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Managing competitive municipal solid waste treatment systems: An agent-based approach

Zhou He [a,b], Jie Xiong [a], Tsan Sheng Ng [a], Bo Fan [c,*], Christine A. Shoemaker [a,d]

[a] Department of Industrial Systems Engineering and Management, National University of Singapore, 1 Engineering Drive 2, Singapore 117576, Singapore
[b] NUS Environmental Research Institute, National University of Singapore, 5A Engineering Drive 1, Singapore 117411, Singapore
[c] School of International and Public Affairs, Shanghai Jiao Tong University, 1954 Huashan Road, Shanghai 200030, China
[d] Department of Civil and Environmental Engineering, National University of Singapore, 1 Engineering Drive 2, Singapore 117576, Singapore

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ABSTRACT

Private sector participation in municipal solid waste (MSW) management is increasingly being applied in many countries recently. However, it remains a largely unexplored issue whether different self-interested treatment operators can co-exist in an economically feasible and sustainable manner. To help the policy-maker s understand and manage competitive MSW treatment systems, this paper proposes an agent-based waste treatment model (AWTM) that consists of four types of agents, namely the refuse collector, specialized treatment unit (STU), the general treatment unit (GTU), and the regulator. An estimation-and-optimization approach is developed for profit-maximizing agents to set optimal gate fee and vie for specific waste in low-information competition. Based on the Singapore case, the experimental results imply that if the regulator deliberately promotes the STUs by intervening in waste allocation, the GTU could give up competing for the waste and greatly increase its gate fees as retaliation. Besides, driven by the increasing gate fee of the GTU, the STUs conservatively raise their gate fee; while the GTU will be the major beneficiary in the AWTM. Finally, to identify the optimal mixed policy under predefined constraints, the AWTM is integrated into a simulation-based optimization problem, which is solved by a genetic algorithm.

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1. Introduction

Sustainable municipal solid waste (MSW[1]) management is a critical issue for cities all over the world, especially for mega-cities that generate millions of tonnes of MSW annually. Take Shanghai as an example, the total MSW generation in 2014 was 7.43 million tonnes. In Singapore, the amount of solid waste generated in 2015 increased to 7.67 million tonnes, up by 159,000 tonnes from 7.51 million tonnes in 2014 (NEA, 2015). Historically, landfill disposal was deemed to be the most conventional way to deal with collected MSWs. However, it consumes and pollutes a considerable amount of land, and sometimes causes hazardous liquid leakage and gas emission. Therefore, only incinerated wastes (i.e., ashes) are allowed to be decomposed by landfilling in some land-scarce cities like Singapore. Although the incineration process significantly reduces the volume of waste, it produces dioxins that contaminate food, pollute the air and be absorbed through skin, posing severe risks to public health. Hence, the traditional incineration-landfilling approach is insufficient for dealing with the rising waste generation.

In recent decades, advances in waste-to-energy treatment technologies have made notable improvement in both environmental sustainability and energy recovery. For example, anaerobic digestion can be applied to efficiently treat organic waste and recover biogas, a mixture of different gases that can be further used in power generation. Moreover, the gasification is now able to recover significant yields of synthesis gas and heat. These innovative MSW treatment technologies are now commercially available in various scales, allowing private capital to enter the MSW treatment market with a relatively low investment. In other words, private treatment plants can be built in small or medium scale to treat specific types of input waste like organic waste. Generally, these treatment units that only treat specific MSW stream components (termed as specialized treatment unit, or *STU*) earn revenue in two ways: by charging a per-tonne tipping fee (also termed *gate fee*) for accepting waste input from the waste collector; and by selling electrical energy output (Ata, Lee, & Tongarlak, 2012). However, residues

* Corresponding author.
E-mail addresses: hezhou@nus.edu.sg (Z. He), xiongjie@u.nus.edu (J. Xiong), isentsa@nus.edu.sg (T.S. Ng), fanbo@sjtu.edu.cn (B. Fan), isesca@nus.edu.sg (C.A. Shoemaker).

[1] Appendix A provides a list of abbreviations and acronyms, which are used to shorten long sentences and achieve better readability.

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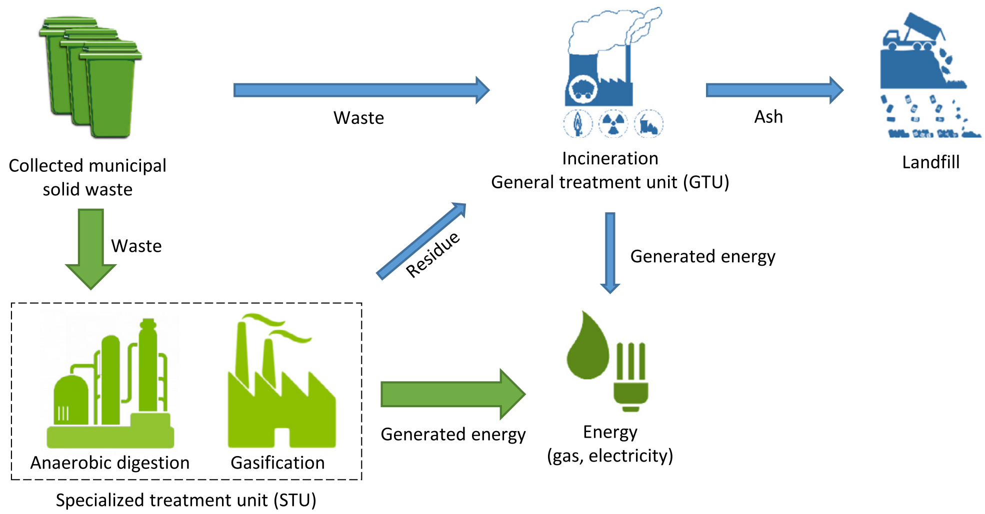

Fig. 1. Modern municipal solid waste treatment system.

generated from the waste-to-energy process could produce secondary pollution emissions in various forms like airborne and waterborne contaminants.

Therefore, such residue requires further processing by the general treatment unit (*GTU*, such as incineration), which can treat any MSW stream component and residue, before final landfilling disposal. As illustrated in Fig. 1, different treatment units, which are integrated to constitute the modern MSW treatment system, can mutually reuse by-products and process residues, and thus they achieve a collective environmental and economic benefit.

Traditionally, waste management is regarded as a public service, with the local government or authority having sole proprietorship of all entities and resources for the end-to-end activities from waste collection to final disposal. However, the public sector often lacks critical professional managerial and technical skills to operate advanced waste-to-energy treatment plants. Therefore, private sector participation in MSW management activities is increasingly being applied in many countries. Singapore, for example, proactively encourages private companies to participate in the MSW treatment industry (Lim, 2000). Currently, two of four incineration plants in Singapore are owned and operated by Keppel Seghers, a private company handling about 50% of combustible waste collected daily in Singapore (Tuan, 2016).

To further improve service efficiency, a competitive MSW treatment market can be established so that profit-maximizing private operators are incentivized to compete for waste by lowering gate fees and introducing innovative operations and technologies (Lim, 2000). Therefore, these private operators (i.e., STU and GTU) interact with each other not only through co-treatment of waste and residues, but also through gate fee competition for the market share of available input waste.

Such a scenario is motivated based on an actual case where the current treatment approach for food waste is via conventional combustion. Singapore's environmental policy-makers are proposing a feasibility study of improving food waste recycling by introducing anaerobic digestion units in the townships (En, 2015). Independent and qualified operators can be authorized to enter the market as anaerobic digestion unit operators and offer their treatment services to the waste collectors. On the other hand, the digestion residuals require post-treatment by conventional combustion for the purpose of volume reduction before landfill disposal.

However, market competition could cause bankruptcy of key private operators and consequently pose a serious risk to the system's stability and sustainability. In Singapore, for instance, the under-utilization issue led to the closure of the largest private anaerobic digestion company *IUT Global* in 2011 (The Straits Times, 2011). Hence, there is a compelling need for the regulator to understand the competitive market and develop appropriate policies, so that the MSW treatment market is able to run in an efficient and sustainable manner.

In this paper we aim to propose an agent-based decision support framework for the regulator in managing competitive MSW treatment systems. Grounded in complex adaptive system (CAS) theory, we create an agent-based waste treatment model (AWTM) consisting of four types of agents, namely one refuse collector, multiple heterogeneous STUs, one GTU, and one regulator. An estimation-and-optimization approach is developed to help private operators to optimize their gate fee decisions in low-information competition. For the government, possible policies for regulating such a market include: (1) controlling the number of private participators; (2) intervening in waste allocation process; (3) imposing an upper bound of gate fee; (4) offering a gate fee discount for waste-to-energy units. We attempt to shed light on the following challenging research and practical issues:

1. For the policy-maker, what are the aforementioned policies' impacts, pros and cons? How to identify the optimal mixed policy to fulfill multiple predefined objectives?
2. For the heterogeneous private operators, what are their performances and optimal decisions under each policy?

The reasons for using the ABM technique to studying the above issues are as follows:

1. Traditional analytical methods are generally not suitable for studying these issues due to the complexities of the AWTM, which are two-fold. Firstly, there are multiple heterogeneous entities in the AWTM, and their relationships are not only competitive, but also symbiotic. Secondly, it is difficult to obtain the full knowledge of all rivals, such as their technical information about waste-to-energy treatment. Therefore, the private operators are not able to forecast precisely the decisions of others, leading to low-information competition. In contrast, the ABM approach has been increasingly applied for studying complex issues in competition (see Section 2.3).
2. Private self-interested operators can be modeled as agents, since they carry out tasks independently and have the full features of a typical agent, namely autonomy, social ability, reactivity, and pro-activeness (Wooldridge & Jennings, 1995). Compared with traditional analytical methods, individual-level modeling allows us to focus on their evolutionary decisions in response to continuing changes in the dynamic environment.

For instance, we are able to create multiple STU agents that are heterogeneous in initial attributes, which are very important in shaping their behaviors.

3. Optimal gate fee decisions of treatment units can be viewed as adaptive behaviors in competition. According to CAS theory, it is adaptation that engenders complexity (Holland, 1996). Adaptive agents iteratively respond to feedbacks by seeking optimal operations and changing their actions in order to survive the "natural selection" process, which is the driving force of evolution in biology (Biava et al., 2011). Therefore, if individual objective functions are established, the long-term optimal strategies can be derived from observing the evolutionary behaviors of surviving agents as emergent phenomena. We focus on the overall operations of private treatment units (i.e., STU) in response to competition throughout the evolution of the agent-based model, rather than the specific optimal solutions of individuals in static competition under traditional models.

The rest of the paper is organized as follows. In Section 2 we review three related research streams. We model agents' decision-making processes explicitly in Section 3. Based on the Singapore case, we consider four practical scenarios and conduct various computational experiments in Section 4. Next, we present the experimental results, highlight our research findings, and discuss their managerial implications for policy-makers in Section 5. Finally, we conclude the paper and suggest potential topics for future research in Section 6.

2. Literature review

We review the literature based on three related research streams, namely (1) decision support models for waste management, (2) analyzing market competition in the waste management industry, and (3) agent-based modeling in market competition.

2.1. Decision support models for waste management

Over the past two decades, there is an increasing number of decision support models developed for guiding decision-makers toward the choice of best strategy or the preferable selection among a set of alternatives in the face of various strategic, tactical and operational issues in MSW management systems. Most of them can be categorized into one of three types: those based on cost-benefit analysis (CBA), those based on life-cycle assessment (LCA), and those based on multi-criteria decision analysis (MCDA) (Morrissey & Browne, 2004).

The CBA-based model generally evaluates and optimizes the system from economic perspective by translating all system impacts into a simple monetary measure. For example, Wu, Huang, Liu, and Li (2006) proposed an interval nonlinear programming model for designing optimal waste flows with the lowest total system cost by applying different economies-of-scale effects in the MSW transportation and treatment process. Li, Huang, Nie, and Nie (2008) developed a two-stage fuzzy robust integer programming model for optimizing waste flow allocation and facility capacity expansion with the purpose of minimizing the total system cost.

By evaluating the direct and indirect environmental impacts associated with the relevant inputs and outputs throughout the system's entire life cycle, the LCA-based model shows significant advantages in comprehensively assessing the system's environmental performance. For instance, Xiong, Ng, and Wang (2016) adopted the LCA modeling approach to analyze the system's environmental performance, and proposed a two-stage mixed-integer stochastic programming model aiming at maximizing the joint probability that each installed treatment unit is able to achieve its own financial target.

MCDA-based models simultaneously take several individual and often conflicting criteria into account in a multidimensional way (Morrissey & Browne, 2004). Therefore, it is suitable for tackling MSW management problems involving multiple stakeholders with different preferences. For example, Erkut, Karagiannidis, Perkoulidis, and Tjandra (2008) built a mixed-integer linear programming model with multiple economic and environmental objectives to solve the technology selection and location, and waste flow planning problems in an integrated MSW management system. As all objectives are considered to be equally important, this model aims at obtaining a "fair" non-dominated solution with all normalized objectives as close to one another as possible by applying the lexicographic minimax approach.

2.2. Analyzing market competition in the waste management industry

Market competition in the waste management industry can stimulate the profit-driven private operators to improve their service quality and operation efficiency. However, there usually exist incompatibilities between the regulator's perspective of realizing long-term sustainability targets and the private operator's focus on short-term investment return (Koppenjan & Enserink, 2009). Therefore, there is an interest and value to study the roles and actions of regulator and private operator in a competitive waste management market. Some relevant research outcomes have been presented in the literature. Davila, Chang, and Diwakaruni (2005) proposed a two-tiered grey integer programming-based game theory approach to help scrutinize scenarios wherever landfills display competitive behavior under an increasing need for their services. The first-tier CBA-based model sifts for optimal solid waste distribution with the objective of minimizing net costs for cities, and the second-tier game theoretic pricing analysis studies the optimal tipping fee strategies at the landfill facilities. Bárcena-Ruiz and Casado-Izaga (2015) studied a two-stage game between two private collection firms who pursue maximal payoffs by deciding their locations (first-stage decision) and prices (second-stage decision) when the government requires private collection firms or consumers to bear the waste transportation fees. Liu, Lei, Deng, Leong, and Huang (2016) developed a quality-based price competition model for the waste electrical and electronic equipment (WEEE) recycling market to explore the impact of subsidy on both informal and formal sector, and discuss the optimal subsidy level for the entire WEEE recycling industry.

2.3. Agent-based modeling in market competition

Although specific optimal solutions can be obtained from analytical models via mathematical analysis, these studies paid little attention on incorporating some key characteristics of realistic market competition, such as incomplete information, multiple heterogeneous players and out-of-equilibrium dynamics. In contrast, agent-based techniques have received considerable attention in recent years as a result of a growing need for tackling complex issues in market competition. In existing ABM studies, agents have to adapt to and co-evolve with the dynamic CAS in which they exist, allowing the modeler to observe the evolutionary behaviors of the surviving agents and understand the systematic emergent phenomena. For example, Sofitra, Takahashi, and Morikawa (2015) used ABM technique to simulate supply networks, in order to understand co-evolving relationships among interacting members (i.e. cooperation, defection, competition and co-opetition). Combined with system dynamics, heuristic algorithms, and other elements, He, Wang, and Cheng (2013), He, Cheng, Dong, and Wang (2014), He, Cheng, Dong, and Wang (2016) proposed many ABMs for the competing firms (e.g., retailers, logistics companies, service merchants), which attempt to optimize their operations (e.g., pricing, location, inventory management) in different complex markets. Stummer, Kiesling, Günther, and Vetschera (2015) designed an ABM to examine the temporal and spatial dimension of innovation diffusion in a multi-product market considering consumers' repeat purchase decisions. To introduce a new product to such a competitive market, the impacts of different pricing strategies were investigated. These studies have enriched our understanding of ABM in market competition. However, we found few research that have developed ABM to examine MSW treatment systems.

Due to the existence of powerful policy-makers, competitive MSW treatment systems are quite different from the above open markets. From the perspective of the regulator, therefore, the ABM technique is expected to serve as not only a simulation platform for qualitative analysis, but also a quantitative decision support tool for policy evaluation and development. To do so, the modeler should be aware of the possible shortcomings of some ABMs discussed in the literature. Windrum, Fagiolo, and Moneta (2007) suggested that there exist many difficulties in validating an ABM, including (a) a lack of standard techniques for comparing ABMs, and (b) the large number of parameters involved, leading to the "over-parameterization" problem, etc. Some critics claim that the ABMs rarely correspond to empirical data, and thus are only for "toy problems" (Rand & Rust, 2011). Besides, the simulation results are variable because of the random factors introduced in the model. Therefore, the reproducibility of an ABM should be considered (Grimm et al., 2006).

2.4. Summary

Our study advances previous research in several aspects. (1) To the best of our knowledge, this paper is the first agent-based study on the competition in integrated municipal solid waste treatment markets. We extend existing studies by considering more realistic situations and designing comprehensive simulation experiments. (2) We provide a promising decision support framework for policy-makers by modeling the decision-making process of individual agent in low-information competition, and by integrating the AWTM into a simulation-based optimization problem. Due to the valuable flexibility of the framework, large-scale and complex studies, which are often cumbersome to model and solve mathematically, can be conducted in a natural and bottom-up way. (3) Our findings are obtained based on the micro interactions among the agents throughout the evolution of the AWTM, rather than on a static mathematical analysis. Therefore, the proposed model is more likely to capture the actual complex decision patterns of private operators, making calculated results more convincing. (4) Our study overcomes some of the aforementioned shortcomings of the agent-based modeling technique by building the AWTM on the actual MSW management practices and evidence in different countries, as well as the empirical data of Singapore's waste industry (see Section 3.1 and Section 4.1). Moreover, we design the Scenario S1 to validate the AWTM, and perform the simulation process 100 times for each of 33 experiments to ensure robust outputs against randomness in the AWTM (see Sections 4.1 and 4.2).

In view of the above advantages, our work is able to provide practical insights not only for the regulator, but also for the private operators that participate in the competitive and integrated municipal solid waste treatment market.

3. Model description

3.1. Overall structure of the AWTM

The general process of MSW management is as follows. Mixed MSW is first collected and presorted by refuse collectors. Next, material recovery takes place for recyclable and re-usable items. The remaining MSW is then sent to treatment units, and treated via various approaches (such as waste-to-energy) for volume compression and useful energy recovery. Residues generated may require further treatment. Finally, all post-treatment residues, and other untreatable components are disposed via landfilling. In the AWTM, we focus on the MSW treatment stage of the process, as illustrated in Fig. 2. Table 1 summarizes agent-related variables used in the AWTM. Based on the actual MSW management practices in different countries, we propose the following basic but essential notions in the context of a competitive MSW treatment market.

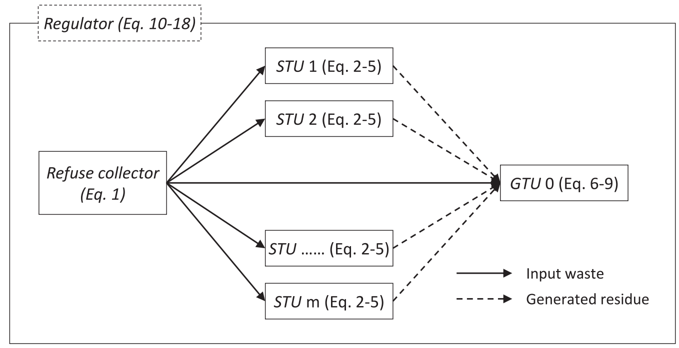

Fig. 2. The overall structure of the AWTM, which is assumed to be a CAS consisting of four types of agents: one refuse collector, multiple heterogeneous STUs, one GTU, and one regulator. The input waste stream and post-treatment residue stream are represented as solid line and dotted line, respectively. For each type of agent, its own model is expressed by the associated equation(s).

- The input waste stream components can be treated by both STUs and the GTU (e.g. food waste). Also, the GTU is able to treat residues from STUs.
- There are m independent STUs competing for the input waste to maximize profits by setting their individual gate fees. The gate fee is an important component of the revenue stream of the operator, and also a key instrument that the private operator can use to make the treatment service economically attractive to users. Empirical evidence of gate fee competition in Iceland and Nigeria can be found in Cointreau-Levine (1994) and FCCA (2016).
- The STUs (denoted by set $\mathcal{I} = \{1, 2, \ldots, m\}$) are heterogeneous in per-tonne comprehensive operation costs ($\mu_f > 0$, where $f \in \mathcal{I}$ is a STU agent) and residual generation coefficients (i.e., the weight ratio of generated residuals to original waste; denoted by $\delta_f \in (0, 1)$) since they may choose different waste-to-energy technologies and equipment etc.
- Due to economies of scale, only one GTU is considered in the AWTM. A GTU (e.g., an incineration plant) is generally built in large scale as it must be able to handle the full array of input waste from MSW suppliers and process-generated residues from STUs (Miranda & Hale, 1997). Consequently, it requires a high investment cost and has a large economics of scale.
- Since the GTU plays an important role in the post-treatment market due to monopoly, the regulator mandates an upper bound ($\overline{\eta}_0$) on its gate fee charge to prevent unrealistically high waste/residues treatment costs, which are finally borne by all citizens. For the STUs, in contrast, a regulated upper bound of their gate fee is not necessary given the presence of competition. Later in Section 5, the experimental results also justify this assumption.
- The regulator implements policies by changing some exogenous variables besides the gate fee upper bound ($\overline{\eta}_0$). Firstly, the regulator is able to intensify competition among agents by introducing more STUs (i.e., enlarging m). Secondly, the regulator

Table 1
Agent-related variables used in the AWTM.

Agent	Variable	Type[a]	Remark	Unit	First equation
Refuse collector	W	XV	Volume of municipal solid waste	Tonne	(4)
	α_g	XV	Price sensitivity to the GTU	–	(1)
	α_s	XV	Price sensitivity to the STUs	–	(1)
	β_g	XV	Waste utilization preference to the GTU	–	(1)
	β_s	XV[b]	Waste utilization preference to the STUs	–	(1)
STU $f \in \mathcal{I}$	$\eta_{f,\,t}$	DV	Gate fee	SGD[c] / Tonne	(1)
	$\pi_{f,\,t}$	NV	Profit	SGD	(2)
	μ_f	XV	Operation cost	SGD / Tonne	(2)
	$\omega_{f,\,t}$	NV	Input waste from the market	Tonne	(2)
	δ_f	XV	Residue generation coefficient	–	(2)
	$\theta_{f,\,t}$	NV	The probability of randomly selecting a gate fee	–	–
GTU	$\eta_{0,\,t}$	DV	Gate fee	SGD / Tonne	(1)
	$\pi_{0,\,t}$	NV	Profit	SGD	(6)
	μ_0	XV	Operation cost	SGD / Tonne	(6)
	$\omega_{0,\,t}$	NV	Input waste from the market	Tonne	(6)
	$\bar{\eta}_0$	XV[b]	The upper bound of the GTU's gate fee	SGD	(7)
	d_0	XV[b]	Gate fee discounting factor for the STUs	–	(2)
	$\theta_{0,\,t}$	NV	The probability of randomly selecting a gate fee	–	–
Regulator[d]	m	XV[b]	Number of STUs	1	–

[a] DV: decision variable; NV: endogenous variable; XV: exogenous variable. The values of DVs and NVs are updated at each time step t; while those of XVs remains unchanged after initialization.
[b] Exogenous variables that the regulator can affect directly or indirectly.
[c] Singapore dollar.
[d] Some indicators measuring the performances of the AWTM are defined in Section 4.2. The regulator attempts to affect these indicators by developing optimal policies, as discussed in Section 4.3.

can affect the refuse collector's preference to STUs by propagating the importance of waste-to-energy treatment (i.e., enlarging β_s), so that the refuse collector will allocate more waste to STUs. Thirdly, the regulator requires that, the GTU should offer a discounted gate fee ($d\eta_0$, $d \in (0, 1)$) to STUs when treating residues, making the waste-to-energy business profitable.

- For the sake of simplicity, all the STUs' price sensitivities and waste utilization preferences are identical, i.e., $\alpha_1 = \alpha_2 = \cdots = \alpha_m = \alpha_s$, $\beta_1 = \beta_2 = \cdots = \beta_m = \beta_s$.

In the following we discuss the various components of the model in detail and explain the behavior of each agent in a static time step t as a snapshot of the AWTM.

3.2. The refuse collector's behavior

After presorting and recycling MSW, the refuse collector in the AWTM forwards the input waste to the treatment units according to their gate fee attractiveness and the refuse collector's preferences. This process is modeled by the multinomial logit demand model (MLDM). In the AWTM, the market share of input waste received by treatment unit $f \in \mathcal{F} = \{0\} \cup \mathcal{I}$ is given by:

$$S_f(\boldsymbol{\eta}) = \frac{e^{\beta_f - \alpha_f \eta_f}}{\sum_{f \in \mathcal{F}} e^{\beta_f - \alpha_f \eta_f}}, \ \ \forall f \in \mathcal{F}, \tag{1}$$

where gate fee vector $\boldsymbol{\eta} = (\eta_0, \eta_1, \ldots, \eta_m)$ and $\alpha > 0$. The function $\beta_f - \alpha_f \eta_f$ associated with treatment unit $f \in \mathcal{F}$ can be regarded as a first-order approximation for the "attractiveness" of using treatment unit *f*. Therefore, the regulator can promote waste-to-energy utilization by affecting the refuse collector's preference to STUs, i.e., $\beta_s > \beta_g$. In that case, more waste will be allocated to STUs rather than the GTU, even though $\alpha_s = \alpha_g$ and all gate fees are identical. The refuse collector needs to pay for using the treatment service provided by private operators after delivering MSW to them.

We select the MLDM to simulate the refuse collector's behavior for two reasons. Firstly, taking the revenue management and marketing research for example, the MLDM can easily capture customer preferences toward different characteristics of a given product and quantify the probability that customers would choose it (Besanko, Gupta, & Jain, 1998; Guadagni & Little, 1983). This feature allows the refuse collector (affected by the regulator) to consider multiple aspects when allocating waste, such as treatment cost and waste-to-energy utilization. Secondly, the MLDM has been applied to describe the behavior of choice-maker in previous waste management studies (Efaw & Lanen, 1979; Ku, Yoo, & Kwak, 2009).

3.3. The STU's behavior

After receiving the input waste and the corresponding gate fee payments from the refuse collector, the STUs convert the incoming wastes into recovered energy product (e.g., electricity and fuel gas) for sales. Real cases of treatment unit's operations can be found in United States (Ata, Lee, & Tongarlak, 2012). Besides, the STUs also need to pay the GTU for its service of post-treating generated residues. For example, in the case of Kalundborg City, public and private enterprises buy and sell residual products, resulting in tons of reduced waste emissions and recycled waste resources each year (Gulipac, 2015). In the AWTM, the per-tonne comprehensive operation costs of a STU f (i.e., μ_f) is equal to all variable treatment operation costs (including transportation and process cost) minus per-tonne energy revenue. In practice, $\mu_f > 0$ because selling recovered energy is much less profitable. In contrast, the gate fee is the major portion of a STU's revenue. Therefore, the profit maximization model for a STU (namely $\forall f \in \mathcal{I}$) can be defined as follows:

$$\max_{\eta_{f,t}} \ \ \pi_{f,t} = \omega_{f,t}(\eta_{f,t} - \mu_f - \delta_f d_0 \eta_{0,t}), \tag{2}$$

$$\text{s.t.} \ \ \eta_{f,t} \geq \mu_f, \tag{3}$$

$$\text{where} \ \ \omega_{f,t} = WS_{f,t}. \tag{4}$$

The objective function (2) maximizes the profit of a STU f at time step t, which is computed by the AWTM using the product of the total input waste received $WS_{f,\,t}$ and profit rate $\eta_{f,t} - \mu_f - \delta_f d_0 \eta_{0,t}$. As mentioned in Section 3.1, for the STUs, a regulated upper bound of their gate fees is not necessary in the presence of competition. Therefore, the STU agent only considers the lower bound μ_f, as expressed by Constraint (3).

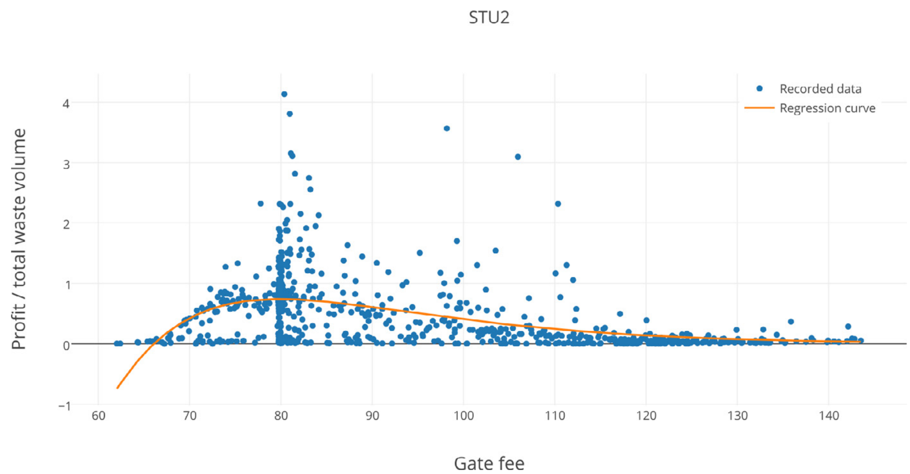

Fig. 3. A sample STU's recorded data and estimated regression curve in a simulation experiment.

The barrier for a STU to tackling the above optimization problem is the difficulty in accessing the sensitive private knowledge of its rivals. Besides, the market share captured by a STU $S_{f,\,t}(\boldsymbol{\eta}_t)$ is also a function of all agents' latest decisions on gate fees. In other words, a precise prediction of other agents' optimally-changing behaviors requires full knowledge of their information, which is deemed to be impossible in reality. Therefore, it is infeasible to directly find the optimal solution for STUs using traditional OR-based mathematical methods due to the complexity, dynamics, non-linear feedbacks among interweaving agents in the integrated AWTM.

To help STUs determine their optimal gate fees in the black-box context, we propose an estimation-and-optimization approach which consists of two steps: (1) estimation of unknown parameters, and (2) searching for the optimal gate fee. Firstly, each agent will record all its previous (gate fee, averaged profit) data. Hence, in time step t, the agent f should have $t-1$ historical records $(X, Y) = \{(\eta_{f,\tau}, \pi_{f,\tau}/W)\}_{\tau=1}^{t}$ to fit the following non-linear regression model:

$$Y = \frac{e^{a_0+a_1X}}{e^{a_0+a_1X}+a_2}(X+a_3). \tag{5}$$

Regression model (5) is converted from Eqs. (1) and (2). The parameters (a_0, a_1, a_2, a_3) are assumed to be unknown or uncertain due to unaccessible information or other agents' changing behaviors. However, this assumption can be easily relaxed in the event that some information is available to the agent. In fact, the parameters $a_0 = \beta_f$ and $a_1 = -\alpha_f$. If agent f can obtain the accurate α_f and β_f from the refuse collector, the good-of-fitness of regression will increase and thus the agent is more likely to make better decisions due to the lessened uncertainty in estimation. After estimating current parameters of the non-linear regression model, the agent f obtains a function describing the relationship between gate fee and profit according to its personal experience in the dynamic black-box competition.

Fig. 3 provides an example of recorded data and estimated regression curve of a STU agent at $t = 1000$ in a simulation experiment. Another important information obtained from Fig. 3 is that, the left side of the regression model (5) is non-decreasing; while the right side is non-increasing. In other words, the STUs are not interested in an unreasonably high gate fee which is likely to yield almost zero profit. Hence, there is no necessity for the regulator to implement gate fee upper bound for the STUs, which is consistent with the fifth assumption presented in Section 3.1. The second step is to decide the gate fee. Here we introduce a probability $\theta_f \in [0, 1]$, which will linearly decrease from 1 to 0 with increasing time step t. If a random number is less than $\theta_{f,\,t}$ in time step t, the agent f will choose a gate fee arbitrarily according to $\eta_{f,t} \sim U(\mu_f,\ 2(\mu_f + \delta_f d_0 \bar{\eta}_0))$. The upper boundary of this uniform distribution is set to be sufficiently large so that the STU agent has a chance to choose a relatively high gate fee. Therefore, given a decreasing θ_f, the agent f randomly selects a gate fee at the beginning of simulation, but the probability of making arbitrary decisions continues to decline since the agent has significantly investigated the possible gate fee decisions. If the agent decides to optimize its decision in time step t, the optimal gate fee $\eta_{f,t+1}$ under Constraint (3) can be identified using general optimization algorithms. According to Fig. 3, for instance, the agent's optimal gate fee is about 80. After submitting new gate fee $\eta_{f,t+1}$ to the refuse collector, new profit will be gained in the next time step $t+1$. Even though $\eta_{f,t+1}$ is equal to $\eta_{f,\,t}$, the new profit $\pi_{f,t+1}$ can be different from $\pi_{f,\,t}$ as the other agents may change gate fee settings. No matter what type of decisions the rivals made previously, the agent only collects and uses the actual (gate fee, averaged profit) data to estimate uncertain parameters of his/her regression model for decision-making.

The advantages for using this date-driven decision-making process are as follows: (1) it mimics the heuristic trial-and-error method, which is often used by people who have little knowledge in the problem area. Initially, there was no knowledge about the "gate fee & profit" relationship. Hence, the STU agent tested a random gate fee and then obtained profit from the market. As the simulation iteratively runs, the STU agent has collected sufficient information to make more reasonable decisions. Therefore, the trial-and-error process ends. (2) it takes full advantage of limited information for decision-making, similar to what people actually do, for example, in predicting future sales and stock prices. In the AWTM, each STU agent only has its own private data such as operation cost and gained profit. As we can see from the aforementioned description, all available information are utilized in the decision-making process. If more information become accessible, this approach can easily utilize them to reduce uncertainty in decision-making process. (3) it can be applied to facilitate similar uncertain decision-making in ABMs. Due to the embedded non-linear regression technique and general optimization algorithms, this approach has great potential for agents to identify their optimal solutions without discretizing some inherent continuous variables.

In conclusion, the STU agents in the AWTM are profit-maximizing and self-interested. In order to search for their optimal gate fee decisions in a competitive and complex market, STUs take full advantage of limited information by employing an estimation-

Table 2
The main components in the AWTM.

Type	Components in the AWTM
Normative	The estimation-and-optimization decision-making process of STU/GTU.
	The refuse collector's behavior (i.e., multinomial logit demand model, MLDM).
Descriptive	The model structure and basic notions of the AWTM.
	The variables and mathematical model of agents.
	The relationships and interactions among agents.

and-optimization approach based on personal historical records. These settings help us simulate the evolutionary behaviors of private operators in a reasonable way.

3.4. The GTU's behavior

For the GTU, its revenue stream comes from collecting gate fee from both the refuse collector and STUs, as well as selling recovered energy products. Similarly, the GTU's profit maximization model is stated as follows:

$$\max_{\eta_{0,t}} \pi_{0,t} = \omega_{0,t} \times (\eta_{0,t} - \mu_0) + \textstyle\sum_{f\in\mathcal{I}} \delta_f \omega_{f,t} \times (d_0\eta_{0,t} - \mu_0), \quad (6)$$

$$\text{s.t. } \mu_0 \le \eta_{0,t} \le \bar{\eta}_0, \quad (7)$$

$$\text{where } \omega_{0,t} = WS_{0,t}. \quad (8)$$

Eq. (6) represents the profit function of the GTU. Note that the per-tonne disposal service cost charged by the landfilling plant has been integrated into the GTU's operation cost μ_0 in Eq. (6). Constraint (7) satisfies the corresponding government regulations.

By applying the same mechanism described in the STU's decision-making process, the GTU is also able to identify its optimal gate fee in black-box competition efficiently and reasonably. By combining Eqs. (1) and (6), the GTU's non-linear regression model can be formulated as follows:

$$Y = \frac{(X-\mu_0)e^{a_0+a_1X} + a_2(d_0X-\mu_0)}{e^{a_0+a_1X}+a_3}. \quad (9)$$

After fitting the model with recorded data $(X,Y) = \{(\eta_{0,\tau}, \pi_{0,\tau}/W)\}_{\tau=1}^{t}$ and searching for the optimal gate fee $\eta_{0,t+1}$ under Constraint (7), the GTU is able to join the competition in the integrated AWTM under low information.

3.5. The regulator's behavior

In the AWTM, the regulator is able to develop and implement policies by changing the initial values of different exogenous variables. As marked in Table 1, the four policies mentioned in Section 1 correspond to the number of STUs (m), waste utilization preferences (β_s), upper bound of the GTU's gate fee ($\bar{\eta}_0$), and the GTU's gate fee discounting factor for the STUs (d_0). We are interested in how the performances of the integrated system change under different policies by the regulator.

In next section, we define a series of indicators that measure the performances of agents and the model. To further support the regulator in optimizing mixed policy, the AWTM is integrated into a simulation-based optimization problem mathematically expressed in Section 4.3.

3.6. Summary

In this section we explicitly define each agent's attributes and behavior interacting with the other agents. Table 2 summarizes the main components in the AWTM. Descriptive components are based on actual MSW management practices in different countries; while normative components are related to norms or standards of waste treatment. We have justified these components and suggest that they are reasonable settings of the AWTM.

Before we start the simulation experiments, the agents' behavior should be scheduled in a time step for implementation in the computer simulation programs. Fig. 4 summarizes the sequence of events in the AWTM in the form of a unified modeling language behavior diagram. Note that the AWTM also performs three important tasks in the simulation. First, it initializes agents' exogenous variables after the regulator develops a policy. Second, the AWTM needs to update the values of all the variables, such as operators' profits, input waste, and other endogenous parameters defined in Table 1. Third, if the AWTM meets the stop criterion, the simulation will be terminated and all important data will be saved for further analysis.

4. Simulation

4.1. Experimental design

We conduct 33 experiments using the AWTM under four different scenarios, namely Scenarios S1, S2, G1 and G2. Table 3 presents the parameter settings of simulation experiments. The default values of some variables mainly come from literature and Singapore's waste statistics. Although we solely select food waste as an example in this computational study, the policy-maker can apply the AWTM for handling with different wastes. Note that the m STUs are heterogeneous in operation cost and residue generation coefficient since random values are assigned to μ_f and δ_f at the beginning of simulation.

Scenarios S1 and S2 are designed to understand the impacts of regulating STUs on the system performances. The only difference among the seven simulation experiments under Scenario S1 is the changing number of STUs, i.e., m. Therefore, the AWTM under Scenario S1 is basically comparable to a perfectly competitive market that has been extensively investigated by economics. In other words, we can use Scenario S1 to validate the AWTM since validation is a crucial step in modeling ABMs (Bonabeau, 2002). Under Scenario S2, the regulator intentionally alters the refuse collector's utilization preference to the STUs (e.g., through education or publicity) so as to influence their received wastes (i.e., ω_f). This situation usually happens when the regulator intends to promote/suppress the utilization of some STUs with better/worse sustainability and operation efficiency. Therefore, the Scenario S2 can be utilized to discover how such regulator's intervention affects the optimal decision and performance of different agents.

Under the other two scenarios, we attempt to examine changes caused by the different regulations on the GTU's operations. In particular, the regulator adjusts the upper bound of the GTU's gate fee $\bar{\eta}_0$ under Scenario G1, and also the GTU's gate fee discounting factor for the STUs d_0 under Scenario G2. We can compare the influences under different scenarios and thus provide managerial insights for policy-makers.

4.2. Implementation and performance measures

We develop the AWTM using Python, and perform each experiment 100 times to ensure robust outputs against randomness in STUs' initial attributes, agents' gate fee decision-making etc. All the 100 independent tests of each experiment can be well compared and reproduced by assigning {0, 1, 2, ..., 99} as random seeds. The events presented in Fig. 4 were carried out 1000 times for each test, i.e., each simulation stops at $t = 1000$. Therefore, the total computation load is: 33 experiments under four scenarios × 100 tests with different random seeds × 1000 time steps.

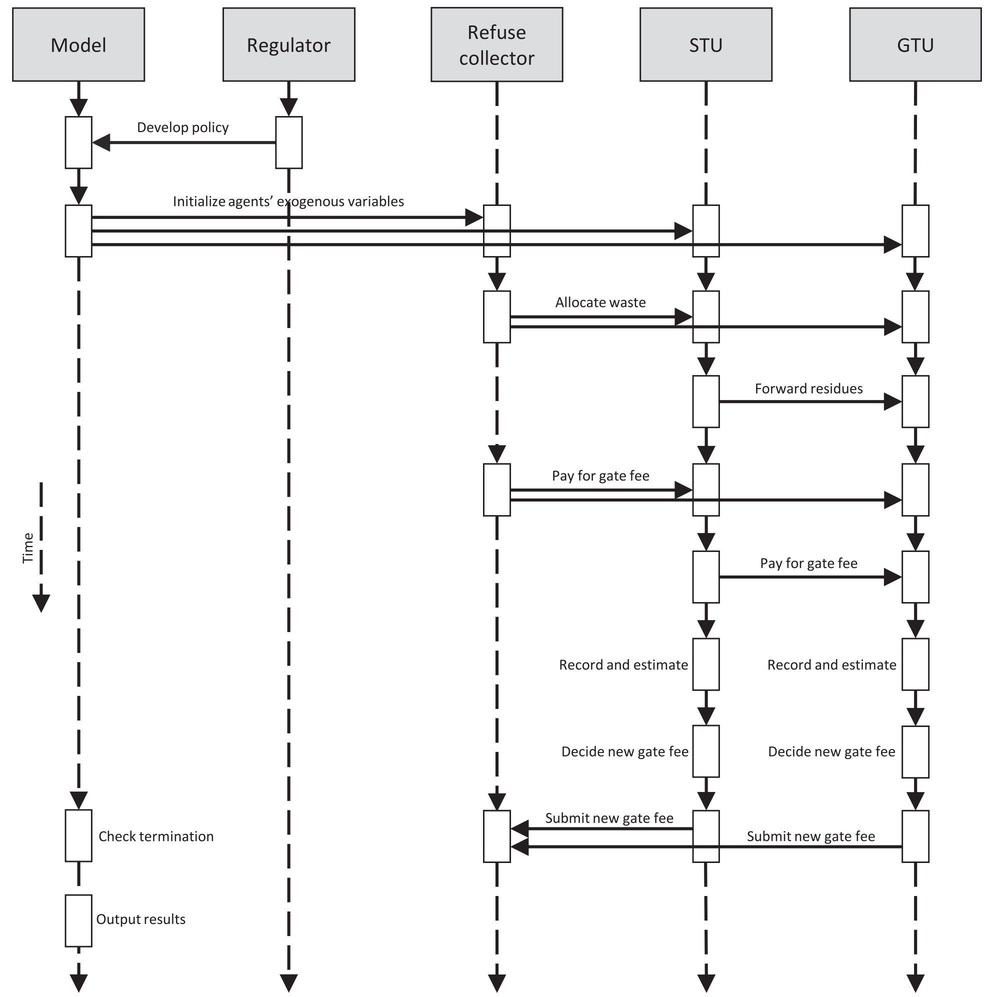

Fig. 4. The time sequence diagram of the AWTM. The grey rectangles represent involved objects such as agents and the model. White rectangles and horizontal solid lines demonstrate the events and interactions among objects, respectively.

Table 3
Values of exogenous parameters in the simulation experiments.

Parameter	Default value	Remark	Unit	Source	Changed values under scenario
m	5	Number of STUs	1	–	$\{2, 3, \ldots, 8\}$ under Scenario S1
W	785,500	Volume of food waste	Tonne	NEA (2015)	Unchanged
α_g	0.1	Price sensitivity to the GTU	–	–	Unchanged
α_s	0.1	Price sensitivity to the STUs	–	–	Unchanged
β_g	15	Waste utilization preference to the GTU	–	–	Unchanged
β_s	15	Waste utilization preference to the STUs	–	–	$\{10, 11, \ldots, 20\}$ under Scenario S2
$\bar{\eta}_0$	100	The upper bound of the GTU's gate fee	SGD	–	$\{20, 40, \ldots, 180\}$ under Scenario G1
d_0	0.5	Gate fee discounting factor for the STUs	–	–	$\{0.1, 0.2, \ldots, 0.9\}$ under Scenario G2
δ_f	$U(0.21, 0.41)$	Residue generation coefficient of STU f	–	De Bere (2000)	Unchanged
μ_f	$U(43.63, 63.63)$	Operation cost of STU f	SGD/Tonne	McCrea, Tan, Ting, and Zuo (2009)	Unchanged
μ_0	6.67	Operation cost of the GTU	SGD/Tonne	McCrea, Tan, Ting, and Zuo (2009)	Unchanged

To comprehensively measure the system performances, we design the following indicators and their values at time step $t = 1000$ for further analysis:

1. Average gate fee of the STUs and the GTU: $\bar{\eta}_s = \frac{1}{m}\sum_{f\in\mathcal{I}}\eta_f$, $\eta_g = \eta_0$.
2. Total profit of the STUs and the GTU: $\Pi_s = \sum_{f\in\mathcal{I}}\pi_f$, $\Pi_g = \pi_0$.
3. Average regression reduced chi-square value (i.e., mean square of residual) of the STUs and the GTU: $\bar{u_s} = \frac{1}{m}\sum_{f\in\mathcal{I}}u_f$, $u_g = u_0$, where u_f is the agent f's residual sum of squares divided by the number of degrees of freedom. These two metrics can be used to measure the prediction uncertainty when the agent is determining its gate fee. For example, if $\bar{u_s}$ or u_g is small, which means the historical data well fits the agent's non-linear regression model, then the agent is more confident about the estimated price-profit curve. Hence, the agent is able to decide the most promising gate fee. In contrast, larger $\bar{u_s}$ or u_g implies that the estimated regression model is more doubtful. Therefore, it is more uncertain for the agent to identify the optimal gate fee.
4. Total allocated waste of the STUs and the GTU: $\Omega_s = \sum_{f\in\mathcal{I}}\omega_f$, $\Omega_g = \omega_0$.
5. Total payment for using treatment service provided by the STUs and the GTU: $\Lambda_s = \sum_{f\in\mathcal{I}}\eta_f * \omega_f$, $\Lambda_g = \eta_0 * \omega_0$, and $\Lambda = \Lambda_s + \Lambda_g$. From the perspective of the public sector, these key indicators record the total waste treatment cost that the citizens have to bear.

6. The correlation coefficient measuring the linear relationship between STU's endowment and earning: R_s^2. Since hundreds of heterogeneous STUs are generated in each experiment, we seek to examine statistically the relationship between their endowments and earnings. In particular, we create 33 multiple linear regression models in the following form: $\pi_f = b_0 - b_\mu \mu_f - b_\delta \delta_f$. The goodness-of-fit is denoted by R_s^2, i.e., the coefficient of determination. We find that all the estimated parameters b_0, b_μ, and b_δ are positive numbers, as expected. However, we are more interested in how strong the relationship is. The correlation coefficient R_s^2 could help STU managers to understand the importance of reducing operation cost and generated residues in competitive and integrated MSW treatment markets.

4.3. Extending the AWTM to a simulation-based optimization problem

The experimental results derived from simulations under above scenarios should be able to answer all the research questions proposed in Section 1, except identifying the optimal mixed policy for the regulator who has multiple predefined objectives. In reality, developing policies can be viewed as a multi-objective decision process, since stakeholders often have conflicting interests. To manage a competitive MSW treatment market with private participation, the regulator may need to consider the following aspects: reducing the total treatment payment for the citizen, minimizing the caused performance fluctuation and negative effects for the private operators, maximizing the expected effectiveness of the policy, promoting waste utilization for the environmental sustainability, difficulties in implementing the policies, etc. In this study, we assume that the regulator has the following optimization problem:

$$\max_{m,\beta_s,\bar{\eta}_0,d_0} \min_{\forall f\in\mathcal{I}} \pi_f, \tag{10}$$

$$\text{s.t. } \Lambda \le \overline{\Lambda}, \tag{11}$$

$$\Omega_s/\Omega_g \ge \underline{\Omega_{s/g}}, \tag{12}$$

$$\Pi_g \ge \underline{\Pi_g}, \tag{13}$$

$$m \in [2, 8], \tag{14}$$

$$m \in \mathbb{Z}, \tag{15}$$

$$\beta_s \in [10, 20], \tag{16}$$

$$\bar{\eta}_0 \in [20, 180], \tag{17}$$

$$d_0 \in [0.1, 0.9], \tag{18}$$

where function (10) represents that the regulator attempts to maximize the minimum profit across all STUs by searching for the optimal mixed policy $(m^*, \beta_s^*, \bar{\eta}_0^*, d_0^*)$, so that the competitive MSW treatment system is attractive to private investment. However, the policy-maker also requires that the performances of the AWTM should meet three following conditions: (1) To save MSW treatment costs, Constraint (11) imposes an upper bound of total payment for using treatment service, i.e., $\overline{\Lambda}$. (2) Based on environmental sustainability targets, Constraint (12) implies that the ratio of total waste captured by STUs to that of the GTU should exceed a desired lower bound $\underline{\Omega_{s/g}}$. 3) Constraint (13) ensures the GTU's profit should be at least above a reasonable lower bound $\underline{\Pi_g}$, so that the economic feasibility of the GTU is secured. Other constraints naturally limit the space of policy development. For the regulator, more aspects can be considered and easily added to the optimization problem if necessary.

In the simulation, we assume that $\overline{\Lambda} = 5 \times 10^7$ SGD, $\underline{\Omega_{s/g}} = 1/2$, and $\underline{\Pi_g} = 1 \times 10^7$ SGD. Due to the complexity of the AWTM and dynamic feedbacks among agents, it is difficult to predict the experimental results. We adopt a genetic algorithm to search for the optimal mixed policy $(m^*, \beta_s^*, \bar{\eta}_0^*, d_0^*)$, since this approach has been widely applied for solving simulation-based optimization problems (see, e.g., Abdelghany, Abdelghany, Mahmassani, & Alhalabi, 2014) and agent-based models (see, e.g., Zhao & Ma, 2016). After balancing solution optimality and computational efficiency, the population size, maximum number of generations, probability of cross over and mutation are set to 50, 100, 0.5, 0.2, respectively. Fig. 5 is the flow chart of the AWTM-nested genetic algorithm.

5. Results and discussion

5.1. Scenario S1 and S2

Under Scenario S1, the STU count m increases from 2 to 8, which means that more STUs are licensed to enter the market. Table 4 and Fig. 6 demonstrate that, all STUs generally have to lower their gate fees $\bar{\eta}_s$ in response to fiercer peer competition. Moreover, as an individual, all STU's key performance indicators such as the average profit $\frac{\Pi_s}{m}$, allocated waste $\frac{\Omega_s}{m}$, and gained treatment payment $\frac{\Lambda_s}{m}$ are declining monotonically and significantly with the number of STUs. For example, the STU's average profit drops drastically from 1.75 to 0.55 million SGD, a remarkable 68.57% decrease. These findings are fully consistent with the practice and classical economic conclusions about near-homogeneous competition, revealing that the AWTM is a suitable agent-based model for studying the competitive MSW treatment market. Interestingly, as a group, the STUs' total profit, waste, and service payment are steadily increasing. Facing the more competitive STU group, the GTU's performances have sharply deteriorated, implying that the GTU is also a victim that suffers from a nearly perfectly competitive market. From the perspective of the individual STU or the GTU, the only good news could be the diminished uncertainty during the agent's decision-making process. In contrast, the regulator is able to easily save a total of 6.2 million SGD to treat the generated food waste, an increasing portion of which is treated by more environmentally friendly STUs (see Table 4).

We now turn our attention to Scenario S2, where the regulator intervenes in waste allocation by indirectly changing the refuse collector's preference to the STUs β_s. Since the β_g is fixed at 15, a $\beta_g > 15$ represents that the regulator tends to forward more waste to the STU than to the GTU under the same condition. Table 4 and Fig. 7 show that such intervention directly affects the waste volume allocated to the treatment units. For the GTU, it has to significantly decline the gate fee η_g to compete for the waste. Even so, all the GTU's performances fall dramatically due to the increasing β_s, i.e., the refuse collector's preference to the STUs. When $\beta_s = 19$, we find that the GTU's gate fee η_g suddenly soars from previous 37.4 to 98. The reason for this phenomenon is that in the presence of such high β_s, the attractiveness of the GTU is insufficient for waste competition, and almost no waste is allocated to the GTU. On the other hand, in this case, the treatment of residues from the STUs forms a substantial revenue stream for the GTU. Therefore, the GTU tends to recover more revenues from post-treatment of the residuals by increasing his own gate fee and thus give up competing for the market share. Only in such extreme cases is the GTU's gate fee η_g higher than the STUs' average gate fee $\bar{\eta}_s$. For

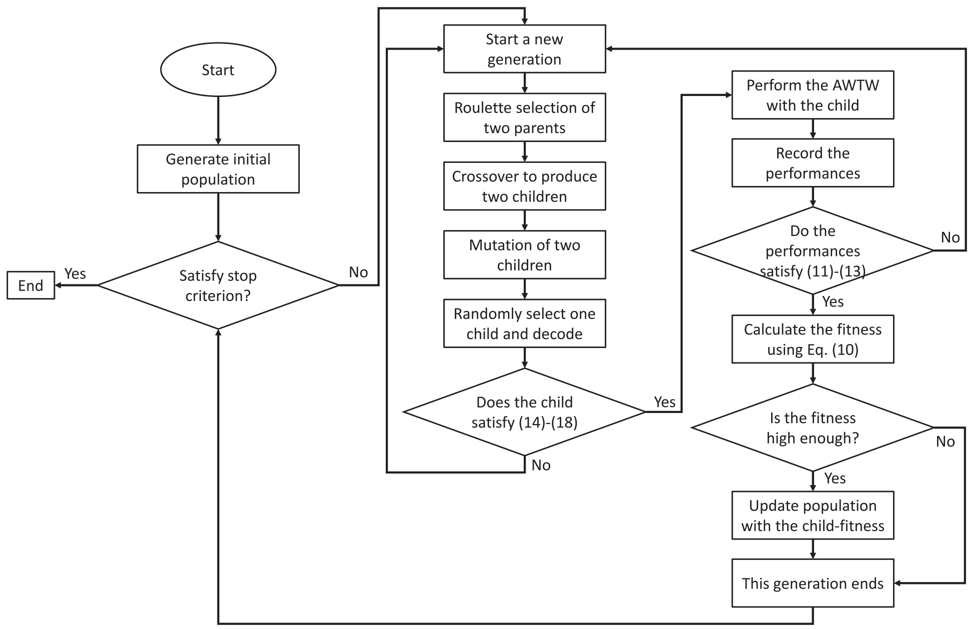

Fig. 5. The flow chart of the AWTM-nested genetic algorithm. In each generation, a child (i.e., a vector of decision variables) is created after parent selection, crossover and mutation. If the child satisfies the constraints of policy variables, the AWTM will be performed with them. If the simulation results of the AWTM satisfy the constraints of performances, the created child and its fitness (which should be sufficiently high) will be recorded for next generation.

Table 4
The means of the indicators under Scenarios S1 and S2.

	Scenario S1 with changing m							Scenario S2 with changing β_s										
Indicator	2	3	4	5	6	7	8	10	11	12	13	14	15	16	17	18	19	20
$\bar{\eta_s}$ (1e1)	7.90	7.78	7.70	7.65	7.60	7.55	7.52	7.48	7.56	7.60	7.65	7.65	7.65	7.59	7.50	7.36	7.56	7.55
η_g (1e1)	6.28	5.99	5.63	5.44	5.26	5.07	4.96	9.15	7.95	7.12	6.56	6.18	5.44	4.72	4.14	3.74	9.80	10.00
Π_s (1e7)	0.35	0.40	0.40	0.42	0.42	0.43	0.44	0.09	0.10	0.13	0.20	0.33	0.42	0.50	0.61	0.71	0.48	0.46
Π_g (1e7)	3.23	2.88	2.67	2.52	2.37	2.25	2.16	5.61	5.03	4.39	3.78	3.12	2.52	1.89	1.32	0.84	1.02	1.04
$\bar{u_s}$ (1e1)	0.34	0.19	0.12	0.08	0.06	0.04	0.03	0.00	0.00	0.01	0.02	0.05	0.08	0.11	0.14	0.18	0.27	0.33
u_g (1e1)	7.34	4.62	3.41	2.52	1.84	1.58	1.09	3.53	2.17	3.21	4.34	3.05	2.52	1.78	1.15	0.68	0.24	0.11
Ω_s (1e5)	2.42	2.84	2.87	2.98	3.12	3.17	3.26	1.44	1.10	1.23	1.67	2.54	2.98	3.67	4.61	5.78	7.84	7.89
Ω_g (1e5)	5.47	5.05	5.02	4.91	4.77	4.72	4.62	6.45	6.79	6.66	6.22	5.35	4.91	4.21	3.27	2.11	0.04	0.00
Λ_s (1e7)	1.87	2.15	2.15	2.22	2.29	2.31	2.36	1.04	0.80	0.90	1.23	1.89	2.22	2.69	3.32	4.10	5.78	5.81
Λ_g (1e7)	3.41	3.01	2.82	2.66	2.50	2.39	2.29	5.86	5.37	4.73	4.06	3.29	2.66	1.98	1.33	0.76	0.02	0.00
Λ (1e7)	5.27	5.16	4.96	4.88	4.79	4.69	4.65	6.91	6.17	5.63	5.30	5.18	4.88	4.67	4.66	4.86	5.80	5.81
R_s^2 (1e-1)	4.80	5.80	6.50	7.60	7.70	8.30	8.10	5.90	5.20	6.20	7.10	8.00	7.60	7.00	7.30	7.30	6.00	6.10
$\frac{\Pi_s}{m}$ (1e6)	1.75	1.32	1.00	0.83	0.71	0.62	0.55	0.17	0.20	0.26	0.41	0.66	0.83	1.00	1.21	1.42	0.97	0.92
$\frac{\Omega_s}{m}$ (1e5)	1.21	0.95	0.72	0.60	0.52	0.45	0.41	0.29	0.22	0.25	0.33	0.51	0.60	0.73	0.92	1.16	1.57	1.58
$\frac{\Lambda_s}{m}$ (1e6)	9.34	7.15	5.37	4.44	3.82	3.29	2.95	2.09	1.61	1.81	2.47	3.77	4.44	5.38	6.64	8.20	11.56	11.63

the regulator, excessive intervention by changing the β_s not only causes the GTU's retaliatory gate fee increase, but also leads to the STU's greater uncertainty $\bar{u_s}$ and, more seriously, a rebounded total payment for using waste treatment service Λ. These findings obtained from Table 4 and Fig. 7 are interesting and helpful for the regulator who attempts to promote the importance of the STUs under competition.

Besides, as mentioned in Section 4.2, the indicator R_s^2 measures the strength of the linear relationship between STUs' initial operation costs μ, residue generation coefficient δ and their profit π. For the private STUs that have participated (or tend to participate) in the competitive and integrated MSW treatment market, such information is critical since both μ and δ are commonly associated with strategic selections, such as determining the waste-to-energy technology and equipment. Under Scenario S1, the increasing R_s^2 implies that the intensified competition generally enhances the linear relationship between cost reduction and profit. In other words, the competing agents turn into the price takers and have to save cost for more profit. Under Scenario S2, such relationship is relatively strong when the attractiveness of the GTU is comparable to that of the STU, i.e., $13 \leq \beta_s \leq 18$. If the GTU is a dominant player ($\beta_s \leq 12$) or an insignificant rival ($\beta_s \geq 19$), R_s^2 drops in these extreme cases, possibly due to the soften waste allocation competition (see Table 4 and Fig. 7).

In conclusion, the experimental results under Scenario S1 have validated the AWTM. It is found that individual treatment units in fiercer competition turn into the price takers and lose considerable profits. As a group, the STUs grabbed partial market share of the GTU. Besides, the STU, who has lower operation cost and generates less residues, is more likely to gain more profits. Under Scenario S2 with the regulator's intervention in waste allocation, if the regulator deliberately promotes the STUs by intervening in waste allocation, the GTU could give up competing for the waste and greatly increase its gate fee as retaliation.

5.2. Scenario G1 and G2

The GTU is a key player in the AWTM not only because it is able to treat both waste and residues, but also due to its monopoly in the post-treatment market. Therefore, it is required to provide a

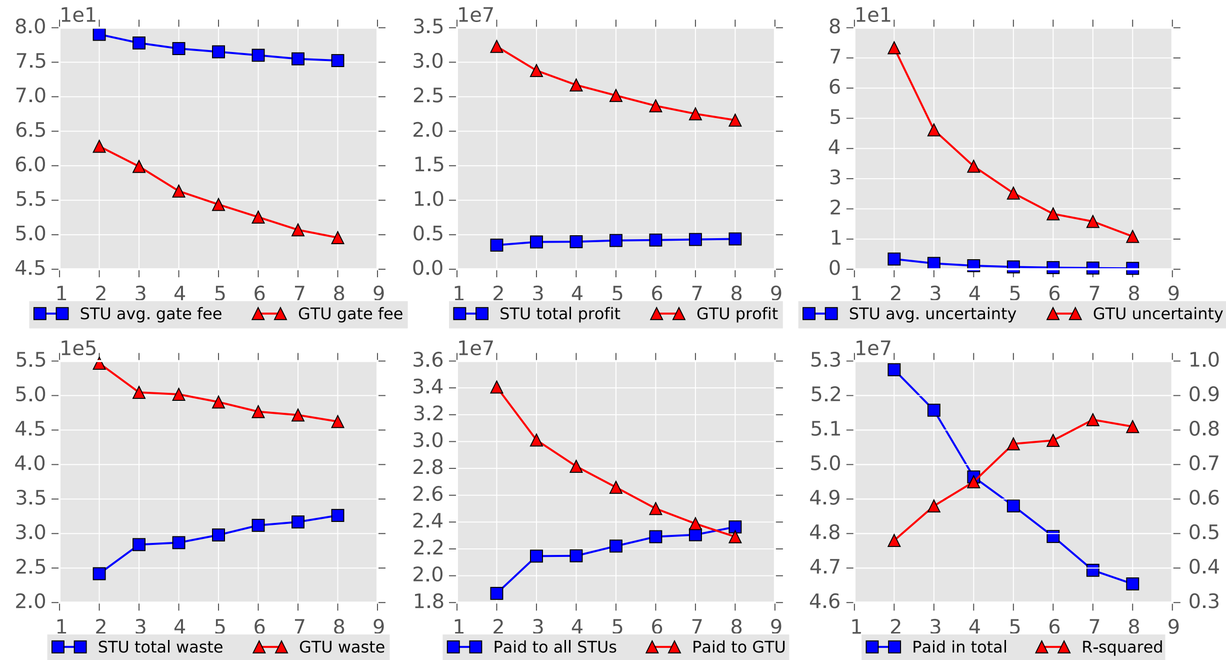

Fig. 6. Experimental results under Scenario S1. All the horizontal axes are the STU count; the vertical axes are gate fee, profit, reduced chi-square value, allocated waste volume, treatment payment, and correlation coefficient, respectively (see Section 4.2 for indicator definitions and Table 1 for units). Scientific notations are used to provide better readability (e.g., *1e1* means × 10, and *1e7* means × 10^7). As the STU count increases from 2 to 8, all STU's key performance indicators such as the gate fees, average profit, allocated waste, and gained treatment payment are declining monotonically and significantly. As a group, however, the STUs' total profit, waste, and service payment are steadily increasing with STU count. Besides, the GTU's performances are sharply deteriorating.

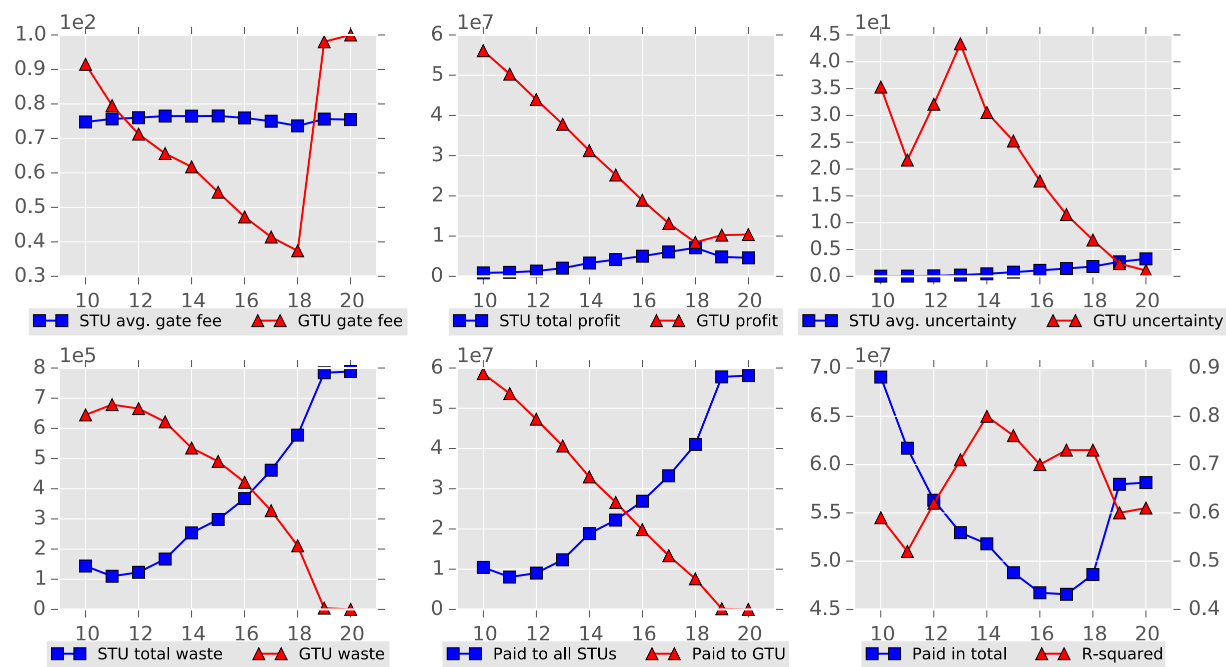

Fig. 7. Experimental results under Scenario S2. See Fig. 6 for axes definitions. As the refuse collector's preference to the STUs (β_s) increases from 10 to 20, all the GTU's performances fall dramatically. When $\beta_s = 19$, the GTU's gate fee η_g suddenly soars from previous 37.4 to 98.

discount d_0 for treating the STUs' residues and to set its gate fee without exceeding the given limit $\bar{\eta_0}$.

Under Scenario G1, the GTU's gate fee upper bound $\bar{\eta_0}$ is linearly lifted from 20 to 180. However, Fig. 8 and Table 5 report that the GTU's gate fee η_g increases in an irregular way: it equals to $\bar{\eta_0}$ when $\bar{\eta_0} < 60$, remains at around 52 when $60 \leq \bar{\eta_0} \leq 140$, and finally climbs to 80.2 and 96.5 when the upper bound is 160 and 180, respectively. The main reason for this result is that, given the parameter settings in Table 3, the GTU's non-linear regression function (9) in the AWTM is similar to the curve illustrated in Fig. 9. It is observed that there are three important points: local maximum η_a, local minimum η_b, and η_c with $Y(\eta_c) = Y(\eta_a)$.

Therefore, the GTU's optimal gate fee η_0^* depends on which interval the specific level of the upper bound $\bar{\eta_0}$ is in: (0, η_a], (η_a, η_c), or [η_c, ∞). Under Scenario G1, the η_a and η_c could be around 60 and 140, respectively. Therefore, when the $\bar{\eta_0}$ is sufficiently

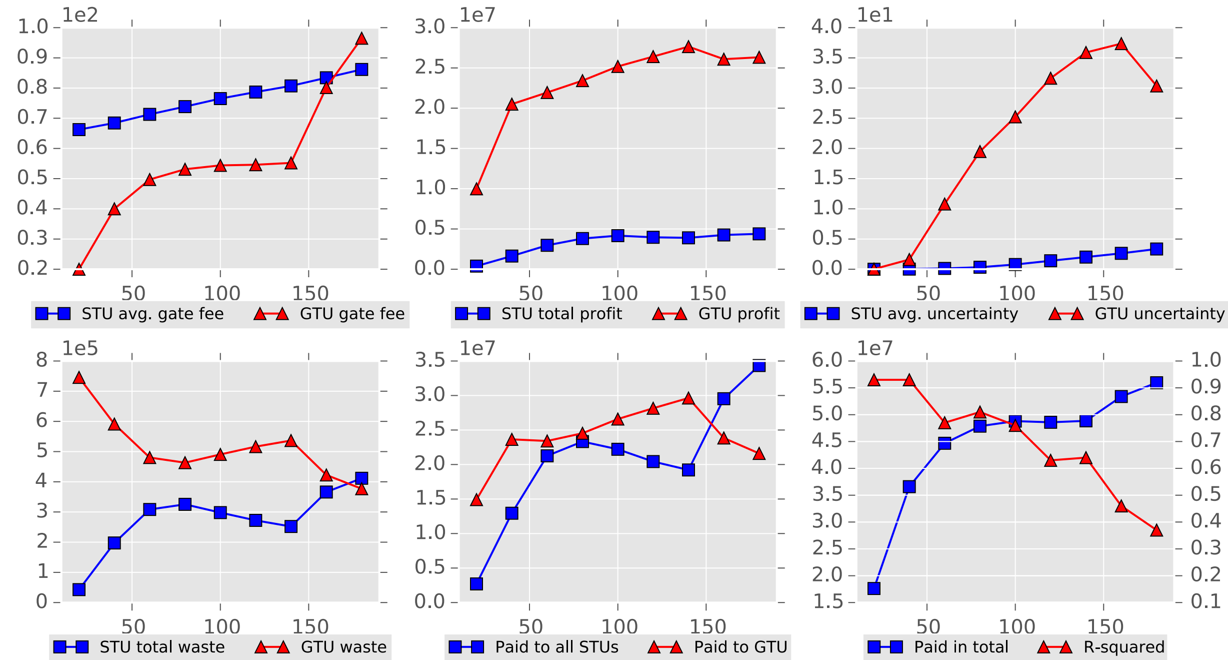

Fig. 8. Experimental results under Scenario G1. See Fig. 6 for axes definitions. As the upper bound increases from 20 to 180, the GTU's gate fee increases in a irregular way.

Table 5
The means of the indicators under Scenario G1 and G2.

	Scenario G1 with changing $\bar{\eta_0}$									Scenario G2 with changing d_0								
Indicator	20	40	60	80	100	120	140	160	180	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
$\bar{\eta_s}$ (1e1)	6.62	6.84	7.13	7.38	7.65	7.87	8.07	8.34	8.62	6.88	7.08	7.28	7.47	7.65	7.81	8.00	8.16	8.35
η_g (1e1)	2.00	4.00	4.97	5.31	5.44	5.46	5.52	8.02	9.65	4.48	4.73	4.98	5.23	5.44	5.60	5.75	5.98	6.17
Π_s (1e7)	0.04	0.16	0.30	0.38	0.42	0.40	0.39	0.43	0.44	0.34	0.37	0.39	0.41	0.42	0.40	0.38	0.36	0.34
Π_g (1e7)	1.00	2.05	2.19	2.34	2.52	2.64	2.76	2.61	2.63	1.98	2.12	2.26	2.38	2.52	2.62	2.74	2.87	3.01
$\bar{u_s}$ (1e1)	0.00	0.00	0.01	0.03	0.08	0.14	0.20	0.26	0.34	0.11	0.10	0.10	0.09	0.08	0.07	0.06	0.06	0.05
u_g (1e1)	0.00	0.16	1.08	1.95	2.52	3.16	3.59	3.74	3.04	1.31	1.54	1.66	1.91	2.52	3.23	3.84	4.55	4.83
Ω_s (1e5)	0.43	1.97	3.08	3.25	2.98	2.72	2.52	3.66	4.12	2.65	2.71	2.82	2.94	2.98	3.03	3.05	3.10	3.11
Ω_g (1e5)	7.46	5.91	4.80	4.63	4.91	5.16	5.37	4.23	3.77	5.23	5.17	5.07	4.94	4.91	4.86	4.84	4.78	4.78
Λ_s (1e7)	0.27	1.29	2.13	2.33	2.22	2.04	1.92	2.95	3.43	1.77	1.87	1.99	2.13	2.22	2.29	2.34	2.45	2.51
Λ_g (1e7)	1.49	2.36	2.34	2.45	2.66	2.82	2.96	2.38	2.16	2.35	2.45	2.52	2.59	2.66	2.70	2.75	2.78	2.84
Λ (1e7)	1.76	3.66	4.47	4.79	4.88	4.86	4.89	5.34	5.60	4.11	4.31	4.51	4.72	4.88	4.98	5.08	5.22	5.36
R_s^2 (1e-1)	9.30	9.30	7.70	8.10	7.60	6.30	6.40	4.60	3.70	8.10	8.20	7.80	7.50	7.60	6.90	6.40	6.10	6.40

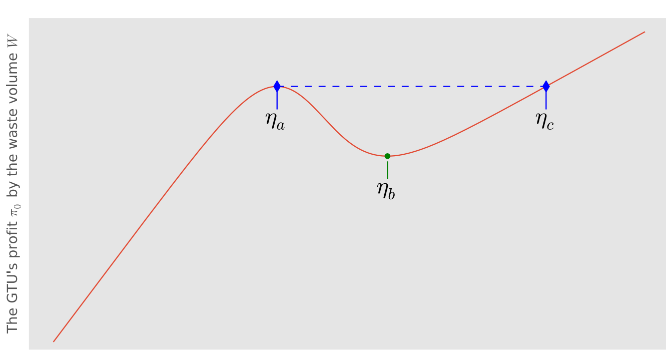

Fig. 9. A sample curve of the GTU's non-linear regression function (9).

large, the GTU's gate fee η_g approaches to the upper bound $\bar{\eta_0}$ with the falling uncertainty. This finding reveals that, it is necessary for the regulator to mandate a sensible upper bound on the gate fee charge to prevent escalating costs of waste treatment. Without such upper bound, the optimal gate fee could tend to infinity. On the other hand, the GTU might not necessarily always choose the upper bound imposed as its optimal gate fee. In particular, whenever $\bar{\eta_0} \in (\eta_a, \eta_c)$, the operator prefers a lower gate fee η_a. In the AWTM, however, the changing $\bar{\eta_0}$ still affects the GTU's gate fee decisions and other performances in a relatively slight manner, because of the varying gate fee intervals, randomness in its estimation-and-optimization decision-making process, and consequently different estimated price-profit curves.

Under Scenario G2, the GTU also has its gate fee increased since the dictated discount for post-treatment d_0 is enlarged from 0.1 to 0.9. Figs. 10 and 8 imply that the GTU's performances share similar trends under two scenarios, such as higher gate fee, profit and uncertainty, and less waste allocated. The only difference is, the changes of performance indicators under Scenario G2 are more smoothly in general. Unlike the GTU that owns two revenue streams, the STUs have to maintain the relatively low service price advantage to capture more waste. Therefore, their pricing decisions seem to be passive and conservative, and consequently other performances have much smaller variances than those of the GTU.

To recap, driven by the increased gate fee of the GTU under both scenarios, the STUs conservatively raise their gate fee to a lesser extent and thus maintain profits. Under Scenario G1 and G2, hence, cost reduction is less important compared with that under Scenario S1 and S2. Besides, the GTU is the major beneficiary and

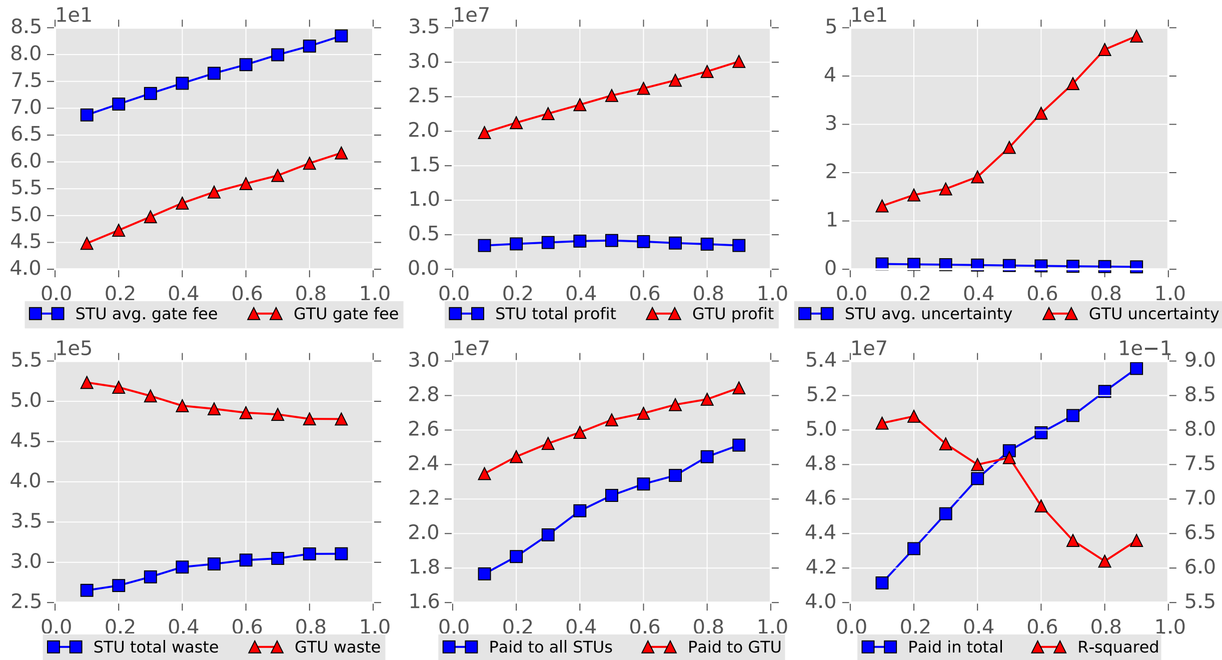

Fig. 10. Experimental results under Scenario G2. See Fig. 6 for axes definitions. As the discount factor for post-treatment increases from 0.1 to 0.9, the GTU obtains higher gate fee, profit and uncertainty, and less waste. The STUs have to maintain the relatively low service price advantage to capture more waste.

Table 6
Payment-saving policies based on experimental results.

Policy & Corresponding scenario	Impact on STU	Impact on GTU	Pros	Cons
P1. License more STUs (Scenario S1)	High and negative	Low and negative	Easy to control and implement	Low payment-saving
P2. Allocate more waste to STUs (Scenario S2)	High and positive	High and negative	1. significant short-term effects 2. high waste utilization	1, difficult to measure and determine appropriate preference 2, may cause extreme market situations
P3. Impose lower gate fee bound to the GTU (Scenario G1)	Medium and negative	Medium and negative	1. cost-effective to promote waste utilization 2. high payment-saving	May seem to be noneffective in lessening the GTU's gate fee sometimes
P4. Lessen the GTU's gate fee discount for the STUs (Scenario G2)	Low and negative	Low and negative	Lowest side effects	Low payment-saving

the regulator has to pay much more for waste treatment service in the AWTM.

5.3. Managerial discussion for policy-makers

We now attempt to shed some light on the competitive and integrated MSW treatment market by discussing the managerial implications of the experimental findings for policy-makers.

Firstly, the above experimental results have identified the effects of each policy on the performances of the AWTM. To compare these four policies comprehensively, we first assume that the regulator mainly focuses on the first objective (i.e., payment-saving) in developing policies, and also consider the other secondary goals listed in Section 4.3. Based on this assumption, four new policies are proposed for saving treatment payment, as summarized in Table 6 and represented by P1–P4, respectively. The degree and property of the impacts on treatment units are evaluated according to the variances of their performances. The pros and cons of the policies come from the other concerns of the regulator. According to Table 6, the third policy P3, imposing lower gate fee bound to the GTU, is the best one due to the following reasons: (1) It is able to obtain the largest payment saving; (2) Unlike the second policy, it can significantly promote waste utilization without paying more to the operators; (3) The medium impacts on the treatment units could be acceptable.

Secondly, we consider that the policy-maker seeks to develop a mixed policy to better regulate the competitive MSW treatment market. As stated in Section 4.3, we employed a genetic algorithm to identify the optimal mixed policy for the regulator, who is assumed to fulfill multiple predefined objectives. In that case, the final best solution is $m^* = 2$, $\beta_s^* = 16.97$, $\bar{\eta}_0^* = 81.58$, and $d_0^* = 0.22$, and each one STU can receive at least SGD 3.8 million profit under this mixed policy and other given constraints. Although the GA spent more than 5.5 hours to reaching the 100th generation, the optimal solution first appeared in the 29th generation within two hours and was always the best one of the candidates till termination, revealing that this approach has a high convergence rate. Therefore, the genetic algorithm has a good potential to solve similar simulation-based policy-development problems.

Finally, it is worthwhile to recommend the agent-based technique to policy-makers as a viable approach to develop and evaluate policies. In this paper, we provide a promising framework of individual modeling about the decision-making process of agents (i.e., stakeholders) in competition. Due to the valuable flexibility of the framework, large-scale and more realistic studies, which are often cumbersome to model and solve mathematically, can be conducted in a natural and bottom-up way. Therefore, our findings, which emerge from micro interactions among agents in the AWTM, are able to generate managerial insights that help the regulator to develop appropriate policies for managing the competitive and integrated municipal solid waste treatment market.

6. Conclusions

In this paper we propose an agent-based waste treatment model (AWTM) to investigate competition among private self-interested operators in integrated municipal solid waste treatment markets. The AWTM consists of four types of agents: (1) one refuse collector which forwards the input waste to the operators according to their gate fee attractiveness and the refuse collector's preferences to them; (2) multiple specialized treatment units (STUs) that are able to treat specific input waste and earn revenue by charging a per-tonne gate fee. However, the residues generated from the waste-to-energy process require further processing before final disposal; (3) one general treatment unit (GTU) which can treat both input waste and the STUs' residues; (4) an abstract regulator, who has developed four policies by changing the initial values of different exogenous variables. We design an estimation-and-optimization approach for the private operators so that they can optimize gate fee decisions in response to low-information competition. Moreover, to help the regulator identify the optimal mixed policy and fulfill multiple predefined objectives, the AWTM is integrated into a simulation-based optimization problem, which is solved by a genetic algorithm.

We conclude our findings based on the simulation outputs of 33 experiments under four scenarios as follows. (1) In a nearly perfectly competitive market, individual treatment units turn into the price takers and lose considerable profits. As a group, the STUs grabbed partial market share of the GTU when more STUs are licensed to enter the market. (2) If the regulator deliberately promotes the STUs by intervening in waste allocation, the GTU could give up competing for the waste and greatly increase its gate fee as retaliation. (3) Driven by the increasing gate fee of the GTU, the STUs conservatively raise their gate fee to a lesser extent and thus maintain profits. (4) In case of higher gate fee upper bound or large gate fee discount for the STUs, the GTU will be the major beneficiary and the regulator will have to pay much more for waste treatment service in the AWTM. Based on the above meaningful findings, we further propose four policies for the payment-saving regulator, and discuss the impacts, pros and cons of these policies comprehensively. Finally, the optimal mixed policy is obtained for the policy-maker who has multiple predefined objectives, revealing that the AWTM can be extended to be a powerful decision support approach for policy development.

This paper provides an application of the complex adaptive system (CAS) theory in the MSW treatment system. Adopting the CAS perspective to model the optimal responses of agents in competition in a bottom-up way, we construct the AWTM to investigate the optimal gate fee decisions of private self-interested operators. From an academic standpoint, our approach provides a promising framework to study competition in integrated municipal solid waste treatment markets under low information (e.g., the agent has little knowledge about its peers and the environment). Based on more realistic modeling of the optimal behaviors of treatment units, our findings generate valuable managerial insights for the market regulator in developing and evaluating policies. Therefore, the enhanced agent-based modeling technique is a viable methodology for managerial research.

We suggest several directions for future research. First, the treatment unit's capacity, location, and other attributes neglected in our model can be taken into account in an extended version of the AWTM, which would make agents' behaviors much more realistic. Second, suppose that the policy-maker attempts to affect the market by selectively disclosing some private information. It could be interesting to examine if this attempt can succeed. Finally, since our approach is a general framework, we consider exploring its applications in studying competition and/or corporation in other integrated systems.

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Appendix A. List of abbreviations and definitions

Term	Meaning/definition in the paper	First appearance
ABM(s)	Agent-based model(s)	Section 1
AWTM	Agent-based waste treatment model	Section 1
Black-box	The situation that decision makers have no knowledge of what results can be obtained	Section 3.3
CAS	Complex adaptive system	Section 1
CBA	Cost-benefit analysis	Section 2.1
DV(s)	Decision variable(s)	Table 1
GTU	General treatment unit who can treat any waste stream via incineration	Section 1
LCA	Life-cycle assessment	Section 2.1
MCDA	Multi-criteria decision analysis	Section 2.1
MLDM	Multinomial logit demand model	Section 3.2
MSW	Municipal solid waste	Section 1
NV(s)	Endogenous variable(s)	Table 1
Refuse collector	The agent who represents the waste collection and distribution function	Section 3.2
Regulator	The government agency who manages the waste treatment system	Section 1
STU	Specialized treatment unit who can only treat specific types of waste	Section 1
WEEE	Waste electrical and electronic equipment	Section 2.2
XV(s)	Exogenous variable(s)	Table 1

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