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Withdrawn Publication	
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NIST Technical Note 2017

Assessing the Performance of Residential Energy Management Control Algorithms: Multi-Criteria Decision Making Using the Analytical Hierarchy Process

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Assessing the Performance of Residential Energy Management Control Algorithms: Multi-Criteria Decision Making Using the Analytical Hierarchy Process

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U.S. Department of Commerce
Wilbur L. Ross, Jr., Secretary

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Abstract

For homes to become active participants in a smart grid, intelligent control algorithms are needed to facilitate autonomous interactions that take homeowner preferences into consideration. Many control algorithms for demand response have been proposed in the literature. Comparing the performance of these algorithms has been difficult because each algorithm makes different assumptions or considers different scenarios, i.e., peak load reduction or minimizing cost in response to the variable price of electricity. This work proposes a flexible assessment framework using the Analytical Hierarchy Process to compare and rank residential energy management control algorithms. The framework is a hybrid mechanism that derives a ranking from a combination of subjective user input representing preferences, and objective data from the algorithm performance related to energy consumption, cost and comfort. The Analytical Hierarchy Process results in a single overall score used to rank the alternatives. The approach is illustrated by applying the assessment process to six residential energy management control algorithms.

Key words

AHP; Analytical Hierarchy Process; assessment of control algorithms; assessment; assessment and ranking; assessment engine; energy management control algorithms; MADA; MCDM; multi criteria decision making; performance assessment; ranking; residential control algorithms.

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Acronyms

AE	assessment engine
AEUI	AE user interface
AHP	Analytical Hierarchy Process
ANSI	American National Standards Institute
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
ASTM	American Society for Testing and Materials
CI	consistency index
CR	consistency ratio
Cscale	comparison scale
DBM	division by maximum
DBS	division by sum
DR	demand response
EIA	Energy Information Administration
EISA	Energy Independence and Security Act
EMCA	energy management control algorithm
FDD	fault detection and diagnostics
HVAC	heating, ventilating, and air-conditioning
IEEE	Institute of Electrical and Electronics Engineers
ISO	independent system operators
ISO	International Organization for Standardization
kWh	kilowatt hour
MATLAB	Matrix Laboratory
MC	mapping cost
MCDM	multi-criteria decision-making
MDC	mapping discomfort
ME	mapping energy consumption
MPC	matrix of pairwise comparisons
NIST	National Institute of Standards and Technology
NZERTF	Net-Zero Energy Residential Test Facility
PJM	Pennsylvania-New Jersey-Maryland Interconnection
PMV	predicted mean vote
PPD	predicted percentage of dissatisfied
PPDwc	PPD-Weighted criterion
RC	cost ratio
RDC	discomfort ratio
RE	energy ratio
RI	random index
RTO	regional transmission organizations
RTP	real-time pricing
SCF	cost scale factor
SDF	discomfort scale factor
SEF	energy scale factor
TRNSYS	Transient System Simulation Tool
YALMIP	Yet Another Linear Matrix Inequalities Parser

1. Introduction

The current electric grid is an essential part of our daily lives. Despite its success, it is under strain from ever-increasing demand and aging infrastructure. In 2016, residential buildings consumed 38 % of the all electricity sold in the U.S. [1]. Space heating, and cooling accounted for 24 % of the electricity consumption in residential buildings [2]. The Energy Independence and Security Act of 2007 (EISA) established a national policy to support the modernization of the national electric grid to maintain a reliable and secure electricity infrastructure that can meet future growth [3]. The vision of a modern, smart electric grid, is “a modernized grid that enables bidirectional flows of energy and uses two-way communication and control capabilities that will lead to an array of new functionalities and applications” [4].

According to Title XIII of EISA [3] a few key characteristics of a smart grid include:

1. “Increased use of digital information and controls technology to improve reliability, security, and efficiency of the electric grid;
2. Development and incorporation of demand response, demand-side resources, and energy-efficiency resources;
3. Deployment of “smart” technologies (real-time, automated, interactive technologies that optimize the physical operation of appliances and consumer devices) for metering, communications concerning grid operations and status, and distribution automation; and
4. Integration of “smart” appliances and consumer devices.”

The new smart electric grid paradigm creates a complex environment that requires decision making, developing and deploying advanced technologies, and facilitating the exchange of energy and information between interested parties. One of the ways that users (customers) could interact with a smart electric grid is through demand response (DR), a process by which electric power consumption (demand) is moderated to support grid needs. DR is commonly used to reduce peaks, but can also be used to increase consumption when the total demand on the grid is low, to support voltage regulation, or for other grid needs. DR can be implemented using dynamic prices or other signals from the grid. Some methods for implementing DR and the possible benefits are described in [5].

Realizing a smart electric grid requires intelligent control algorithms to facilitate autonomous interaction between homeowners and the grid. Many optimization models and control algorithms for DR have been proposed in the literature to achieve this goal. Comprehensive reviews of utility DR programs, approaches, and optimization techniques are presented in [6]–[8]. Common optimization objectives include cutting cost, reducing energy consumption, or both, while trying to maintain thermal comfort. The actions resulting from the optimization include controlling appliances, performing temperature setbacks, and preheating or precooling. However, it has been hard to compare these approaches because they make different assumptions and consider different objectives. Furthermore, they may consider the perspective of the utility (cost, profit, peak load shaving, capacity, etc.), but fail to consider that the perspective of the homeowner whose needs or interests (energy, cost, comfort, etc.) may be different. A user may also have conflicting goals such as reducing cost and maintaining comfort. Therefore, an assessment framework is needed that can evaluate the impact of control actions on multiple and potentially conflicting objectives such as minimizing cost or energy while maintaining thermal comfort or other user preferences. Considering those objectives, the framework must also enable a direct comparison of the performance of residential energy management control algorithms (EMCA).

There is an extensive literature describing approaches for comparing residential EMCAs. A unifying theme throughout the literature is centered on comparing the performance of proposed residential EMCAs on energy cost savings [9]–[14], energy savings [11], [13], [15], [16], peak load reduction [9], [10], [13], [17], and thermal comfort [11], [13], [15] to an established baseline. In [18] the authors proposed a data-driven framework for comparing the energy performance of residential thermostats controlling central heating, ventilating, and air-conditioning (HVAC) systems. Using thermostat field data, the proposed framework applied different assessment techniques to separately consider behavioral attributes (setpoint-related) from non-behavioral attributes such as HVAC control strategies and fault detection and diagnostics (FDD). Setpoint-related energy impacts were evaluated from a data-driven method using a building simulation model, while HVAC and FDD control impacts were determined using traditional testing methods such as field experiments. The results were integrated to determine typical energy performance of residential thermostats relative to a specified baseline. The baseline was a fixed seasonal temperature that a typical homeowner would prefer to maintain if setbacks were not available. Using historical data, a user's preferred baseline was determined from seasonal hourly setpoints by calculating the 90th percentile value for heating season and 10th percentile value for the cooling season.

However, little has been reported on a comprehensive framework for assessing the performance of residential EMCAs considering multiple objectives and users' subjective preferences simultaneously. Developing a comprehensive framework requires the use of a multi-criteria decision-making mechanism that can handle both subjective preferences from users and objective analyses from performance data generated because of using residential EMCAs. A few examples of using such a hybrid mechanism (subjective and objective analyses) have been given in the literature. The authors in [19], [20] presented an assessment framework based on the Analytical Hierarchy Process (AHP) that combines subjective analyses from expert judgments with objective data derived from analytical methods to rank alternatives. The assessment framework in [19] was used to choose the best sustainable building envelope design among alternatives, while in [20] a case study was presented for choosing the best HVAC system design for a building. The decision was informed by incorporating uncertainty analysis into selecting building design parameters.

Although the frameworks presented in [19], [20], in concept, are similar to the work described in this study, the domain of the problems are fundamentally different. The objective of [19], [20] was to make design decisions, but the main objective of this study is to develop an assessment framework capable of comparing and ranking different residential EMCAs. Assessing the performance of residential EMCAs is a multi-criteria decision making problem because multiple and conflicting objectives (such as minimizing cost while maintaining comfort or other user preferences) apply simultaneously.

Unlike prior studies, the proposed framework will:

1. Provide a systematic mechanism for comparing the overall performance of residential EMCAs in terms of energy consumption, cost, and comfort while actively allowing users to interact with the framework to capture the impact of their preferences on the ranking and decision making;
2. Provide an algorithm for mapping quantitative performance data to the comparison scale of the AHP and consequently creating a matrix of pairwise comparison (MPC), and
3. Calculate all relative weights (priorities) for both subjective (user's preferences) and objective performance data using the methodology described in the AHP framework.

To implement the proposed framework, an assessment engine (AE) was developed as shown schematically in Figure 1. The AE incorporates subjective and objective analyses, deriving priorities from user's input and performance data resulting from different residential EMCAs. It performs the evaluation and ranking of residential EMCAs using AHP. A case study of the proposed AE, applied to six residential EMCAs, is presented.

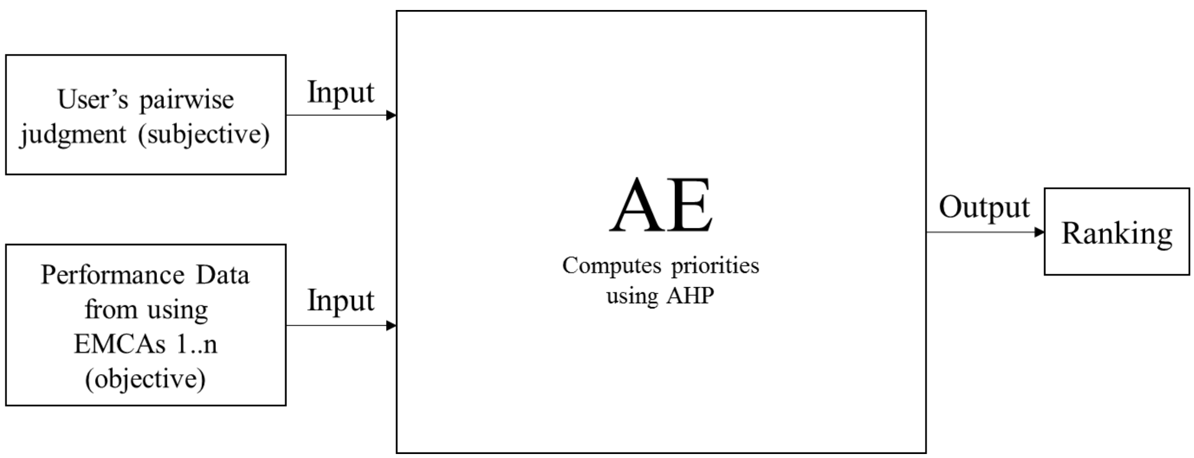

Figure 1. A schematic representation of the assessment process

2. Analytical Hierarchy Process

AHP is a multi-criteria decision-making (MCDM) method developed by Saaty [21]. It has been commonly used in solving decision-making problems that consider both quantitative and qualitative analysis [19], [20], [22], [23]. A comprehensive review of the application of AHP to planning, choosing among alternatives, allocating resource, etc., is presented in [24]. The American Society for Testing and Materials (ASTM) Standard E1765 documents a procedure for applying AHP to investments related to buildings and building systems [25]. The main principles of the AHP are hierarchy, pairwise comparison, and principle eigenvector. AHP decomposes a MCDM problem into a hierarchy to handle its numerous or multi-faceted criteria and to keep the number of pairwise comparisons manageable [23]. The goal (objective) of the problem is placed at the top of the hierarchy. The alternatives are positioned at the bottom of the hierarchy, while the criteria and sub-criteria occupy the intermediate levels. To illustrate this, consider a hypothetical example of a couple that is purchasing a house. The couple decided to use the AHP and follow its prescribed steps to achieve their goal. At the first step, they have determined their goal. The goal is to find the house that best suits their needs. At the second step, they have identified the three most important criteria (building size, location, and price) for selecting their desired home. At the third step, they identified three existing homes (alternatives) labeled as *H1*, *H2*, and *H3*. Figure 2 shows the decomposition of this hypothetical problem into a hierarchical arrangement. Each line shows a relationship between an alternative and the criterion above it, or the relationship between the criterion and the goal. These relationships are mathematically represented by priorities, for example, $P_{H1,Size}$ is the priority of the alternative *H1* with respect to the criterion Size and $P_{Size,Goal}$ represents the priority of the criterion Size to the Goal.

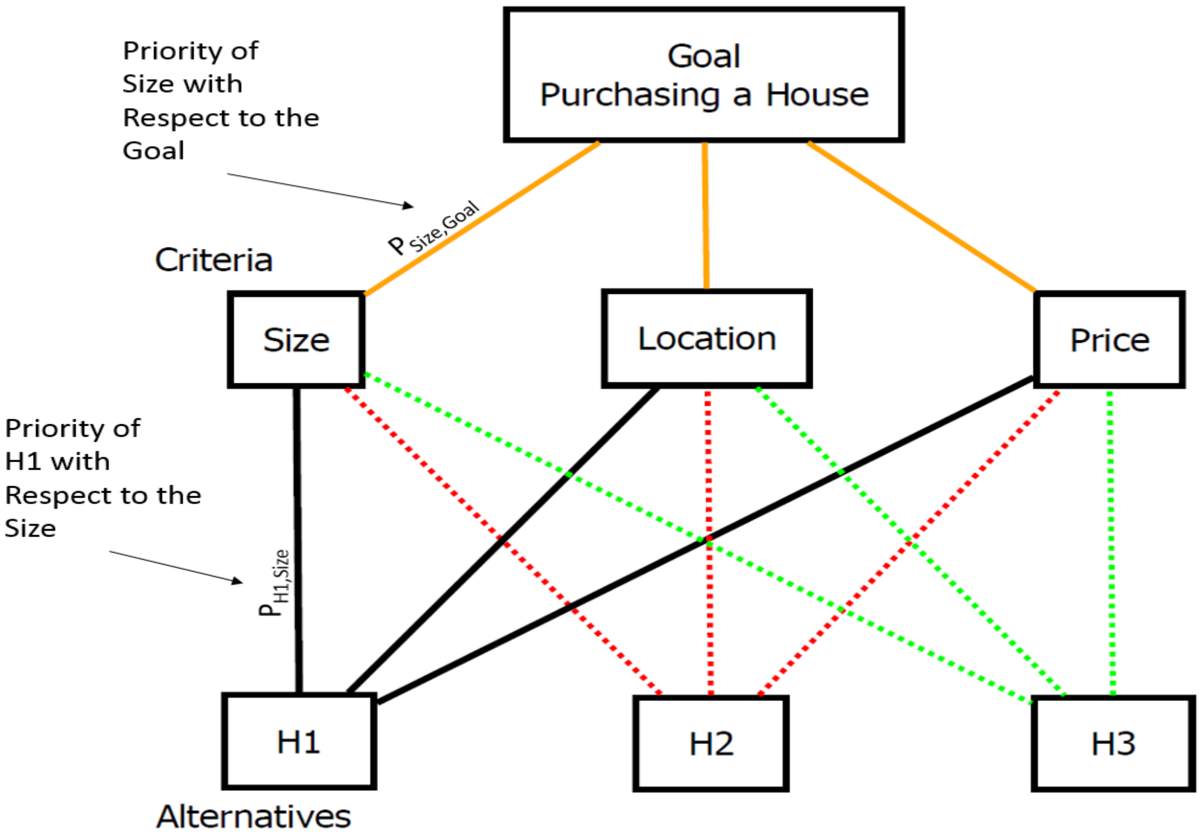

Figure 2. Decomposition of the hypothetical problem of purchasing a house into a hierarchy

At the fourth step, the couple needs to build an MPC (decision matrix) for comparing criteria to each other with respect to the goal of purchasing a house. Each element of an MPC is created by comparing one criterion with another criterion i.e., Size (activity *i*) is compared with Location (activity *j*). To create an MPC, the couple must first judge which criterion is more desirable with respect to reaching their goal. After much discussion, the couple expresses their subjective judgments (expert knowledge) as follows:

1. Location of the house is strongly preferred over the size of the house because of a desire to be near schools and shopping centers;
2. Price of the house is slightly preferred over the size of the house because the budget is fixed; and
3. Location of the house is slightly preferred over the price of the house because of a desire to be near schools and shopping centers.

AHP enables the couple (decision makers) to translate their preferences (subjective judgments) into precise numbers using a 1-9 numerical scale shown in Table 1.

Table 1. **The AHP Fundamental Scale, Adapted from Table 3-1 p. 54 of** [21]

The Fundamental Scale for Pairwise Comparisons		
Intensity of Importance	**Definition**	**Explanation**
1	Equal importance	Two activities contribute equally to the objective
3	Weak importance of one over another	Experience and judgment slightly favor one activity over another
5	Essential or strong importance	Experience and judgment strongly favor one activity over another
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
9	Absolute importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2,4,6,8	Intermediate values between adjacent scale values	When compromise is needed

Using AHP's fundamental scale, the couple translated their subjective preferences into numeric values as shown in Table 2. For example, since the location of the house is strongly preferred over its size, the table entry for the intersection of the Location row and Size column is assigned the value 5, indicating that location is five times more important than size. The inverse value, 1/5, is assigned to the table entry for the intersection of the Size row and Location column. The couple translates all preferences to numerical values in a similar manner.

Table 2. Criteria compared with respect the Goal for purchasing a house

	Size	**Location**	**Price**
Size	1	1/5	1/3
Location	5	1	3
Price	3	1/3	1

At the fifth step, the couple needs to build an MPC for comparing alternatives to each other with respect to each criterion. Each element of an MPC is created by comparing one alternative with another alternative i.e., H1 (activity *i*) is compared with H2 (activity *j*). To create an MPC, the couple must first judge which alternative is more desirable with respect to the criterion that is being considered i.e., Size. After much discussion, the couple expresses their subjective judgments as follows:

1. H1 is very strongly preferred over H2 because it meets the space requirement of our family;
2. Although H1 and H3 meets the space requirement, the bathroom in H3 is somewhat smaller so H1 is strongly preferred over H3; and
3. H3 is slightly preferred over H2 because the kitchen is somewhat bigger.

Using the procedure highlighted in the step four, the couple forms the following MPC for comparing alternatives with respect to the criterion Size:

Table 3. Alternatives compared with respect the criterion Size

	H1	**H2**	**H3**
H1	1	7	5
H2	1/7	1	1/3
H3	1/5	3	1

The MPCs for comparing alternatives with respect to Location and Price criteria are obtained in a similar manner. In general, the result of pairwise comparisons between activity *i* and activity *j* are stored in an MPC (*n-by-n* matrix) of the form

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \vdots\vdots\vdots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix},$$

where a_{ij} is the numerical representation of the quantified judgments on pairs (activity *i*, activity *j*) for all activities ($i, j = 1, 2, \ldots, n$) [21] where *i* denotes a row and *j* denotes a column entry of the matrix A. The diagonal of the matrix A is equal to one because activity *i* is always as important as itself. The activities below the diagonal are the reciprocal values of the corresponding activities above the diagonal because if activity *i* is four times as important as activity *j*, then activity *j* is one fourth as important as activity *i*. More explicitly, the following rules adapted from [21] define the a_{ij} entries:

Rule 1. If $a_{ij} = \sigma$ then $a_{ji} = 1/\sigma$, $\sigma \neq 0$; and
Rule 2. If activity *i* is judged to be of equal relative importance as activity *j*, then $a_{ij} = 1$, $a_{ji} = 1$, and $a_{ii} = 1$ for all *i*.

Once the judgments are recorded in the matrix A, AHP uses the principle eigenvector method to derive priorities or weights (normalized to sum to one) for the criteria and alternatives. It also uses the principle eigenvalue, λ_{max}, to check for consistency between pairwise comparisons. The eigenvalue/eigenvector in matrix notation is given by

$$Aw = \lambda_{\max} w \ , \tag{1.1}$$

where:

A is the reciprocal matrix with entries a_{ij} for all ($i, j = 1,2, \ldots, n$);
w is the eigenvector; and
λ_{max} is the principle eigenvalue.

If the judgments in the matrix A are perfectly consistent, then the value of λ_{max} is equal to n (number of activities). In AHP, the deviation from consistency is a violation of proportionality [21] and shows an inherent possibility of bias and errors in the judgements [23]. Two metrics are recommended in [21] as measure of the consistency of pairwise comparisons, the consistency index (CI) and consistency ratio (CR). *CI* is the difference between the principle eigenvalue and n, and is mathematically defined as $(\lambda_{max} - n)/(n-1)$. *CR* is a measure of the goodness of *CI* and it is defined as *CI/RI*. The random index *RI*, is an average *CI* of randomly generated reciprocal matrices [21] as shown in Table 4. A *CR* of 10 % or less is desirable, indicating good judgments when activities are pairwise compared.

Table 4. The Average RI for Matrices of Order 1-15, Adopted from p. 21of [21]

Matrix Order	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Average RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

The final step in AHP is to calculate the overall score for each alternative with respect to the goal. Consider the hierarchical arrangement of the hypothetical problem of purchasing a house with three levels: the goal, criteria, and alternatives. Let *wg* represent the vector of priorities derived for each criterion with respect to the goal (that is, the principal eigenvector of the MPC for the goals), and *m* be the number of criteria. Let p_a represent the vector of priorities derived for an alternative with respect to criteria in the level above it (that is, the principal eigenvector of the MPC for each of the criteria). The overall score for alternative *a* (S_a) with respect to the goal is computed by

$$S_a = \sum_{k=1}^{m} p_a(k)\, wg(k) \ . \tag{1.2}$$

Using Eq. (1.2), the overall scores for all alternatives are computed. The sum of priorities at each level of the hierarchy must equal one. The alternative with the highest score is the most desirable one. Applying these definitions to the hypothetical problem of purchasing a house, give us the following results:

$$wg = [0.11, 0.63, 0.26]$$

$$p_{size} = [0.73, 0.08, 0.19],$$

where:

wg is the vector of priorities derived for each criterion with respect to the *Goal* and is computed from the MPC shown in Table 2; and

p_{size} is the vector of priorities derived for each alternative with respect to the criterion *Size* from the MPC shown in Table 3.

The vector of priorities for each alternative with respect to the criteria *Location* and *Price* are obtained in a similar manner as p_{size}. These priorities are given below:

$$p_{location} = [0.16, 0.59, 0.25]$$
$$p_{price} = [0.25, 0.50, 0.25],$$

where:

$p_{location}$ is the vector of priorities derived for each alternative with respect to the criterion Location; and

p_{price} is the vector of priorities derived for each alternative with respect to the criterion Size.

Therefore, the vector of priorities for each alternative with respect to the criteria is given by

$$p_{H1} = [0.73, 0.16, 0.25]$$
$$p_{H2} = [0.08, 0.59, 0.50]$$
$$p_{H3} = [0.19, 0.25, 0.25].$$

The relationship between alternative houses, criteria, and the goal of purchasing a house are shown in Figure 3.

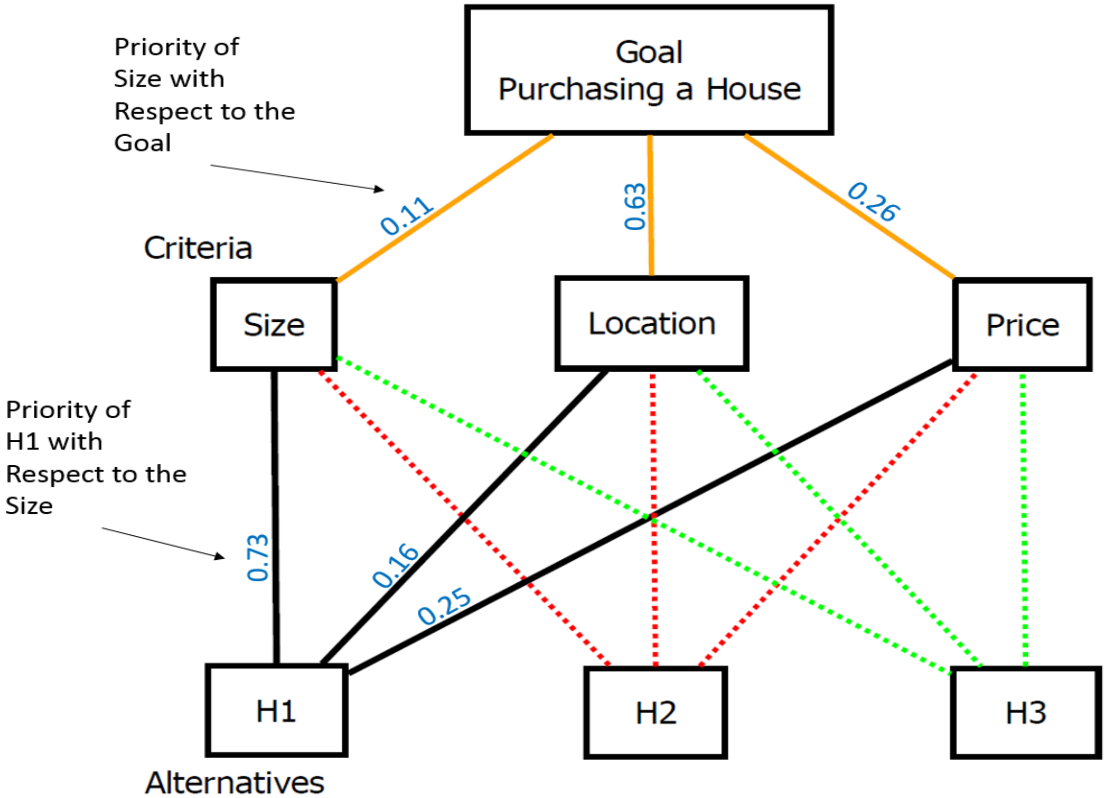

Figure 3. Summary figure showing the relationship between alternatives, criteria, and the goal using priorities for one alternative

Applying Eq. (1.2) to the derived priorities, the overall scores for each alternative with respect to the Goal is given in Table 5. For example, the overall score for H1 is computed by

$$\begin{aligned} S_{H1} &= \sum_{k=1}^{3} p_{H1}(k)\, wg(k) \\ &= 0.25. \end{aligned}$$

Table 5. The overall scores of alternatives for purchasing a house

Alternatives	Overall Score (S_a)
H1	0.25
H2	0.51
H3	0.24

Based on the overall scores in Table 5, the most desirable outcome for the couple is to purchase the second house (H2).

3. Problem Hierarchy Assessing EMCAs

The proposed AE splits the problem of assessing the performance of residential EMCAs into a three-level hierarchy: the goal, criteria, and alternatives as shown in Figure 4.

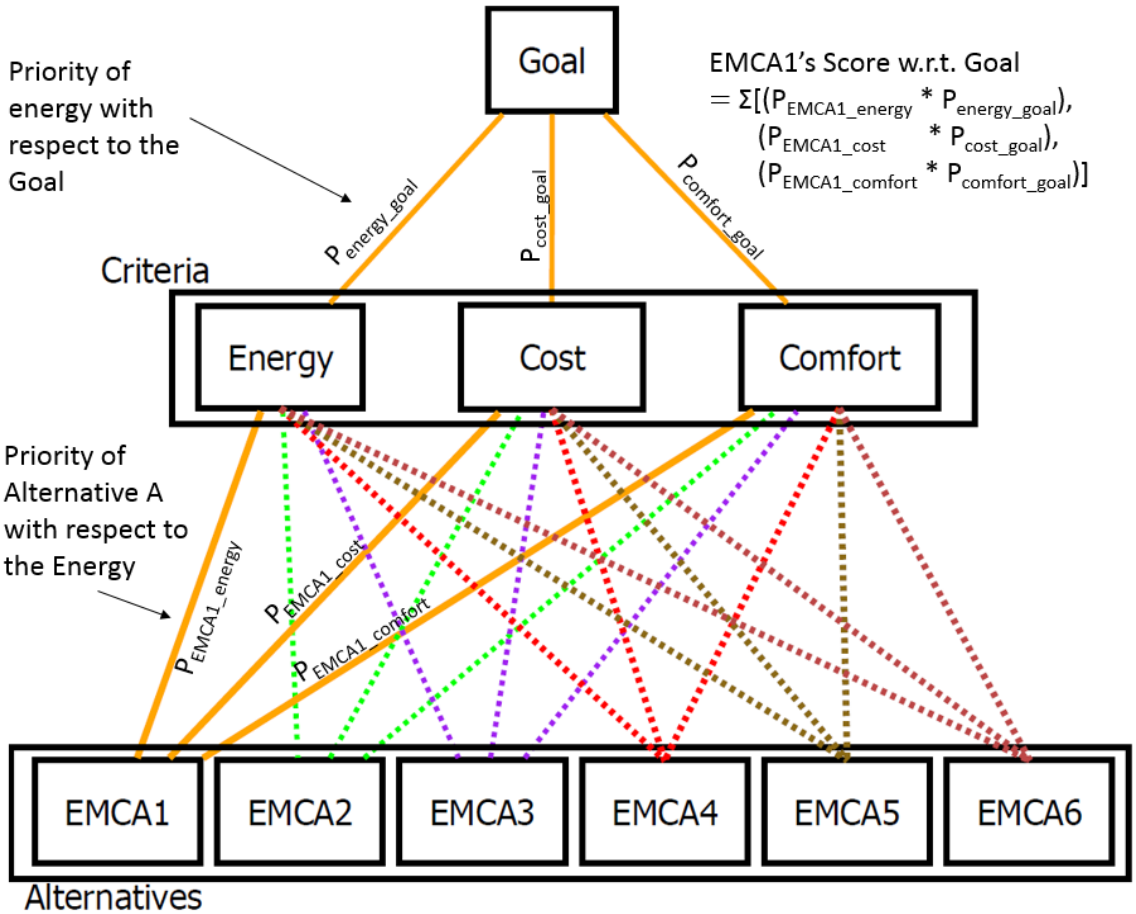

Figure 4. The assessment problem hierarchy showing the relationship of the alternatives to the criteria and the goal

The goal is to identify the best alternative given the user's preferences and the performance data resulting from the use of residential EMCAs. Energy, cost, and comfort were selected as the criteria because they can be controlled by a residential EMCA and have a significant impact on the overall well-being of the occupants and because they can help utilities with peak demand reduction. In this study YALMIP [26], a MATLAB toolbox, was used to implement six residential EMCAs that controlled a two-stage heat pump with auxiliary electric heating.

The main objective of developing these residential EMCAs was to create a diverse set of realistic operating scenarios for the AE to evaluate and rank. A detailed description of these algorithms is provided in [27]. A summary of important parameters for residential EMCAs used in this study is presented in Table 6. The (✓,Yes) and (×, No) markers are used to indicate whether an algorithm is single-objective or multi-objective or limited by the upper or lower bound indoor temperature constraints. For example, residential EMCA3 used optimization (✓), was not limited by upper and lower bound constraints (×), and was multi-objective (✓).

Table 6. **Summary Description of Residential EMCAs**

Residential EMCAs	Optimization Used	Objective Description	Thermostat Setpoints (°C) (heating, cooling)	Heating Lower Bound (°C)		Cooling Upper Bound (°C)		Multi-Objective	Dominance Factor (λ, 1-λ)	Forecast Horizon (min)
1	✓	Minimize Energy	(20.5, 23.9)	20.2		24.2		×	×	30
2	✓	Minimize Cost	(20.5, 23.9)	20.2		24.2		×	×	1440
3	✓	Minimize Discomfort + Cost	(20.5, 23.9)	×		×		✓	(0.45, 0.55)	240
4	✓	Minimize Discomfort + Cost	(20.5, 23.9)	×		×		✓	(0.55, 0.45)	240
5	×	NZERTF Case	(20.5, 23.9)	1st Stage	20.4	1st Stage	24.1	×	×	×
				2nd Stage	19.4	2nd Stage	27.1			
				3rd Stage	17.2	×	×			
6	×	NZERTF Case with Relaxed Deadbands	(20.5, 23.9)	1st Stage	20.0	1st Stage	24.5	×	×	×
				2nd Stage	19.0	2nd Stage	27.1			
				3rd Stage	16.8	×	×			

The first four residential EMCAs in Table 6 utilize an integer linear programming solver (intlinprog) in MATLAB to forecast control actions for operating the heat pump unit. The forecast horizon time is shown in Table 6.

Residential EMCA1 and residential EMCA2 are formulated as single-objective optimization problems. They both have the same upper and lower bound indoor temperature constraints, but different optimization horizons. In the heating season, the residential EMCAs are constrained to forecast the indoor temperature such that it remains between the heating setpoint and its lower bound limit. In the cooling season, the residential EMCAs are constrained to forecast the indoor temperature such that it remains between the cooling setpoint and its upper bound limit. The forecast horizon for the two algorithms are different because residential EMCA2 is trying to minimize the operating cost of using the heat pump by taking advantage of a real-time pricing (RTP) structure.

Residential EMCA3 and residential EMCA4 are formulated as multi-objective optimization problems with two competing terms, one is trying to maintain the thermal comfort of the occupants while the other one is trying to minimize the energy cost. The comfort term is the absolute value of the difference between the forecasted indoor temperature and the thermostat setpoint (for both heating and cooling seasons). The cost term is the sum of the product of the heat pump energy and the price of electricity during each hour. Both algorithms have the same structure, but they emphasize different terms of the objective function as reflected by the

Dominance Factor. Residential EMCA3 emphasizes cost savings while residential EMCA4 emphasizes comfort.

Residential EMCA5 was designed, as a best effort, to replicate the operation of the heat pump differential controllers used a TRNSYS model of the Net-Zero Energy Residential Test Facility (NZERTF) [28]. In the heating season, residential EMCA5 uses the heating lower bound temperatures, as given in Table 6, to manage the operation of the heat pump. The 1st Stage of the heat pump is activated when the indoor temperature falls below the 1st Stage lower bound temperature. The 2nd Stage of the heat pump is activated when the indoor temperature either falls below the 2nd Stage lower bound or the heat pump has operated in the 1st Stage for more than 10 minutes. The 3rd Stage electric heating is activated when the indoor temperature either falls below the 3rd Stage lower bound temperature or the heat pump has operated in 2nd Stage for more than 40 minutes. In the cooling season, the 1st Stage of the heat pump is activated when the indoor temperature rises above the 1st Stage upper bound temperature. The 2nd Stage is turned on when either the indoor temperature has risen above the 2nd Stage upper bound or the heat pump has operated in the 1st Stage for more than 40 minutes. Residential EMCA6 uses the same control logic to operate the heat pump, but its upper and lower bounds are relaxed.

The residential EMCAs were linked to a TRNSYS simulation model [28] of the NZERTF at NIST in Gaithersburg, Maryland [29]. Measured data from the NZERTF were used to validate the model. NZERTF is a research house that is comparable in size and aesthetics to the houses in the greater Washington, DC metro area. The NZERTF serves two purposes: (1) to demonstrate the feasibility of achieving net zero energy operation (energy generated equals the total energy consumed) over the course of one year; and (2) to test existing and new energy efficiency and smart grid technologies. The exterior of the NZERTF is shown in Figure 5.

Figure 5. The exterior of the NZERTF on the campus of NIST in Gaithersburg, MD

4. The AE User Interface

The AE utilizes subjective preferences (inputs from a user) and objective performance data (generated in response to the use of a residential EMCA) to perform pairwise comparisons and ultimately help users select the best alternative among all alternatives. The AE user interface (AEUI), shown in Figure 6, was developed to capture user's preferences and obtain/process performance data. In its current form, users can perform the following tasks:

1. Import up to six hourly and minutely performance data files;
2. Solicit a user's preferences (expert knowledge or judgments) for pairwise comparison of energy, cost, and comfort; and
3. Perform an overall ranking of the residential EMCAs with respect to the goal.

Additionally, the AEUI provides a set of diagnostic analyses and plots comparing the residential EMCAs with respect to a base case. Any residential EMCA can be used as a base case. The diagnostic analyses can be used as a benchmarking tool, independent of the assessment and ranking.

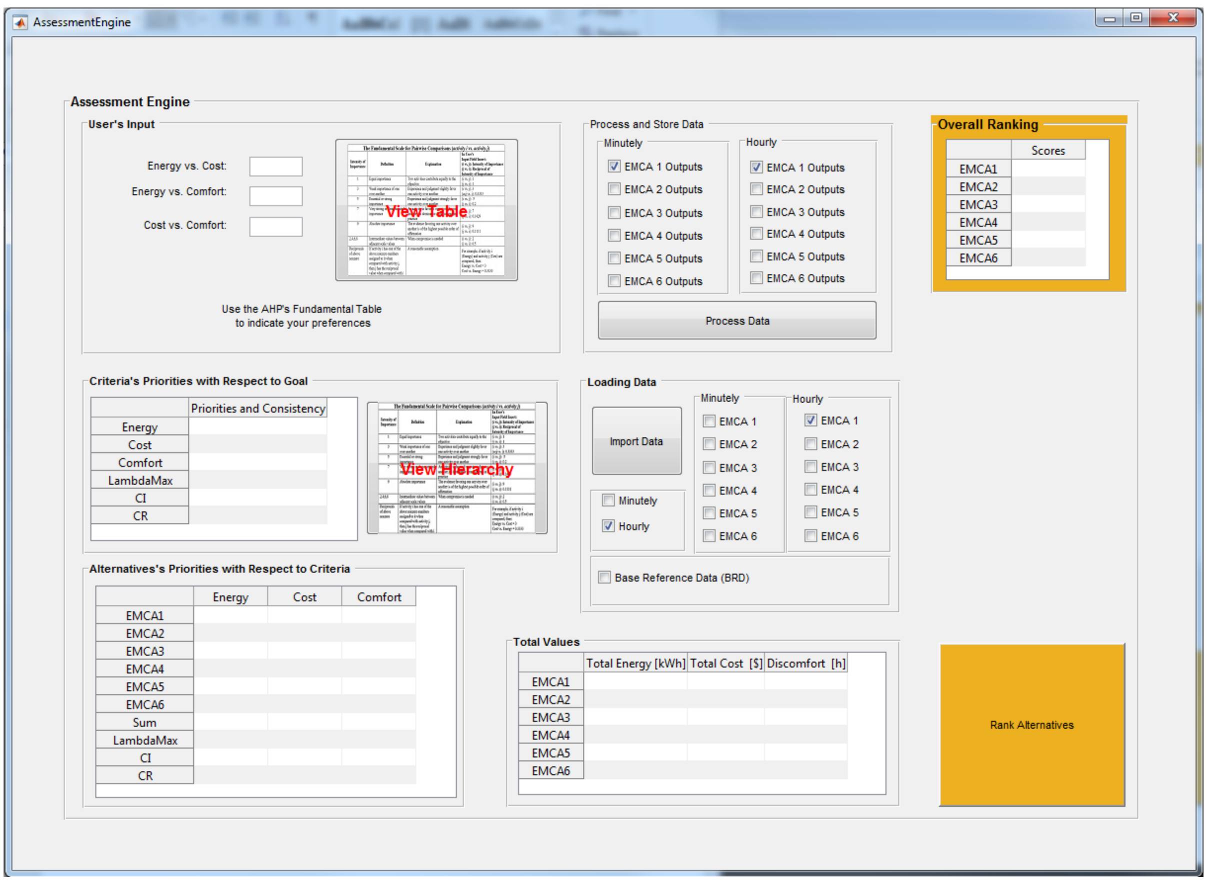

Figure 6. The AE user interface captures user's input, loads performance data, and performs ranking

5. Priorities from User's Judgments

Using a user's input, the AE computes the relative priorities of the criteria with respect to the goal. A user uses the AHP's fundamental scale shown in Table 1 to express his/her desire (or expert judgment) for comparing two criteria in pairs. For example, when the cost criterion is favored very strongly over the energy criterion, the user would enter 0.1429 (1/7) in the Energy vs. Cost input field. However, if the cost criterion is slightly favored over the comfort criterion, the user would enter 3 in the Cost vs. Comfort input filed. The User's Input fields shown in Figure 7 captures these preferences.

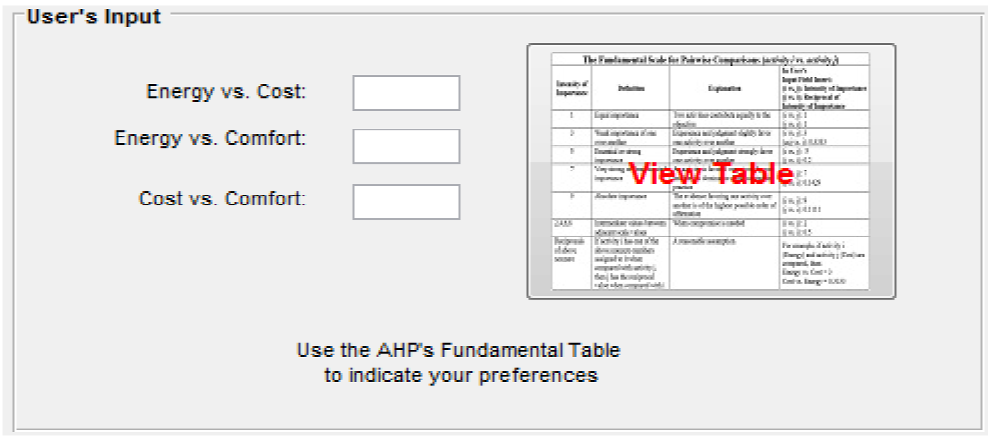

Figure 7. User's Input fields capturing preferences between criteria

Using the provided preferences, the AE forms the corresponding MPC for pairwise comparisons between selected criteria as shown in Table 7.

Table 7. MPC between Criteria

	Energy	**Cost**	**Comfort**
Energy	1	0.1429	0.2
Cost	7	1	3
Comfort	5	0.3333	1

From this user input, the AE uses the AHP's principle eigenvector method to compute the relative priorities of each criterion with respect to the goal and the consistency of a user in judging the intensity of importance when the criteria were compared in pairs. The results from the user input shown in Table 7 are summarized in Table 8.

Table 8. Priorities and Consistency metrics

Criteria and consistency metrics	**Priorities and consistency**
Energy	0.07
Cost	0.65
Comfort	0.28
Sum	1
λ_{max}	3.07
CI	0.03
CR	0.06

For this example, cost is the most important factor for the decision maker followed by comfort and energy. Recall from Table 4 that for a matrix of order 3, the *CR* value of 6 % indicates that the decision maker was consistent in providing subjective judgments.

6. Calculating Energy, Cost, and Comfort

Using the performance data, the AE calculates the total energy consumption, total cost, and a discomfort index for each residential EMCA. These calculations, collectively, form the basis for computing the relative priorities of each alternative EMCA with respect to each criterion.

6.1. Energy

The total energy consumption is computed by

$$E_{total,k} = \sum_{h=1}^{H} e_h \text{ for } k = 1, \ldots, n \,, \tag{1.3}$$

where:

n is the number of alternatives (six residential EMCAs in this case);
H is the number of hours (i.e., 8760 h for one year); and
e_h is the energy consumed by the HVAC unit in hour h [kWh].

6.2. Cost

The cost of consuming energy is computed by

$$C_{total,k} = \sum_{h=1}^{H} e_h \times p_h \text{ for } k = 1, \ldots, n \,, \tag{1.4}$$

where:

H, e_h and n are the same as described in Eq. (1.3); and
p_h is the RTP tariff in hour h [¢/kWh].

The RTP tariff was derived from the day-ahead wholesale hourly price of electricity from a regional transmission organization (RTO), the Pennsylvania-New Jersey-Maryland Interconnection (PJM). The data is from January 2013 to December 2013. The day-ahead wholesale price, shown in Figure 8, was scaled to generate a forecasted retail RTP structure, resulting in an average of 15 ¢/kWh. The average cost of consuming energy in a residential home in Gaithersburg, Maryland is approximately 15 ¢/kWh (including transmission, distribution, taxes, and fees).

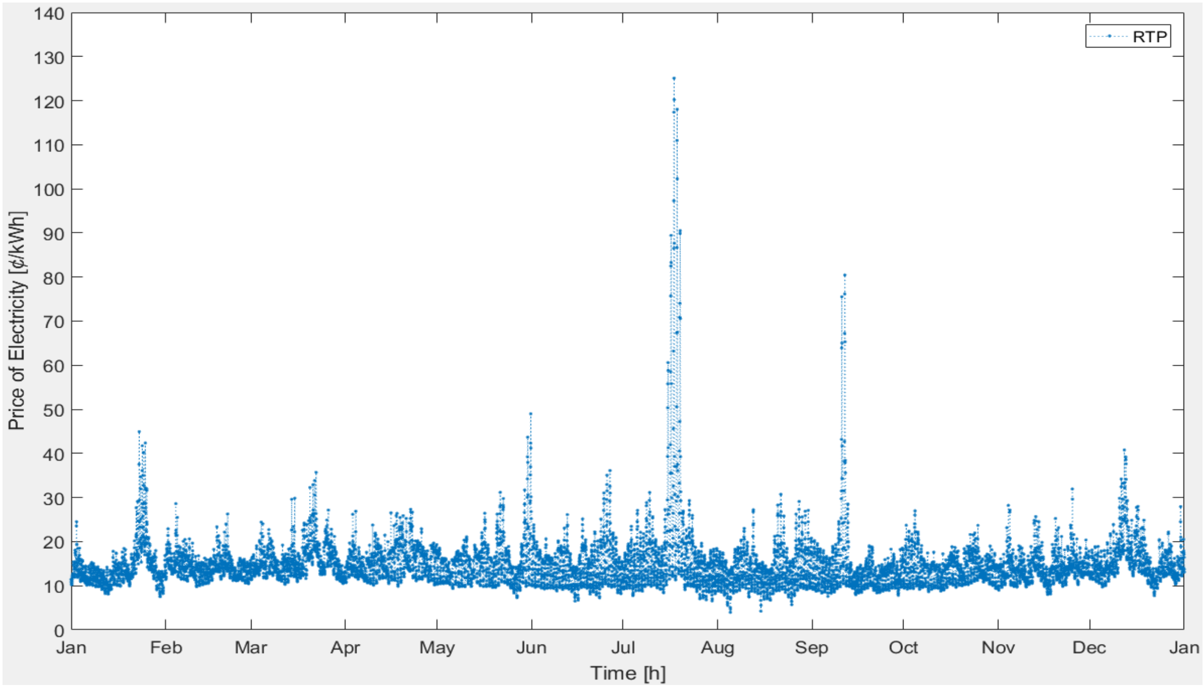

Figure 8. The hourly RTP tariff used to compute the cost of energy consumption

6.3. Comfort

Many long-term discomfort indices that evaluate the thermal response of humans to changes in indoor climatic conditions have been reported in the literature and standards. A review of these indices, their strengths and weaknesses are documented in [30]. In this study, a discomfort index was chosen that produced a single value, was based on well-known thermal comfort standards, and considered both the duration and severity of the thermal discomfort. The AE computes the long-term discomfort index using a methodology that is based on predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD). The methodology for computing the long-term index is the PPD-weighted criterion (PPD_{wc}) documented in Method C of International Organization for Standardization standard 7730 (ISO 7730) [31] and summarized in [30]. This measure of discomfort index is described as "the time during which the actual PMV exceeds the comfort boundaries is weighted with a factor that is a function of the PPD" [31].

6.3.1. Calculating PMV and PPD

The *PMV* index is the mean value that predicts the response of a large group of people on the seven-point thermal sensation scale defined in [31], [32] and shown in Table 9.

Table 9. **Seven-point Thermal Sensation Scale**

+3	Hot
+2	Warm
+1	Slightly warm
0	Neutral
-1	Slightly Cool
-2	Cool
-3	Cold

Using heat balance principles, the *PMV* index relates key primary thermal factors such as metabolic rate, clothing insulation, air temperature, radiant temperature, air speed, and humidity to the thermal sensation scale in Table 9. Many assumptions must be made about some of the inputs for calculating *PMV*, including that the difference between T_{air} and T_{mrt} is negligible. This assumption is common in previous indoor climate studies [33], [34]. Table 10 shows the input values used in this study to calculate *PMV*.

Table 10. **Assumed Values for Calculating PMV**

Input data (unit)	Assumed Value	
Clothing (clo)	Summer months (May, June, July, August, September)	0.36 (Walking shorts, short-sleeve shirt [32])
	Other months	0.6 (Trousers, long-sleeve shirt [32])
Metabolic rate (met)	1.7 (Office activities, walking about [32])	
External work (met)	0 [32]	
Air temperature T_{air} (°C)	Indoor dry bulb temperature	
Mean radiant temperature T_{mrt} (°C)	Indoor dry bulb temperature	
Relative air velocity (m/s)	0.05 [35]	
Relative humidity (%)	Indoor relative humidity	

The *PMV* metric is iteratively calculated by using of the following four equations given in ISO 7730 [31].

$$PMV = [0.0303 \times \exp(-0.036 \times M) + 0.028] \times \left\{ \begin{array}{l} (M - W) - 3.05 \times 10^{-3} \\ \times [5733 - 6.99 \times (M - W) - p_a] \\ -0.42 \times [(M - W) - 58.15] \\ -1.7 \times 10^{-5} \times M \times (5867 - p_a) \\ -0.0014 \times M \times (34 - t_a) \\ -3.96 \times 10^{-8} \times f_{cl} \times [(t_{cl} + 273)^4 \\ -(\overline{t_r} + 273)^4] - f_{cl} \times h_c \times (t_{cl} - t_a) \end{array} \right\} \quad (1.5)$$

$$t_{cl} = 35.7 - 0.028 \times (M - W) - I_{cl} \times \left\{ \begin{array}{l} 3.96 \times 10^{-8} \times f_{cl} \\ \times \left[(t_{cl} + 237)^4 - (\bar{t}_r + 273)^4 \right] \\ + f_{cl} \times h_c \times (t_{cl} - t_a) \end{array} \right\} \tag{1.6}$$

$$h_c = \begin{cases} 2.38 \times \left| t_{cl} - t_a \right|^{0.25} & \text{for } 2.38 \times \left| t_{cl} - t_a \right|^{0.25} > 12.1 \times \sqrt{v_{ar}} \\ 12.1 \times \sqrt{v_{ar}} & \text{for } 2.38 \times \left| t_{cl} - t_a \right|^{0.25} < 12.1 \times \sqrt{v_{ar}} \end{cases} \tag{1.7}$$

$$f_{cl} = \begin{cases} 1.00 + 1.290\, l_{cl} & \text{for } l_{cl} \le 0.078\ m^2 \times K/W \\ 1.05 + 0.645\, l_{cl} & \text{for } l_{cl} > 0.078\ m^2 \times K/W \end{cases}, \tag{1.8}$$

where:

- M is the metabolic rate in (W/m^2), 1 metabolic unit = 1 met = 58.2 W/m^2;
- W is the effective mechanical power in (W/m^2);
- I_{cl} is the clothing insulation in (m^2 K/W), 1 clothing unit = 1 clo = 0.155 m^2 °C/W;
- f_{cl} is the clothing surface area factor;
- t_a is the air temperature in (°C);
- $\bar{t}_r$ is the mean radiant temperature in (°C);
- v_{ar} is the relative air velocity in (m/s);
- p_a is the water vapor partial pressure in (P_a);
- h_c is the convective heat transfer coefficient in [W/(m^2 K)]; and
- t_{cl} is the clothing surface temperature in (°C).

It is noted that the conversion of 1 met equals to 58.2 W/m^2 is based on (ANSI/ASHRAE) Standard 55 [32]. This conversion neglects body size, sex, and age of an individual, for more information regarding this conversion and topic see [36].

The *PPD* index is determined from the *PMV*. It is a quantitative prediction of thermally dissatisfied people in percentage (%) and it is computed by

$$PPD = 100 - 95 \times \exp(-0.03353 \times PMV^4 - 0.2179 \times PMV^2)\,. \tag{1.9}$$

Computer instructions for calculating *PMV* and *PPD* is provided in Appendix D of American Nation Standards Institute /American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ANSI/ASHRAE) Standard 55 [32]. The instructions were implemented in Matlab [35]. In a typical application, ANSI/ASHRAE Standard 55 also defines a recommended *PMV* and *PPD* range, shown in Table 11, for general thermal comfort. If the calculated values for the *PMV* and hence for the *PPD* are within the defined ranges, the conditions are considered to be comfortable.

Table 11. **The PMV and PPD Ranges for Thermal Comfort**

PMV Range	PPD (%)
-0.5 < PMV < +0.5	< 10

Figure 9 shows the annual results from calculating *PMV* and *PPD* when residential EMCA1 is applied.

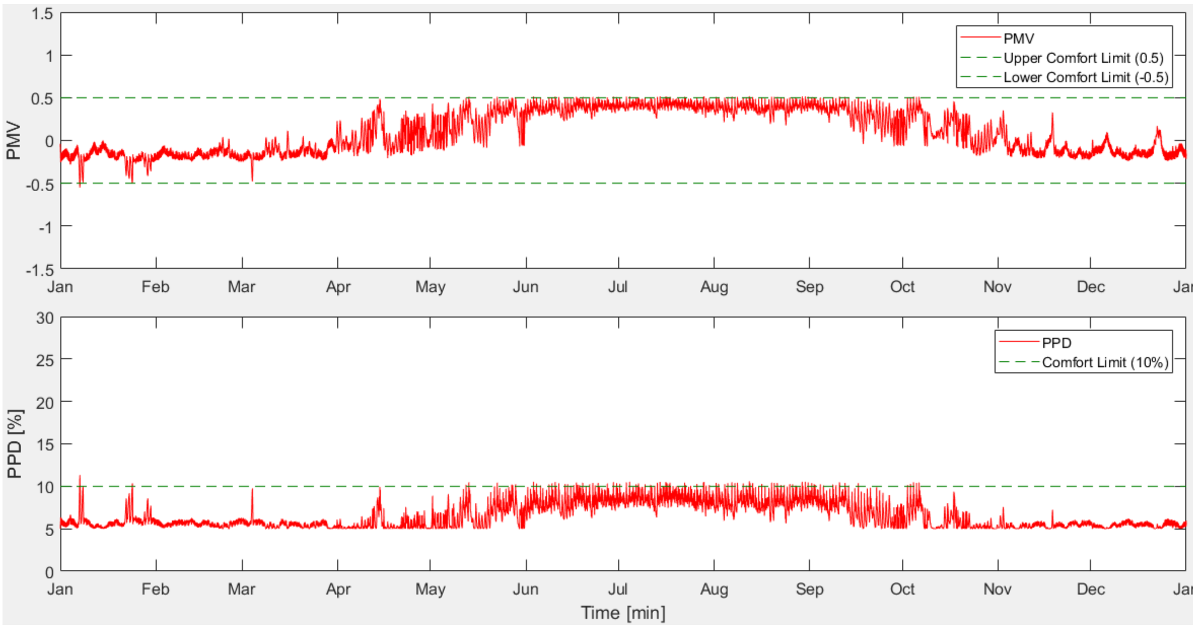

Figure 9. Annual comfort results for residential EMCA1 as measured by PMV and PPD

6.3.2. Calculating the Discomfort Index

The discomfort index (PPD_{wc}) is the sum of the product of a weighting factor and time when a building is occupied. In this study, the value of PPD_{wc} is computed in every occupied minute and the result is reported in hours. PPD_{wc} is computed by

$$PPD_{wc,k} = \sum_{j=1}^{om} \left(wf_j \cdot t_j \right) \text{ for } k = 1, \ldots, n \, , \qquad (1.10)$$

where:

n is the number of alternatives;
wf_j is the weighting factor in each occupied minute;
om is the total number of occupied minutes; and
t_j is the time step, 1 min.

The weighting factor is computed by

$$wf_j = \begin{cases} \dfrac{PPD_{\text{actualPMV}}}{PPD_{\text{PMVlimit}}} & , \; |PMV| > |PMV_{\text{limit}}| \\ 1 & , \; PMV = PMV_{\text{limit}} \\ 0 & , \; |PMV| < |PMV_{\text{limit}}| \end{cases} , \quad (1.11)$$

where:

$PPD_{actualPMV}$ is the *PPD* corresponding to the actual *PMV*; and

$PPD_{PMVlimit}$ is the *PPD* corresponding to PMV_{limit}.

7. Priorities from Performance Data

The results of applying Eq. (1.3), Eq. (1.4), and Eq. (1.10) to the performance data for each residential EMCA are shown in Table 12. In this document, Table 12 is referred to as the Performance Table. The values in the Performance Table are used to derive priorities for each residential EMCA relative to the criteria.

Table 12. **EMCA Performance Summary**

Residential EMCA	Total Energy (E_{total}) [kWh]	Total Cost (C_{total}) [$]	Discomfort Index (PPD_{wc}) [h]
1	5605	901	9
2	5588	880	339
3	5484	847	1176
4	5762	918	222
5	5882	938	0
6	6589	1050	0

Having computed the total energy consumption (E_{total}), cost of consuming energy (C_{total}), and the discomfort index (PPD_{wc}) for all residential EMCAs, the next step is to compute a set of relative priorities when alternatives are pairwise compared. To compute these priorities, an algorithm was developed to first map each column of the Performance Table to the Intensity of Importance in Table 1 then form an MPC using the derived quantified judgements a_{ij} in matrix A. Using AHP's standard procedure described in Sec. 2 on matrix A will result in relative priorities (a set of weights) with respect to criteria along with λ_{max}, *CI*, and *CR*. When creating the MPC, the following main assumptions form the basis of the computations:

1. Lower energy consumption is desired over higher energy consumption;
2. Lower monetary cost is desired over higher cost; and
3. More comfortable environment is desired over less comfortable environment.

The following steps describe the algorithm for computing priorities:

1. For each entry in each column in the Performance Table, scale the values by dividing the maximum of each column by the value of each entry in the column. Let R_E, R_C, and R_{DC} represent energy, cost, and discomfort ratios, respectively. These ratios are mathematically represented by:

$$R_{E,k} = \beta_{\max} / E_{total,k}, \forall\ k = 1,\ldots,n, \tag{1.12}$$

where $\beta_{\max} = \max\left(\left\{E_{total,k} : k = 1,\ldots,n\right\}\right)$.

$$R_{C,k} = \gamma_{\max} / C_{total,k}, \forall\ k = 1,\ldots,n, \tag{1.13}$$

where $\gamma_{\max} = \max\left(\left\{C_{total,k} : k = 1,\ldots,n\right\}\right)$.

$$R_{DC,k} = \delta_{\max} / PPD_{wc,k}, \forall\ k = 1,\ldots,n, \tag{1.14}$$

where $\delta_{\max} = \max\left(\left\{PPD_{wc,k} : k = 1,\ldots,n\right\}\right)$ and for numerical stability

$$PPD_{wc,k} = \begin{cases} PPD_{wc,k}, & \text{if } PPD_{wc,k} > 0 \\ 1, & \text{if PPD}_{wc,k} = 0 \end{cases}. \tag{1.15}$$

For instance, the energy ratios $R_{E,k}$ (for $k = 1,\ldots, n$), where n is the number of residential EMCAs, is computed by Eq. (1.12) and is shown in Table 13.

Table 13. **Energy Ratio (R_E)**

Residential EMCA	**E_{total} (kWh)**	**R_E (dimensionless)**
1	5605	1.18
2	5588	1.18
3	5484	1.20
4	5762	1.14
5	5882	1.12
6	6589	1.00

2. Define scale factors for energy (S_{Ef}), cost (S_{Cf}), and discomfort (S_{Df}). Let C_{scale} represent the AHP Intensity of Importance shown in Table 1.

$$S_{Ef} = \left(\max\left(C_{scale}\right) - \min\left(C_{scale}\right)\right) / \left(\eta_{\max} - \eta_{\min}\right), \tag{1.16}$$

where $\eta_{\max} = \max\left(\left\{R_{E,k} : k = 1,\ldots,n\right\}\right)$ and $\eta_{\min} = \min\left(\left\{R_{E,k} : k = 1,\ldots,n\right\}\right)$.

$$S_{Cf} = \left(\max\left(C_{scale}\right) - \min\left(C_{scale}\right)\right) / \left(\nu_{\max} - \nu_{\min}\right), \tag{1.17}$$

where $\nu_{\max} = \max\left(\left\{R_{C,k} : k = 1,\ldots,n\right\}\right)$ and $\nu_{\min} = \min\left(\left\{R_{C,k} : k = 1,\ldots,n\right\}\right)$.

$$S_{Df} = \left(\max\left(C_{scale}\right) - \min\left(C_{scale}\right)\right) / \left(\mu_{\max} - \mu_{\min}\right), \tag{1.18}$$

where $\mu_{\max} = \max\left(\left\{R_{DC,k} : k = 1,\ldots,n\right\}\right)$ and $\mu_{\min} = \min\left(\left\{R_{DC,k} : k = 1,\ldots,n\right\}\right)$.

For instance, using Eq. (1.16), the S_{Ef} for the values in R_E (given in Table 13) is 39.68.

3. Map energy consumption (M_E), cost (M_C), and discomfort (M_{DC}) to C_{scale} to create a vector of preferences, rounded to the nearest integer

$$M_{E,k} = round\left(\left(R_{E,k} - \eta_{\min}\right) \times S_{Ef} + \min\left(C_{scale}\right), 0\right), \forall\ k = 1, \ldots, n \tag{1.19}$$

$$M_{C,k} = round\left(\left(R_{C,k} - \nu_{\min}\right) \times S_{Cf} + \min\left(C_{scale}\right), 0\right), \forall\ k = 1, \ldots, n \tag{1.20}$$

$$M_{DC,k} = round\left(\left(R_{DC,k} - \mu_{\min}\right) \times S_{Df} + \min\left(C_{scale}\right), 0\right), \forall\ k = 1, \ldots, n\ . \tag{1.21}$$

For instance, using Eq. (1.19), mapping the values in R_E (given in Table 13) to C_{scale} resulted in $M_E = [8,8,9,7,6,1]$.

4. Find the differences between each element of M_E, M_C, and M_{DC} with respect to all other elements of the same vector. The result is an $n \times n$ matrix of the form $D_E(d_{ij})$, $D_C(d_{ij})$, and $D_{DC}(d_{ij})$. More explicitly

Let d represent a vector of mapped preferences (i.e., M_E)

$$d_{ij} = d(i) - d(j)$$

and

$$D(i, j) = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \vdots\vdots\vdots & \vdots \\ d_{n1} & d_{n2} & \cdots & d_{nn} \end{bmatrix},$$

where n is the number of elements in d. For instance, finding the differences between each element of vector M_E results in the matrix $D_E(d_{ij})$

$$D_E(i, j) = \begin{array}{lcccccc} & EMCA1 & EMCA2 & EMCA3 & EMCA4 & EMCA5 & EMCA6 \\ EMCA1 & 0 & 0 & -1 & 1 & 2 & 7 \\ EMCA2 & 0 & 0 & -1 & 1 & 2 & 7 \\ EMCA3 & 1 & 1 & 0 & 2 & 3 & 8 \\ EMCA4 & -1 & -1 & -2 & 0 & 1 & 6 \\ EMCA5 & -2 & -2 & -3 & -1 & 0 & 5 \\ EMCA6 & -7 & -7 & -8 & -6 & -5 & 0 \end{array}.$$

The first row of $D_E(1,j)$ for $j=1,2,\ldots,6$ represents the differences between the first element of M_E (8 in this case) and all other elements of M_E, including the first element itself. $D_C(d_{ij})$ and $D_{DC}(d_{ij})$ are determined in a similar manner.

5. In the AHP framework, no MPC can contain any values (d_{ij}) that are less than or equal to zero. The smallest value for an entry is one, which corresponds to equal importance in pairwise comparison. Thus, matrix *D(i,j)* needs to be modified. Let q_{ij} represent the modified entries replacing d_{ij} and let *Q(i,j)* represent the modified matrix replacing *D(i,j)*, where

$$q_{ij} = \begin{cases} d_{ij} + 1, & \text{if } d_{ij} \geq 0 \\ d_{ij} - 1, & \text{if } d_{ij} < 0 \end{cases} \tag{1.22}$$

the new matrix is

$$Q(i,j) = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1n} \\ q_{21} & q_{22} & \cdots & q_{2n} \\ \vdots & \vdots & \vdots\vdots\vdots & \vdots \\ q_{n1} & q_{n2} & \cdots & q_{nn} \end{bmatrix}$$

and $D_E(i,j)$ becomes

$$Q_E(i,j) = \begin{array}{ccccccc} & EMCA1 & EMCA2 & EMCA3 & EMCA4 & EMCA5 & EMCA6 \\ EMCA1 & 1 & 1 & -2 & 2 & 3 & 8 \\ EMCA2 & 1 & 1 & -2 & 2 & 3 & 8 \\ EMCA3 & 2 & 2 & 1 & 3 & 4 & 9 \\ EMCA4 & -2 & -2 & -3 & 1 & 2 & 7 \\ EMCA5 & -3 & -3 & -4 & -2 & 1 & 6 \\ EMCA6 & -8 & -8 & -9 & -7 & -6 & 1 \end{array} .$$

Q(i,j) still contains entries q_{ij} that are less than zero and converting it to MPC requires a few additional modifications. Let f_{ij} represent the modified entries replacing q_{ij} and *F(i,j)* replacing *Q(i,j)*, then

$$f_{ij} = \begin{cases} q_{ij}, & \text{if } q_{ij} > 0 \\ \dfrac{1}{|q_{ij}|}, & \text{if } q_{ij} < 0 \end{cases} \tag{1.23}$$

the new matrix is

$$F(i,j) = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \vdots\vdots\vdots & \vdots \\ f_{n1} & f_{n2} & \cdots & f_{nn} \end{bmatrix}$$

and $Q_E(i,j)$ becomes

$$
F_E(i,j) = \begin{array}{c} \\ EMCA1 \\ EMCA2 \\ EMCA3 \\ EMCA4 \\ EMCA5 \\ EMCA6 \end{array}
\begin{array}{cccccc}
EMCA1 & EMCA2 & EMCA3 & EMCA4 & EMCA5 & EMCA6 \\
1.0000 & 1.0000 & 0.5000 & 2.0000 & 3.0000 & 8.0000 \\
1.0000 & 1.0000 & 0.5000 & 2.0000 & 3.0000 & 8.0000 \\
2.0000 & 2.0000 & 1.0000 & 3.0000 & 4.0000 & 9.0000 \\
0.5000 & 0.5000 & 0.3333 & 1.0000 & 2.0000 & 7.0000 \\
0.3333 & 0.3333 & 0.2500 & 0.5000 & 1.0000 & 6.0000 \\
0.1250 & 0.1250 & 0.1111 & 0.1429 & 0.1667 & 1.0000
\end{array} .
$$

F(i,j) is an MPC that satisfies *Rule 1* and *Rule 2* described in Section 2 and reflects the derived objective judgments obtained from the performance data documented in the Performance Table for each alternative residential EMCA with respect to the energy, cost, and comfort criteria. Applying AHP's standard eigenvector and eigenvalue methods to *F(i,j)*, the relative priorities for each alternative with respect to the criteria, as well as consistency metrics *CI* and *CR*, are computed. For instance, the relative priorities of residential EMCAs with respect to the energy criterion, using $F_E(i,j)$, is given in Table 14.

Table 14. Priorities and Consistency Metrics

Residential EMCAs	**Priorities with respect to energy criterion and consistency metrics**	
1	0.21	Priorities
2	0.21	
3	0.34	
4	0.13	
5	0.08	
6	0.02	
λ_{max}	6.15	Consistency
CI	0.03	
CR	0.025	

In Table 14, residential EMCA3 has the highest priority with respect to the energy criterion compared to other alternatives, which is consistent with our assumption that less energy consumption is more desirable. The *CR* value of 2.5 % is less than the recommended consistency of 10 %, suggesting that the judgments for comparing alternatives are consistent.

8. Overall Scores

Having computed priorities of criteria with respect to the goal (*wg*) and priorities of each alternative with respect to criteria (p_a), the overall score for each alternative with respect to the goal is computed by Eq. (1.2). Recall that the priorities of criteria with respect to the goal along with consistency metrics were given in Table 8. The priorities (p_a) for each alternative with respect to the criteria for residential EMCAs and the consistency metrics are given in Table 15. For example, priorities of residential EMCA1 with respect to the energy, cost, and comfort criteria is p_a = [0.21,0.18,0.07].

Table 15. **Priorities and Consistency Metrics**

Residential EMCAs and consistency metrics	Energy	Cost	Comfort	
1	0.21	0.18	0.07	Priorities
2	0.21	0.18	0.04	
3	0.34	0.42	0.04	
4	0.13	0.11	0.04	
5	0.08	0.08	0.40	
6	0.02	0.03	0.40	
Sum	1	1	1	Normalization
λ_{max}	6.15	6.20	6.06	Consistency
CI	0.03	0.04	0.01	
CR	0.03	0.03	0.01	

The overall scores for residential EMCAs with respect to the goal are calculated using Eq. (1.2) and shown in Table 16.

Table 16. **The Overall Scores**

Residential EMCAs	Overall scores (ranking)
1	0.15
2	0.14
3	0.31
4	0.09
5	0.17
6	0.13

Based on the overall scores in Table 16, residential EMCA3 is the most desirable alternative with respect to the overall goal reflecting user's very strong preference in an alternative that saves the most money (lowest cost) followed by a strong desire for comfort over energy savings, and weak preference for comfort over cost. The relationship between alternatives, criteria, and the goal are shown in Figure 10. It shows the problem hierarchy, an example of computed priorities for two residential EMCAs, and the overall scores (ranking) for all residential EMCAs.

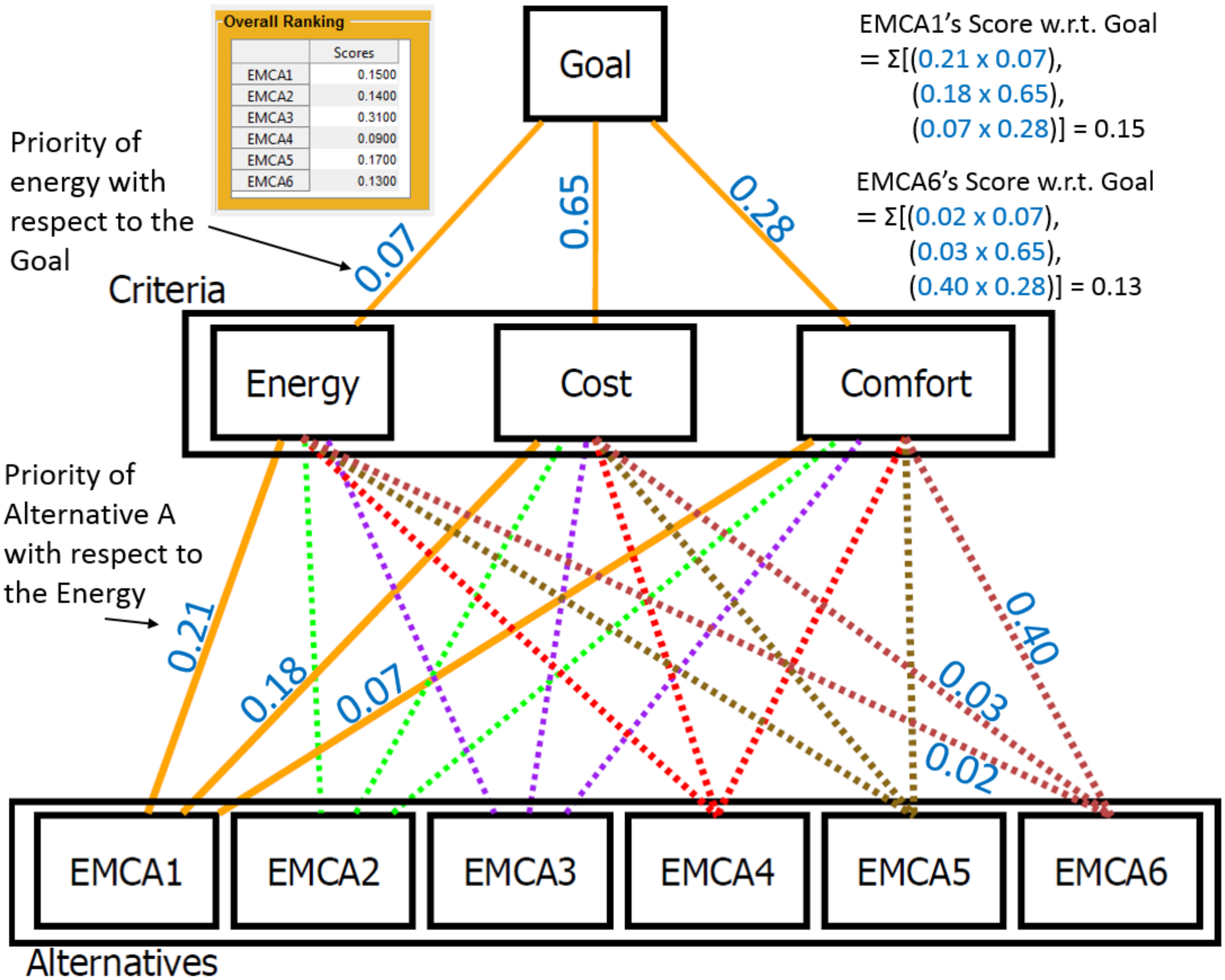

Figure 10. Summary figure showing the problem hierarchy, priorities and the overall scores for each alternative with respect to the goal

As previously mentioned, based on the performance data and user preferences, residential EMCA3 was ranked the highest by the AE. Depending on user preferences, a different algorithm other than residential EMCA3 can be ranked the highest by the AE. Recall that user preferences can only impact priorities of criteria with respect to the goal. For example, a user conveys a very strong desire in an alternative that provides the most comfort over cost, a strong preference for comfort over energy consumption, but a weak preference for energy consumption over cost. These preferences are captured by the AE in inputs fields of Figure 7 as following:

Energy vs. Cost = 3;

Energy vs. Comfort = 0.2; and

Cost vs. Comfort = 0.1429.

The AE forms the corresponding MPC for pairwise comparisons between criteria as shown in Table 17. It also calculates priorities for criteria with respect to the goal and the overall scores based on the new priorities.

Table 17. **MPC for Capturing User Preferences**

	Energy	Cost	Comfort
Energy	1	3	0.2
Cost	0.3333	1	0.1429
Comfort	5	7	1

The *CR* value of 5.6 % suggests that the user's judgments in Table 17 were consistent and the overall scores for residential EMCAs with respect to the goal are given in Table 18.

Table 18. **The Overall Scores**

Residential EMCAs	Overall scores (ranking)
1	0.11
2	0.08
3	0.13
4	0.06
5	0.31
6	0.30

The overall scores in Table 18 show that residential EMCA5 is the most desirable alternative followed by residential EMCA6. The top two choices both offer the same level of comfort (lowest discomfort index), however, residential EMCA5 is the top-ranked because it consumes less energy and has a lower cost compared to residential EMCA6.

9. Sensitivity Analysis

In general, when quantitative data are used to describe the performance of alternatives with respect to the criteria, priorities are either computed by normalization methods or derived from *MPCs*. The need for normalization arises from the fact that one cannot directly compare quantitative data having different units. Two popular normalization methods are division by sum (*DBS*) and division by maximum (*DBM*) [23]. *DBS* involves dividing each column of a Performance Table (Table 12) by the sum of those values, while *DBM* involves dividing each column of the Performance Table by the maximum of those values. The advantages of using normalization methods are that the results can be explained unambiguously; the solutions are obtained more quickly because no pairwise comparisons are needed; and no preference judgments are involved in deriving priorities. The disadvantages are that the choice of normalization method can impact the overall scores; and there is an implied strictly linear (or inverse linear) functional relationship between overall scores and the magnitude of the values in a Performance Table. That is, if alternative n_2 consumes twice as much energy as alternative n_1, then using a normalization method implies that alternative n_1 is twice as desirable as alternative n_2.

In contrast, *MPCs* do not assume linear functional relationships between the overall scores and the magnitude of the values in a decision matrix. They are the preferred methods when the relationships between the magnitude of the values and the overall scores are nonlinear. *MPCs* implicitly consider the decision maker's preference in relation to the performance data. The disadvantages of using *MPCs* are the time spent in performing pairwise comparisons of each alternative with respect to each criterion; lack of precision in documenting the justification for obtaining priorities from subjective comparisons and judgments; and sensitivity of the overall scores to a choice of selecting an eigenvector normalization (i.e., *DBS* or *DBM*) method [23].

To analyze the impact of using direct normalization and *MPC* methods for deriving the overall scores, five cases were studied using the data in the Performance Table. The cases involved using *DBS*, *DBM*, *MPC* using maximum ratios, *MPC* using *DBS*, and *MPC* using *DBM* (see Table 19). Recall that the maximum ratios for the *MPC* method were obtained by applying Eq. (1.12), Eq. (1.13), and Eq. (1.14) to the data in the Performance Table. As previously mentioned, it was assumed that lower values for the energy consumption, monetary cost, and discomfort criteria are more desirable. When lower values are desirable, a common technique is to invert the data before applying the *DBS* or *DBM* methods. Therefore; the data in the Performance Table was first inverted (*1/value*) and then each inverted value was divided by *DBS* and *DBM* methods. To demonstrate the impact of using these methods on the overall score, let's assume that all criteria (energy, cost, and comfort) are judged to be of equal importance and each has a priority (weight) of approximately wg = 0.3. Using Eq. (1.2) the overall scores for each alternative residential EMCA relative to the overall goal were computed and are given in
Table 19.

Table 19. The Overall Scores Using Direct Normalization and MPC Methods

Residential EMCAs	Overall Scores Using DBS	Overall Scores Using DBM	MPC Using Maximum Ratios	MPC Using Ratios Obtained by DBS	MPC Using Ratios Obtained by DBM
1	0.13	0.68	0.15	0.15	0.15
2	0.12	0.65	0.14	0.14	0.14
3	0.12	0.67	0.27	0.27	0.27
4	0.11	0.63	0.10	0.10	0.10
5	0.27	0.95	0.19	0.19	0.19
6	0.25	0.88	0.15	0.15	0.15

To create a common scale for plotting the results given in Table 19, the values in each column were normalized by the *DBM* of the same column. The results are shown in Figure 11.

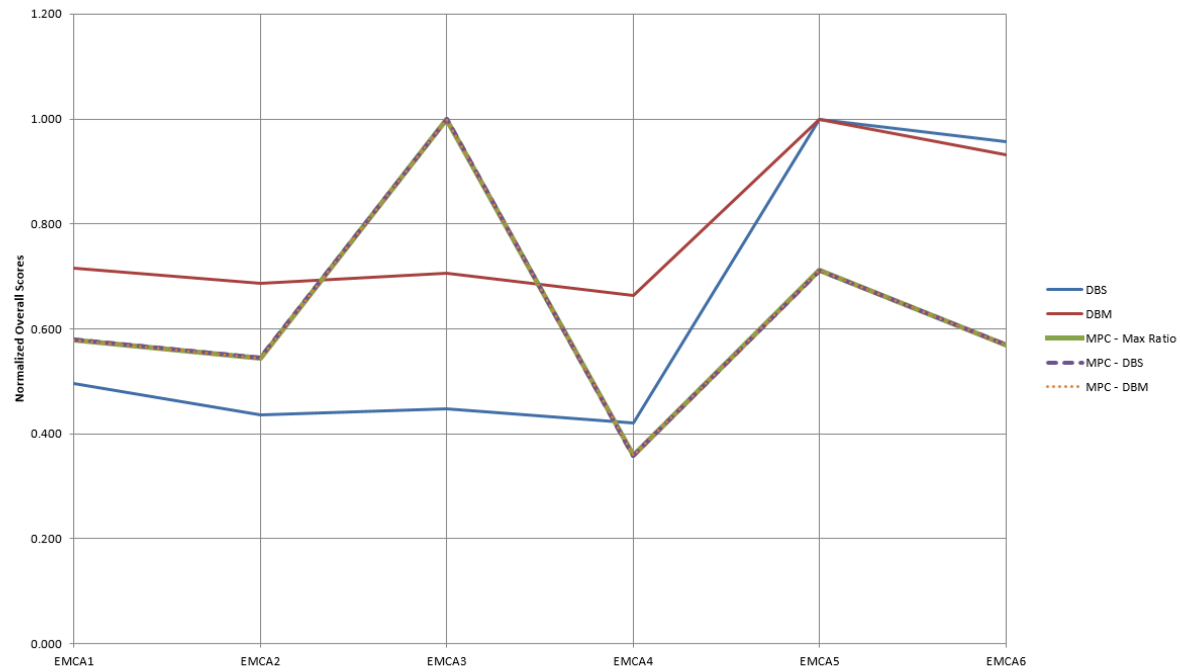

Figure 11. The overall score for each residential EMCA using normalization methods and MPC

The data in Figure 11 show that the overall scores calculated using direct normalization methods (*DBS* and *DBM*) have the same trend for residential EMCAs even though the magnitudes are different. In both direct normalization methods, residential EMCA5 has been scored the highest followed by residential EMCA6. The data in the Performance Table show that both EMCA5 and EMCA6 have the highest values for energy consumption and cost, but the lowest discomfort values. To understand the driving factors behind this ranking, the priorities of residential EMCAs, using the *DBS* and *DBM* methods, relative to the criteria are given in Table 20.

Table 20. **Priorities Computed Using the *DBS* and *DBM* methods**

Residential EMCAs	Criteria Priorities - *DBS*			Criteria Priorities - *DBM*		
	Energy	Cost	Discomfort	Energy	Cost	Discomfort
1	0.17	0.17	0.053	0.98	0.94	0.113
2	0.17	0.17	0.001	0.98	0.94	0.003
3	0.18	0.18	0.000	1.00	1.00	0.001
4	0.17	0.17	0.002	0.95	0.92	0.005
5	0.16	0.16	0.471	0.93	0.90	1.000
6	0.15	0.15	0.471	0.83	0.81	1.000

Table 20 show that both residential EMCA5 and residential EMCA6 have the highest priorities for the discomfort criterion, but the lowest priorities for the energy and cost criteria, suggesting that the overall scores have been dominated by the discomfort criterion. In terms of thermal comfort, the difference between residential EMCA5 and residential EMCA6 is insignificant; however, residential EMCA6 consumes 12.1 % more energy and 11.9 % greater cost relative to residential EMCA5. In contrast, residential EMCA3 has the highest priorities for the energy and cost criteria, but much smaller priority for the discomfort criterion. Residential EMCA3 is ranked fourth. In terms of thermal comfort, the difference between residential EMCA5 and residential EMCA3 is significant; however, residential EMCA3 consumes 6.8 % less energy and 9.7 % greater cost savings relative to residential EMCA5. In terms of thermal comfort, the difference between residential EMCA6 and residential EMCA3 is significant; however, residential EMCA3 consumes 16.8 % less energy and 19.3 % greater cost savings relative to residential EMCA6. The results of Table 20 suggest that using *DBS* and *DBM* methods could ignore the contribution of other criteria to the overall scores when one criterion exhibits dominant performance with respect to other criteria. If energy and cost savings are important factors, using the direct normalization methods can produce incorrect rankings.

As previously mentioned, the choice of normalization method can impact the overall scores, leading to different rankings. Although applying *DBS* and *DBM* to the data in the Performance Table generated consistent rankings, it is possible for these methods to produce different rankings. An example of this inconsistency in ranking, using the two methods, is given in Exhibit 4-6 of [23]. This example was reproduced in Table 21 and compared to the rankings produced by the *MPC* method described in this document. In this example, there are three alternatives characterized by numerical data with respect to the two criteria, warranty and price. Table 21 shows the overall scores for choosing among alternatives, comparing the ranking consistencies of the overall scores, for three alternatives, obtained by applying the *DBS*, *DBM*, and *MPC* methods.

Table 21. Comparison of the ranking consistency of the overall scores using the DBS, DBM, and MPC methods

Alternatives	Warranty Criteria (y)	Price Criteria ($)	Overall Scores			
			DBS	DBM	MPCDBS	MPCDBM
A	1	100	0.353	0.667	0.209	0.209
B	2	200	0.301	0.583	0.093	0.093
C	3	280	0.346	0.679	0.198	0.198

As can be seen from Table 21, the *DBS* and *DBM* methods lead to different rankings of the alternatives. The *DBS* method leads to ranking Alternative A higher than Alternative C. However, the *DBM* method leads to ranking Alternative C higher than Alternative A. In contrast, Alternative A is consistently ranked higher than Alternative C when priorities are computed by the *MPC* method described in this document. The *MPC* method ranks Alternative A higher regardless of using *DBS* or *DBM* normalization methods. Similar consistencies in rankings, regardless of using different normalization methods, were observed in Figure 11.

Lastly, the impact of using different linear comparison scales, i.e., C_{scale}, on the overall scores and possible rank reversal were studied. In addition to C_{scale}, two other comparison scales were used:

$$\begin{aligned} C_{scale1-5} &= [1,2,3,4,5] \\ C_{scale1-15} &= [1,2,3,4,5,6,7,8,9,10,11,12,13,14,15] \end{aligned} . \tag{1.24}$$

Using Eq. (1.2), the overall scores for each alternative residential EMCA for different comparison scales are given in Figure 12.

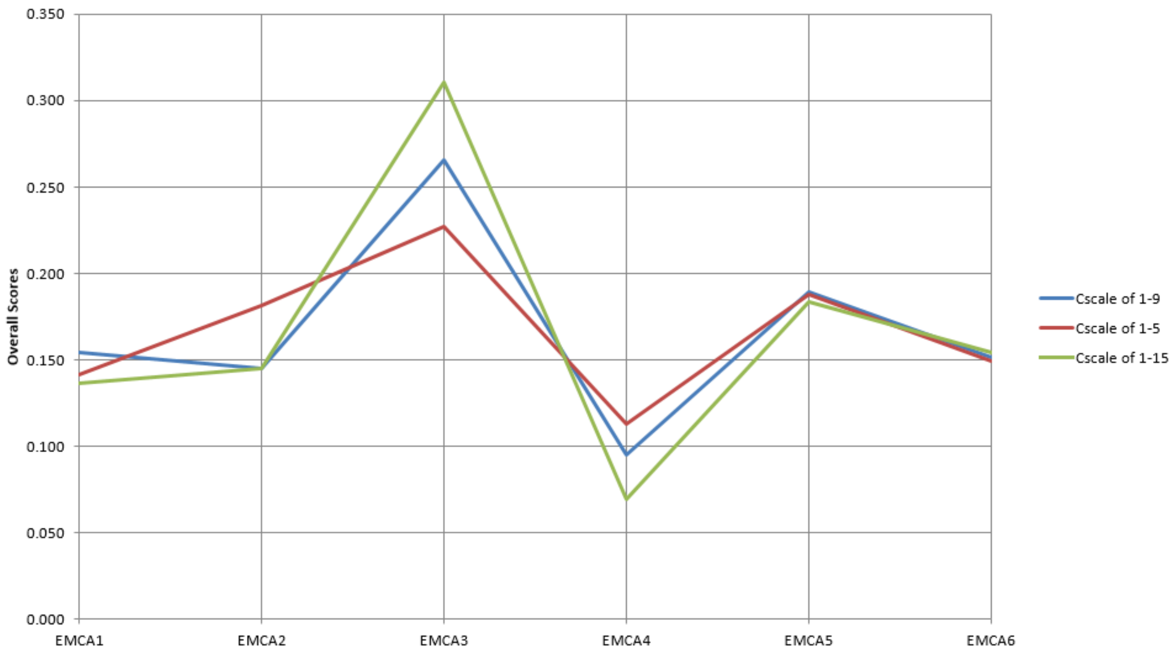

Figure 12. The overall scores for residential EMCAs using three different linear comparison scales

For all comparison scales, the data in Figure 12 shows that residential EMCA3 and residential EMCA5 are ranked the highest and the second highest, respectively; while residential EMCA4 is ranked the lowest. Rank reversal only affected the residential EMCAs with close overall scores and not the ones with the dominant scores. Table 22 shows the overall scores for residential EMCAs and their corresponding rankings in descending order for all comparison scales.

Table 22. The Overall Scores Ranked in Descending Order

Comparison scale 1-9		Comparison scale 1-5		Comparison scale 1-15	
Residential EMCAs	**Overall Scores**	**Residential EMCAs**	**Overall Scores**	**Residential EMCAs**	**Overall Scores**
3	0.266	3	0.227	3	0.311
5	0.189	5	0.188	5	0.184
1	0.154	2	0.181	6	0.154
6	0.151	6	0.150	2	0.145
2	0.145	1	0.142	1	0.136
4	0.095	4	0.113	4	0.070

As shown in Table 22, rank reversal only affected residential EMCA1, residential EMCA2, and residential EMCA6 as their overall scores are close to each other. However, the best and worst residential EMCAs, in terms of ranking, remain in their positions.

10. Limitations

Even though the AHP's theoretical foundations has been subject of debate in the literature [23], [37], it is the most widely used [24], [38] approach for solving practical multi-criteria decision making problems. Therefore, AHP was chosen for this study to develop the AE. Application of the AE requires hourly energy consumption data from HVAC equipment and the hourly price of electricity for computing the cost. It also requires one-minute sampling of indoor air temperature, mean radiant temperature, relative humidity, and an occupancy schedule. In the current study, to calculate PPD_{wc} the mean radiant temperature in the NZERTF was assumed to be the same as the indoor air temperature. This assumption may not be valid for residential homes where the indoor temperatures are significantly impacted by direct solar radiation. Additionally, the current implementation of the AE only considers a three-level hierarchy (goal, criteria, and alternatives), while AHP provides a much more flexible framework for incorporating additional levels, criteria, and sub-hierarchies. The scope of this study was limited to three criteria and six residential EMCAs.

11. Conclusion

For homes to become active participants in a smart grid, intelligent control algorithms are needed to facilitate autonomous interactions that take homeowner preferences into consideration. Many control algorithms for demand response have been proposed in the literature. Comparing the performance of these algorithms has been difficult because each algorithm makes different assumptions or considers different scenarios, i.e., peak load reduction or minimizing cost in response to the variable price of electricity. This work proposes a flexible assessment framework using the Analytical Hierarchy Process to compare and rank residential energy management control algorithms. The framework is a hybrid mechanism that derives a ranking from a combination of subjective user input representing preferences, and object data from the algorithm performance related to energy consumption, cost and comfort. The Analytical Hierarchy Process results in a single overall score used to rank the alternatives. The approach is illustrated by applying the assessment process to six residential energy management control algorithms. The assessment and ranking of residential EMCAs was successfully demonstrated, showing that residential EMCA3 was ranked the highest.

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References

[1] EIA, "Monthly Energy Review," *Table 7.6 Electricity End Use, U.S. Energy Information Administration*, 2018. [Online]. Available: https://www.eia.gov/totalenergy/data/monthly/pdf/sec7_19.pdf. [Accessed: 13-Mar-2018].

[2] EIA, "Annual Energy Outlook 2018 with projections to 2050," *Table 4: Residential Sector Key Indicator and Consumption, U.S. Energy Information Administration*, 2018. [Online]. Available: https://www.eia.gov/outlooks/aeo/pdf/AEO2018.pdf. [Accessed: 13-Mar-2018].

[3] "Energy Independence and Security Act of 2007," United States, Public Law 110-140, 2007.

[4] NIST, "NIST Framework and Roadmap for Smart Grid Interoperability Standards, Release 3.0," *NIST Spec. Publ. 1108R3*, 2014.

[5] U.S. Department of Energy, "Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them," 2006.

[6] J. S. Vardakas, N. Zorba, and C. V. Verikoukis, "A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms," *IEEE Commun. Surv. Tutorials*, vol. 17, no. c, pp. 1–1, 2014.

[7] R. Deng, Z. Yang, M.-Y. Chow, and J. Chen, "A Survey on Demand Response in Smart Grids: Mathematical Models and Approaches," *IEEE Trans. Ind. Informatics*, vol. 11, no. 3, pp. 1–1, 2015.

[8] P. Siano, "Demand response and smart grids—A survey," *Renew. Sustain. Energy Rev.*, vol. 30, pp. 461–478, 2014.

[9] C. Chen, S. Kishore, and L. V. Snyder, "An innovative RTP-based residential power scheduling scheme for smart grids," *ICASSP, IEEE Int. Conf. Acoust. Speech Signal Process. - Proc.*, pp. 5956–5959, 2011.

[10] A. H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 120–133, 2010.

[11] M. Avci, M. Erkoc, A. Rahmani, and S. Asfour, "Model predictive HVAC load control in Buildings using real-time electricity pricing," *Energy Build.*, vol. 60, pp. 199–209, 2013.

[12] A. Afram, F. Janabi-sharifi, A. S. Fung, and K. Raahemifar, "Artificial neural network (ANN) based model predictive control (MPC) and optimization of HVAC systems : A state of the art review and case study of a residential HVAC system," *Energy Build.*, vol. 141, pp. 96–113, 2017.

[13] J. H. Yoon, R. Baldick, and A. Novoselac, "Demand response control of residential HVAC loads based on dynamic electricity prices and economic analysis," *Sci. Technol. Built Environ.*, vol. 22, no. 6, pp. 705–719, 2016.

[14] T. Cui, S. Chen, Y. Wang, Q. Zhu, S. Nazarian, and M. Pedram, "Optimal co-scheduling of HVAC control and battery management for energy-efficient buildings considering state-of-health degradation," *Proc. Asia South Pacific Des. Autom. Conf. ASP-DAC*, vol. 25–28–Janu, pp. 775–780, 2016.

[15] F. Nägele, T. Kasper, and B. Girod, "Turning up the heat on obsolete thermostats: a simulation-based comparison of intelligent control approaches for residential heating systems," *Renew. Sustain. Energy Rev.*, vol. 75, pp. 1254–1268, 2017.

[16] J. Lu, T. Sookoor, V. Srinivasan, G. Gao, B. Holben, J. Stankovic, E. Field, and K. Whitehouse, “The Smart Thermostat: Using Occupancy Sensors to Save Energy in Homes,” *Proc. ACM SenSys*, vol. 55, pp. 211–224, 2010.
[17] K. X. Perez, M. Baldea, and T. F. Edgar, “Integrated smart appliance scheduling and HVAC control for peak residential load management,” *Proc. Am. Control Conf.*, vol. 2016–July, pp. 1458–1463, 2016.
[18] B. Urban and K. Roth, “A Data-Driven Framework for Comparing Residential Thermostat Energy Performance,” Fraunhofer Center for Sustainable Energy Systems, Final Report | Co-Developed with NEST, 2014.
[19] J. Iwaro, a Mwasha, R. Williams, and R. Zico, “An Integrated Criteria Weighting Framework for the sustainable performance assessment and design of building envelope,” *Renew. Sustain. Energy Rev.*, vol. 29, pp. 417–434, 2014.
[20] C. J. Hopfe, G. L. M. Augenbroe, and J. L. M. Hensen, “Multi-criteria decision making under uncertainty in building performance assessment,” *Build. Environ.*, vol. 69, pp. 81–90, 2013.
[21] T. L. Saaty, *Multicriteria Decsion Making: The Analytic Hierarchy Process*. University of Pittsburgh, 1988.
[22] S. D. Pohekar and M. Ramachandran, “Application of multi-criteria decision making to sustainable energy planning - A review,” *Renew. Sustain. Energy Rev.*, vol. 8, no. 4, pp. 365–381, 2004.
[23] G. A. Norris and H. E. Marshall, “Multiattribute decision analysis method for evaluating buildings and building systems.,” *NIST Tech. Note 5663*, 1995.
[24] O. S. Vaidya and S. Kumar, “Analytic hierarchy process: An overview of applications,” *Eur. J. Oper. Res.*, vol. 169, no. 1, pp. 1–29, 2006.
[25] ASTM, “Standard Practice for Applying Analytical Hierarchy Process (AHP) to Multiattribute Decision Analysis of Investments Related to Buildings and Building Systems 1,” 2016.
[26] J. Lofberg, “YALMIP : a toolbox for modeling and optimization in MATLAB,” in *2004 IEEE International Conference on Robotics and Automation (IEEE Cat. No.04CH37508)*, 2004, pp. 284–289.
[27] F. Omar, S. T. Bushby, and R. D. Williams, “Energy Management Control Algorithms for the Net Zero Residential Test Facility,” *NIST Tech. Note xxxx*, 2018.
[28] E. Balke, G. Nellis, S. Klein, H. Skye, V. Payne, and T. Ullah, “Detailed energy model of the National Institute of Standards and Technology Net-Zero Energy Residential Test Facility: Development, modification, and validation,” *Sci. Technol. Built Environ.*, vol. 0, no. 0, pp. 1–14, 2017.
[29] F. Omar and S. T. Bushby, “Simulating Occupancy in The NIST Net-Zero Energy Residential Test Facility,” *NIST Tech. Note 1817*, 2013.
[30] S. Carlucci and L. Pagliano, “A review of indices for the long-term evaluation of the general thermal comfort conditions in buildings,” *Energy Build.*, vol. 53, pp. 194–205, 2012.
[31] ISO 7730, “Erogonomics of the Thermal Environment - Analytical Determination and Interpretation of Thermal Comfort Using Calculation of the PMV and PPD Indices and Local Thermal Comfort Criteria,” 2005.
[32] ASHRAE, “Standard 55-2010. Thermal Environmental Conditions for Human Occupancy.Atlanta: American Society of Heating Refrigerating and Air Conditioning

Engineers," Atlanta, USA, 2010.
[33] N. Walikewitz, B. Jänicke, M. Langner, F. Meier, and W. Endlicher, "The difference between the mean radiant temperature and the air temperature within indoor environments: A case study during summer conditions," *Build. Environ.*, vol. 84, pp. 151–161, 2015.
[34] M. Langner, K. Scherber, and W. R. Endlicher, "Indoor heat stress: An assessment of human bioclimate using the UTCI in different buildings in Berlin," *DIE ERDE*, vol. 144, no. 3–4, pp. 260–273, 2013.
[35] L. Ng, "A Software Program for Calculating PMV and PPD." Private Communications, National Institute of Standards and Technology, MD, 2017.
[36] A. Persily and L. de Jonge, "Carbon dioxide generation rates for building occupants," *Indoor Air*, vol. 27, no. 5, pp. 868–879, 2017.
[37] A. Ishizaka and M. Lusti, "How to derive priorities in AHP: A comparative study," in *Central European Journal of Operations Research*, 2006, vol. 14, no. 4, pp. 387–400.
[38] R. D. F. S. M. Russo and R. Camanho, "Criteria in AHP: A systematic review of literature," *Procedia Comput. Sci.*, vol. 55, no. Itqm, pp. 1123–1132, 2015.