and an electric two-stage variable capacity ASHP to generate hot air through the air handling unit (AHU) to meet the space heating demand. The

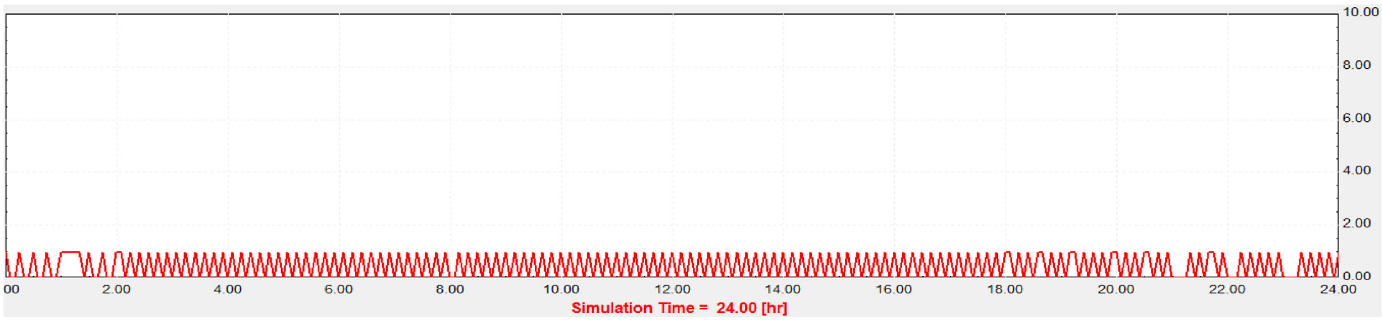


Fig. 6. Operational command matrix graph—TRNSYS program.

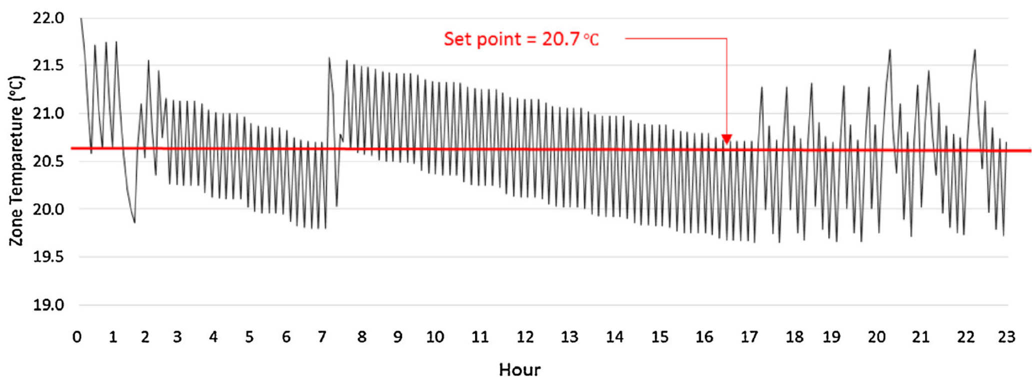


Fig. 7. Zone (1st floor) Temperature after running TRNSYS program with weather forecast data.

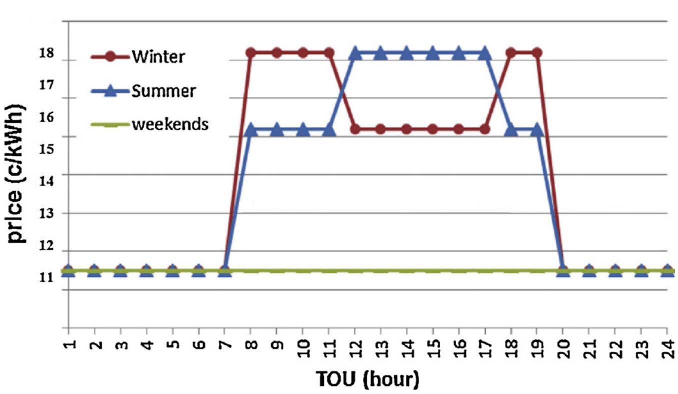


Fig. 8. Price of electricity in Ontario since November 1st, 2014 for winter and summer [50].

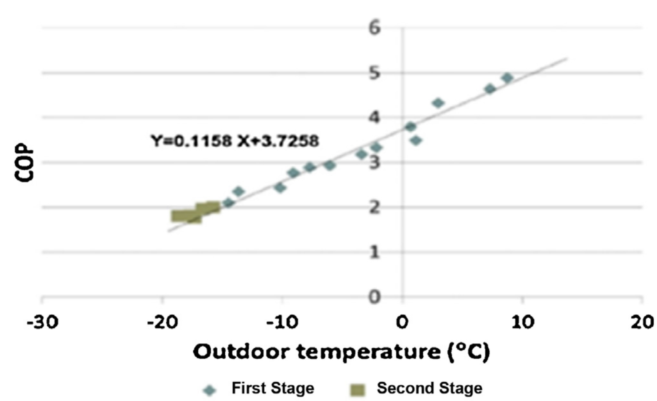


Fig. 9. House A ASHP COP validated with outdoor temperature [50].

objective of this strategy planning model is to reduce the HVAC system energy cost by selecting the least expensive hot air supplier at each particular hour. After selecting the least expensive hot air supplier, the corresponding system (ASHP or mini boiler) would be set up to meet the space heating demand.

2.3.1. *Estimating ASHP fuel cost*

Outdoor temperature and electricity price are the two most important parameters affecting the ASHP energy cost. Outdoor temperature directly affects the ASHP coefficient of performance (COP). Fig. 9 shows the experimentally validated House A ASHP COP curve [41,50]. After determining COP and electricity price for a given hour, the cost of the unit of energy produced by the ASHP is calculated using Eq. (1):

$$\text{ASHPelectricity cost for preparing one unit of heat energy(\$)/kWh} = \frac{\text{electricityprice(¢ /kWh)}}{\text{COP} \times 100} \quad (1)$$

where Electricity price indicates the cost of electricity $(¢\ /kWh)$ at the given hour based on TOU pricing scheme and *COP* shows the ASHP coefficient of performance determined based on the outdoor temperature at the given hour.

2.3.2. *Estimating mini boiler fuel cost*

Natural gas price (41.60 $¢/m^3$, determined based on OEB prices) is the same for all hours. Thus, mini boiler efficiency is the only variable used to determine the cost of each unit of thermal energy produced by the boiler. The efficiency of the boiler is determined based on the flow rate of water (load percentage) circulating through the boiler. Fig. 10 illustrates the mini boiler efficiency curve provided by the manufacturer [44]. The fuel cost of mini boiler (for preparing one unit of thermal energy) is calculated by Eq. (2):

$$\text{Mini boiler natural gas cost for preparing one unit of heat energy (\$/kWh)} = \frac{\text{Natural Gas price(\$/m}^3)}{\text{Efficiency} \times 10.3} \quad (2)$$

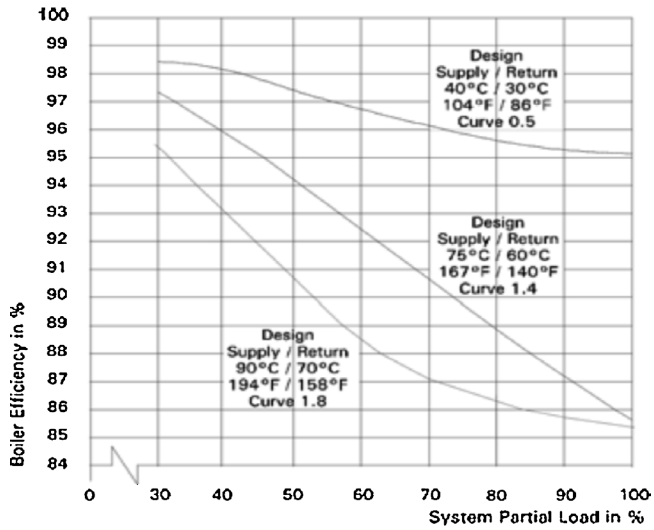


Fig. 10. VIESMAN Co Technical Data Manual—Mini boiler efficiency curve [44].

where Natural Gas price indicates the cost of natural gas $\left(\$/m^3\right)$ and *Efficincy* shows the mini boiler efficiency determined based on the load percentage at the given time. The 10.3 constant is used for converting 1 m^3 of natural gas energy content into kWh.

At each particular hour, the cheaper hot air supplier is directly selected by comparing the expected fuel cost of ASHP and mini boiler. At House A, the ASHP is selected as the primary hot air supplier and the mini boiler is used just as a backup system. This prioritization can be changed by sending a command signal to AHU controller relay.

2.3.3. *Using SDFS system as a strategy planning model*

Fig. 11 shows the operational boundaries of ASHP and mini boiler classified according to off-, mid- and peak-hours. These functional limits/switching points are calculated by solving Eqs. (1) and (2) at different TOU prices and outdoor temperatures. In Fig. 11, the minimum and maximum temperatures are selected based on the minimum and maximum temperatures of Toronto reported by Environment Canada [45,46].

As the figure shows, −14 °C is the switching point during off-peak hours. In other words, during the off-peak hours when the outdoor temperature falls below −14 °C, a unit of heat energy generated by the mini boiler becomes less expensive than a unit of heat energy generated by the ASHP. Based on this methodology, the switching points at mid-peak and on-peak hours are −5 °C and 0 °C, respectively.

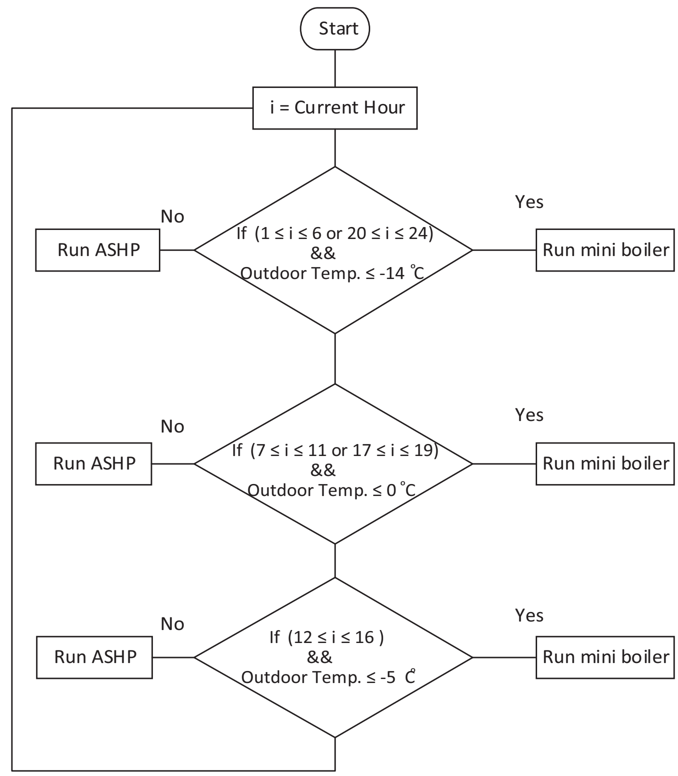


Fig. 12. SDFSS strategy planning model.

Fig. 12 demonstrates the SDFSS strategy planning model used for determining the switching point at different hours. The HVAC daily fuel cost could be minimized by modifying the operational command matrix presented in Section 2.2 based on the results of the SDFSS strategy planning model.

Fig. 13 shows the developed operational command matrix after using SDFSS-SPM. In this Figure ‘A’ and ‘M’ represent the ASHP and

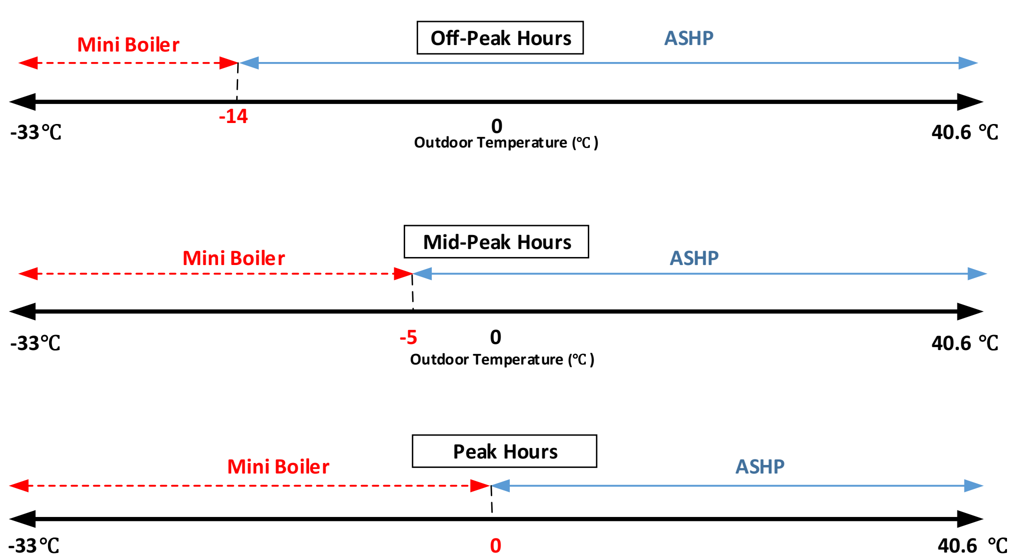


Fig. 11. Switching points on different TOU prices.

First 6 Hours	0												1												2												3												4												5											
Command Signals	A	O	O	A	O	O	A	O	O	A	O	O	A	A	A	A	A	O	A	O	O	A	O	O	A	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A	O	A
Second 6 Hours	6												7												8												9												10												11											
Command Signals	O	A	O	A	O	A	O	A	O	A	O	A	O	M	O	M	O	M	O	M	O	M	O	M	O	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O
Third 6 Hours	12												13												14												15												16												17											
Command Signals	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O	M	O
Fourth 6 Hours	18												19												20												21												22												23											
Command Signals	M	M	O	M	O	M	O	M	M	O	M	O	A	O	A	A	O	A	O	A	O	A	O	A	A	O	A	O	A	O	A	A	O	A	O	A	O	O	O	O	A	O	A	O	A	A	O	A	O	O	O	A	O	A	O	A	O	A	O	A	O	O	O	O	A	O	A	O	A	O	A	O

Fig. 13. Developed operational command matrix after using SDFSS-SPM.

mini boiler, respectively, and 'O' marks the time at which the HVAC system was off. Based on Fig. 5(2), since the outdoor temperature during the peak and mid-peak hours is below the 0 °C and −5 °C, the mini boiler is selected as the cheaper hot-air supplier system during these hours.

2.3.4. Calculating the impact of SDFSS-SPM on HVAC system daily fuel cost (DFC) at different outdoor temperatures

To calculate the impact of SDFSS-SPM on DFC, the Matlab model was run when the daily average outdoor temperature was fluctuating between −20 °C and 0 °C. Table 1 demonstrates the simulation results.

As Table 1 shows, the energy cost saving rate continuously increased as the outdoor temperature decreased. This is because the ASHP COP, the parameter with the greatest effect on potential energy cost saving, varies based on the outdoor temperature.

According to Fig. 9, ASHP COP changes between 1.64 and 5.31. One of the most significant trends in ASHP COP is the rate of reduction of COP, which directly affects the rate of energy cost saving. As outdoor temperature decreases, the rate of reduction of COP increases.

Looking at Table 1, it is concluded that the role of SDFSS-SPM on DFC and subsequently fuel cost saving is significantly greater during cold and very cold weather conditions. For example at −20 °C, $5.28 could be saved by using SDFSS-SPM for a day. Fig. 14 shows the savings due to using SDFSS-SPM in different outdoor temperatures. As the figure shows, SDFSS-SPM is more efficient in energy cost saving when the outdoor temperature is colder.

2.4. HVAC system demand management using load shifting strategy planning model (LSH-SPM)

Buildings are complex entities. Many variables such as building construction/material, equipment capacity, solar irradiance, thermal mass, occupant behavior, and outdoor condition significantly affect the result of strategy planning and especially load shifting models in buildings. Since buildings are part of the total energy system, their behavior has a significant influence on the entire energy network. For example, in terms of peak loads, managing the load of a building's HVAC system by shifting the load from peak to off-peak hours can notably decrease the grid overloading during peak hours. This is achieved by designing smart strategy planning models to avoid electricity consumption during peak hours. The only parameter that significantly affects the thermal energy stored in a house is outdoor temperature. When it is not very cold outside, it is possible to store the heat energy inside the house for immediate future use. However, in cold and extremely cold weather, this is less likely. It should also be noted that house construction/component, interior design, wall layers/thickness, thermal mass, house orientation, and windows size have significant impacts on the capacity of stored thermal energy and consequently the behavior of the house in cold and very cold outdoor temperature. The R-value of an insulating material is a measure of its thermal resistance. The higher the R-value, the more effective the insulator. In the case study house, the R-values of basement walls, wall's insulation, and roof are R-20, *R*-30, and R-40, respectively. A light thermal mass material has been considered for the house in the TRNSYS model. House A was assumed to have four occupants (two adults and two children) with sensible internal heat gain of 2.4 kWh/day.

2.4.1. Methodology

As mentioned in Section 2.2.4, TRNSYS simulation time step was 5 min. However, considering the house space heating, the thermal energy stored in House A after the HVAC system has been running for 5 min is not sufficient to keep the HVAC system off in the next five minutes. On the other hand, the zone temperature drops quickly soon after the HVAC system is turned off. In this case, to improve the efficiency of LSH-SPM, 15 min is selected as a time step for controlling the operation of the HVAC system during peak hours. Since LSH-SPM is used during peak hours, simulation results showed that keeping the HVAC system on for more than 15 min increased the ASHP consumption, which is not ideal according to load shifting strategy.

2.4.2. Pre-heating starting time (winter operation)

The HVAC load cannot be shifted to off/mid-peak hours without storing thermal energy with the pre-heating process. The most important issue before starting a pre-heating process is determining the pre-heating starting time. The starting time changes based on different parameters. The first and most important of these parameters is the outdoor temperature during the hour prior to the peak hours (i.e., 6:00 am and 16:00 pm in winter). The second parameter is a set of house characteristics, and the third one is zone temperature before starting the pre-heating process.

If the pre-heating process starts sooner than its optimum time, more electricity will be consumed and the room temperature will exceed the ASHRAE Standard range. If the pre-heating starts later than its optimum time, the stored heat energy will not be sufficient to support fully LSH-SPM during peak load hours. In this study, House A TRNSYS model was run at each outdoor temperature to seek the optimum starting time. To this end, first the HVAC set-point was set to 20.7 °C (the heating set-point temperature selected by TRNSYS model developers). Then, the HVAC system was turned on after 6:00 am (rise up time) and was forced to remain on till zone temperature reached its maximum permitted temperature (24 °C), also known as the saturation point. The time constant (TC) factor, which is used to calculate the starting time, was obtained by subtracting rise up and saturation point times. The time constant factor ensures that the maximum heating energy is stored in the house without the zone temperature exceeding the upper comfort level (24 °C). Table 2 summarizes the simulation results.

For outdoor temperatures between 17 °C and 20 °C, the TC is 10 min. This means pre-heating should start 10 min before the peak hours begin (i.e., 6:50 am or 16:50 pm).

Table 1
Comparison between DFC before and after running SDFSS-SPM.

Daily Average Outdoor Temperature (°C)	Maximum Outdoor Temperature (°C)	Minimum Outdoor Temperature (°C)	DFC before Running SDFSS-SPM (¢)	DFC after Running SDFSS-SPM (¢)	Energy Cost Saving (¢)
0	3	−2	265.64	265.64	0.00
−2	3	−4	287.74	276.20	11.54
−4	2	−5	308.85	290.85	18.00
−6	0	−8	343.78	317.14	26.64
−8	−2	−10	366.51	336.24	30.27
−10	−6	−13	389.24	345.34	43.90
−12	−6	−16	515.93	452.19	63.74
−14	−8	−16	705.30	543.15	162.16
−16	−12	−18	870.80	562.91	307.89
−18	−14	−21	1030.27	612.63	417.64
−20	−15	−23	1194.80	666.33	528.47

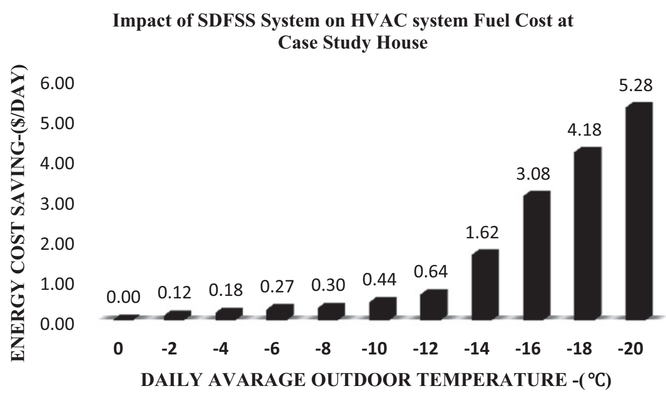


Fig. 14. Energy cost saved by using SDFSS-SPM at House A at different outdoor temperatures.

Table 2
TRNSYS simulation results—Calculating TC factor.

Outdoor Temperature (OT) (°C)	Rise up Time (am)	Saturation Time (am)	Duration (TRNSYS-Scale)	TC Factor (minutes)	Pre-heating Starting time (am)	Pre-heating Starting time (pm)
$20 < OT \leq 17$	6.41	6.58	0.17	10	6.50	16.50
$17 < OT \leq 14$	6.41	6.66	0.25	15	6.45	16.45
$14 < OT \leq 11$	6.33	6.58	0.25	15	6.45	16.45
$11 < OT \leq 8$	6.41	6.69	0.28	17	6.43	16.43
$8 < OT \leq 5$	6.41	6.75	0.34	20	6.40	16.40
$5 < OT \leq 2$	6.41	6.75	0.34	20	6.40	16.40
$2 < OT \leq -1$	6.33	6.83	0.50	30	6.30	16.30
$-1 < OT \leq -4$	6.41	7.08	0.67	40	6.20	16.20
$-4 < OT \leq -7$	6.41	7.11	0.70	42	6.18	16.18
$-7 < OT \leq -10$	6.50	7.15	0.65	39	6.21	16.21
$-10 < OT \leq -13$	6.41	6.75	0.34	20	6.40	16.40
$-13 < OT \leq -16$	6.41	6.58	0.17	10	6.50	16.50
$-16 < OT \leq -19$	6.41	6.58	0.17	10	6.50	16.50
$-19 < OT \leq -22$	6.41	6.58	0.17	10	6.50	16.50
$-22 < OT \leq -25$	6.41	6.50	0.09	05	6.55	16.91

From the simulation results it is concluded that when it is warm (outdoor temperature of 17 °C or higher) a shorter time is required to pre-heat the house (TC). This is because heat loss is low due to the high outdoor temperature. For example, TC increases to a maximum of 42 min when the outdoor temperature is between −7 °C and −4 °C. As the outdoor temperature drops, TC factor decreases, reaching 5 min at −25 °C. This is because at the very cold temperatures the HVAC system will be working almost continuously and there is no time left for the pre-heating process.

In winter, peak hours start at 7:00 am and end at 11:00 am In order to design a grid-friendly house, the HVAC system should remain off during this period. In this study we call such situation the best case scenario (BCS). However, BCS cannot be utilized all time. The only parameter that poses a problem for using this SPM is the outdoor temperature. To examine the effect of outdoor temperature on zone temperature and to determine whether the zone temperature remained within the ASHRAE Standard range in each hour, TRNSYS model was run based on weather forecast data. If zone temperature falls below the standard range in any time step, the HVAC system will turn on during that specific time step. With this strategy planning model, the most appropriate operational command matrix with respects to ASHRAE Standard is built. Fig. 15 shows the abovementioned procedure using simple logic diagrams.

In worst case scenario, when the outdoor temperature is cold, there is no opportunity for storing enough thermal energy inside the house because of high heat loss. Thus, the HVAC system should continuously work at peak hours to ensure thermal comfort. In such condition, there is no chance of shifting the HVAC load to off-

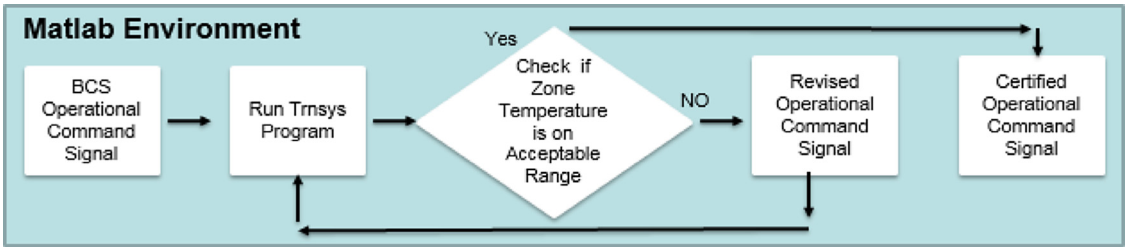


Fig. 15. The operational mechanism of LSH-SPM model.

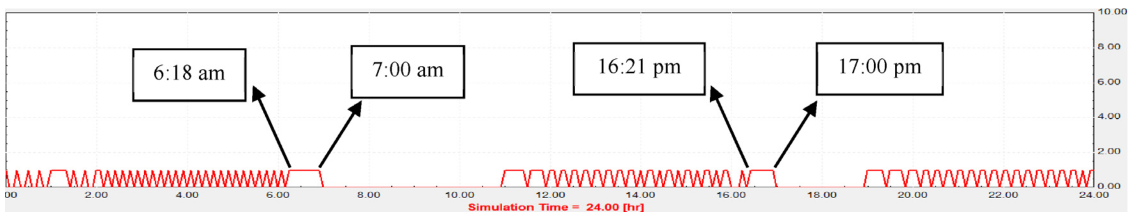


Fig. 16. First operational command matrix generated based on BCS strategic plan.

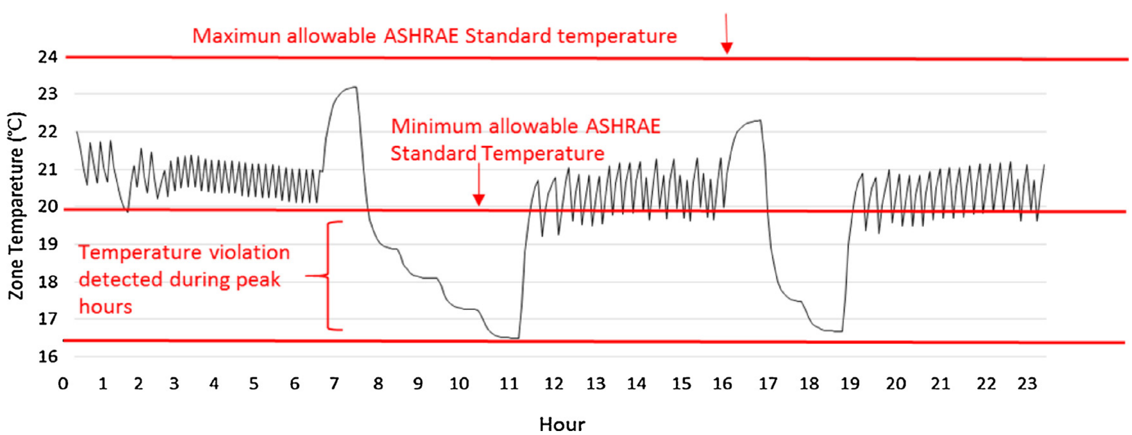


Fig. 17. Zone Temperature after running BCS operational command matrix.

peak hours. The same methodology is used for evening peak hours. Fig. 16 shows the first operation command matrix (for Jan 4th, 2015 sample day) generated based on the BCS strategic plan. As Fig. 16 shows, the ASHP ran from 6:18 am till 7:00 am and 16:21 pm till 17:00 pm to pre-heat the house and was kept off during peak hours.

Fig. 17 illustrates the zone temperature after running the BCS operational command matrix. As evident from the figure, zone temperature increased to 23.4 °C by pre-heating the house between 6:18 am and 7:00 am However, it decreased to 16.43 °C at 11:00 am (and 16.53 °Cat 19:00 pm) at the end of peak hours. In other words, HVAC system energy cost was minimized during peak hours by running the BCS operational command matrix. However, this operational command matrix led to temperature violation during this period because of the cold outdoor temperature. Since zone temperature did not fall within the ASHRAE Standard limit (between 20 °C and 24 °C) during occupied hours, operational command matrix was changed with Matlab in the next iteration to bring zone temperature above the lower set point (20 °C) at that particular time step.

In this sample day, after ten iterations the zone temperature remained above the minimum allowable SHRAE Standard temperature at all time steps. Fig. 18 shows the final operational command matrix.

2.4.3. Calculating the impact of LSH-SPM on HVAC system daily electricity cost (DEC) at different outdoor temperatures

To examine the impact of LSH-SPM on House A HVAC system DEC, different simulations were run on various outdoor temperatures. Table 3 shows the simulation results.

Looking at Table 3, it is concluded that when the daily average outdoor temperature is warm (equal to or greater than 14 °C), the heat demand of the house is low, and therefore the ASHP is off almost the entire time. Hence, the daily cost of electricity is increased when using LSH-SPM.

The effect of LSH-SPM on the house energy system increased as the outdoor temperature decreased. The maximum saving (17.52 cent) happened when the outdoor temperature was 6 °C and the HVAC system remained off for 126 min in the morning and 67 min in

First 6 Hours	0	1	2	3	4	5
Command Signals	1 0 0 1 0 0 1 0 0 1 0 0	1 1 1 1 1 0 1 0 0 1 0 0	1 1 0 1 0 1 0 1 0 1 0 1	0 1 0 1 0 1 0 1 0 1 0 1	0 1 0 1 0 1 0 1 0 1 0 1	0 1 0 1 0 1 0 1 0 1 0 1
Second 6 Hours	**6**	**7**	**8**	**9**	**10**	**11**
Command Signals	0 1 0 1 1 1 1 1 1 1 1 1	0 0 0 1 1 1 0 0 0 1 1 1	0 0 0 1 1 1 0 0 0 1 1 1	0 0 0 1 1 1 1 1 1 0 0 0	1 1 1 1 1 1 0 0 0 1 1 1	0 1 0 1 0 1 0 1 0 1 0 1
Third 6 Hours	**12**	**13**	**14**	**15**	**16**	**17**
Command Signals	0 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1
Fourth 6 Hours	**18**	**19**	**20**	**21**	**22**	**23**
Command Signals	1 1 1 0 0 0 1 1 1 1 1 1	0 0 1 0 1 0 1 0 1 0 1 0	1 1 0 1 0 1 0 1 0 1 0 1	0 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0	1 0 1 0 1 0 1 0 1 0 1 0

Fig. 18. Final operational command matrix generated with Matlab program.

Table 3
Impact of LSH-SPM on House A energy system in different outdoor temperatures.

Average Outdoor Temperature (°C)	Energy Cost Saving (¢)	HVAC Off-time Morning (min)	HVAC Off-time Evening (min)	Additional Used Power at Off-Peak Hours (kWh)	Reduced Demand at Peak Hours (kWh)
14	−1.94	–	–	0.74	0.53
12	4.31	240	120	0.63	1.06
10	10.05	213	120	0.63	1.58
8	12.10	186	93	0.45	1.69
6	17.52	126	67	0.84	1.80
4	6.34	93	33	0.51	1.14
2	4.77	33	15	0.54	1.07
0	1.62	24	6	0.85	0.42
−2	−14.35	–	–	1.19	0.00

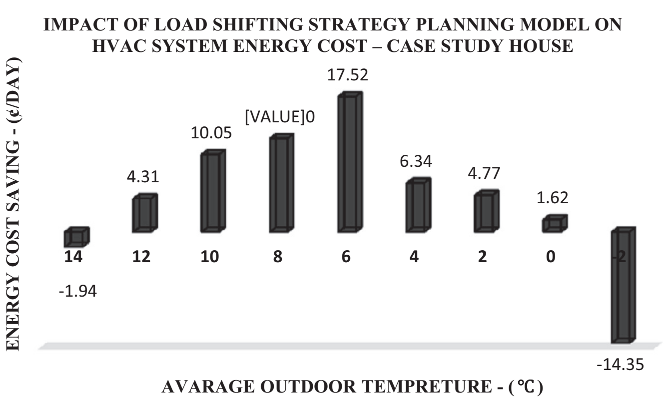


Fig. 19. Energy cost saving using LSH-SPM at House A in different outdoor temperatures.

the afternoon. At this temperature, 0.84 kWh additional electricity was consumed during off-peak hours while 1.80 kWh was saved during peak hours.

When the outdoor temperature was negative (for example −2 °C), the DEC of HVAC system when using LSH-SPM was again higher than its DEC when no SPM was used. Fig. 19 shows the money saved by using LSH-SPM at different outdoor temperatures.

As Fig. 19 shows, the LSH-SPM is beneficial when the daily average outdoor temperature is between −2 °C and 14 °C. It is also evident that HVAC system DEC before and after using LSH-SPM is increased with decreasing outdoor temperature.

Fig. 20 shows the additional consumption for pre-heating the house as well as the reduced demand during peak hours for different outdoor temperatures. As the figure shows the additional cost for pre-heating the house is greater than the saving when the outdoor temperature is higher than 14 °C or lower than −2 °C.

2.5. LSH-SPM development by integrating smart dual fuel switching system strategy planning model (LSHSDFSS-SPM)

In this scenario, the SDFSS-SPM and LSH-SPM models are combined to construct a developed intelligent strategy planning model named LSHSDFSS-SPM. This model takes advantage of both load shifting and fuel switching system to generate a novel HVAC operational command matrix. Fig. 21 illustrates the procedures. Using this strategy planning model, not only the electrical demand of ASHP during peak hours is minimized, but also a cheaper hot air supplier system is selected in each hour. Thus, both residents and local grid benefit from such system; the residents will pay minimum fuel cost for HVAC operation while the electrical demand of the ASHP stays minimum during the peak hours.

Fig. 22 shows the operational command matrix generated after using LSHSDFSS–SPM.

3. Results and discussion

To demonstrate the effectiveness of Matlab-TRNSYS predictive controller, different SPMs were implemented on the system. The result of simulation before and after implementing each SPM is presented for three consecutive sample days: January 4th, 5th and 6th, 2015. Weather forecast dataset is used for estimating the house thermal demand during these days.

3.1. First sample day (January 4th, 2015) simulation result

3.1.1. Baseline case

Table 4 shows the result of TRNSYS simulation. Forecast outdoor temperature, House A thermal demand, ASHP electric demand, and ASHP electricity cost are presented in the first, second, third and fourth rows of Table 4, respectively. The DEC of the HVAC system for this sample day is $3.61. It should be noted that no strategy planning model has been implemented on the system yet.

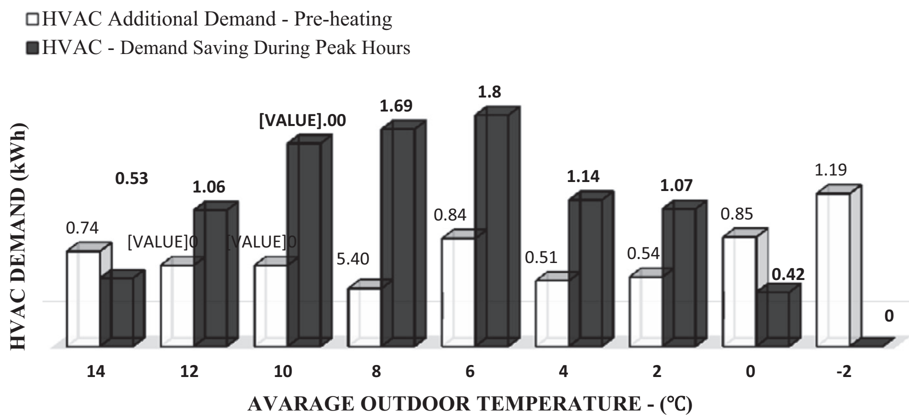


Fig. 20. LSH-SPM additional/saving demand during different outdoor temperatures.

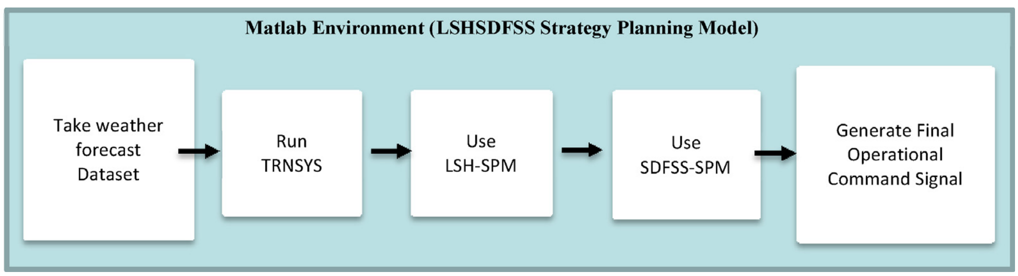


Fig. 21. LSHSDFSS-SPM framework.

First 6 Hours	0	1	2	3	4	5
Command Signals	A O O A O O A O O A O O	A A A A A O A O O A O O	A A O A O A O A O A O A	O A O A O A O A O A O A	O A O A O A O A O A O A	O A O A O A O A O A O A
Second 6 Hours	**6**	**7**	**8**	**9**	**10**	**11**
Command Signals	O A O A A A A A A A A A	O O O M M M O O O M M M	O O O M M M O O O M M M	O O O M M M M M M O O O	M M M M M M O O O M M M	O M O M O M O M O M O M
Third 6 Hours	**12**	**13**	**14**	**15**	**16**	**17**
Command Signals	O O M O M O M O M O M O	M O M O M O M O M O M O	M O M O M O M O M O M O	M O M O M O M O M O M O	M O M O M M M M M M M M	M M M M M M M M M M M M
Fourth 6 Hours	**18**	**19**	**20**	**21**	**22**	**23**
Command Signals	M M M O O O M M M M M M	O O A O A O A O A O A O	A A O A O A O A O A O A	O O A O A O A O A O A O	A O A O A O A O A O A O	A O A O A O A O A O A O

Fig. 22. Developed operational command matrix after using LSHSDFSS-SPM.

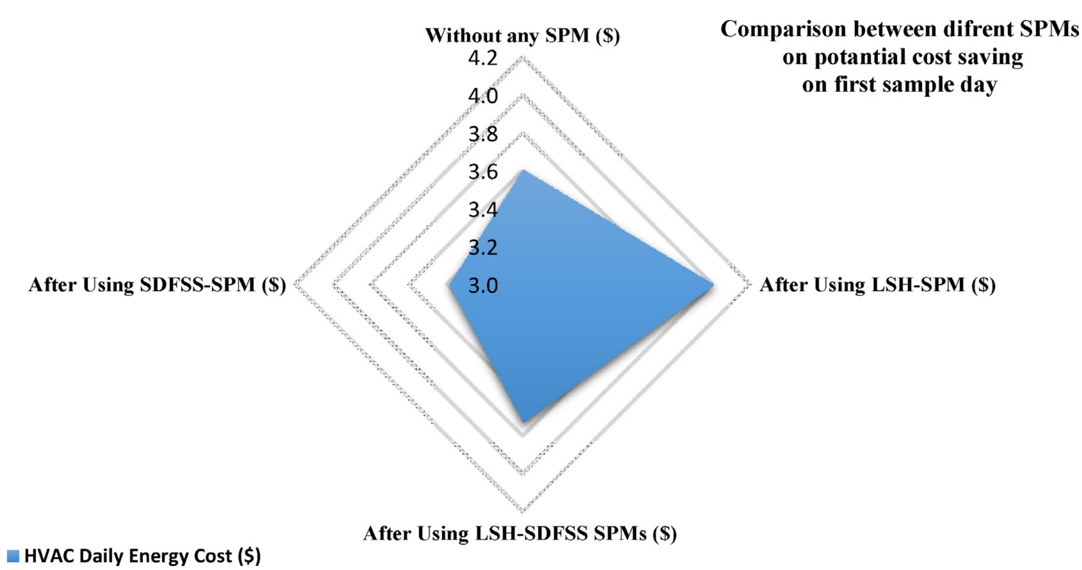


Fig. 23. Comparing the potential energy cost savings of different SPMs on first sample day.

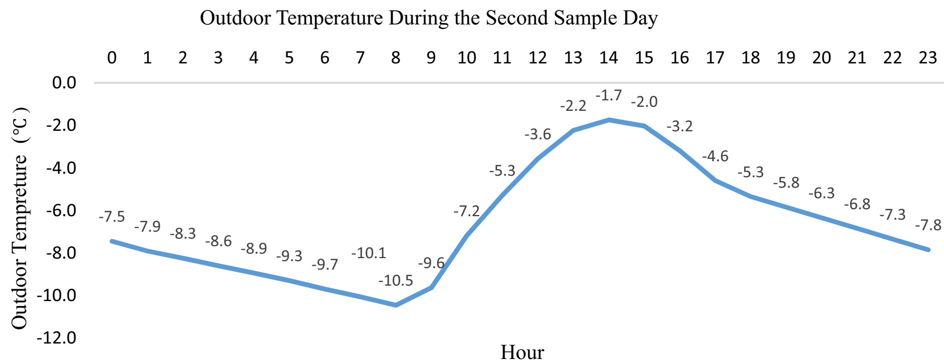


Fig. 24. Outdoor temperature on January 5th, 2015.

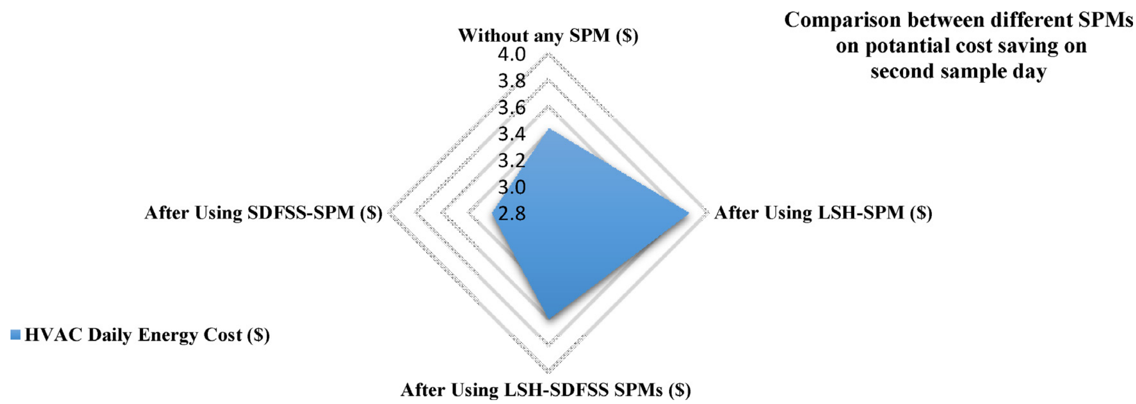


Fig. 25. Comparing the potential energy cost savings of different SPMs on the second sample day.

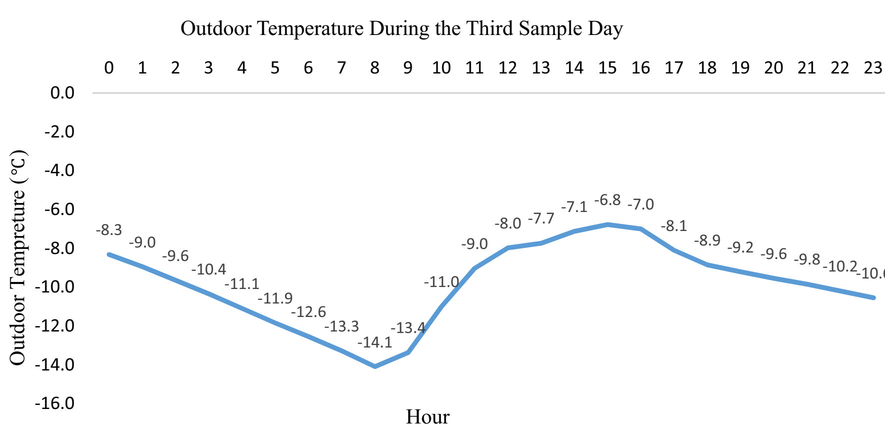


Fig. 26. Outdoor temperature on January 6th, 2015.

3.1.2. Implementing SDFSS-SPM

Table 5 demonstrates the HVAC system fuel cost after using SDFSS strategy planning model. The Daily Fuel Cost (DFC) of the HVAC system after using SDFSS-SPM is found $3.39 which is less than the baseline case DEC ($3.61) calculated in Section 3.1.1.

3.1.3. Implementing LSH-SPM

Table 6 shows the DEC of the HVAC system after running LSH-SPM for the same sample day. The DEC of HVAC system after using LSH-SPM is found $4.01which is higher than the HVAC energy cost ($3.61 and $3.39) calculated in Sections 3.1.1 and 3.1.2.

3.1.4. Implementing LSHSDFSS-SPM

After running the model by LSHSDFSS-SPM, the DFC of HVAC system (calculated based on Table 7) for the same sample day isfound to be $3.73.

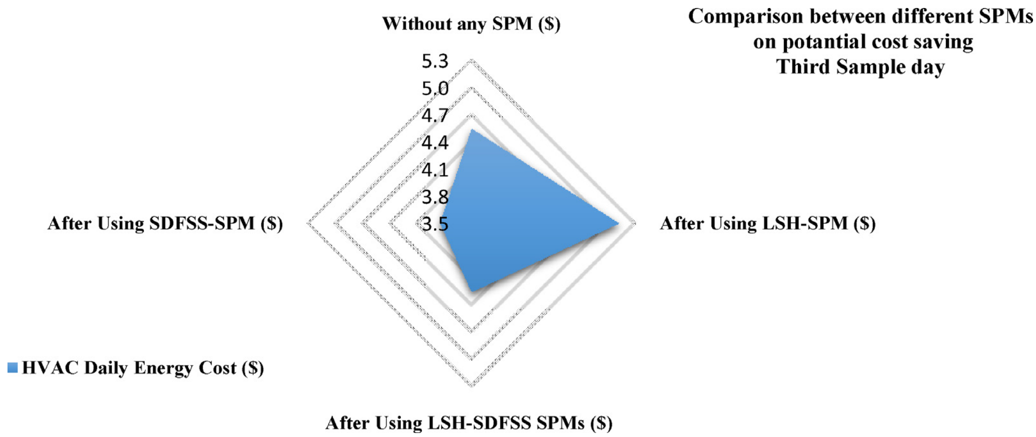


Fig. 27. Comparing the potential energy cost savings of different SPMs on the third sample day.

3.2. Comparing the results of different SPMs—first sample day

Fig. 23 shows the potential energy cost savings on the first sample day at House A as the result of using different SPMs. The baseline daily energy cost of the HVAC system when no strategy planning model was applied to the system was $3.61. Using SDFSS-SPM the daily energy cost decreased to $3.39. However, the HVAC energy cost increased to $4.01 when LSH-SPM was used. This was due to the fact that the outdoor temperature on the sample day was very cold and out of the temperature range that allows the system to benefit from LSH-SPM. Using LSHSDFSS-SPM, the HVAC energy cost increased to $3.73. Fig. 23 shows that SDFSS allowed maximum saving during the sample day.

3.3. Comparing the results of different SPMs—second sample day, January 5th

Fig. 24 shows the outdoor temperature on January 5th.

Fig. 25 shows the potential energy cost savings on the second sample day at house A as the result of using different SPMs. The baseline daily energy cost of the HVAC system when no strategy planning model was applied to the system was $3.44. Using SDFSS-SPM the daily energy cost decreased to $3.23. However, the HVAC energy cost increased to $3.86 when LSH-SPM was used. This was due to the fact that the outdoor temperature on January 5th was also cold and out of the range that allows the system to benefit from LSH-SPM. Using LSHSDFSS-SPM, the HVAC energy cost increased to $3.60. Fig. 25 shows that SDFSS allowed maximum saving during the second sample day.

3.4. Comparing the results of different SPMs—third sample day, January 6th

Fig. 26 shows the outdoor temperature on January 6th. Fig. 27 shows the potential energy cost savings on the third sample day at house A as the result of using different SPMs. The baseline daily energy cost of the HVAC system when no strategy planning model was applied to the system was $4.55. Using SDFSS-SPM the daily energy cost decreased to $3.85. On this sample day, the HVAC energy cost increased to $5.13 when LSH-SPM was used. This was due to the fact that the outdoor temperature on January 6th was also out of the range that allows the system to benefit from LSH-SPM. Using LSHSDFSS-SPM, the HVAC energy cost decreased to $4.26. Fig. 27 shows that SDFSS allowed maximum saving during the third sample day.

3.5. Effectiveness of various SPMs during different outdoor temperatures

SDFSS-SPM was the first strategy planning model applied for selecting the least expensive hot-air supplier system at each hour. This SPM could notably reduce the owners' overall HVAC energy cost. In addition to reducing the energy cost, this SPM model manages HVAC energy demand by consuming less electricity during the peak and mid-peak hours. Based on the simulation result presented in Section 2.3, when the outdoor temperature is above 0 °C there is no opportunity for taking advantage of SDFSS-SPM. However, when the outdoor temperature is below 0 °C, the DFC of HVAC system decreases using this model. As the outdoor temperature gets colder, more saving takes place. The second strategy planning model used in this project was LSH-SPM model. This control strategy shifts the HVAC load from peak to off or mid-peak hours. This grid-friendly SPM model reduces local grid overloading by decreasing the HVAC energy demand during peak hours. Since outdoor temperature and house characteristics directly impact the thermal energy stored in a house, a smart method is used to determine the best starting time for pre-heating the house. This method not only ensures the thermal comfort, but also minimizes the electricity consumed by the ASHP to pre-heat the house. Based on the simulation results presented in Section 2.4, when the outdoor temperature is between −2 °C and 14 °C, the best results are obtained by implementing the LSH-SPM model. When the outdoor temperature is above 14 °C, the potential cost saving achieved during the peak hours is less than the additional energy cost related to pre-heating the house during off-peak hours. Additionally, when the outdoor temperature is below 0 °C, there is no chance for storing enough thermal energy in the house (based on our light thermal mass test case house) to keep the HVAC system off during peak hours.

LSHSDFSS-SPM was the third strategy planning model examined and was developed by integrating SDFSS-SPM and LSH-SPM models into a single system. LSHSDFSS-SPM takes advantage of both load shifting and fuel switching system. LSHSDFSS-SPM allows for maximum cost saving when the outdoor temperature changes between −2 °C and 0 °C.

Table 4
TRNSYS simulation result after using weather forecast dataset-baseline.

Hours	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Sum
Outdoor Temperature (°C)	−4.8	−4.6	−5.2	−5.4	−5.8	−6.0	−6.2	−6.3	−6.4	−6.9	−7.7	−8.7	−9.1	−9.4	−9.6	−9.8	−9.6	−9.5	−9.3	−9.2	−9.2	−9.1	−8.7	−8.4	- -
Heat Demand (kWh)	1.44	1.45	2.91	2.95	2.99	3.03	3.06	3.08	3.09	3.15	3.27	3.42	3.47	3.52	3.55	3.57	3.55	3.52	4.08	4.07	4.07	4.62	3.98	3.93	79.77
ASHP Demand (kWh)	0.48	0.47	0.96	0.97	0.98	0.99	0.99	1.00	1.00	1.01	1.04	1.08	1.09	1.10	1.11	1.11	1.11	1.10	1.28	1.27	1.27	1.45	1.25	1.24	25.35
HVAC Electricity Cost (₵)	5.56	5.54	11.24	11.34	11.46	11.55	11.64	17.97	18.01	18.26	18.76	16.57	16.76	16.93	17.03	17.08	17.03	19.80	22.98	14.91	14.90	16.96	14.67	14.53	361.47

Table 5
HVAC DFC cost after using SDFSS-SPM.

Hours	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Sum
Outdoor Temperature (°C)	−4.8	−4.6	−5.2	−5.4	−5.8	−6.0	−6.2	−6.3	−6.4	−6.9	−7.7	−8.7	−9.1	−9.4	−9.6	−9.8	−9.6	−9.5	−9.3	−9.2	−9.2	−9.1	−8.7	−8.4	- -
HVAC Fuel Cost (₵)	5.60	5.50	11.20	11.30	11.50	11.50	11.60	14.60	14.60	14.90	15.50	16.20	16.40	16.70	16.80	16.90	16.80	16.70	19.30	14.90	14.90	17.00	14.70	14.50	339.60

Table 6
HVAC DEC cost after using LSH-SPM.

Hours	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Sum
Outdoor Temperature (°C)	−4.8	−4.6	−5.2	−5.4	−5.8	−6.0	−6.2	−6.3	−6.4	−6.9	−7.7	−8.7	−9.1	−9.4	−9.6	−9.8	−9.6	−9.5	−9.3	−9.2	−9.2	−9.1	−8.7	−8.4	- -
ASHP Demand (kWh)	0.48	0.47	0.96	0.97	0.98	0.99	1.66	1.00	1.00	1.01	1.56	1.08	1.09	1.10	1.11	1.11	1.84	2.20	1.64	0.91	1.09	1.09	1.07	1.06	27.47
HVAC Electricity Cost (₵)	5.60	5.50	11.20	11.30	11.50	11.50	19.40	18.00	18.00	18.30	28.10	16.60	16.80	16.90	17.00	17.10	28.40	39.60	29.50	10.60	12.80	12.70	12.60	12.50	401.50

Table 7
HVAC DFC cost after using LSHSDFSS-SPM.

Hours	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Sum
Outdoor Temperature (°)	−4.8	−4.6	−5.2	−5.4	−5.8	−6.0	−6.2	−6.3	−6.4	−6.9	−7.7	−8.7	−9.1	−9.4	−9.6	−9.8	−9.6	−9.5	−9.3	−9.2	−9.2	−9.1	−8.7	−8.4	- -
HVAC Fuel Cost (₵)	5.60	5.50	11.20	11.30	11.50	11.50	19.40	14.60	14.60	14.90	23.20	16.20	16.40	16.70	16.80	16.90	28.00	33.40	24.80	10.60	12.80	12.70	12.60	12.50	373.70

4. Conclusion

Different powerful house energy simulators such as TRNSYS, EnergyPlus, Mathcad, and Esp-r have been used by the researchers for simulating house and building energy systems. These simulators offer an excellent opportunity for detailed design and modeling of a house and its HVAC system and provide very accurate simulation results useful for performance analysis and optimization process. However, these simulators do not include sub-models of advanced devices/strategies for controlling HVAC system operation and suffer from poor control mechanism. In addition to the lack of advanced controllers, the aforementioned simulators mostly use operational/historical weather dataset (given in a library file) for simulating the house energy system. Hence, they inherently offer no mechanism for estimating the future state of their process models based on the forecast weather dataset. Therefore, no predictive controller can be designed and run within these simulators. In this project, a Matlab-TRNSYS co-simulator was developed to control/manage the TRNSYS program as one of the most powerful house energy simulators with an advanced predictive controller. This co-simulator can be utilized as a test bed for implementing different SPMs. To show the effectiveness of this co-simulator which acts as a smart grid-friendly controller, three distinct strategy planning models were developed and applied in order to manage the hourly load demand of an HVAC system on the upcoming 24 h. SDFSS-SPM was the first strategy planning model employed for selecting the least expensive hot-air supplier system at each hour. Simulation results on three consecutive sample days show that this SPM could bring a total of $1.14 (9.2%) saving in the house's HVAC energy cost. In addition to reducing the energy cost, this SPM model manages HVAC demand by consuming less electricity during the peak hours. The second strategy planning model developed in this project was LSH-SPM model. LSH-SPM model shifts the HVAC load from peak to off- or mid-peak hours. This grid-friendly SPM model is aimed to reduce overloading on the local grid by decreasing the demand during peak hours. Due to very cold outdoor temperature on the sample days, LSH-SPM increased HVAC energy cost by $1.42 (10.7%) in total. LSHSDFSS-SPM was the third strategy planning model investigated. LSHSDFSS-SPM was developed by integrating SDFSS-SPM and LSH-SPM models. LSHSDFSS-SPM takes advantage of both load shifting and fuel switching system. LSHSDFSS-SPM increased the HVAC energy cost on the first and second sample days due to the very cold outdoor temperature during these days. However, HVAC energy cost decreased by applying LSHSDFSS-SPM on the third sample day due to the effect of SDFSS-SPM. In total, LSHSDFSS-SPM decreased HVAC energy cost by $0.01 (0.3%).

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