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Making incentive policies more effective: An agent-based model for energy efficiency retrofit in China

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Abstract

The building sector is responsible for a major share of energy consumption, with the most energy being consumed during the operation stage of buildings. Energy-efficiency retrofit (EER) policies have been promoted by numerous countries. However, the effectiveness of these incentive policies has been insufficient, a main reason being the agency problem between the government and building owners. In addition, most policies ignored the diversity of buildings and building owners, resulting in a lack of reaction from owners. To address this problem, this study proposed an agent-based model for policy making on EER. The model defined the government and owners as agents and their decision-making behaviors were modeled with principal-agent theory. A platform based on the proposed model was then developed and the incentive policy was optimized under different circumstances. To verify the effectiveness of the proposed model, three policy scenarios were compared on the platform, which are the policy by the proposed model, the incentive policy in Shanghai and Shenzhen, China. The results showed that the incentive policy based on the proposed model has the best performance on energy savings, returns on investment, and leverage effects. A sensitivity analysis indicated that the government should pay more attention to energy price.

1. Introduction

The building sector accounts for around 40% of total energy consumption around the world (Hong et al., 2015). In the life cycle of a building, more than 80% of the energy consumption occurs during the actual occupancy operation stage, rather than during the construction stage (UNEP, 2007). Therefore, the energy-efficiency retrofit (EER) approach for existing buildings has attracted attention, owing to its essential influence on energy saving (Zhang et al., 2015).

EER has become an increasingly critical strategy for energy conservation in many countries. For example, the Chinese government has launched various incentive policies to promote EER. In the 12th FiveYear Plan[12]

(2011–2015), 400 million m^2 of residential buildings and 60 million m^2 of public buildings were required to be retrofitted as pilot projects to improve the energy efficiency of buildings (MOHURD, 2012). By contrast, EER projects remain inadequately pursued in practice. Although the targets for retrofitted areas in the 12th Five-Year Plan were achieved, most retrofitted public buildings were state-owned, according to government reports, including hospitals, schools, office buildings of government, and commercial buildings of state-owned enterprises (Hou et al., 2016). In other words, most EER projects were implemented due to administrative order rather than through market conduct. A main problem is that few private building owners were enthusiastic about EER (Ali et al., 2008; Stiess and Dunkelberg, 2013).

To address the issue of insufficient private participation, a few previous studies have analyzed the reasons for the failure of EER policies. Menassa (2011) indicated that the challenge of financial support impacts policy effectiveness adversely, particularly after the 2008 global economic recession. Kasivisvanathan et al. (2012) indicated that subsidies may not cover the high cost and long payback period of EER, so that the total profits of EER are not realized. High uncertainty in the incentive is also a barrier to EER policy, since the incentive depends on the performance of EER, which is influenced by environment, highly complex solutions, interdisciplinary collaboration, and other uncertain factors (Davies and Osmani, 2011; Korkmaz et al., 2010; Lapinski et al., 2006).

These previous studies attempted to mitigate policy barriers and improve the effectiveness of incentive policies. Most of them were conducted from a macro perspective (e.g., economy, finance, and technology), but ignored micro factors. Few of them, if not none, have investigated this issue from the perspective of building owners and their decision-making behavior. The agency problem between the government and building owners is not effectively addressed. In addition, building conditions and the individual differences of building owners are neglected when designing EER policies. In fact, building conditions (e.g., occupied types of buildings) and the characteristics of building owners (e.g., different property rights of owners) can significantly influence the decision making on EER (Liang et al., 2016). Therefore, neglecting the critical role of building owners and their diversity in EER will lead to erratic outcomes and low effectiveness of incentive policies.

To address the aforementioned problems, this study proposes a novel agent-based model to analyze decision-making behaviors of various building owners and to optimize incentive policies in EER, with consideration given to building conditions and owner characteristics. Agent-based modeling has been identified as an effective method for dealing with agency problem because it has advantages to analyze the motivations and behaviors of self-interested participants (Vetschera, 2000). This method can be used to figure out an optimal solution for agency problem, through simulating the dynamic negotiations, arguments, and conflicts among stakeholders (Anumba et al., 2003; Dzeng and Lin, 2004; Kraus, 1997; Ren et al., 2003; Xue et al., 2009). Therefore, this study applied agent-based modeling to investigate the decision-making behaviors of stakeholders and identify optimal incentive policy to address the agency problem in EER.

2. Literature review

2.1. Incentive policies for EER

In the last decade, EER has been emphasized by governments all over the world. As mentioned in Section 1, the government of China started to consider EER as an important national energy strategy in the 12th Five-Year Plan from 2010. The US government passed the Energy Policy Act (EPA) of 2005 and Executive Order 13423, which require retrofitting 15% of the total number of existing buildings to improve energy efficiency by 2015 compared with the 2003 baseline (EPA, 2005). The Energy Efficiency Plan 2011 of the European Union (EU) emphasized that the greatest energy saving potential lay in buildings. The plan provisioned that public authorities in EU should retrofit at least 3% of their buildings each year, and the buildings after retrofit should be in the top 10% energy performance in the national building stock (EU, 2011).

Although various incentive policies have been launched, the majority of them fail to investigate the decision-making behaviors of building owners. Building owners play important roles in EER, particularly at the very early stage, namely, the initial intention or setup phase (Marchiori and Han, 2010). Ma et al. (2012)

argued this phase is the key phase of an EER project. Furthermore, the government has incomplete information on the decision-making behaviors of owners, which is a typical agency problem (Han et al., 2008). This principalagent relationship between the government and building owners can adversely affect the effectiveness of EER policies. Thus, to promote EER, it is essential to analyze the decision-making behaviors of building owners when designing EER policies. This study contributes toward addressing the aforementioned research gaps by developing an agentbased model to investigate the decision-making behaviors of building owners in EER.

2.2. Agent-based modeling

Agent-based modeling has developed rapidly in the recent years. It uses intelligent agents to simulate real-world human activities that follow different behavior criteria, knowledge, and objectives without global control (Ren and Anumba, 2004). Agent-based modeling is essentially suitable for solving problems that are: 1) too large to be solved by a single agent because of limited time or resources (Taghaddos et al., 2012); 2) inherently distributed, but require collaboration and interaction (Sycara, 1998); 3) related to the self-interest of the participants; and 4) in a dynamic environment. In EER, each building owner pursues his own interests in the situational dynamics with particular cost, benefit, objective, and preference. Therefore, agent-based modeling is suitable for modeling the decision-making behavior of owners and optimizing incentive policy in EER.

Compared with methods widely used in previous studies (e.g., Markov chains and system dynamics), agent-based modeling is a bottom-up method, rather than a top-down method. It can model the behavior of individual building owners, focusing on their personal objectives, needs, and drivers, which can help to achieve a deep understanding of decision-making behavior with heterogeneous characteristics. Agent-based modeling has been widely applied in policy making in the research area of energy efficiency improvement, for example, the policy of dynamic electricity tariffs (Kowalska-Pyzalska et al., 2014), incentives for renewable heat pump adoption (Snape et al., 2015), and carbon emission trading schemes (Tang et al., 2015).

According to the advantages of agent-based modeling, this study developed a bottom-up agent-based model to investigate the decision-making behavior and optimal incentives for EER.

2.3. Principal-agent theory

Principal-agent theory aims to design the most efficient contracts for ubiquitous agency problems, in which the principal delegates work or decision-making authority to the agent, but faces some problems, such as 1) split incentive problem—the desires or the goals of the principal and agent conflict; 2) asymmetric information—it is difficult or too expensive to verify the agent's actions (Macho-Stadler and PérezCastrillo, 2012). Principal-agent theory has been applied to explain this kind of market failure problem. Blumstein (2010) proposed a program evaluation method based on principal-agent theory to solve the agency problem in which the principal is the regulator (the California Public Utilities Commission) and the agents are private corporations (the regulated energy utilities). In the energy efficiency area, this theory has been applied to investigate various agency problems in previous studies, including energy efficiency in shipping (Rehmatulla and Smith, 2015), energy efficiency decisions in the trucking industry (Vernon and Meier, 2012), and agency problem quantification in energy efficiency (IEA, 2007). As mentioned in Section 2.1, the agency problem between the government and building owners should be considered when designing EER policies. Accordingly, the principal-agent theory was employed in this study to develop the model for EER policy analysis.

3. The model

3.1. Model description

3.1.1. Agent definition

Agents normally represent key stakeholders and objects in research problems. In EER, the main stakeholders were identified in previous studies, including building owner, tenant, government, facilities manager, consultant/designer, contractor, etc. (Gultekin et al., 2013; Juan et al., 2009; Kaklauskas et al., 2008, 2004; Miller and Buys, 2008; Yang and Zou, 2014). Although there are numerous stakeholders in EER, government and building owners play the most important role in decision making on whether to launch a retrofit, particularly at the very early stage (Marchiori and Han, 2010). The current study attempts to optimize incentive policies from the perspective of decision-making behavior analysis. Accordingly, our model focuses on building owners and government. In addition, since building conditions can significantly affect the effectiveness of EER policies, buildings are also selected as agents. In summary, this model considers three types of agents as follows.

3.1.1.1. Building owner agent. Building owners play a critical role in our model. They make decisions on whether to launch an EER project or not. If owners are approached by initiatives to undertake EER, they will evaluate their benefits from EER. The incentive policy by government is an important impact factor in the evaluation. If the benefit is sufficiently high, the building owners will undertake EER. Since conditions of buildings and building owners are different, they will make different decisions on EER to maximize their own utility.

3.1.1.2. Government agent. The government plays an important role in EER. Different incentive policies adopted by government can influence the owners' economic benefits from EER and further influence their decision making on EER. In return, the government can receive environmental benefits from energy saving. Since most building owners do not initiate EER without incentives (Liang et al., 2016), the government has to provide incentives to promote EER. The objective of government is to optimize the utility of incentive policy.

3.1.1.3. Building agent. It may be argued that buildings should not be considered as true "agents" because they are not autonomous decision makers. To this extent, buildings can be considered to possess only collaborative behavior (Nwana, 1996). The energy consumption of a building changes over time according to many environmental conditions and the retrofit by building owner agents. Therefore, in this study, a building is considered a type of agent.

3.1.2. Agent relationship

The relationship between the government and building owners in EER is shown in Fig. 1. The government gives incentives to building owners accordingly, shown by the red line in Fig. 1, and gains environmental benefits from EER projects, shown by the green line in

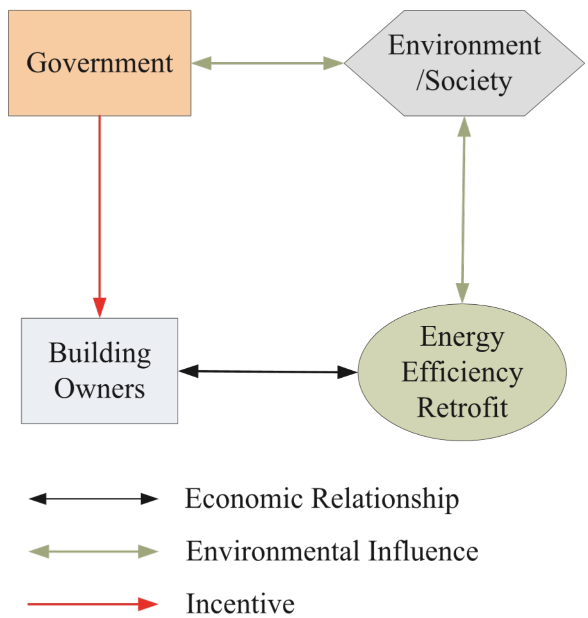


Fig. 1. The government incentives will increase the owner's benefit from EER. Building owners will evaluate benefit and cost from EER. An incentive from government is a key factor; if the incentives are high enough, the owners will undertake initiatives to implement EER.

As mentioned in the literature review, the relationship between government and building owners in EER is a typical agency problem. The government is the principal, which delegates EER to building owners and provides incentives to them. First, the objectives of principal and agent, namely the government and building owners, are different. The government aims to maximize the utility of incentive policy, while the building owners aim to maximize their own utility, shown in Table 1. Second, the benefits of principal and agent are also different and even conflicting. For example, the incentives are costs for government, but benefits for owners. Finally, there is asymmetric information between the government and owners. The government does not have complete information of owners' decisions and efforts on EER. Therefore, the government has to create an efficient contract, namely the incentive policy, to motivate building owners to put more efforts into EER.

To address the aforementioned agency problem between the government and building owners, an approach based on principal-agent theory is applied in this study. The problem can be defined as how much incentive should be given by the government to maximize the owners' decisions and efforts on EER. To achieve this objective, the optimal balance between the two players should be identified. The conceptual model of this agency problem is shown in Fig. 2.

As shown in the conceptual model, the aim of the government is to maximize the effectiveness and efficiency of the incentive policy, which is defined as environmental benefit from retrofit minus incentive paid by government. The aim of building owners is to maximize their own benefit, which is defined as energy bill saving from retrofit plus incentive by government minus the retrofit cost. There are two constraints in principal-agent theory (Macho-Stadler and Pérez-Castrillo, 2012): 1) the individual rationality constraint (IR), which means the benefit of players should be more than the threshold; and 2) the incentive compatibility constraint (IC), which means the optimal choice for government should be compatible with the decisions of owners. The details of the derivation for solving this agency problem are illustrated in the following sections.

3.2. Decision making of agents

Fig. 1. Relationship between government and building owners in EER.

3.2.1. Variable definition

The variables in the model are listed in Table 2 and comprise five types of variables, namely, owner, government, building, environmental, and intermediate variables. The variables of the first three types are attributes of agents. The environmental variables depend on the external situation, which cannot be changed by the agents in EER. The last type is intermediate variables, which are applied to facilitate calculation. There are four categories of variables, which are action, static, time dependent, and action &

time dependent. The static attributes do not change with time; the action attributes and time dependent attributes change with time; the action & time dependent attributes change with both time and actions of players.

The variables and agent interactions of the proposed agent-based model are shown in Fig. 3. The variables of an agent can impact other variables and also can be impacted by other variables. The agents interact with each other through their actions and the changes of variables. The large boxes represent the three agent types (i.e., building, owner, and government) and environment variables. The categories of variables are represented by different shapes, as shown in the legend in Fig. 3.

3.2.1.1. Variables of owner

3.2.1.1.1. Risk preference ρ. This variable determines the risk preference degree of owners. If the risk preference coefficient $\rho = 0$,

Table 1

Costs and benefits of stakeholders with government incentives.

Players	Objective	Benefits	Costs
Principal: Government	Maximize the utility of incentive policy	Environment and social benefit	Incentives to owners
Agent: Building owners	Maximize their own utility	Economic benefits from energy saving Incentives from government	Cost of EER

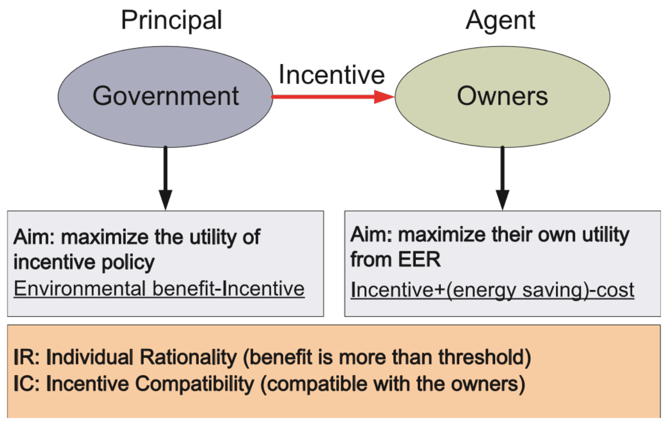


Fig. 2. The conceptual model of the agency problem in EER.

owners are risk neutral; if $\rho>0$, owners have risk appetite; and if $\rho<0$, owners are risk averse. The higher the absolute value of ρ, the more extreme the risk appetite or risk aversion. Normally, owners are risk averse (Juan et al., 2009). The more risk averse the owners, the less effort they want to put into EER (Juan et al., 2009; Liang et al., 2016).

3.2.1.1.2. Owner's economic benefit from EER ω^o. This variable represents the owner's profit from EER, which is the income minus the cost. Besides the costs of EER, owners have to undertake numerous efforts and carry risks, which create opportunity costs for them. Owners also have various expectations of profits (Fuerst and McAllister, 2011; Wu et al., 2014). Therefore, the profits of EER are needed to cover this opportunity cost and match the expectation of owners. The value of this variable will influence the utility of owners U^o.

3.2.1.1.3. Owner's cost of EER c^o. This variable represents the owner's costs of EER. It is mainly influenced by the efforts of the owner a^o. The more efforts owners put into EER, the more costs they will pay. The costs will impact the benefit of EER ω^o, in that higher costs will lead to fewer benefits (Caccavelli and Gugerli, 2002; Juan et al.,

Table 2

Type	Variable	Definition	Category

Owner	ao	Owner's effort to EER	Action
	co	Owner's cost of EER	Time and action depend
	ωo	Owner's economic benefit from EER	Time and action depend
	Uo	Owner's utility	Time and action depend
	ρ	Risk preference of owners	Static
	T	Threshold of EER	Static
Government	sg	Incentive of government to owners	Action
	Ug	Utility of government	Time and action depend
Building	S	Building area (m^2)	Static
	w	Energy efficiency per square meter (w/m^2)	Time and action depend
	e	Total energy consumption (kwh)	Time and action depend
Environment variable	p	Energy price (CNY/kW h)	Time depend
	θ	Exogenous uncertainty probability distribution (risk of EER), mean is 0, variance is σ	Time depend
Intermediate variable	βo	Coefficient of the incentive to owners	Time and action depend
	bo	Coefficient of owner's cost	Time depend

kec	Coefficient of economic benefit from EER, $k_{ec} \geq 0$	Time depend
ken	Coefficient of environmental benefit from EER, $k_{en} \geq 0$	Time depend
πec	Economic benefit of EER	Time and action depend
πen	Environmental benefit of EER	Time and action depend

Variable definition in the model.

2010; Newsham et al., 2009; Rey, 2004).

3.2.1.1.4. Owner's effort to EER a^o. This variable represents the degree of effort an owner makes toward EER. It is an abstract variable, including not only money, but also time, human resources, and so on. The value of this variable is from 0 to 1, where 0 means owners do not put any efforts into EER, and 1 means owners put 100% efforts into EER. The efforts will influence the cost of EER c^o and improvement of energy efficiency w. The more efforts made by owners, the more cost and energy saving from EER (Stiess and Dunkelberg, 2013).

3.2.1.1.5. Threshold of EER T . For each building owner, there is a threshold of EER. The threshold is the minimum utility that the owner wants to get from EER. If the utility of the owner is lower than the threshold, the owner will not undertake the EER ($a^o = 0$).

3.2.1.1.6. Owner's utility U^o. Owner's utility U^o represents the owner's overall satisfaction experienced through EER, which is an important underpinning in game theory (Fudenberg and Tirole, 1991). It has been also applied in agent-based modeling, where each agent aims to maximize its own utility (Panait and Luke, 2005). In this study, the owner's utility U^o is the economic benefit of EER ω^o plus the risk premium.

3.2.1.2. Variables of government

3.2.1.2.1. Utility of government U^g. Similar to the owner's utility U^o, this variable represents the overall satisfaction that government gets from EER. The main benefits for the government are energy saving and, accordingly, improvement of the environment. The more the energy saving, the more benefits the government can obtain (Menassa and Baer, 2014). But high incentive s^g will decrease the utility of government. Therefore, the government has to balance the benefit and cost of EER to maximize its utility.

3.2.1.2.2. Incentive of government to owners s^g. This variable represents the incentive owners are given by

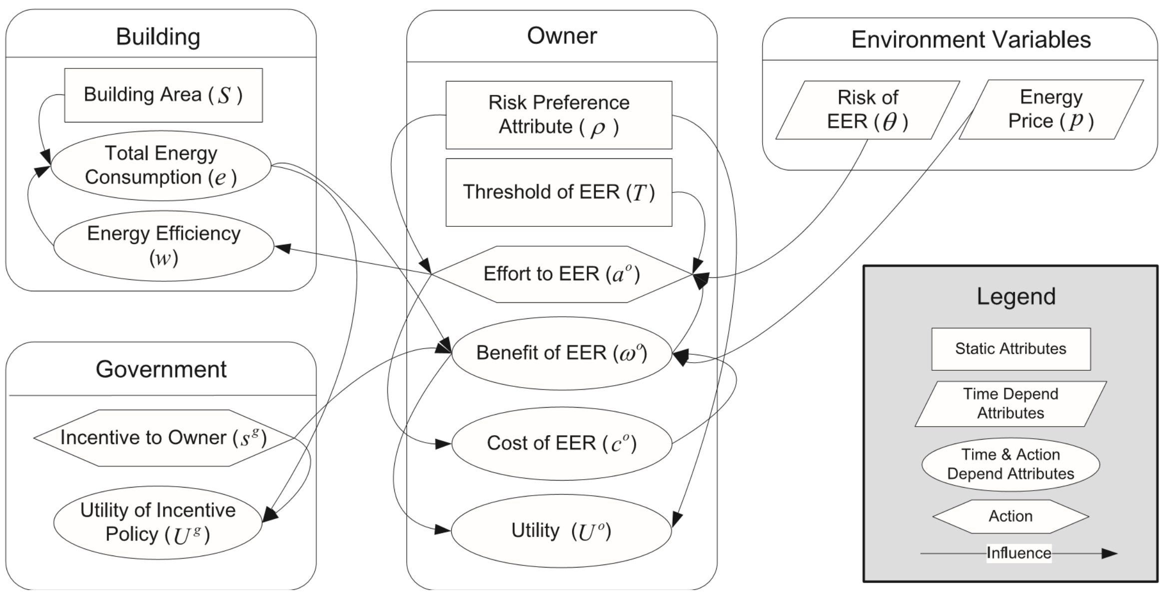


Fig. 3. Variables and agent interactions in the model.

the government to promote EER. It is a part of benefit of EER for owners, but is the cost for the government. Thus, on one hand, it influences the owners' benefit. The more incentive s^g, the more benefit ω^o the owners can get. On the other hand, it influences the utility of government U^g. The more incentive s^g, the more cost the government should pay.

3.2.1.3. Environment variables

3.2.1.3.1. Probability distribution of exogenous uncertainty θ. This variable represents the exogenous uncertainty, which leads to risks of both building owners and government. The uncertainties of EER have been identified by previous studies, including fluctuation of energy price, climate change, diversified energy use behavior, complex design, and interdisciplinary collaboration (Davies and Osmani, 2011; Newsham et al., 2009; Wu et al., 2016).

3.2.1.3.2. Energy price p. Energy price is an important factor in decision making of EER, since it directly influences the economic benefits of EER (Menassa, 2011). When the energy price is high, saving the same volume of energy will create more economic benefits.

3.2.1.4. Intermediate variables

3.2.1.4.1. Coefficient of the Incentive β^o. This variable indicates the coefficient of the incentive paid by the government to owners. The incentive from the government to owners is positively correlated with the environmental benefit of EER. The incentive coefficient determines the benefit redistribution between the government and building owners. The higher the incentive coefficient, the more benefit owners can get from EER, but the lower benefit the government can have (Fuerst and McAllister, 2011; Ouyang et al., 2011).

3.2.1.4.2. Coefficient of owner's cost b^o. This variable is the intermediate variable of the owner's cost c^o, which indicates the transformation coefficient from owner's effort to owner's cost. Since the marginal cost normally increases, the cost function is defined as a quadratic function, $c^o = \frac{1}{2} b {a^o}^2$.

3.2.1.4.3. Economic benefit π_{ec} and environmental benefit of EER π_{en}. EER can bring both economic and environment benefits (Fuerst and McAllister, 2011; Peng et al., 2012; Thomas, 2010). Economic benefit π_{ec} represents the economic benefit from EER, which is an intermediate variable for the owner's benefit ($\omega^o = + -\pi_{ec}\, s^g\, c^o$). Environmental benefit π_{en} represents the environmental benefit from EER, which is an intermediate variable for the government's utility (U^g).

3.2.1.4.4. Coefficient of economic and environmental benefit k_{ec} and k_{en}. These variables are the respective coefficients of the economic and environmental benefits from EER. They depend mainly on technology development and the building condition (e.g., HVAC system, lighting system, windows) (Kaklauskas et al., 2005). They are the intermediate variables for the economic benefit π_{ec} and environmental benefit π_{en} of EER.

3.2.2. Optimal decisions

3.2.2.1. Preparatory work. In a building, the energy consumption e (kWh) in a day can be defined as building area S (m^2) multiplied by the energy efficiency per square meter w(W/m^2) multiplied by 24 h, as shown in Eq. (1):

$$e = S\, w^{*} *24/1000 \qquad (1)$$

The economic benefit of energy saving is the difference of energy consumption after retrofit ($e_{pre} - e_{after}$) multiplied by energy price p, as shown in Eq. (2):

$$\pi ec = (epre - eafter)*p \qquad (2)$$

The economic benefit of EER π_{ec} depends on the efforts of owners $k\ a_{ec}{}^{o}$ and the exogenous uncertainty θ. k_{ec} is in direct proportion to energy price p and building area, while θ indicates uncertainties in the exogenous environment (e.g., climate change). π_{ec} can be calculated by Eq. (3):

$$\pi_{ec} = k\ a_{ec} \qquad {}^{o} + \theta.(3)$$

Similarly, the environmental benefit of EER π_{en} depends on the efforts of owners $k\ a_{en}{}^{o\ o}$ and exogenous uncertainty θ. Thus, π_{en} can be calculated by Eq. (4):

$$\pi en = k\ aeno \qquad o + \theta.(4)$$

To encourage owners to make greater efforts towards EER and achieve better effects, the incentives must have a positive correlation with the environmental benefit of EER π_{en}. β^{o} is the coefficient of the incentive. The higher the β^{o}, the more incentives the government will give for the same EER results. This linear incentive contract is shown in Eq. (5).

$$s^{g} = +\alpha^{o}\beta\ \pi^{o}{}_{en}. \qquad (5)$$

3.2.2.2. Optimal decisions for building owners. As illustrated in Section 3.2.1, the owner's economic benefit ω^o can be defined as the economic benefits from EER π_{ec} plus government incentives s^g minus the costs of EER c^o, as shown in Eq. (6):

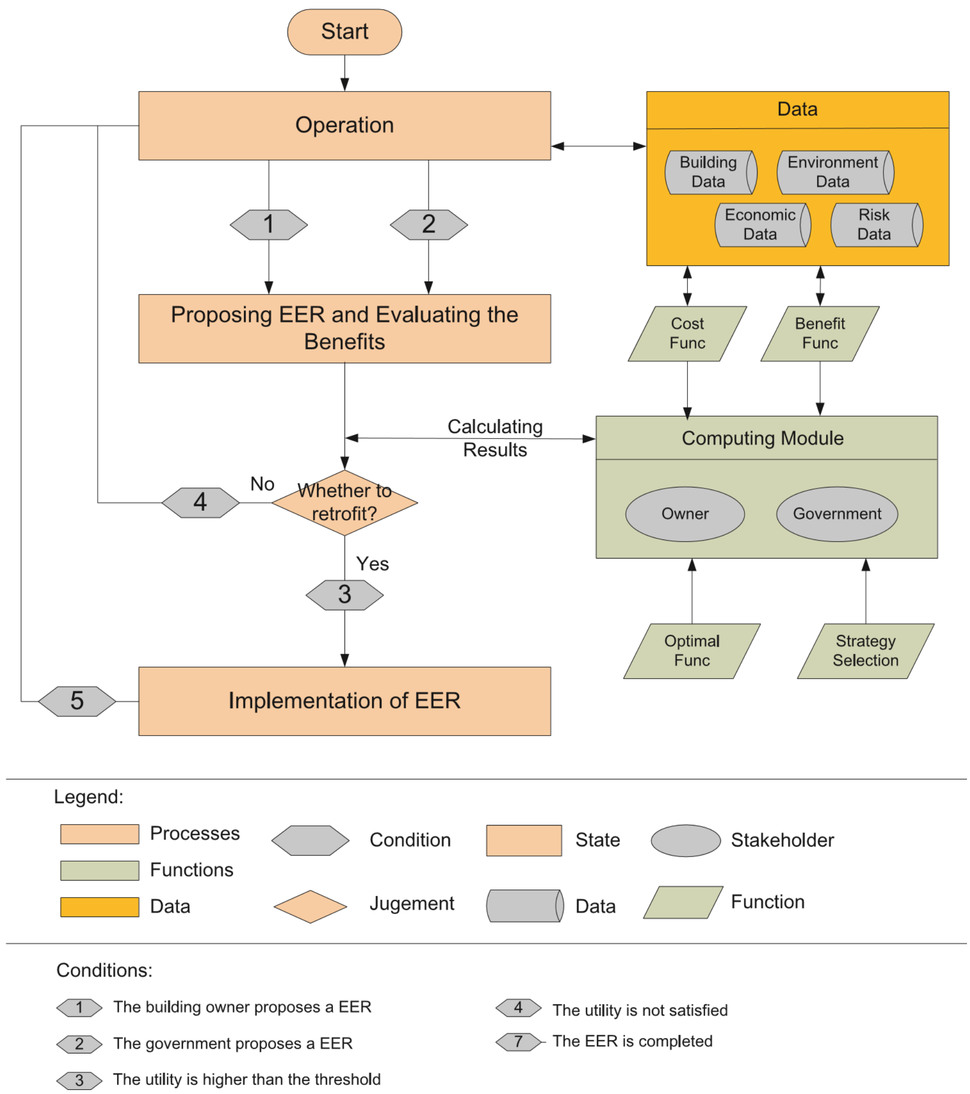


Fig. 4. Framework of the agent-based platform.

$\omega^o = + -\pi_{ec} s^g$ c^o(6)

As illustrated in Section 3.2.1, the cost function is defined as a quadratic function.

– $o = 1b\ ao\ o2$

Let c

2 (7)

where b^o is the coefficient of cost. The higher the b^o, the greater the costs for the same effort. Furthermore, the cost function is a convex function, which means marginal cost increases with effort; that is, marginal efficiency decreases when effort increases.

By substituting Eqs. (3), (5), and (7) into Eq. (6), Eq. (6) can be transformed into

$$\omega o = k\ aecoo + + + \theta \quad \alpha o \beta\ k\ ao(\ eno \qquad o + -\theta)\_12b\ ao\ \mathrm{o}2 \qquad (8)$$

Assuming the owner is risk averse and has a constant absolute risk aversion (Arrow, 1971), the utility function of owners is

$$Uo = -e\rho\omega,\ \rho = -\frac{Uo''}{U^{o'}} \qquad .(9)$$

where ρ is the absolute risk aversion coefficient, which indicates the constant degree of risk aversion (Arrow, 1971). The higher the value of ρ, the higher the risk aversion the owners have.

The certainty equivalent of owners is the expectation of income minus risk premium $\frac{1}{2}\rho\beta\ \sigma^{o2\ 2}$, which is the risk cost of owners (Eeckhoudt et al., 2005). The higher the $\frac{1}{2}\rho\beta\ \sigma^{o2\ 2}$, the higher the risk cost the owners have. The expected utility of owners is shown in Eq. (10).

$$E\ U(^o) = E\ \omega(\ ^o) - \frac{1}{2}\rho\beta\ \sigma^{o2} \qquad 2$$

$$= k\ aecoo + + \alpha o \qquad \beta\ k\ ao\ \bar{e}\bar{n}oo - 1b\ ao\ o2 - 1\rho\beta\ \sigma o2 \quad 2$$

$$2 \qquad 2 \qquad\qquad (10)$$

According to Section 3.1.2, owners aim to maximize their utility from EER, $\frac{}{\partial a^o} = {}^0\partial E\ U(\ o)$. Therefore,

$$ao = \frac{ec + \beta\ ko\ eno\ ko}{b^o} \qquad (11)$$

3.2.2.3. Optimal decisions for the government. Assuming the government is risk neutral, the utility function of the government is the overall environmental benefit from EER minus the incentives to owners, as shown in Eq. (12).

$U^g = -\pi_{en}$ s^g(12)

The certainty equivalent of the government is the expectation of government utility, shown in Eq. (13).

$E\,(U^g) = E\,\pi(_{en} - s^g).$ (13)

By substituting Eqs. (4) and (5) into (13), Eq. (13) can be transformed into

$E\,U(^g) = E\,\pi(_{en} - -\alpha^o \beta\, k\, a^o(_{en}{}^o$ $^o + \theta))$

$= - + -\alpha^o$ $(1\beta\, k\, a^o)\,_{en}{}^o$ ^{o}(14)

Under incomplete information, the government faces the problem of how to choose the most efficient incentive to induce the efforts of owners for EER and optimize government utility. This principal-agent problem can be mapped into the mathematical expression shown in Eq.

(7). $^{o\,o\,o}\max,\beta\, a,\, E\,U(\,g) = \alpha\,\beta\, a\max\,(- + -\alpha o$ $(1$ $\beta\, k\, ao)\, eno$ $o)$

α $o\,o\,o,$,(15)

s.t.

(IR): $E\,U(^o \geq {}^o_0$ $)\,\omega$

$^o = \underline{keco} + \beta\, ko\, \underline{eno}$. (IC): a

bo

The optimal incentive coefficient β^o can be calculated by solving the optimization problem. The result for the optimal incentive coefficient is defined by Eq. (16), which will be applied in the agent-based modeling in the next step.

$ko2$

$$\beta o = b\, \rho\sigma^{o} \qquad {}^{2}en + k_{eno2} \quad (16)$$

3.3. Model implementation

3.3.1. Platform description

The agent-based platform is implemented in Anylogic 7.2. AnyLogic is a widely used simulation tool of agent-based modeling. The programming language of Anylogic is Java. Due to the high compatibility of Java, the developed platform can be adopted in any device supporting Java toolkit, including PC, MAC, mobile phone and etc.

Based on the aforementioned agent definitions and decision-making methods, an agent-based platform is developed to implement the proposed model in this study. The framework of the platform is shown in Fig. 4. There are three parts in the framework, namely, process, functions, and data. These parts are shown in different colors in Fig. 4 (see the legend). The process part illustrates the whole workflow of the system. The function part divides the requirements to functions and provides support to the workflow. The data part stores the data and interacts with the system.

The architecture of the proposed agent-based platform is shown in Fig. 5. The agent-based platform is developed based on the layered architecture. This architecture is developed based on the Open Systems Interconnection (OSI) model, which is a general conceptual model that standardizes the information interaction in computing system, defined in standard ISO/IEC 7498-1. This architecture partitions a system into several abstraction layers. Contiguous layers are connected by standard interfaces between the two layers. This architecture is highly modularized, that if some new modules are added in the platform, only a few related modules and interfaces need to be modified while other layers do not need to be changed. Therefore, this layered architecture provides strong flexibility and extendibility of the system.

There are five layers in the platform, namely, user layer, agent layer, application layer, logic layer, and hardware layer. The user layer is mainly for the UI. Users can give input to the system and get output from the system. The agent layer is mainly for relation definition of agents, which is introduced in Section 3.1. The application layer is mainly for functions in the platform (e.g., the cost function and the utility function), which is introduced in Section 3.2. The logic layer is for the algorithms and processes of the system, which can be reused in the function layer. The hardware layer is the fundamental layer for the whole system, including data storage device, workstation, network, and server (for the website version). In this study, the platform runs on a workstation with a Windows 7 64-bit operation system, Intel Core i7–3770 CPU, 8GB RAM and 1TB hard disk. In Anylogic 7.2, the database is integrated in the software. The main concepts, relations and interactions in the model are mainly in the agent and function model. The logic layer and the hardware layer are mainly background processes designed to support up-layers.

The primary end user of this platform is the government. The platform can be used to evaluate cost and benefit of EER projects and generate suggestions for the government in terms of the optimal incentives for EER. This platform can also be used by other key stakeholders (e.g., owners and tenants) in EER to support their decisionmaking. For example, the evaluation results based on the platform can serve as a strong reference for owners and tenants to decide whether launch an EER project at the initial decision-making stage.

3.3.2. Policy scenarios

In this study, there are three policy scenarios to be evaluated on the platform, which are the incentive policy by the proposed model (introduced in Sections 3.1 and 3.2), the incentive policy in Shanghai and the incentive policy in Shenzhen. Chinese government selected Shanghai, Shenzhen, Tianjin, and Chongqing as pilot cities to test different incentive policies (Hou et al., 2016). Of the four pilot cities, Shanghai and Shenzhen are two first-tier cities in China (first-tier cities in China are Beijing, Shanghai, Guangzhou, and Shenzhen). Typically, first-tier cities play more important roles in the sustainable development of China. Therefore, this study selects Shanghai and Shenzhen as cases to evaluate the incentive policies. These three policy scenarios will be simulated on the proposed platform, and the results will show the performance of each policy in Section 4. The details of each policy scenario are shown as follows.

Scenario 1: The policy of Scenario 1 is based on the agent-based model introduced in Sections 3.1 and 3.2. This model aims to optimize incentive, particularly the value of β^o, to maximize the effect of EER.

Scenario 2: The policy of Scenario 2 is based on the case in Shanghai, which is from "Guidance for Further Promoting Building Energy Efficiency in Public Buildings" produced by the Ministry of Housing and Urban-Rural Development, China (MOHURD, 2011). In this scenario, if the energy-efficiency improvement is higher than 20%, the incentive is 40 CNY/m^2, otherwise, no incentive (Hou et al., 2016), as shown in Fig. 6(a).

Scenario 3: The policy of Scenario 3 is based on the case in Shenzhen. Shenzhen is a newly developed city, while Shanghai has a combination of buildings built before 1980 (dating back as far as the 1930s) and new constructions. Therefore, the energy efficiency of buildings in Shenzhen is much higher than in Shanghai. In this scenario, if the energy-efficiency improvement is higher than 20%, the incentive is 40 CNY/m^2. If the energy-efficiency improvement is lower than 20%, but higher than 10%, the incentive will be linear with the improvement rate. If the improvement of energy efficiency is lower than 10%, there will be no incentive (Hou et al., 2016), as shown in Fig. 6(b).

It is worth noting that the value of β^o in Scenario 1 is achieved based on the optimization analysis of the agent-based model. While, the incentive parameters in Scenarios 2 and 3 are directly determined according to the real conditions of Shanghai and Shenzhen.

4. Case study and results

4.1. Results

Three policy scenarios are evaluated on the platform. The configuration of the variables and simulation

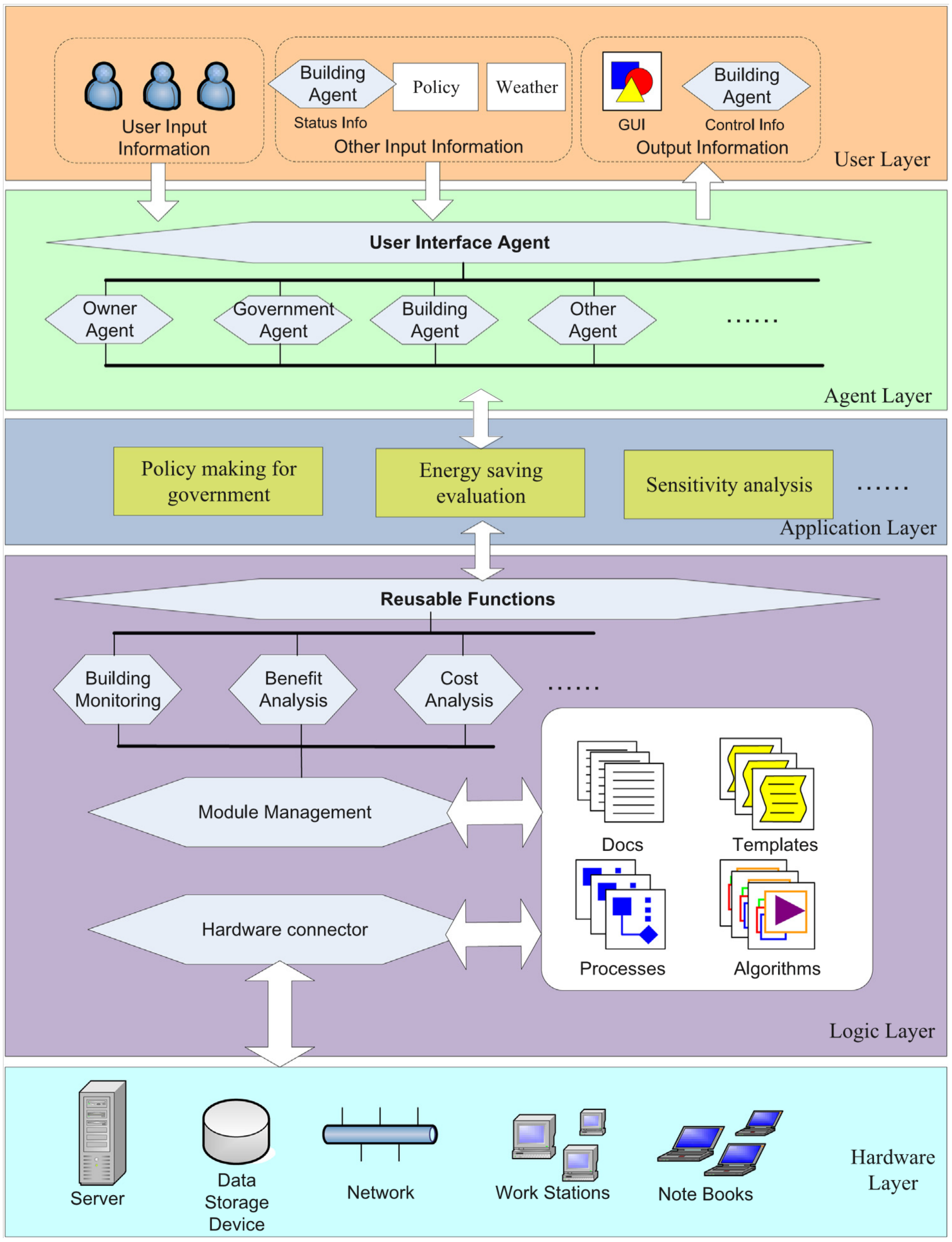


Fig. 5. Architecture of the agent-based platform.

environment are shown in Table 3. The main aim of the simulation is to compare the performance of three types of incentive policies (i.e., Shenzhen, Shanghai and the proposed policy in this study). Accordingly, the parameters in the three scenarios, except incentive policy-related variables, are set to the same values to exclude their impacts on policy comparisons. There are 100 buildings in the simulation. According to the report of China Association of Building Energy Efficiency (CABEE), the variable of building area is set from 2000 m^2 to 10,000 m^2 and the unit power is set from 10 W/m^2 to 30 W/m^2 (CABEE, 2016). Both of them are assumed to be in uniform distribution.

This study applied 10 simulated years, from January 1, 2017 to December 31, 2026. The timestep in simulation is one day. Under different policies, the agents in the simulation undertake different actions to optimize their benefits. After simulating a decade of time lapse, the results of the three scenarios are shown in Table 4. The changes of energy consumption per square meter during the simulated time are shown in Fig. 7, which illustrates the energy-efficiency improvement.

4.2. Sensitivity analysis

To verify the robustness of the model and identify sensitive factors for the incentive policy, sensitivity analysis is conducted in this study. Four factors are tested, which are unit cost, risk, acceptable threshold, and energy price. Value fluctuations of these factors may influence the results of incentive policies in different scenarios. Two dimensions are shown in the results of the sensitivity analysis, which are incentive from government and energy-efficiency improvement. The former indicates the influence on economy, namely the investment, while the latter indicates the influence on energy saving, namely the output. Analyzing the sensitivity of each factor in these two dimensions can reveal its influence on incentive policy. The results of the sensitivity analysis are shown in Fig. 8.

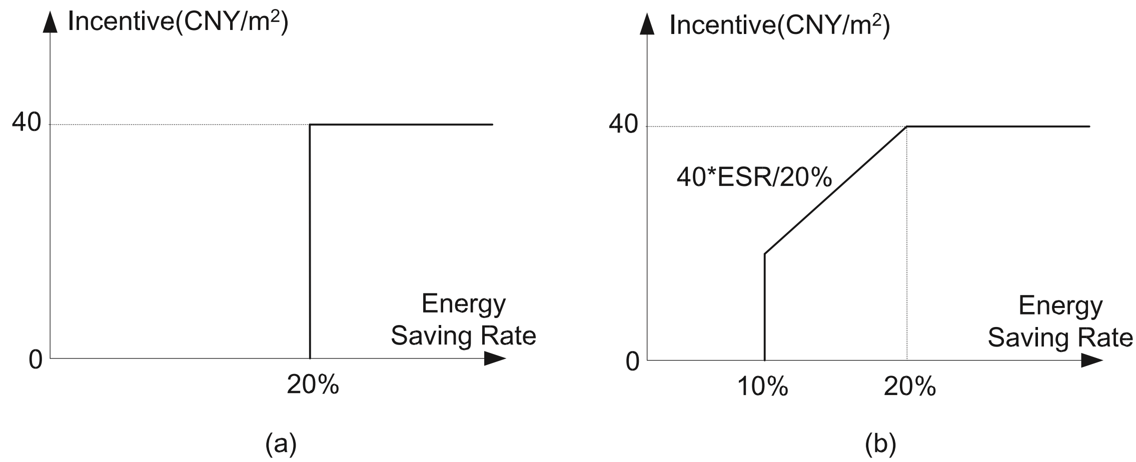


Fig. 6. Schema of incentive policy for EER (Hou et al., 2016). (a) Shanghai, (b) Shenzhen.

Table 3

Configuration of the experiment on the agent-based platform.

Variable	Symbol	Unit	Initial value
Building number		NA	100
Area of building	S	k m^2	2–10
Variance of uncertainty	σ	NA	3
Effort coefficient	*bo*	NA	0.5
Risk preference	ρ	NA	3
Energy price	p	CNY/kWh	1
Unit power	w	W/m^2	10–30
Threshold of owner	T	%	0

5. Discussion

5.1. Critical factors affecting the optimal incentive policy

The decision making of both the government and building owner is analyzed based on principal-agent theory in Section 2.3. The optimal incentive policy is shown in Eq. (16), which indicates that the higher the degree of risk aversion (ρ) and the uncertainty (σ), the lower the optimal incentive coefficient (β^o). The incentive coefficient (β^o) reflects the risk share between government and owner. When the owners' degree of risk aversion (ρ) is high, the incentive they are prepared to accept is limited. Considering a particular situation, if the owners are extremely risk-averse ($\rho \rightarrow \infty$), then the most efficient incentive should be close to 0 ($\beta^o \approx 0$), which means that the owners do not want to accept incentives for EER and undertake efforts toward EER according to Eq. (7). Similarly, if the project uncertainty (σ) is extremely high, the owners also do not want to undertake EER and take incentives. This indicates that project risks and risk management play a significant role in EER projects.

The primary risks of EER are listed as follows. First, EER may fail to improve energy efficiency under certain conditions. Even with green

Table 4

Simulation results	Policy based on Proposed model	Policy in Shanghai	Policy in Shenzhen
(a) Incentive (M CNY)	169	366	360
(b) Energy Efficiency Improvement (%)	39	15	14
(c) Investment of Owner (M CNY)	351	234	233
(d) Total Energy Save (MWh)	1,589,616	434,051	423,024
(e) Improvement per Incentive (b)/(a)	0.231	0.039	0.041

(f) Improvement per Total Cost (b)/((a)+(c))	0.075	0.024	0.025
(g) Energy Save per Total Cost (d)/((a)+(c))	3057	713	723

Results of the three policy scenarios.

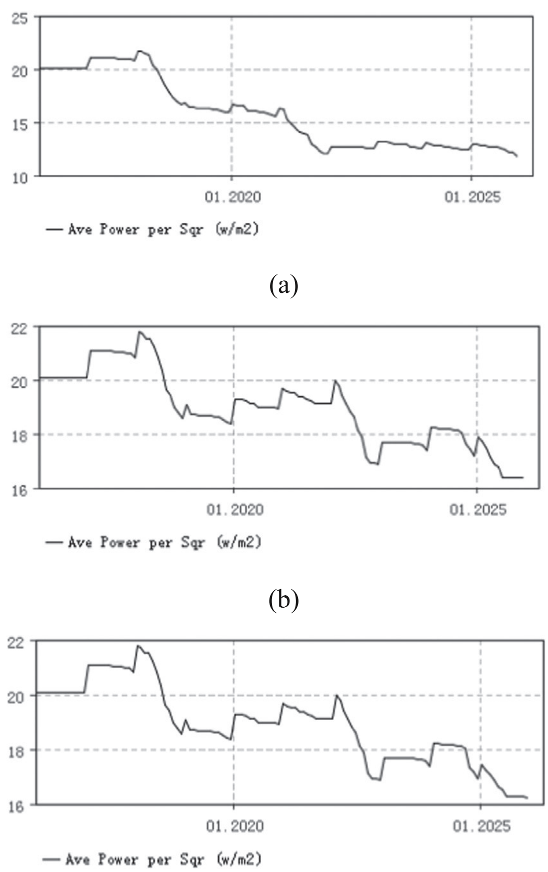
certification such as LEED, realizing energy savings in operation remains uncertain (Newsham et al., 2009; Scofield, 2009). As a result, owners and the government may not obtain economic or environmental benefits from EER. Second, most owners do not have sufficient experience in EER (Davies and Osmani, 2011; Kasivisvanathan et al., 2012). EER activities typically involve complex design analysis, intense interdisciplinary collaboration, and a wide range of stakeholders (e.g., the occupiers) (Davies and Osmani, 2011; Lapinski et al., 2006). Due to lack of experience, most building owners cannot deal effectively with these challenges. Finally, the payback period of EER is relatively long (Kasivisvanathan et al., 2012; Menassa, 2011). In China, the payback periods of EER for commercial buildings are normally around 10 years. During this time, numerous uncertain factors (e.g., changes in EER polices and interest rates) may affect the benefits of EER. These risks may cause building owners to be more cautious and create negative influences on EER incentive policies. Accordingly, to promote EER projects, effective measures should be taken to manage project risks.

The coefficient of environmental benefit from EER (k_{en}) is also an essential factor for incentive policy. A higher k_{en} means that the government can obtain environmental benefits from EER more easily. The incentive coefficient (β^o) is negatively correlated with k_{en}, which indicates that improving the environmental benefit coefficient can lower the incentives government should provide. This indicates that technological development impacts significantly on EER policies.

5.2. Comparative analysis of the three scenarios

The results of the three scenarios in the case study are shown in Table 4 and indicate that the incentive policy based on the proposed model has the best performance compared with the policies in the other two scenarios (i.e., Shanghai and Shenzhen).

(1) More energy saving: The energy-efficiency improvement of the



(c)

Fig. 7. Change of energy consumption per square meter during simulation for 10 years: (a) the proposed model, (b) Shanghai, and (c) Shenzhen.

proposed model is 39% in 10 years, which is more than two times that of the other two, as shown in Table 4(b). The total energy saving of the proposed model is also more than three times that of the other two, as shown in Table 4(d). This indicates that the energy-saving performance of the incentive policy based on the proposed model is significantly better.

(2) Higher return on investment (ROI): We consider two types of investment in ROI. One is the incentive, namely the investment of government, and the other one is incentive plus owners' investments, namely the total investment of the whole society. The return in ROI is defined as the energy efficiency improvement. The results are shown in Table 4(e) and (f). For the government, the ROI in the proposed model is 0.231% per million CNY, which is around five times that of the other two. For the whole society, the ROI in the proposed model is 0.075% per million CNY, which is around three times that of the other two. Therefore, the ROI of the proposed model is much higher than those of the other two.

(3) Higher leverage effect: Leverage effect means that a certain incentive by the government can induce a number of investments by building owners. This measure is an important assessment criterion of policy and indicates the effectiveness of the incentive. The higher the leverage effect, the more effective the incentive is. In the proposed model, the 169 million CNY incentive leveraged 351 million CNY owner investment. The leverage ratio is 2.1, which is much higher than the leverage ratio in the other two scenarios. Therefore, the leverage effect of the proposed model is better than those of the other two.

5.3. Sensitive factors in policy design

Based on the results in Fig. 8, the sensitivity of impact factors on incentive policy is further summarized, shown in Table 5. The sensitivities of factors are classified into three levels, namely low, medium and high, which can intuitively describe the degree of sensitivity. The levels are defined as follows: for the value of energy-efficiency improvement (column of Policy Effect in Table 5), 0–20% is Low; 20–40% is medium; more than 40% is High. For the value of incentive by government (column of Incentive in Table 5): 0–200 M is Low; 200–400 M is medium; more than 400 M is High. The values of incentive and energy-efficiency improvement are from results shown in vertical axis in Fig. 8.

For the policy scenarios in Shanghai and Shenzhen, all four factors are highly sensitive in their policy effects, namely energy-efficiency improvement. The sensitivity of three factors (except threshold) is strong.

It means the incentive policies in Shanghai and Shenzhen are very sensitive to all four factors. For the proposed model, unit cost and energy price influence policy effects strongly, while all four factors have limited influence on incentive. In summary, the proposed model is more robust than the other two.

5.3.1. Unit cost

The results in Fig. 8(a) indicate that, in the proposed model, the government incentive increases slightly when the unit cost is low, and nearly maintains invariability when the cost coefficient is higher. In all three scenarios, the energy efficiency improvement of EER is negatively correlated with the cost coefficient, because the higher the cost coefficient, the less effort will be made by owners. The energy efficiency improvement is negatively correlated with the unit cost, which indicates that higher unit costs of EER will hinder the energy savings.

To control the sensitive factor of cost, the government should try to reduce the owners' costs of EER. "Shared energy savings" is an effective business model normally used in energy performance contracting (EPC). In this business model, the energy management companies (EMCs) pay the cost of EER and the post-retrofit savings are shared by the EMCs and the building owners. The allocation proportion and time period during which the savings are shared can be specified by their contract. "Shared energy savings" has been promoted in China and is welcomed by building owners, which reduces the sensitivity of the cost factor (Hou et al., 2016).

5.3.2. Risk

The results in Fig. 8(b) indicate that in the proposed model, the government incentive is essentially constant when the variance of uncertainty is low, and decreases significantly when the variance of uncertainty is higher. In the Shanghai and Shenzhen scenarios, the incentive of government decreases sharply when the variance of uncertainty increases, and maintains a value of zero when the variance of uncertainty is beyond 1. This indicates that the incentive of government is sensitive to risk under the policies of Shanghai and Shenzhen; and if the risk is too high, the policies will fail. The proposed model is less sensitive to risk, and when risk is high, an optimal solution for the incentive still can be found. The trend of energy efficiency improvement indicates that the high risk of EER will hinder the effect of incentive policies.

To mitigate the influence of risks in EER, the government should try to control these risks, for example, reducing the uncertainty of policies and maintaining stable incentives and interest rates. Furthermore, the uncertainty of EER results can be reduced through EPC, which introduces professional EMCs to implement EER. In fact, EPCs are promoted by the Chinese government. In Chongqing, a pilot city for EER, if the building owners choose EPC, the cost of EER will be paid by EMCs and the owners can still have a 20% incentive from the government. This means the owners have significantly fewer risks in EER. As a result of this policy design, as many as 96% EER projects in Chongqing were

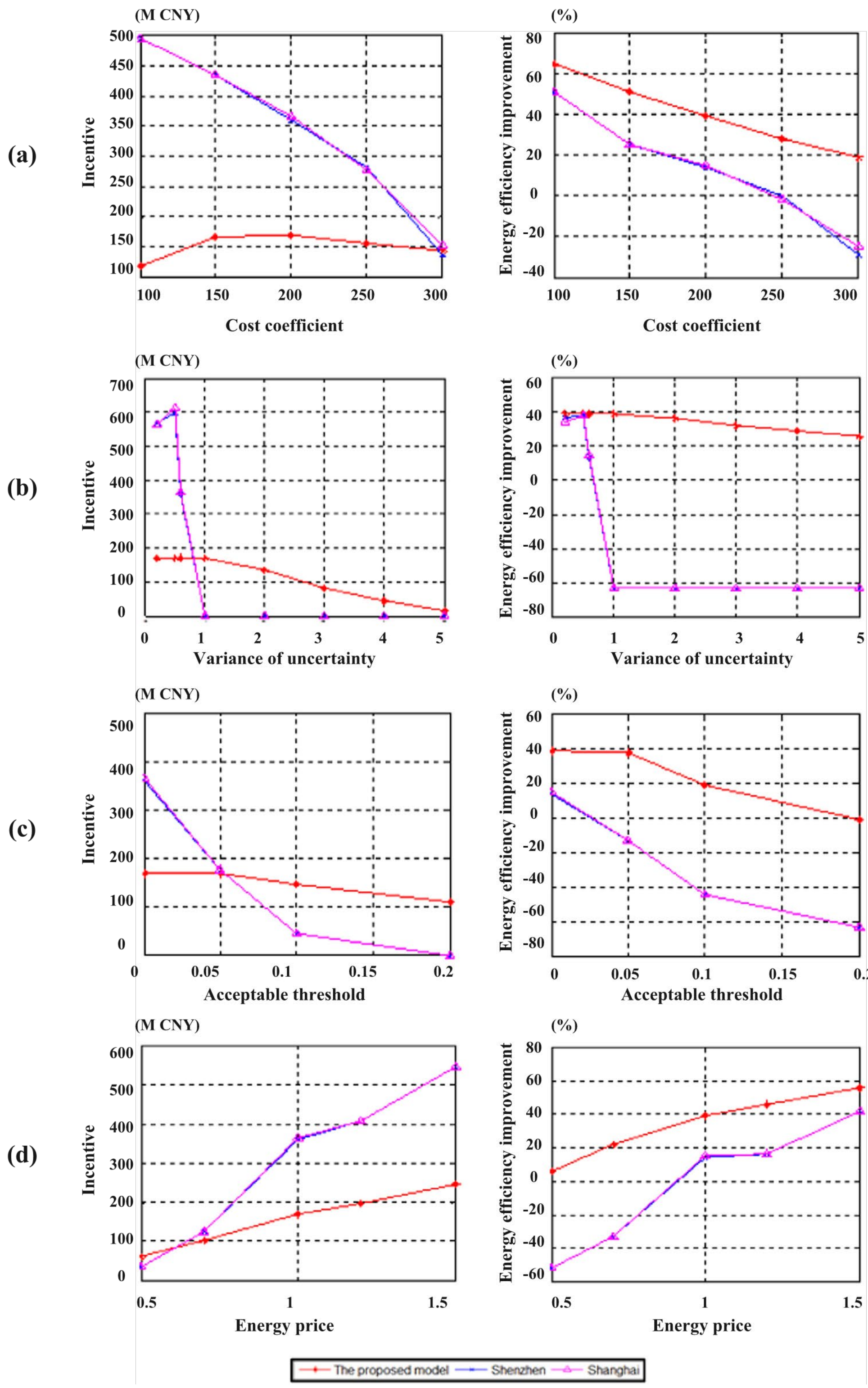


Fig. 8. Results of sensitivity analysis. (a) Unit cost, (b) Uncertainty, (c) Acceptable threshold, (d) Energy price.

carried out by EMCs (Hou et al., 2016).

In addition, to relieve the influence of risks in EER, the government should also try to reduce the degree of owners' risk aversion through advertising and education. If building owners are risk neutral, namely, ρ=0, then β = 1. The incentive coefficient is a constant, which is not related to k_{ec}, k_{en}, and σ. This means that the government incentives are not related to the external environment and are more efficient when building owners are risk neutral. Successful examples can help owners accept EER more easily and help diffuse EER more rapidly (Bartiaux et al., 2016). This is also the aim of selecting pilot cities for EER in China, with the intention of setting good examples to building owners. This will reduce their risk aversion towards EER and help promote EER in the future.

5.3.3. Acceptable threshold

The results in Fig. 8(c) indicate that the incentive of government

Table 5

Sensitivity of impact factors in each policy scenario.

Factors	Proposed model		Shanghai		Shenzhen	
	Policy effect[a]	Incentive[b]	Policy effect	Incentive	Policy effect	Incentive
Unit cost	High	Low	High	High	High	High
Risk	Low	Low	High	High	High	High
Threshold	Medium	Low	High	Medium	High	Medium
Energy price	High	Low	High	High	High	High

[a] Total energy-efficiency improvement: 0–20% is Low; 20–40% is medium; more than 40% is High.

[b] Total incentive by government: 0–200 M is Low; 200–400M is medium; more than 400 M is High.

decreases slightly with the acceptable threshold increasing in the proposed model. This means that the higher the acceptable threshold, the less the government incentive, but the changes are not very significant. In the

Shanghai and Shenzhen scenarios, the incentive of government decreases significantly with the acceptable threshold. The incentive of government is higher than that of the proposed model when the acceptable threshold is low, and is lower when the acceptable threshold is high. The trend of the energy efficiency improvement indicates that the higher the threshold, the lower the effect of EER.

The acceptable thresholds are different according to different building owners. For example, if the owners are large-scale companies with substantial revenues each year, a few benefits from EER are not attractive for them (Gucyeter and Gunaydin, 2012). On the contrary, if the owners are small-scale companies with limited revenues each year, they will emphasize the benefits from EER. Additionally, corporate social responsibility (CSR) can also impact the acceptable threshold. Owners with high CSR have more initiative to undertake EER (Davies and Osmani, 2011); thus, their threshold is lower. Since owners have different thresholds, the government should investigate these thresholds before policy design and also adjust policies with changes in this factor.

5.3.4. Energy price

The results in Fig. 8(d) indicate that the incentive of government increases significantly with the energy price increasing. Greater incentives should be provided when the energy price is higher. In the Shanghai and Shenzhen scenarios, the incentive increases more significantly with the energy price, which means the incentive is more sensitive to energy price. The energy efficiency improvement of EER is positively correlated with the energy price. This means that when the energy price is higher, the effect of the incentive policy will be stronger, since owners will be prepared to expend more effort on EER when their energy bill is higher.

Among the four factors, energy price is the most sensitive one in policy design. The fluctuations of energy price are influenced by the global economy, international politics, wars, etc. In China, the energy price is influenced by global prices and is also under the control of the central government. Since local governments do not have power to change the energy price, they should keep tracking the variation tendency of energy price. If the changes of energy price significantly impact incentive policy, the local government should adjust the incentive policy accordingly. The incentive policy can then track the energy price dynamically.

6. Conclusions and policy implications

This study proposed an agent-based model to analyze the decision making of building owners and to find an optimal incentive policy for EER. In particular, the proposed model can consider various characteristics of different buildings and building owners. The contributions of this study lie mainly in three aspects. First, the agent-based model can provide customized policy suggestions for different buildings and building owners according to their different characteristics. At present, the incentive policy is identical for all building owners, a "one-size-fitsall" policy. The proposed model can adjust policy suggestions for different conditions, which can mitigate this problem in EER. Second, the model provides an approach based on principal-agent theory to address agency problems in EER. Most previous studies analyze the agency issue through empirical studies and econometric methods, which cannot reveal the internal logic of this issue. In this study, the decision-making behavior is modeled based on the principal-agent theory and is simulated on the agent-based platform. The analytical results can reveal the internal logic of the agency issue with consideration given to dynamic environments. Third, the proposed platform can provide real-time suggestions for the government. Most previous studies analyze incentive policies of EER based on static data. But the data change frequently in practice, which makes the results not appropriate to the present situation. The dynamic adaptive ability of the agent-based model makes it possible to provide appropriate policy suggestions in real time.

The results of the case study verified the effectiveness and robustness of the proposed model and provide interesting implications for EER incentive policies. First, with consideration of various owners' characteristics, the effectiveness of incentive policy will be improved significantly. Second, the optimization method based on principalagent theory can mitigate agency problems and enhance the leverage effect of an incentive policy. Third, the proposed model is more robust than the policies of Shanghai and Shenzhen. Finally, the policy based on the proposed model is relatively sensitive to the relevant factors, including unit cost and energy price. In particular, the government should pay more attention to the energy price. If the energy price fluctuates, the incentive policy should be adjusted accordingly.

Although it has been proved that the policy given by the proposed model has better performance compared with the two real cases, practical barriers to policy implementation should be acknowledged as well. First, the data of building energy consumption may not be available. In China, some developed cities have built energy audit systems in recent years, such as Shenzhen and Shanghai, in which almost all the commercial buildings are connected into the systems and the energy consumption of buildings has been recorded in corresponding databases. However, most cities in China have not built such systems to supervise and record energy consumption data, so the proposed policy may face data challenges in these areas. In addition, even the data is available, the proposed policy still has difficulties associated with implementation due to heavy administrative burden of local governments. Compared with the current "one-size-fits-all" policy, the proposed policy needs to evaluate the conditions of each building, which increases the workload of local governments. To remove the two barriers, energy audit systems and databases should be established to provide data support for policy makers. Then, an automatic assistant system should be developed to analyze the data and provide decision-making support for local governments, which can significantly reduce the workload of government officials. The platform in this study provides a prototype for such systems, but still has long way to go. This is the future research direction for the authors as well as other researchers in related fields.

In terms of research limitations, at the present stage of platform development, the agent-based model does not capture the learning behaviors of stakeholders. However, in practice, stakeholders can learn from each other. For example, the owner agents can observe the costs and revenues of other owners in EER, and they will modify their EER strategies according to what they have observed. In future studies, the current model should be enhanced to investigate such learning behaviors. In addition, the results of this study were not verified via empirical data with a large sample size because the detailed information related to EER is confidential in the studied cases. The model should be further validated when data is available. Thirdly, consistent with classical agency theory-based models, this study assumes that all of the involved stakeholders make their decisions in a rational approach. However, in real world, the decision-making of stakeholders may be affected by irrational factors such as personal emotion. In future studies, the irrational behaviors of stakeholders should be further analyzed. Finally, the stakeholder attributes defined in this model may not comprehensively represent all the characteristics of the stakeholder behaviors in some complex cases. The proposed platform is a prototype which demonstrated that the agent-based model can improve the policy making on the EER. In future studies, more functions and attributes of stakeholder behaviors may be added to the proposed platform to improve the accuracy of results.

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