

Fuzzy model of residential energy decision-making considering behavioral economic concepts

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HIGHLIGHTS

- Fuzzy logic is used to predict cooling energy use considering behavioral economic principles.
- The model accounts for both the efficiency and curtailment dimensions of household consumption.
- The model produces plausible behaviors and the results match historical values reasonably well.

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ABSTRACT

To gain a fundamental understanding of the factors driving consumer energy behavior and for more effective policy-making, the development of energy consumption models taking into account key behavioral economic concepts is essential. In this direction, this paper presents a fuzzy logic decision-making model incorporating the concepts of bounded rationality, time discounting of gains, and pro-environmental behavior. The fuzzy model is used to characterize and predict consumer energy efficiency and curtailment behaviors in the context of residential cooling energy consumption. The model is developed from the perspective of the human decision-maker and the rules based on human reasoning and intuition. It takes into consideration monetary, personal comfort and environmental responsibility variables to yield predictions of one's air-conditioning purchase and usage decisions. The results from running the model multiple times to simulate a real large urban population are found to match historical cooling energy use data reasonably well. This allows modelers some degree of confidence in the model. Moreover, perturbing key input variables produces plausible behaviors, thus providing additional validation to the model. This work demonstrates the feasibility of fuzzy logic as a powerful method for combining quantitative economic and physical factors with qualitative behavioral concepts in a single mathematical framework for better prediction of human energy behavior, and greater fundamental understanding of the “why” behind energy use that conventional building energy simulation models do not address.

1. Introduction

The residential sector accounts for significant amounts of energy consumption and greenhouse gas (GHG) emissions. Residential buildings account for 16–50% of total energy use at the national level and 31% globally [1,2]. Therefore, energy efficiency policies targeting the residential sector are crucial for reducing overall energy demand and GHG generation. Oftentimes, however, there are significant differences between the realized and targeted levels of efficiency [3]. In other words, “energy efficiency gaps” or “energy efficiency paradoxes” [4–6] are widespread in markets. This is likely because policy-makers typically neglect the behavioral aspect of energy use despite the large body of evidence proving the significance of “non-economically rational”

human behavior in residential energy decision-making.

Conventionally, energy policies are formulated largely based on traditional, neoclassical economic principles, which view human decision-making as independent from non-monetary values and goals [7], and assume agents make decisions under complete economic rationality, i.e., that they are perfectly capable of making utility maximizing choices. It is starting to be recognized though, by behavioral economists [8] who strive to integrate psychological insights into economic analysis, that human decisions are also driven by personal values, judgment and feelings, and that human rationality is bounded. Nevertheless, the application of behavioral economics to the formulation of energy policies is still very limited.

Hence, this paper aims to advance the integration of behavioral

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economic concepts to residential energy behavior modeling for the purpose of policy-making. Specifically, fuzzy logic [9] is employed to construct an integrated energy behavior model to characterize and predict consumer energy efficiency and curtailment behaviors [10]. The former is about consumers' decisions to invest in energy-efficient appliances, while the latter concerns their day-to-day use of the appliances. Though the two behaviors are motivated by different psychological drivers [11,12], they are best studied simultaneously [12] for a holistic view of the problem. However, efficiency behavior is under-represented in past studies [13]. This is despite policies targeting it (as compared to policies targeting curtailment behavior) being generally more acceptable to the public [14–16] and having greater energy saving potential [13,17]. Thus, this paper seeks to combine the two behaviors in a single fuzzy framework.

This paper also seeks to incorporate pro-environmental behavioral constructs and their effects on consumer energy behavior to the fuzzy model. At present, while the existence of these altruistic constructs is well accepted in behavioral economics, it is still unclear their exact relationship with energy efficiency and curtailment behaviors [18–22]. In this paper, through experimentation with different configurations of the fuzzy model developed, it is gained new insights into the matter.

Fuzzy logic, an artificial intelligence method, uses linguistic variables and heuristic associations to approximate, in numerical terms, human reasoning and intuition. It is thereby suitable for combining quantitative economic and physical factors with qualitative behavioral concepts. However, only a few fuzzy logic-based simulations of residential energy management have thus far been conducted [23–28]. These studies focused mostly on just energy usage relating to users' curtailment behavior with little or no regards for their efficiency behavior. Further, some of the past studies included only the effects of monetary terms [26]. Others included also non-monetary manifestations [23–25,27,28] but without proper consideration of the underlying behavioral drivers. Thus, the fuzzy model developed in this present paper can be seen as a major improvement over existing related fuzzy models given its incorporation of major behavioral economic principles, and integration of consumer energy efficiency and curtailment behaviors to yield a more holistic take on modeling residential energy decision-making.

To the best of knowledge, this present work is the first to use fuzzy logic to model residential energy consumption from the perspective of behavioral economics. As such, it contributes to the literature in its innovative use of fuzzy logic: (i) to integrate key behavioral concepts (bounded rationality, time discounting and pro-environmental behavior) with economic, demographic and climate variables in the context of residential energy management; (ii) to capture both the efficiency and curtailment behaviors of residential consumers by modeling energy decisions not only at the stage of usage, but also at the prior stage of appliance purchase; and (iii) to simulate the long-term energy consumption of a large urban population. As emphasized by Stern [29], the integrating of variables and concepts of different natures by this study is essential for a comprehensive fundamental understanding of the factors driving domestic energy use. The fuzzy model developed is used to predict the average monthly and annual cooling energy consumptions in Hong Kong, and is validated by comparing the results against historical data. Further validation of the model is realized by conducting sensitivity analyses of key model inputs. From the results, new insights are obtained especially in regards to pro-environmental behavior whose exact influence on residential energy behavior is still uncertain. It is hoped the results will contribute to the development of more effective energy policies.

2. Background

2.1. Modeling residential energy decision-making

Energy behavior is a multidisciplinary subject that has been studied

by investigators from a wide range of disciplines, from social sciences to engineering. Thus, studies on the topic can vary significantly in their objectives and methods. In a comprehensive review on residential energy behavior modeling studies, Lopes et al. [30] grouped the studies into three main categories: (i) quantitative studies which relied mostly on engineering and statistical methods to predict energy use; (ii) qualitative studies which focused on socio-psychological frameworks and theories to explain energy consumption; (iii) and finally, hybrid studies combining elements from the 1st and 2nd categories. This present study can be placed under the 3rd category.

2.1.1. Quantitative studies

Studies in this category rely primarily on technical models to quantify energy consumption. The models can be classified as either “top-down” or “bottom-up” [2,31–35]. Top-down models typically focus on energy supply and demand at the macro level to capture long-term trends, and are usually such that the residential sector is just one among many sub-systems. Top-down models can be further divided into technological and econometric models; the former are mostly about the effects of housing stock characteristics, appliance ownership and trends in technology, while the latter mostly about the effects of pricing (e.g. time-of-use rates and dynamic pricing [34]), income and other economic variables [2,31]. In contrast, bottom-up models aim to predict energy consumption at the regional and national levels by extrapolating from estimated data for selected individuals, households and/or buildings. Bottom-up models can be further characterized as statistical or engineering. The former employs statistical techniques (e.g. regression, conditional demand analysis, neural networks) [35–38] to identify representative patterns, while the latter utilizes detailed simulation models based on building characteristics and climate variables to make predictions [39,40]. In addition, there also exist hybrid models that rely on a combination of both statistical and engineering methods [41]. For more on top-down and bottom-up models and their differences, refer to Swan and Ugursal [2], Kavgić et al. [31], Grandjean et al. [33], Suganthi and Samuel [32], and Fumo and Biswas [35].

Quantitative studies are important as they provide reliable ways of quantifying consumption, and are essential for assessing energy policies, e.g. technology adoption and energy efficiency policies. However, they do not adequately consider human behavioral factors and their effects. This is especially true in the case of top-down models that pay scant attention to individual end-users, and where any reference to human behavior is typically through the traditional economic notions of complete rationality and utility maximization. As for bottom-up models, thus far, their use to represent human behavior is still limited and mostly confined to the contexts of pre-determined occupancy schedules and equipment use patterns [30]. (While there are exceptions outside these contexts [42–44], they are few.) This is despite their greater focus on the decisions of individual agents and greater acknowledgment of the role of behavioral factors (as compared to top-down models).

2.1.2. Qualitative studies and behavioral economic concepts

Studies in this category are essentially behavioral studies concerned with the role of behavioral factors in human energy decision-making. See Wilson and Dowlatabadi [18], Faiers et al. [45] and Frederiks et al. [46] for comprehensive reviews of the subject. The reviews demonstrate the complexity of the problem given the large number of cognitive biases and behavioral anomalies at play. Behavioral economic theories are of central importance to studies of this category as they are essential for explaining decision-making inconsistencies due to the bounded rationality of humans, their time discounting of gains and pro-social behavioral influences [47].

Bounded rationality refers to the deviation of individuals from complete economic rationality due to constraints in knowledge, cognition and time [48]. According to Nobre [49], it leads to decision-making based on imperfect information and heuristics that prevents

agents from identifying optimal solutions to everyday life problems. This leads to them making alternative decisions that are just adequate or approximately optimal. Bounded rationality, however, does not mean acting irrationally or in an unreasonable manner [50]. Instead, boundedly rational behavior can be thought of as a deviation from that is “expected” (as dictated by monetary terms and as defined by classical economics) due to the above-mentioned limitation as well as non-monetary considerations, viz. personal preferences and values, emotions, social interactions and psychological factors. [8]. The failure of energy policies to properly account for bounded rationality has been identified as a primary reason for energy efficiency gaps due to unanticipated consumer responses [5,51]. However, to account for bounded rationality is not straightforward as there still lacks a single widely accepted method to model and predict its effects on one’s energy decisions [5].

Agents’ time discounting of gains occurs due to differences in their valuation of future benefits versus present ones. Agents time discount not only monetary items, but non-monetary gains and pleasures as well. Those with a high time discount rate regard future rewards as highly discounted and thus, of lesser importance than present rewards. In their deliberations, these individuals (often characterized as “present-biased”) tend to give a low weight to the future consequences of present actions. In contrast, agents with a low time discount rate are more willing to pay a cost today to reap future benefits [52]. Compared to those with a high discount rate, these individuals assign greater importance to future consequences. In relation to energy decisions, individuals with a high time discount rate are less likely to purchase energy-efficient appliances as compared to those with a low time discount rate since such appliances are generally more expensive to purchase but cheaper to operate [53]. Finally, it is worth noting that individuals’ time discount rates can change with time; when this is the case, the rates are said to be time inconsistent [18].

Pro-social behavior often manifests as pro-environmental behavior, of which the antecedents are certain psychological constructs [21] that when triggered, prompt one to take appropriate actions to protect the environment. These constructs have been referred to in the literature as one’s environmental “values” [20,54,55], “beliefs” [19,21,54,56–58], “concerns” [20,57], “attitudes” [19,21,56], “drivers” [59], “awareness” [60], etc. (While some have viewed these different terms to mean the same concept [19], most distinguish between them and see them as having subtle differences.) However, it is as yet unclear their exact role in pro-environmental behavior with specific regard to energy management. This has led to the debate on whether these constructs indeed constitute significant drivers of energy efficiency and curtailment behaviors [18,21]. Some survey-based studies have found just a weak correlation between the constructs and home energy use [19,20], while others have observed a strong correlation [21,22].

To summarize, qualitative energy studies are more theoretical (as opposed to quantitative studies) and are mostly about the psychological factors (affecting consumer values, preferences, and personal habits) and contextual considerations (as defined by the choices available, economic and technological incentives afforded, and social habits of peers) driving energy decisions [18]. Different from quantitative studies, qualitative studies mainly rely on methods involving surveys, interviews, and focus groups [30,61]. However, while these studies have made great progress in explaining the non-monetary aspects of residential energy consumption, there still lacks a unified framework integrating the various concepts and principles. Without a single framework, the studies reduce to simply a series of ad-hoc examples and narratives [46] that stand isolated and unable to link to any quantitative simulation.

2.1.3. Integrated studies

As described above, relying on just either a quantitative or qualitative approach leads to weaknesses. Specifically, taking a quantitative approach employing traditional economic, engineering and/or

statistical techniques exclude consideration of key behavioral factors, while taking a qualitative approach employing surveys, interviews and/or focus groups results in disjointed findings due to the lack of a unified framework to integrate major concepts. Thus, as energy behavior is complex with multiple dimensions, an integrated approach combining both quantitative and qualitative methods and their findings is essential. Such an approach however, is not simple given the multi-disciplinary interdisciplinary nature of the problem.

In practice, very few integrated studies exist to date. An early study combined energy modeling with interviews aimed at revealing consumers’ energy consumption preferences. In the study, an energy accounting software was used to inform participants of their energy use amounts, and to present them with alternative choices [62]. The results based on the participant responses revealed a wide range of user energy consumption profiles of varying levels of willingness to change. In other studies, user energy profiles were extracted by comparing data from modeling simulations with empirical data acquired through examining written time diaries of participants detailing their daily activities [63,64]. While these studies have provided new insights and initial guidance on conducting integrated studies, they are still few and limited in scope. This leaves a gap in the literature that remains to be filled.

To contribute to filling this gap, this current paper aims to develop an integrated energy behavior model using fuzzy logic, an artificial intelligence method. Unlike the previous studies described above, integration in this study is performed not by quantitative analysis of empirical behavioral data, but instead, by using fuzzy logic to provide a means for the mathematical expression of human behavioral factors, preferences and perspectives, and the placing of these elements in a single framework in coherence with other physical and socio-economic variables. This allows for the mapping of the different components and their interactions, which is vital for identifying the relative importance of each in regard to the decision-making process as a whole. As discussed by Stern [29], research of this kind and in this direction is presently considered key towards a much needed holistic understanding of household energy use.

2.2. Fuzzy logic

2.2.1. Basic concepts

The theory of fuzzy sets was first introduced by Zadeh [9] in 1965 in an attempt to mathematically represent imprecise (or “fuzzy”) data. Fuzzy logic enables the assignment of numerical values to linguistic terms (e.g. “large,” “small,” “hot,” “cold,” “better”) whose boundaries are inexact. Fuzzy logic has been mooted by some [49,65,66] as suitable for simulating natural, real-life situations fairly correctly. In this subsection, to introduce fuzzy logic, it is provided a brief description of its main concepts. For a more detailed description, refer to [9,67–72].

In fuzzy logic, subsets are characterized as either crisp or fuzzy. To illustrate the difference between the two, consider the crisp subset A of the universe of discourse X. As A is crisp, its boundaries are exact and hence, the belonging of a certain variable x in A is also exact. And thus, the statement “ x belongs in A” is either completely true or completely false depending on the value of x and the boundaries of A. On the contrary, if subset A were instead fuzzy with inexact boundaries, the belonging of x in A is then inexact. When this is the case, the statement “ x belongs in A” can now also be partially true, and the degree to which it is true (or in other words, the degree of satisfaction of the statement) representable as a fraction between 0 and 1. A value of 0 implies the statement to be completely false, a value of 1 implies it to be completely true, and any other value in between implies it to be partially true. The value of this fraction given a particular value of x is as defined by the assigned membership function relating the two variables. Membership functions can take any form depending on the system that is being modeled and the subjective perceptions of agents. In practice, membership functions are usually defined as triangular, trapezoidal, Gaussian, or bell-shaped.

A fuzzy logic problem is typically solved through a fuzzy inference system (FIS) comprising a set of algorithms [24]. A FIS facilitates the mapping of inputs to one or several outputs via an inference mechanism and a series of fuzzy if-then rules. Fuzzy rules are commonly constructed based on human knowledge, intuition and heuristics [24]. They follow the format “if x is A then y is B .” The former part is known as the antecedent and represents the application of specific values to the inputs, while the latter part is the consequent and represents the resulting output value or values [24].

2.2.2. Fuzzy logic and behavioral economics

Various scholars from different disciplines ranging from psychology to economics to engineering have proposed fuzzy logic as a suitable tool for modeling human behavior. Tron and Margalio [65] described fuzzy logic as an effective means of creating models according to intuition and observed behaviors of agents. Nobre et al. [49] considered it an adequate computational and mathematical framework for representing approximate reasoning considering natural concepts in everyday life, which one forms from personal self-knowledge, observations and experiences, and which according to Bernstein [73], have “fuzzy boundaries.”

Against this backdrop, fuzzy logic can be deemed as particularly appropriate for the measurement and understanding of behavioral economic principles. E.g., Trillas [66] regarded it as an effective method for incorporating realistic model assumptions based on “non-standard” preferences (as defined in behavioral economics, and which have also been characterized as fuzzy [66,74]), and for measuring an individual’s different degrees of rationality. The behavioral economic concept most strongly associated with fuzzy logic thus far is bounded rationality. Since bounded rationality manifests as a degree of deviation from the expected behavior (where, as described above, is as defined by classical economics considering solely monetary factors), it can be seen as analogous to a variable’s degree of membership in a fuzzy subset [49].

However, as discussed by Trillas [66], research on behavioral economics and bounded rationality is still not sufficiently influenced by fuzzy logic. This is likely due to the yet limited number of studies with practical examples demonstrating the use of the method to explain or mimic human behavior. Herein lies an area of contribution of this present paper. It is hoped the fuzzy integrated energy behavior model developed here will be of interest to behavioral economists as an application of fuzzy logic to capture and investigate key concepts from the field.

2.2.3. Applications in energy demand modeling

2.2.3.1. *Without consideration of behavioral factors.* Traditionally, the large majority of fuzzy logic applications have been to solve engineering problems [75] e.g. to optimize automated system controllers [76,77]. In energy use modeling, there too have been engineering applications of fuzzy logic, e.g. to make quantitative predictions of short-term energy loads of power systems [78–82], but these studies considered just physical factors with no regard for human behavioral aspects. For instance, Pandian et al. [83] considered the effects of time and climatic variables, while Al-Anbuky et al. [84] geographic and demographic variables. For more accurate predictions, some studies have combined fuzzy logic with neural networks [85–87]. Fuzzy logic has also been combined with clustering; e.g. Räsänen et al. [88] used self-organizing maps and the k-means algorithm to categorize consumers into groups, then fuzzy logic to further characterize them. In the field of energy, fuzzy logic has also been used to develop intelligent controllers for optimizing building cooling and/or heating systems to achieve maximum thermal comfort. Such fuzzy controllers, which have been applied in both residential and commercial settings, commonly receive the inputs of weather conditions and building characteristics. For salient examples of studies on this topic, see Ahmed et al. [89], Lygouras et al. [90] and Karunakaran et al. [91].

2.2.3.2. *With partial consideration of behavioral factors.* There have also been energy studies using fuzzy logic that have sought to formulate the problem from the consumer’s perspective (even though not exclusively) and with some consideration of behavioral factors. For example, Kiartzis et al. [78], Mamlook et al. [82] and Ranaweera et al. [92] developed fuzzy models to predict short-term electricity load from consumers’ historical energy consumption (which can be taken as a representation of human behavior). Also, Zhai and Williams [93] employed fuzzy logic to relate consumer perception variables to the adoption of renewable energy systems. Such studies are still few, however.

As for fuzzy logic studies specifically focused on residential energy consumption (as in this present study), those including behavioral factors are even fewer. E.g. Michalik et al. [23] used fuzzy linguistic variables to account for uncertainties in individuals’ preferences in regard to their use of home appliances. In another study, Zúñiga et al. [24] used fuzzy logic to model the energy consumption from the use of home appliances by considering users’ schedules and routines given their individual energy behaviors. Similarly, Ciabattini et al. [25] developed a fuzzy model of residential electricity use considering consumer scheduling patterns, and also their sensibility towards rational energy use depending on monetary factors. Further, Keshtkar and Arzanpour [28] developed a fuzzy controller for the thermostat of a residential system considering electricity prices and occupant schedules. Rezeko et al. [27] also developed a fuzzy controller to optimize the temperature and humidity of residential buildings, but one based on the order of importance of rooms, which indirectly depends on their use patterns by occupants.

While the above-mentioned studies constitute a promising start in employing fuzzy logic as an instrument to model human behavior in energy management, they were mostly confined to short-term consumption problems and represented human behavior only partially, i.e., they considered mostly curtailment behavior, and solely by the modeling of schedules, consumption histories and household routines. The studies did not consider at all behavioral economic principles nor investigated the behavioral drivers behind energy usage. Thus, this present paper is an advancement over the previous studies. Not only does the fuzzy model developed herein explicitly incorporate key behavioral economic concepts, it also considers both curtailment and efficiency actions. Moreover, the fuzzy model in this paper is targeted at predicting long-term energy consumption (as opposed to the fuzzy models of the previous studies, which aimed at making short-term estimations).

3. Methods and data

3.1. Overview of fuzzy model

Fuzzy logic is used to develop a model to simulate the energy efficiency and curtailment behaviors of residential agents to predict the cooling energy consumption in Hong Kong. Each agent is assumed as the decision-making member of his or her household. Thus, for the remainder of the paper, the terms “agent” and “household” shall be used interchangeably. (In this paper, no differentiation is made between the two even though the energy behavior literature does differentiate between individual-level and household-level [30] energy decision-making, and the different factors affecting them.) See the following for the main equation and principles of the model. The model centers around Eq. (1) below to estimate the cooling energy consumption of a household in a given month m :

$$E_m = Cap \left(\frac{1}{EER} \right) H_m \quad (1)$$

E_m is the energy consumed (in kWh) over the month, Cap the total cooling capacity of the household’s air-conditioning (AC) system (in kW), EER the energy efficiency ratio of the AC system (in W/W), and H_m the AC system’s total number of hours of operation in month m . Note

that inherent to the equation is the assumption that the AC system runs at full capacity whenever operated. Summing E_m over all months in the cooling season (which in the case of Hong Kong, starts in May and ends in October) gives the annual cooling energy demand for the year, E_a .

The Fuzzy Logic Toolbox of MATLAB [72] is used to construct the model, which comprises three FISs [24]. Each FIS predicts a decision corresponding to a particular variable in Eq. (1): FIS 1 predicts Cap , FIS 2 predicts EER and FIS 3 predicts H_m . FISs 1 and 2 aim to represent the efficiency behavior of the household and are applied at the start of the simulation. FIS 3 aims at representing the household’s curtailment behavior and is applied on an ongoing basis. The FISs consist of membership functions defined according to common practices in the literature [69–71] and intuition, and by trial and error to produce results of the highest accuracy possible when compared to historical data. Each receives a unique set of inputs fixed according to expert knowledge and

intuition. The inputs represent demographic and psychographic [22] variables deemed as having the greatest influence on consumer AC purchase and usage decisions [44], and are fed to the FISs as crisp numerical values. The inputs are first fuzzified by the FISs according to the membership functions constituting the FISs to identify their corresponding linguistic terms. Fuzzy rules (Table 1) which have been defined following intuition and tuned to yield the most accurate results (as in the case of the membership functions) are then applied to yield intermediate fuzzy outputs. Finally, to produce the final desired crisp outcomes, the fuzzy intermediates are defuzzified by the centroid method [72] according to, again, the membership functions of the FISs.

All 3 FISs are of the Mamdani type, the most widely used FIS type [24,72,94]. Mamdani inference is selected as it is considered to be the most intuitive and well suited to human input [72,95] making it befitting for use here considering the study objective to model energy

Table 1
Fuzzy if-then rules constituting FISs 1, 2 and 3; the antecedent and consequent variables, and linguistic terms are as defined in the main text.

Rule	Antecedent (IF)						Consequent (THEN)			Rule	Antecedent (IF)						Consequent (THEN)		
	PH	I	PE	T	RH	ENV	Cap	EER	PU		PH	I	PE	T	RH	ENV	Cap	EER	PU
FIS 1									FIS 2 (con't)										
1	-	VL	-	-	-	-	VL	-	-	45	L	H	N	-	-	-	-	H	-
2	-	L	-	-	-	-	L	-	-	46	L	H	E	-	-	-	-	VH	-
3	-	M	-	-	-	-	M	-	-	47	L	H	VE	-	-	-	-	VH	-
4	-	H	-	-	-	-	H	-	-	48	-	VH	VC	-	-	-	-	M	-
5	-	VH	-	-	-	-	VH	-	-	49	-	VH	C	-	-	-	-	H	-
										50	S	VH	N	-	-	-	-	H	-
										51	S	VH	E	-	-	VH	-	H	-
										52	S	VH	VE	-	-	-	-	VH	-
										53	N	VH	N	-	-	-	-	VH	-
										54	N	VH	E	-	-	-	-	VH	-
										55	N	VH	VE	-	-	-	-	VH	-
										56	L	VH	N	-	-	-	-	VH	-
										57	L	VH	E	-	-	-	-	VH	-
										58	L	VH	VE	-	-	-	-	VH	-
FIS 2									FIS 3										
1	-	-	-	-	-	I	-	L	-	1	-	-	-	-	-	I	-	-	H
2	-	-	-	-	-	NR	-	L	-	2	-	-	-	-	-	NR	-	-	M
3	-	-	-	-	-	A	-	M	-	3	-	-	-	-	-	A	-	-	M
4	-	-	-	-	-	R	-	H	-	4	-	-	-	-	-	R	-	-	M
5	-	-	-	-	-	VR	-	VH	-	5	-	-	-	-	-	VR	-	-	L
6	-	VL	VC	-	-	-	-	VL	-	6	-	-	-	CD	VD	-	-	-	VL
7	-	L	C	-	-	-	-	VL	-	7	-	-	-	CL	D	-	-	-	L
8	S	VL	N	-	-	-	-	VL	-	8	-	-	-	W	N	-	-	-	M
9	S	VL	E	-	-	-	-	VL	-	9	-	-	-	H	W	-	-	-	H
10	S	VL	VE	-	-	-	-	VL	-	10	-	-	-	VH	VW	-	-	-	VH
11	N	VL	N	-	-	-	-	L	-	11	-	VL	VC	-	-	-	-	-	H
12	N	VL	E	-	-	-	-	L	-	12	-	VL	C	-	-	-	-	-	M
13	N	VL	VE	-	-	-	-	L	-	13	-	VL	N	-	-	-	-	-	L
14	L	VL	N	-	-	-	-	VL	-	14	-	VL	E	-	-	-	-	-	VL
15	L	VL	E	-	-	-	-	L	-	15	-	VL	VE	-	-	-	-	-	VL
16	L	VL	VE	-	-	-	-	M	-	16	-	L	VC	-	-	-	-	-	H
17	-	L	VC	-	-	-	-	VL	-	17	-	L	C	-	-	-	-	-	M
18	-	L	C	-	-	-	-	VL	-	18	-	L	N	-	-	-	-	-	M
19	S	L	N	-	-	-	-	VL	-	19	-	L	E	-	-	-	-	-	L
20	S	L	VE	-	-	-	-	L	-	20	-	L	VE	-	-	-	-	-	VL
21	N	L	N	-	-	-	-	L	-	21	-	M	VC	-	-	-	-	-	VH
22	N	L	E	-	-	-	-	M	-	22	-	M	C	-	-	-	-	-	H
23	N	L	VE	-	-	-	-	M	-	23	-	M	N	-	-	-	-	-	M
24	L	L	N	-	-	-	-	L	-	24	-	M	E	-	-	-	-	-	M
25	L	L	E	-	-	-	-	M	-	25	-	M	VE	-	-	-	-	-	L
26	L	L	VE	-	-	-	-	H	-	26	-	H	VC	-	-	-	-	-	VH
27	-	M	VC	-	-	-	-	VL	-	27	-	H	C	-	-	-	-	-	VH
28	-	M	C	-	-	-	-	L	-	28	-	H	N	-	-	-	-	-	H
29	S	M	N	-	-	-	-	L	-	29	-	H	E	-	-	-	-	-	M
30	S	M	E	-	-	-	-	M	-	30	-	H	VE	-	-	-	-	-	L
31	S	M	VE	-	-	-	-	M	-	31	-	VH	VC	-	-	-	-	-	VH
32	N	M	N	-	-	-	-	M	-	32	-	VH	C	-	-	-	-	-	VH
33	N	M	E	-	-	-	-	H	-	33	-	VH	N	-	-	-	-	-	VH
34	L	M	N	-	-	-	-	M	-	34	-	VH	E	-	-	-	-	-	H
35	L	M	E	-	-	-	-	H	-	35	-	VH	VE	-	-	-	-	-	M
36	L	M	VE	-	-	-	-	VH	-										
37	-	H	VC	-	-	-	-	L	-										
38	-	H	C	-	-	-	-	M	-										
39	S	H	N	-	-	-	-	M	-										
40	S	H	E	-	-	-	-	H	-										
41	S	H	VE	-	-	-	-	H	-										
42	N	H	N	-	-	-	-	H	-										
43	N	H	E	-	-	-	-	H	-										
44	N	H	VE	-	-	-	-	VH	-										

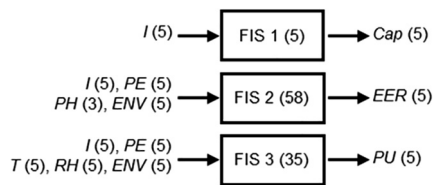


Fig. 1. Schematic representation of the fuzzy inference systems (FISs) 1, 2 and 3 developed; the numbers in parentheses associated with the inputs and outputs denote the number of linguistic terms each variable takes; the numbers in parentheses associated with the FISs denote the number of fuzzy rules in each FIS; the input and output variables are as defined in the main text.

consumption according to human intuition and from the perspective of the individual decision-maker. Examples of previous studies that have used Mamdani FISs for similar purposes are [24] and [96]; the former employed fuzzy logic to model human behavior and the latter to model human emotions. See Fig. 1 for a schematic representation of the 3 FISs and the following subsections for their detailed description.

3.2. Input variables

There are 3 groups of inputs to the FISs comprising altogether 6 variables. The first group consists of variables affecting household finance, namely the monthly income, I and planning horizon, PH of the household of interest, and electricity price, PE . The roles these factors play in energy efficiency and curtailment behaviors are well documented [13,22,44,97]. Depending on their individual roles, I is made present in all three FISs of the model, while PE in only FISs 2 and 3. PH is made present in FIS 2 to capture the influence of delayed payoffs from investing in higher energy efficiency devices [12] on consumer purchase decisions.

The second group of inputs comprises 2 variables, namely ambient temperature, T and relative humidity, RH , both of which affect thermal comfort, and which vary by the hour and from month to month. Thermal comfort has been strongly associated with energy curtailment behavior in the literature [12]. It has been suggested that curtailment actions often correlate with sacrificing thermal comfort, which blocks energy-saving behavior [12]. This implies that consumers would consider energy conservation actions only if there is zero or minimal loss of comfort [98,99]. In this study, to depict these effects, T and RH are set as, among others, inputs to FIS 3, which, as mentioned above, is the sole FIS among the 3 relating to the curtailment aspect of the problem.

In contrast to the first two groups of inputs whose members concern “selfish” considerations [47], the third group comprises a single 0-to-1 variable representing the sense of environmental responsibility, ENV of the household modeled, which is “selfless” [47] and which leads to pro-environmental actions. (In this paper, “environmental responsibility” is meant in a general way that is encompassing all of one’s environmental “values,” “beliefs,” and “attitudes” which to some, are different concepts [18,21] but to others, the same [19].) An ENV of 0 denotes complete indifference towards the environment. A non-zero ENV denotes some consideration for the environment that increases as ENV increases and peaks when ENV is 1. Here, ENV is included in FIS 2 to incorporate its effects on efficiency behavior, and FIS 3 on curtailment behavior. See Section 3.6 below for more on the variable and this study’s treatment of it.

3.3. FIS 1

As described above, FIS 1 predicts Cap , i.e. the total AC capacity of the household modeled. FIS 1 estimates Cap from a single input, I , the household’s monthly income, which it fuzzifies using a set of bell-shaped membership functions for five linguistic values, “VL” (very low), “L” (low), “M” (medium), “H” (high) and “VH” (very high) over the universe of discourse [USD 0, USD 6500]. The universe of discourse is

defined so that its mid-point coincides with the median household income in Hong Kong of approximately USD 3250 [100]. The fuzzy value of Cap is inferred from the fuzzy value of I via 5 fuzzy if-then rules (see Table 1) developed assuming positive correlations between income and property size, and property size and AC capacity [101]. Generally, the rules assume that low-income households occupy small properties, and hence, require relatively small AC capacities. Likewise, high-income households presumably inhabit large properties with greater AC capacities. Finally, Cap is defuzzified according to Gaussian membership functions for five linguistic values, “VL” (very low), “L” (low), “M” (medium), “H” (high) and “VH” (very high) over the universe of discourse [0 kW, 7 kW]. The universe of discourse is specified such that its mid-point corresponds to 3.5 kW, the cooling capacity typically required for a 40 m² apartment [101], the average residential property in Hong Kong [102]. See Fig. 2 for a summary and graphical view of the membership functions in FIS 1.

3.4. FIS 2

FIS 2 predicts EER , the energy efficiency ratio of the AC system of the household modeled. FIS 2 applies a series of fuzzy if-then rules (Table 1) to estimate the fuzzy value of EER , which it subsequently defuzzifies according to a set of Gaussian membership functions for five linguistic values, “VL” (very low), “L” (low), “M” (medium), “H” (high) and “VH” (very high). The membership functions are over the universe of discourse [0 W/W, 6.6 W/W] whose upper limit of 6.6 W/W is set based on the highest EER of residential cooling devices currently available in Hong Kong [103].

FIS 2 receives I (representing monthly income), PE (representing electricity price), PH (representing planning horizon) and ENV (representing environmental responsibility) as inputs. It contains 58 fuzzy rules. The input I is fuzzified according to the same I membership functions in FIS 1 (as described in Section 3.3 above). As for the input PE , it is fuzzified using bell-shaped membership functions for five linguistic terms, “VC” (very cheap), “C” (cheap), “N” (normal), “E” (expensive) and “VE” (very expensive) over the universe of discourse [0 USD/kWh, 0.3 USD/kWh], which is set considering real electricity prices in Hong Kong [104,105].

The input PH serves as a proxy for biased discount rate, which has been identified [47,106,107] as a major behavioral factor affecting consumer purchase decisions but which is less straightforward to assign appropriate linguistic values to (as needed to fuzzify the variable). The use of PH as a proxy is justified. Behavioral economists have suggested that due to hyperbolic discounting, the two variables are highly correlated such that, typically, the higher the discount rate, the shorter is PH , and vice versa [106]. In FIS 2, PH is fuzzified using bell-shaped membership functions for three linguistic terms, “S” (short), “N” (normal) and “L” (long) over the universe of discourse [0 years, 30 years]. This range is defined so that its mid-point is 15 years, which is about the average lifetime of AC units [108]. The choice of bell-shaped functions is dictated by their performance in preliminary runs.

As mentioned above in Section 3.2, the input ENV is included to capture the behavioral economic concept of pro-environmental psychological constructs [47]. It is fuzzified using trapezoidal membership functions for five linguistic terms, “I” (indifferent), “NR” (not responsible), “A” (aware), “R” (responsible), and “VR” (very responsible) on the universe of discourse [0, 1]. Again, the trapezoidal functions are favored over other function types considering their performance in preliminary runs.

For a summary and graphical view of the membership functions in FIS 2, see Fig. 2. The transition from the inputs to the output is performed by the associated fuzzy rules in Table 1. The rules are based on the following logic: It is presumed that a household’s tendency to select a high EER device increases with PE and PH as agents typically view purchases of energy-efficient devices, which are usually more expensive, as investments that can be expected to lead to savings in the

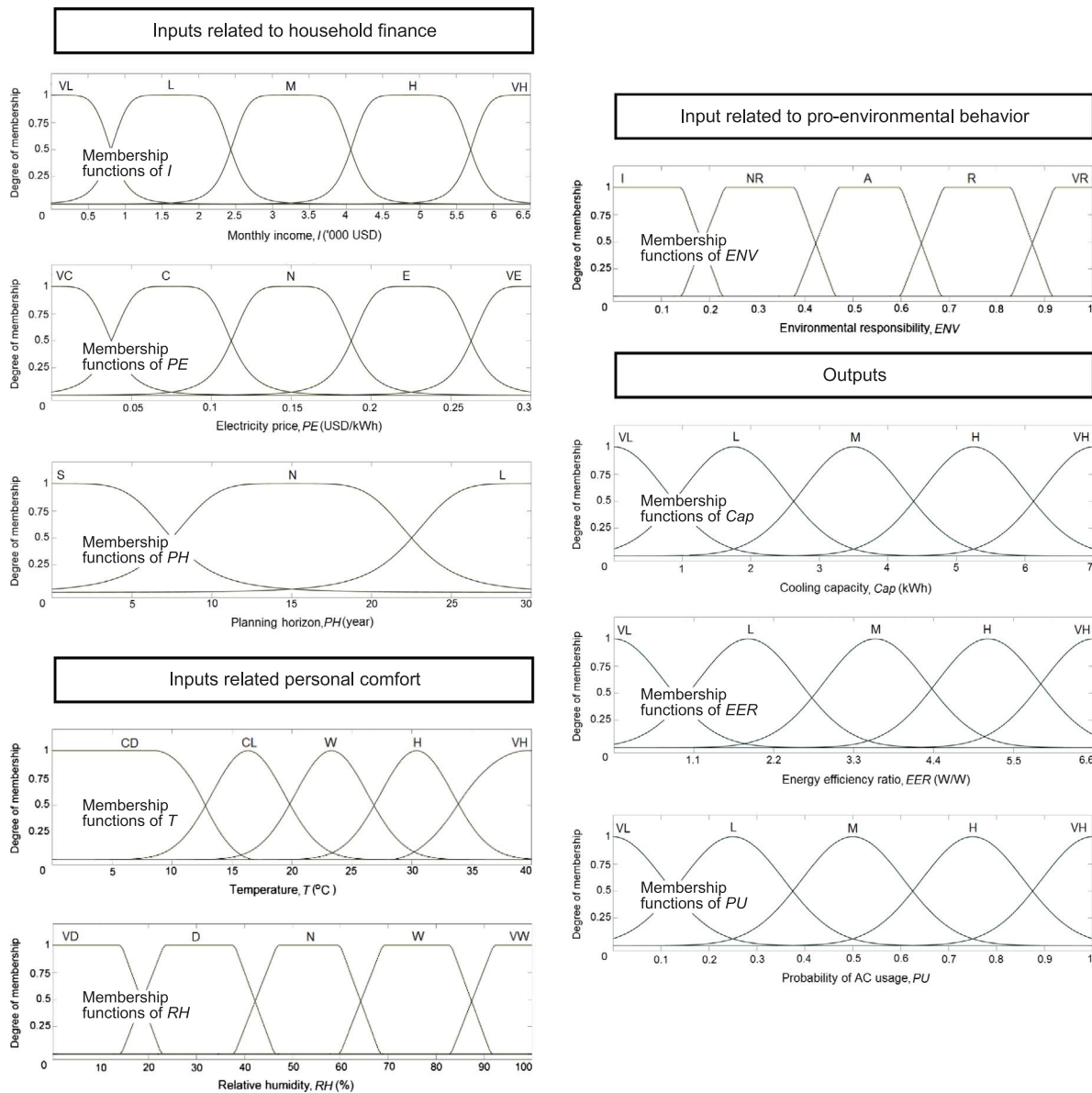


Fig. 2. Membership functions of the fuzzy model; the linguistic terms in the figure are as defined in the main text.

long term through lower energy consumption and hence, lower power bills. Agents with short PH values are incapable of recognizing this potential for cost savings, especially when PE is low, while agents with longer PH values can better perceive the potential. It is further presumed that the inclination to purchase a high EER device increases with I . This is supported by behavioral economics, which have found a positive correlation between income and energy efficiency, and have suggested the higher literacy levels of affluent households to possibly explain the correlation between the two [109]. Finally, when specifying the fuzzy rules pertaining to ENV , it is presumed the prospect of selecting a high EER device to increase with ENV .

3.5. FIS 3

FIS 3 aims to capture the cooling energy curtailment behavior of the household modeled. By running the FIS multiple times, once for every hour that 1 or more occupants are home, an approximation can be made of the household’s hourly probabilities of AC usage and from there, H_m , the monthly hours of AC operation over the cooling season. FIS 3 first predicts hourly AC usage probability, PU as either “VL” (very

low), “L” (low), “M” (medium), “H” (high), or “VH” (very high). It then defuzzifies the result according to Gaussian membership functions over the universe of discourse [0, 1] to yield the final output of a crisp 0–1 number. An outcome of PU close to 1 indicates a high probability and vice versa. The membership functions are set following Ciabattoni et al. [110] and Zúñiga et al. [24], who used fuzzy logic to model the availability of users to activate electric appliances. Where PU is predicted to be greater than a certain threshold, the AC system is taken to be in operation. In the present study, this threshold is set by trial and error at about 0.6 based on preliminary results.

Among the inputs to FIS 3 are I and PE , representing monthly income and electricity price respectively, from the 1st group of inputs relating to household finance. They are fuzzified following the same I and PE membership functions in FIS 2 (see Section 3.4 above). Inputs to FIS 3 also include two climate parameters, as climate has been found to have significant effect on residential cooling energy consumption as residents’ use of AC devices is more a function of exterior conditions than interior ones [44]. The two climate inputs are ambient temperature, T and relative humidity, RH from the 2nd group of inputs relating to personal thermal comfort. Gaussian membership functions for five

linguistic values, “CD” (cold), “CL” (cool), “W” (warm), “H” (hot) and “VH” (very hot) over the universe of discourse [0 °C, 40 °C] are used to fuzzify T . The universe of discourse is defined considering the climate in Hong Kong. To fuzzify RH , trapezoidal membership functions for five linguistic terms, “VD” (very dry), “D” (dry), “N” (normal), “W” (wet) and “VW” (very wet) over the universe of discourse [0%, 100%] are used. In both cases, the function types are selected based on common (but not exclusive) practices in the literature [69,71]. In addition, FIS 3 receives as input ENV (denoting environmental responsibility) of the 3rd group of inputs, which it fuzzifies using the same ENV membership functions in FIS 2. See Fig. 2 for a graphical view of the membership functions in FIS 3.

The transition from the inputs to the output is realized by 35 fuzzy rules (Table 1) developed assuming PU to be medium under moderate values of T , RH and ENV , and that it increases (decreases) as T or RH increases (decreases). It is also assumed PU to be inversely proportional to PE , based on intuition, but proportional to I , in accordance with behavioral economics, which have identified a positive correlation between income and energy consumption [22,109]. Lastly, the ENV -related fuzzy rules of the FIS presume that PU decreases as ENV increases and increases as ENV decreases, in line with basic sense.

3.6. Fuzzy model configuration

To reflect the ongoing debate in the literature if pro-environmental psychological constructs constitute antecedents of just energy efficiency behavior or curtailment behavior, or both [20–22,30], results are obtained for several configurations of the fuzzy model. That many of the existing studies were not about energy behavior specifically in relation to cooling device purchase and usage adds to the uncertainty. Thus, to reflect the ambiguity, and to study specifically the matter in the context of this current study, 4 alternative model structures are defined and examined. The structures differ in their treatment of the environmental responsibility input, ENV which is present in FISs 2 and 3: (a) In Structure A, ENV is an antecedent for both efficiency and curtailment behaviors and thus, is set to the provided input value in both FISs 2 and 3. (b) In Structure B, ENV is an antecedent to only efficiency behavior and thus, is set to its input value in just FIS 2 but 0 in FIS 3. (c) In Structure C, ENV is an antecedent to only curtailment behavior and thus, is set to 0 in FIS 2 but its input value in FIS 3. (d) In Structure D, ENV affects neither behavior, and thus, is set to 0 in both FISs 2 and 3. (As described in Section 3.2, an ENV of 0 denotes environmental indifference.)

As the true distribution of ENV values among consumers in Hong Kong (and elsewhere) is yet unknown, for each of Structures A–C, it is further defined 10 scenarios of non-zero ENV input ranging from 0.1 to 1. This yields 30 scenarios: A1–A10, B1–B10 and C1–C10 with A1, B1 and C1 being assigned the lowest ENV value of 0.1, and A10, B10 and C10 the highest ENV value of 1. Combining the scenarios with Scenario D, the sole scenario where the model structure is D, makes there altogether 31 scenarios for this study.

3.7. Model validation

The results are validated against historical 2010–2014 data on the average monthly consumptions of residential cooling energy in Hong Kong during that period. The historical data are estimated from recent annual statistics published by the Electrical and Mechanical Services Department (EMSD) of Hong Kong [111] and monthly per capita data for 1970–2009 by Lee et al. [112]. (Monthly EMSD statistics are unavailable.)

There are altogether 4 sets of results, one for each of the 4 model structures, A to D defined above. For each structure, the fuzzy model is run multiple times with different inputs of monthly income, I to capture the distribution of household income in Hong Kong as reported by the city’s Census and Statistics Department [100] and provided in Table 2.

Table 2
Distribution of household income in Hong Kong (adapted from [100]).

Monthly household income (USD)	Percentage of total households (%)
Less than 773	10.7
774–2577	31.6
2578–3866	17.6
3877–5155	12.7
5156–6444	8.1
More than 6445	19.2

For all income levels, the simulations are made assuming 80% of the population follow a 12-h household occupancy pattern (where occupants are presumed home every 6 pm to 6 am the following day), while the remaining 20% follow a 19-h pattern (where occupants are presumed home every 1 pm to 8 am the following day) [113]. Weight averaging the outputs yields the final results for validation.

To generate the results, the simulations are run on an hourly basis over the 5 year validation period given hourly ambient temperature, T and relative humidity, RH data derived using the method of Erbs et al. [114] (described in detail by Papakostas et al. [115] and Peng et al. [116]). The T and RH data are derived based on historical monthly mean ambient dry-bulb temperature and humidity data from the Hong Kong Observatory [117], and monthly averages of the solar clearness index [118,119] from the Atmospheric Science Data Center (ADSC) of the National Aeronautics and Space Administration (NASA) of the United States (US) [120].

In all the simulations, wherever it is present and non-zero, the input ENV (representing environmental responsibility) is assumed constant across all households regardless of income or occupancy pattern at a particular 0.1-to-1 value as its true distribution is unknown. Though, the value of ENV is varied across scenarios, as explained in Section 3.6, to investigate its effects. Further, for simplicity, the inputs PE (denoting electricity price) and PH (denoting planning horizon) are also assumed constant across all households, and across all scenarios too, at 0.15 USD/kWh and 15 years respectively. These values represent the mid-points of the universes of discourse underlying the membership functions of the two variables. It is kept constant across all households and scenarios as well the membership functions and fuzzy rules of the model, again for simplicity.

4. Results and discussion

4.1. Performance among model scenarios

In this section, to prove the viability of the fuzzy model developed, and to examine the differences in model performance among the model structures A to D, the simulation results are compared against estimates of the monthly means of residential cooling energy use in Hong Kong over 2010–2014. The model performance is evaluated using the measure coefficient of determination, R^2 . A positive R^2 close to unity indicates a high model accuracy, while a negative R^2 denotes poor accuracy. Alongside R^2 , the measure root mean square error (RMSE) is also used to make the evaluation; the smaller the RMSE, the higher the accuracy and vice versa.

Of the 31 scenarios of varying model structures and input values of ENV (representing environmental responsibility) defined in Section 3.6, 14 yield results matching the historical data with a positive R^2 . Of the 14, 7 are of the model structure C, which considers ENV to influence just energy curtailment behavior; 5 of the structure A, which considers ENV to influence both efficiency and curtailment behaviors; and the remaining of the structure B, which considers ENV to influence just efficiency behavior. Under Scenario D, the sole scenario where the model structure is D, which considers ENV to influence neither behavior, the R^2 is negative. Table 3 and Fig. 3 present the results for the 14 well-performing scenarios, and Scenario D as well for reference.

Table 3

A, B and C scenarios of the fuzzy model, differentiated by their assumptions of ENV, with results matching historical 2010–2014 data with a positive R^2 and relatively small RMSE; the scenarios are ranked according to their R^2 values; the results for Scenario D are also given for reference; estimates of E_a , as predicted by the fuzzy model following Eq. (1), under the various scenarios are provided for comparison against the historical average of 1592 kWh/hh.

Rank	Scenario	R^2 (%)	RMSE (kWh/hh)	Input value of ENV	Actual value of ENV in FIS 2	Actual value of ENV in FIS 3	E_a (kWh/hh)
1	A4	65.9	28.3	0.4	0.4	0.4	1616.4
2	A3	60.2	30.6	0.3	0.3	0.3	1681.4
3	A2	58.7	31.2	0.2	0.2	0.2	1696.3
4	C2	58.7	31.2	0.2	0	0.2	1696.3
4	C3	58.7	31.2	0.3	0	0.3	1696.3
4	C4	58.7	31.2	0.4	0	0.4	1696.3
4	C5	58.7	31.2	0.5	0	0.5	1696.3
8	C6	56.9	31.8	0.6	0	0.6	1656.1
8	C7	56.9	31.8	0.7	0	0.7	1656.1
8	C8	56.9	31.8	0.8	0	0.8	1656.1
11	B5	34	39.4	0.5	0.5	0	1599.5
12	B6	33.2	39.7	0.6	0.6	0	1587.6
13	A5	20.9	43.1	0.5	0.5	0.5	1403.8
14	A6	16.8	44.3	0.6	0.6	0.6	1397
21	D	-90	66.9	0	0	0	1924.7

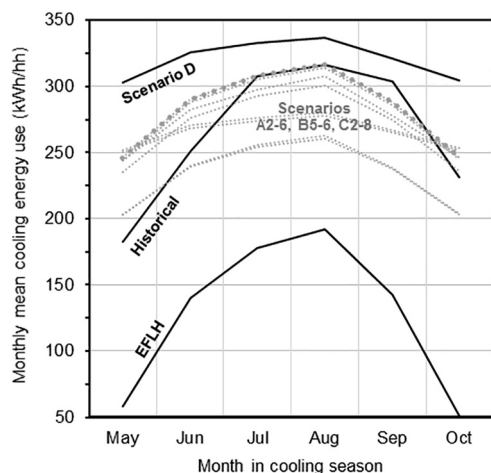


Fig. 3. Monthly means of household cooling energy use in Hong Kong from 2010 to 2014 as predicted by the fuzzy model under the 15 scenarios in Table 3 in comparison with historical values estimated from the literature, and predictions obtained from EFLH data.

As can be seen from Table 3, where the model structure is A, 5 out of the 10 scenarios considered (A1-A10) yield a positive R^2 . The 5 scenarios correspond to ENV values between 0.2 and 0.6. When ENV is 0.4, under Scenario A4, the results are the best among all the 31 A and non-A scenarios considered with the highest R^2 of 65.9%, and least RMSE of 28.3 kWh/hh. When ENV is 0.1, or 0.7 and higher, R^2 becomes negative. Where the model structure is B, 2 out of the 10 B scenarios considered (B1-B10) yield a positive R^2 . They are Scenarios B5 and B6 with ENV inputs of 0.5 and 0.6 respectively. Finally, where the model structure is C, the ENV inputs for the 7 scenarios yielding a positive R^2 range from 0.2 to 0.8.

The results show the model performance to be highly sensitive to ENV, and suggest ENV inputs between 0.2 and 0.6 to be most accurate when in relation to efficiency behavior, and 0.2–0.8 when in relation to curtailment behavior. The results also show the model performance to be highly sensitive to the model structure, if A, B, C or D, and suggest A-C to be better performing than D. This finding is consistent with past studies [21,22], which have found pro-environmental psychological constructs to be antecedents of energy behavior and to have at least some effect on it, however small. Thus, since Structure D assumes total

environmental indifference, and therefore, environmental concerns to have zero impact on both efficiency and curtailment behaviors, that Structure D performs worse than Structures A-C is as can be expected.

The results though cannot be taken definitively given the sensitivity of the outputs to the fuzzy rules and membership functions defining the fuzzy model which, admittedly, are to some extent, subjective (but not arbitrary). The results are nonetheless, meaningful as they demonstrate the feasibility of using fuzzy logic to explicitly incorporate key behavioral economic principles in a single coherent mathematical framework and encapsulate the inexact intuitive nature of human decision-making for predictive purposes and deeper fundamental understanding. The model, though preliminary, provides a valuable basis for further research on modeling human decision-making, whether within or without the context of consumer energy behavior.

4.2. Comparison with alternative results

To further examine the fuzzy model’s feasibility, Fig. 3 compares the model predictions of the monthly means of household cooling energy use in Hong Kong from 2010 to 2014 for the 15 scenarios in Table 3 against those of an alternative non-fuzzy approach based on the equivalent full load hours (EFLH) metric [121,122]. The EFLH of a cooling system are the number of hours the system would need to operate at full load to consume the same amount of energy it consumes on average. The method recently gained favor as EFLH data can be readily calculated from just local annual or monthly temperature, humidity and solar clearness data [121], making the method easily accessible. The EFLH method is selected for use here over other simplified energy estimation methods (e.g. degree-days methods) as it is flexible to accommodate mixed building occupancy patterns, thus allowing for, to a certain degree, the consideration of human behavior.

EFLH data for 2010–2014 for Hong Kong are calculated using the method of Papakostas et al. [121,122]. To derive the EFLH data, the required inputs of monthly means of ambient dry-bulb temperature, ambient humidity, and the solar clearness index are obtained as described in Section 3.7. In addition, the required inputs of cooling balance-point temperature and outdoor design temperature are taken from, respectively, the Ministry of Housing and Urban-Rural Development of China [123], and the 2009 edition of the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) Handbook [124]. EFLH data are derived for 12-h and 19-h household occupancy patterns. See Table 4 for monthly averages of the derived 12- and 19-h EFLH data, and their weighted means that have been computed assuming the same 80:20 ratio [113] as presumed when specifying the fuzzy model (as described in Section 3.7). The final results in Fig. 3 are computed from the EFLH data using Eq. (1) but with weighted EFLH values in place of H_m (which denote the hours of AC operation) and assuming an AC system capacity, Cap of 3.5 kW and energy efficiency ratio, EER of 3.12 W/W based on their averages for the city [103]. (Unlike for the fuzzy model, single values of Cap and EER are used here instead of distributions since the EFLH method, as it is typically applied, has no means of estimating their distributions.)

Table 4

19-h and 12-h monthly EFLH values for Hong Kong, and their weighted means computed assuming 20% of the population follow a 19-h household occupancy pattern and the remaining 80% follow a 12-h pattern.

Month	19-h EFLH	12-h EFLH	Weighted mean EFLH
May	84	44	52
June	197	107	125
July	247	136	159
August	269	147	171
September	206	107	127
October	84	36	46
Total	1087	577	680

As Fig. 3 demonstrates, the EFLH results can broadly capture the major trends of the historical data, i.e., like the historical data, the EFLH results predict cooling energy use to increase from May to July, peak in August, and decrease from August to October. However, the results show a systematic underestimation of the historical values. Conversely, the fuzzy model predictions in the figure all not only capture the trends of the historical data, but by and large, their magnitudes as well. This difference in performance between the 2 approaches to energy estimation can be attributed to the EFLH method, unlike the fuzzy model, not having any inherent mechanism to predict the distributions of EER and Cap across the population and thus, not accounting for them. Further, again unlike the fuzzy model, the EFLH method is based on mostly just climate factors without considering the human behavioral aspect of the problem. The results highlight the potential of the fuzzy model as a promising alternative that is capable of making predictions of even better, or at least comparable, quality than traditional energy estimation methods.

4.3. Model sensitivity to inputs

This section examines the sensitivity of the output average annual cooling energy demand, E_a as predicted by the fuzzy model (according to Eq. [1]) to selected inputs. See Figs. 4 and 5 for the results. The results provide additional validation to the fuzzy model, i.e., that it behaves plausibly when the inputs are perturbed. (Where there is lack of or insufficient validation data, sensitivity analyses have been applied as a way of verifying model plausibility [125–127].)

Fig. 4 shows the sensitivity of E_a to ENV , which as has been described above, is a 0–1 variable representing environmental responsibility that is present in FISs 2 and 3. The sensitivity analysis is performed by varying the input value of ENV between 0 and 1 while keeping the other 5 inputs constant at their “base” values, i.e., their values applied when generating the results in Section 4.1 and as specified in Section 3.7. In the figure, results are presented for all 4 model structures, A–D. For Structure D though, the outcome is simply a horizontal line as the structure fixes the actual value of ENV in FISs 2 and 3 constant at 0 irrespective of its input value. (As explained in Section 3.6, the actual value of ENV applied in computations is not necessarily the same as its input but set to 0 depending on the model structure.)

From the results for Structures A–C in Fig. 4, it can be observed several patterns, all of which are plausible: (i) For all the 3 structures, E_a decreases as the input of ENV increases. (ii) The different predictions of E_a by the different model structures converge to a single value corresponding to Structure D’s estimate of E_a as the input of ENV approaches 0. (iii) As the input of ENV approaches its maximum of 1, E_a as estimated by Structures A and C approaches 0 but E_a as estimated by

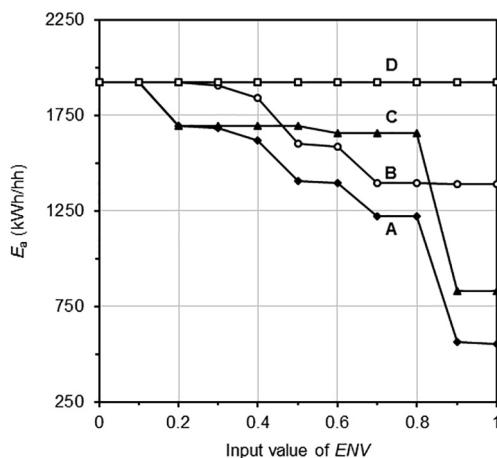


Fig. 4. Sensitivity of E_a as predicted by the fuzzy model to the input value of ENV ; results are presented for each of Structures A–D.

Structure B remains relatively high. (iv) As the input of ENV increases, E_a reduces at a faster rate under Structure A than under Structure B or C.

Fig. 5 shows the results of a sensitivity analysis to evaluate the impacts of varying monthly income, I , electricity price, PE and consumer planning horizon, PH on E_a . Each line in the 3 subplots corresponds to a scenario in Table 3. To obtain the results for I , the income levels in Table 2 are perturbed by percentages of 10% increments while retaining all other inputs, including PE and PH constant at their base values. Similarly, the results for PE are obtained by perturbing its value from its initial value of 0.15 USD/kWh while maintaining the other inputs constant. PE is perturbed from 0.03 to 0.30 USD/kWh following the universe of discourse of its membership functions in the fuzzy model. In the same manner, the results for PH are obtained by perturbing its value from the initial value of 15 years over the universe of discourse of its membership functions.

Subplot (a) of Fig. 5 shows E_a to increase with I . In the fuzzy model, in line with literature findings [109], I is positively correlated with both AC device efficiency, EER , and probability of AC usage, PU . The results are such that, as I increases, the energy reduction from an increased EER is insufficient to offset the growth in energy use from an increased PU . Instead, the aggregated outcome is an increasing E_a with an increasing I . The results are consistent with past studies on consumer AC habits [128–133].

From subplot (b) of Fig. 5, it can be seen that E_a reduces as PE increases. Again, this is consistent with the literature; past studies have observed the same trend [130,132,134]. It has also been found from the same past studies the sensitivity of energy use to electricity price to be relatively modest [130,132,134]. This is in contrast to the results of subplot (b), which show the sensitivity to PE to be relatively significant. A possible reason for this discrepancy is that this present study incorporates the effects of PE on both efficiency and curtailment behaviors, whereas the past studies limited their investigation to just the price effects on curtailment behavior and considered electricity price to have no effect on efficiency behavior, which the studies treated as a matter of lifestyle choice [130,132].

Finally, as shown in subplot (c), increasing PH from 3 to 15 years generally results in a slight decrease in energy use, and any additional increase in PH thereafter brings no further reduction. The results also show the sensitivity of E_a to PH as compared to ENV , I and PE to be minor. This is likely because PH affects only efficiency behavior, while ENV , I and PE affect both efficiency and curtailment behaviors. There are no firm findings as yet in the literature to confirm or disprove the results here. Nonetheless, the results are plausible as it is reasonable to expect that the longer the PH of consumers, the greater the value placed on future rewards, and thus, the more probable the selection of higher efficiency AC devices considering their greater prospect for future savings in electricity cost. This in turn can be expected to lead to, on the overall, a reduction in energy use.

4.4. Initial policy recommendations

The results of this study may be of interest to energy decision-makers such as the Hong Kong Green Building Council, which recently launched the HK3030 Campaign targeting by 2030, a 30% reduction in Hong Kong’s total building electricity use from the consumption in 2005 [135]. Given that space cooling accounts for 25% of the total residential electricity consumption in the city [111], minimizing cooling energy would contribute significantly to achieving the 30% reduction target. As guidance for policy-making, Figs. 4 and 5 suggest increasing consumer responsibility towards the environment, ENV , electricity price, PE , and consumer planning horizon, PH as possible ways of cutting cooling energy. The results also suggest that increasing ENV and PE to have greater potentials for larger cuts than increasing PH . (As shown in subplot (b) in Fig. 5, reducing household income, I leads to less cooling energy consumption as well. However, lower I

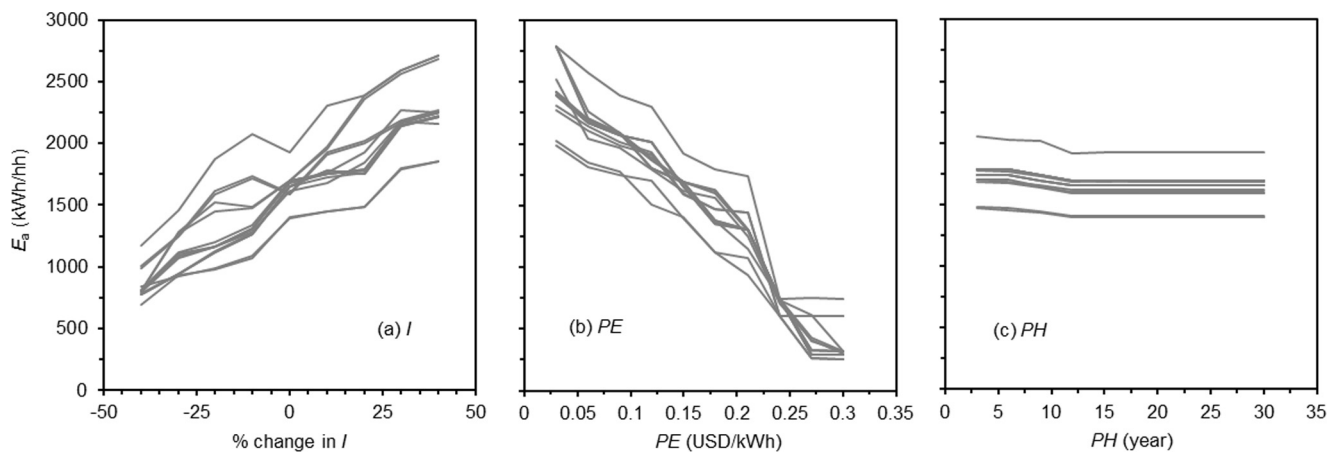


Fig. 5. Effects of varying (a) I , (b) PE and (c) PH on E_a ; each line in the subplots corresponds to a scenario in Table 3; the results for I in subplot (a) are obtained by perturbing the income levels in Table 2 by percentages of 10% increments while retaining all other inputs constant at their base values; the results for PE in subplot (b) are obtained by perturbing its value from 0.03 to 0.3 USD/kWh; the results for PH in subplot (c) are obtained by perturbing its value from 0 to 30 years.

values are undesirable from the societal welfare point of view. Hence, no further discussion on adjusting I for the said purpose shall be made hereafter.)

Between increasing ENV and increasing PE , in most societies, the former is more practicable. This is despite the latter being more straightforward to implement. To increase PE would typically simply require the local utility provider to take action, but can result in immense public resistance and hence, increasing PE is often seen as socially or politically unacceptable [47]. In light of this, a significant portion of the targeted 30% reduction in Hong Kong's total electricity use under HK3030 is to be met through behavioral changes, including changes to consumers' curtailment and efficiency behaviors in regard to their AC device purchase and usage decisions [135]. According to plans, this will be achieved not by price interventions, but rather through extensive education and publicity programs that will target residents, educators, building industry professionals, energy specialists, and the general public. The programs will contribute to creating shared pro-environmental interests leading to increased ENV values among the population.

Furthermore, considering the social construction of energy-related decisions [18,30], peer pressure and peer comparison may lead to further increases in ENV and with that, even greater reductions in energy consumption [136,137]. In fact, studies have shown individuals to likely reduce their household energy consumption when informed of the energy-saving performances of peers, especially when framed as a positive social norm [138,139]. In a large social experiment conducted in the US, the marketing company Opower found sending reports to households comparing their energy consumptions to neighbors' to result in satisfactory energy reductions [139]. The experiment demonstrated that even without face-to-face interaction, peer influence can be an effective force when distributed via appropriate information channels. Indeed, some consider the effects of peer influence to be more lasting in the long-term than monetary interventions [4,23].

Further on increasing ENV to reduce energy use, Fig. 4 highlights the importance of more empirical research to ascertain the influence of pro-environmental constructs on human energy behavior, i.e., if they are antecedents to just efficiency or curtailment behavior, or both. As the figure shows, the effects of ENV on energy consumption can differ quite significantly across Structures A to D, especially when ENV is high. Thus, a clearer understanding of which of the 4 structures best represents reality (which at present, is still uncertain) will lead to more correct expectations of the potential of targeting increases in ENV for reducing cooling energy consumption.

Future empirical work in this direction will also yield insight into which of the two energy behaviors to target, if not both, for maximum

reductions in cooling energy use. While in the past, energy conservation policies were mostly targeted at the curtailment side of the problem, recent studies [13,15,16] have pointed toward the need for more investigation into the efficiency aspect as well. To motivate change in efficiency behavior can be said to be more realizable with less effort as it involves just one-time decisions, as opposed to modifying curtailment behavior, which involves numerous repetitive actions [13]. Further, changing efficiency behavior has been found by some to have a greater energy saving potential than changing curtailment behavior [12,140]. Should future work find Structure B to be the more realistic, then it is recommended that policy efforts concentrate on altering efficiency behavior. However, should Structure A or C be found to be the more realistic, then policy efforts should include altering curtailment behavior as well.

Lastly, increasing PH can be problematic as it is a personal norm that is internally motivated (as opposed to ENV which is a social norm that is, at least partially, externally motivated) and thus, often quite resistant to change [10]. Nonetheless, it may be possible to change a consumer's present bias, and with that, PH by increasing the awareness of lifetime energy demands and operating costs of appliances, e.g., by attaching labels with the relevant details [141]. This in turn will cause consumers to value future rewards more and be more willing to purchase energy efficient devices despite their higher purchase prices. In time, a suggested program in Hong Kong [135] and ongoing programs in the United Kingdom and Switzerland [141] will reveal the effectiveness of energy and cost information labels on domestic appliances in modifying the preferences of consumers for energy-efficient products. Until there is solid evidence of the effectiveness of such programs, and given the results in Fig. 4 that imply the influence of increasing PH on energy consumption to be relatively small, it is recommended priority be given to programs targeted at increasing ENV over those aimed at increasing PH .

4.5. Limitations and future work

A major limitation of the fuzzy model developed, like most, if not all, fuzzy models, is its subjective (but not arbitrary) nature. Specifically, its membership functions and fuzzy rules are based mostly on intuition, insights from behavioral economics and common practices in the literature, and not on hard science as typically would equations in a physical model. It should be noted though that this subjectivity is unavoidable considering the intangible nature of the model objective, i.e., to model human energy behavior. Nonetheless, it is hoped the model provides a valuable start toward modeling human energy decision-making from the perspective of the decision-maker, a challenging

subject precisely because of the intangibility.

The fuzzy model is also limited by the difficulty in specifying certain inputs, namely *ENV* and *PH* that are hard to measure and which vary across individuals. For the same reasons, the membership functions of the model representing the perceptions of the decision-maker can also be problematic to define. In this paper, due to the lack of data, *PH* and the membership functions are fixed according to best estimates and assumed uniform across all individuals. *ENV* is also assumed uniform across individuals, though varied from 0 to 1 for different scenarios. For the purpose of this study, which are mainly to prove the concept of using fuzzy logic to model human energy behavior, it suffices the approach taken. However, for further progress, future work is necessary to determine the true values of *ENV* and *PH*, and true shapes of the membership functions of the fuzzy model, and how they distribute across different population groups.

Additional possible future work includes modeling real energy conservation programs currently implemented (or planned to be implemented) using the fuzzy model developed. For further understanding, it is worth modeling economic schemes such as rebate programs to lower the costs of energy efficient AC devices in the US [142] and Australia [143], and/or social policies such as those in the US [136,139] and Canada [144] targeting peer pressure as a potential tool for promoting energy saving behavior. The results will provide new insights into the role of such measures in influencing energy decisions.

The modeling of these programs can be achieved by defining additional FISs to represent the effects of key policy actions on energy efficiency and curtailment decisions. To adapt the model to different programs, for each program, the membership functions of the model will need to be altered to reflect the local climate, electricity prices, etc. It may also be necessary to adjust the model's fuzzy rules to capture the consumer perceptions of the program's particular location as affected by the culture, demographics and economy of the region. Finally, comparing the model predictions with real data and tweaking the model so that the results replicate well the data will help validate the model. Real detailed energy consumption data for this purpose are not easily available; nevertheless, there exist projects such as the Pecan Street Project by the University of Texas at Austin [145] that have made great progress in collating and making accessible valuable location-specific energy data.

5. Summary and conclusions

In this paper, fuzzy logic is used to develop an integrated model of residential AC purchase and usage decisions. The work is driven by weaknesses in existing energy policies based largely on traditional economic theory, which assumes individuals to be completely rational (profit-maximizing) and self-interested. Many of these policies have failed to deliver the expected results leading to energy efficiency gaps, often due to their negligence of behavioral factors. Thus, for more effective policy-making, behavioral factors can no longer be ignored. Hence, the importance of integrated models combining traditional economic theory with newer behavioral economic principles in a single mathematical framework that promise deeper insights. Such models however, are still relatively underdeveloped and limited in number.

This study has developed a fuzzy logic model to predict consumer energy efficiency and curtailment behaviors, and the ensuing AC purchase and usage decisions. The model is unique in that it is formulated from the perspective of the human decision-maker. Key behavioral economic concepts are captured in various ways. Bounded rationality is captured by the employment of fuzzy logic itself, which is used to formulate decision rules based on human intuition and perceptions. The time discounting of gains is captured by the inclusion of the variable *PH* (representing the consumer's planning horizon) and its associated fuzzy rules. Similarly, pro-environmental behavior is captured by the variable *ENV* (representing the consumer's level of environmental responsibility) and the associated fuzzy rules.

To capture the ongoing debate if *ENV* drives just efficiency behavior or curtailment behavior, or both, this study has considered 4 alternative structures of the fuzzy model: Structure A assumes *ENV* affects both efficiency and curtailment behaviors; Structure B assumes it affects only efficiency behavior; Structure C assumes it affects only curtailment behavior; and Structure D assumes it affects neither behavior. Results are generated for each structure presuming conditions in Hong Kong and compared against historical 2010–2014 data. The results are also compared against estimates obtained using a different more traditional approach, i.e., from specially derived EFLH data.

The results show Structures A-C to reproduce the historical data reasonably well with positive R^2 values up to over 65%. This allows modelers some degree of confidence in the fuzzy model. Moreover, perturbing key input variables produces plausible behaviors, thus providing additional validation to the model. Finally, comparing the fuzzy model results with the EFLH estimates suggests the fuzzy model to be capable of producing predictions of comparable or even better quality than traditional methods.

While Structures A-C have been found to perform fairly well, the same cannot be said of Structure D. Since Structures A-C assume environmentally concerned consumers while Structure D assumes environmentally indifferent ones, the results suggest environmental considerations to constitute a non-insignificant driver affecting cooling energy decisions. The results however, do not indicate which of Structures A-C best represents reality. To ascertain this, future work is recommended. As an analysis of the sensitivity of the fuzzy model to *ENV* shows (Fig. 4), the effectiveness of increasing *ENV* for reducing energy consumption can differ quite markedly across the different model structures. Thus, greater clarity of which structure best matches reality will enable better designs of energy conservation policies, especially those directed at promoting environmental awareness.

To conclude, this paper has demonstrated the feasibility of fuzzy logic as a means of mathematically expressing and integrating, in a single coherent framework, behavioral economic principles to model consumer AC purchase and usage decisions, and from there, predict residential cooling energy consumption. The fuzzy model developed relies solely on related behavioral and social parameters consistent with human logic, perception and experience. It is useful for representing human reasoning pertaining to the model objective for greater fundamental understanding of the “why” behind cooling energy use that conventional building energy simulation models do not address. This in turn, is essential for formulating more effective energy conservation policies.

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