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Heuristic method for automakers' technological strategy making towards fuel economy regulations based on genetic algorithm: A China's case under corporate average fuel consumption regulation

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HIGHLIGHTS

- Technology combination problem is formulated and proven NP-hard.
- The proposed heuristic algorithm can decrease the compliance cost by 14.1%
- The commonly used method overvalues the effectiveness of mass reduction technology.
- Conventional technologies are more cost-effective to meet China's 2020 regulation.

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ABSTRACT

The vehicle fuel economy standards have been implemented worldwide. However, it is quite difficult for the automakers to secure an optimal portfolio of fuel-efficient technologies which complies with these strengthened standards and minimizes the overall cost at the same time. In this paper, a genetic-algorithm-based heuristic method is proposed for technological strategy planning. In particular, a case study of the Corporate Average Fuel Economy standards in China is presented. Moreover, the mathematical model is constructed with the considerations of the technology cost, effect of reducing fuel consumption and technology physical weight. Problem complexity is analyzed and proven NP-hard. Moreover, a comparison analysis of performance is carried out between the elaborated genetic algorithm and the greedy algorithm that is currently used by most automakers to determine the technological strategies in China. The results imply that genetic algorithm outperforms the common method because it provides more economical and reasonable strategies. In addition, the incremental cost under the greedy algorithm is 16.4% higher than that under genetic algorithm. Due to the counteractive effect under the weight-based standards in China, the mass reduction technologies should be given lower priorities compared with current strategies. To satisfy the standards by 2020, automakers should implement more conventional engine and transmission technologies instead of the hybrid electric vehicle technologies. It is recommended that automakers should develop heuristic algorithms to make strategic decisions more reasonably.

1. Introduction

Since the Corporate Average Fuel Economy (CAFE) was first established in the United States in 1970s, the standards to improve the vehicle fuel economy have been spreading worldwide. Especially in the past decade, 9 countries and regions have initially issued or updated their fuel economy standards. Table 1 presents the fuel economy targets and standards structures in the main vehicle markets [1]. As the fuel

Abbreviations: ABC, Artificial bee colony; AT, Automatic transmission; ANN, Artificial neural network; AWD, All wheel drive; BEV, Battery electric vehicle; CAFC, Corporate average fuel consumption; CAFE, Corporate average fuel economy; CVT, Continuous variable transmission; DCT, Duel clutch transmission; DOHC, Double overhead camshaft; EGR, Exhaust gas recirculation; FCR, Fuel consumption rate; FCV, Fuel cell vehicle; GA, Genetic algorithm; GDI, Gasoline direct injection; HEV, Hybrid electric vehicle; ICE, Internal combustion engine; MPG, Mile per gallon; NP-complete, Nondeterministic polynomial-time complete; NP-hard, Nondeterministic polynomial-time hard; OEM, Original equipment manufacturer; PDA, Partial discrete approximation; PHEV, Plug-in hybrid electric vehicle; PSO, Particle swarm optimization; SA, Simulated annealing; SOHC, Single overhead camshaft; TC, Technology Combination problem; TCAFC, Target of corporate average fuel consumption; TIES, Technology identification, evaluation and selection; TRS, Three rows of seats; TS, Tabu search; V6, V engine six cylinders

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Table 1
Fuel economy regulations and structures in main automobile markets.

Country or Region	Target year	Standard type	Fleet target/ Measure	Converted fleet target (g/km)	Structure	Test cycle
EU	2021	CO2	95 gCO2/km	95	Weight-based corporate average	NEDC
China	2020	Fuel consumption	4.9 L/100 km	117	Weight-class based per vehicle and corporate average	NEDC
U.S.	2025	Fuel economy	56.2 mpg	97	Footprint-based corporate avg.	U.S. combined
Canada	2025	GHG	56.2 mpg	97	Footprint-based corporate avg.	U.S. combined
Japan	2020	Fuel economy	20.3 km/L	122 (exceeded by 2013)	Weight-class based corporate average	JC08
India	2021	CO2	113 g/km	113	Weight-based corporate average	NEDC
South Korea	2020	Fuel economy	24.3 km/L	97	Weight-based corporate average	U.S. combined

economy targets are getting more stringent, technology strategy satisfying the standards will become the main subject in automobile industry. It should be noted that China is the main contributor in the growing vehicle market. In particular, the automotive industry has been developed dramatically in China over the past 15 years. By the end of 2015, the vehicle stock has increased tenfold to 172.2 million [2]. Hao et al. estimated that by 2050, the vehicle population would reach 606.7 million [3]. Subsequently, the on-road vehicles have become the major CO_2 emitters and oil consumers as the result of the booming automotive industry.

China has announced four phases of fuel economy standards concerning the light-duty vehicles. In particular, the Corporate Average Fuel Consumption (CAFC) system has been established since Phase III, which requires Original Equipment Manufacturers (OEM) to meet the fleet average fuel consumption rate (FCR) targets. During the past 9 years after the release of the Phase I regulation, a 14.7% national fleet-wide fuel economy improvement has been achieved [4,5]. However, the strengthening CAFC regulation at the current phase requires OEMs in China to improve the fleet FCR by 4.5 ~ 9.1% annually, as shown in Fig. 1. Therefore, the technological strategy making is of vital importance to comply with the standards. An OEM needs to optimally select several sets of fuel-efficient technologies to its assortment.

2. Literature review

Two strategies for regulation compliance have been widely explored. One strategy is to measure the technology improvements and compromise the trade-offs of vehicle attributes, which mostly includes fuel economy, acceleration time and size. Lutsey and Sperling [6] assessed the standards in terms of technology improvements. Luk, et al. carried out the simulation of tradeoffs among vehicle price, performance and interior volume to meet the 2025 fuel economy target [7]. By measuring the vehicle potential fuel economy improvement with the consideration of vehicle attribute trade-offs, the difficulty complying with next phase standard could be quantified [8]. Another strategy is to evaluate the promising and advanced technology roadmaps. Some studies assessed the potential of improving fleet-wide vehicle fuel economy by setting various scenarios with different policy instruments and penetration rates of the advanced technologies [9,10,11]. Meanwhile, some studies analyzed the availability and potential of fuel-efficient technologies as well as the technology roadmaps to meet current standards and beyond [12,13]. Simmons et al. reviewed the fuel economy technologies that were available in 2014 model year. The results demonstrated OEMs with new insights into what the fuel-efficient technology roadmap would be [14].

There were several methods used in the OEM's decision-making studies. In particular, these methods include the utility function in conceptual and preliminary design stages [15], strategic decisions to improve profitability according to the vehicle production volume in flexible manufacturing system [16], design decisions with demand distributions forecasted by exogenous variables [17], and cost-benefit analysis to minimize the technology cost while complying with the energy-saving requirement [18]. Moreover, the responses of OEMs are examined under various regulation stages and scenarios in other studies. Oh et al. generated several strategies for the main OEMs to satisfy the fuel economy regulations in Korea and made scenario analysis. They found OEMs could only satisfy the standards by employing at least two strategies [19]. Shiau et al. simulated OEMs' responses under low, moderate and high CAFE requirements respectively. They found that improving the CAFE standards should cooperate with the increase of the penalty for violation to guarantee the effectiveness of CAFE [20]. Besides the stringency of the standards, an appropriate regulatory lead-

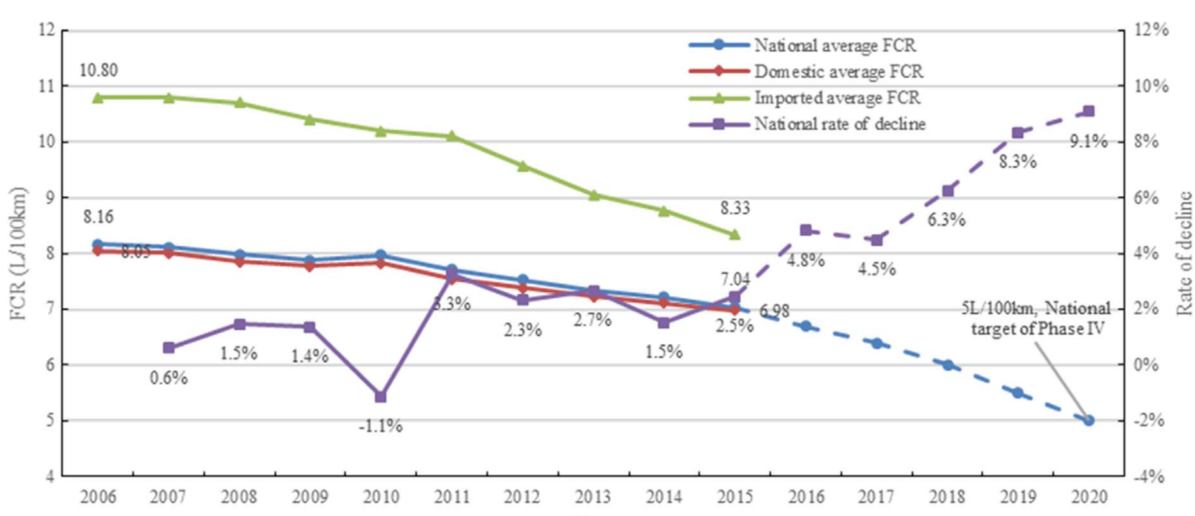

Fig. 1. China's fleet-wide FCR and the future targets. Note: dotted line is estimated according to the phasing in of phase IV CAFC standards.

time could also significantly affect the sustained technology deployment and investment plans [21].

It should be noted that the optimization method is employed in some studies to analyze fuel-efficient technologies and the trend of future technology roadmaps. However, the bulk of studies above did not consider the standards compliance strategy as the combinatorial optimization problem of technology and product. In general, the combinatorial optimization problems could be solved by heuristic algorithms due to the computational complexity, In particular, the algorithms include tabu search (TS), simulated annealing (SA), genetic algorithm (GA), particle swarm optimization (PSO), artificial neural network (ANN), artificial bee colony (ABC), etc. Conventionally, the heuristic algorithms could effectively solve vehicle routing and scheduling problems [22]. Substantially, these algorithms are also employed in the vehicle development process and other corresponding decision making problems nowadays. In the industrial sector, GA, PSO and ANN are the most commonly used algorithms. In particular, GA and PSO were mostly used in developing the vehicle control strategy, which includes the gear shift [23,24] and energy management strategies [25], and vehicle parameter design. For example, the light-weighting decision-makings consider the attribute trade-offs [26], and vehicle shape optimization [27]. Furthermore, ANN and deep-learning methods could also be implemented in the vehicle development and parameter optimization. However, a large database for training or supervised learning is usually required. In the academia sector, the mature and robust GA, PSO and ANN are still the most commonly used methods. For example, Chaos enhanced accelerated PSO was implemented in series HEV sizing optimization [28], and ANN was used in designing Atkinson cycle of conventional engines [29]. The other heuristic algorithms such as TS, SA and ABC were mostly employed in the decision making of electric vehicle charging and battery switching station distribution and concentration studies [30,31,32]. In theory, there exist some limitations when a combinational optimization problem is solved using any heuristic algorithm. For instance, since the solution candidate of PSO is commonly a vector of real numbers, it needs relaxation to solve a problem whose solution are integers. Also as discussed above, ANN and deep learning usually needs a large database to finish the training or learning process as discussed above, where the data is collected from markets or generated through simulation., to finish the training or learning process. For a novel problem without much data for reference, ANN could hardly be applied.

Despite vehicle development processes, GA is also widely used in the decision making of technology evaluation and selection as well as system design and product combination. However, few existing studies have considered the OEMs' optimal decision making, which selects a suite of technologies and formulates a portfolio of models to satisfy environmental regulations as a combinatorial problem. Likewise, even fewer studies solved it using heuristic algorithms [33,34]. The integrated model consisting of vehicle engineering performance, manufacturer profits, regulatory penalty and market demand was developed to investigate the vehicle optimal design and conduct policy analysis. Moreover, game theory was utilized with a sequential iterative method to optimize the objective function, which was so computationally intensive that the producer was limited to a maximum of 2 [35]. Although a multi-stage approach was proposed to solve this model more efficiently, heuristic algorithms were not employed [36]. There was another integrated model incorporating product pricing, production plan and inventory, market demand and regulation constraints. For this integrated model, the mix-integrated programming method was utilized to make strategic assortment plans for OEMs [37]. To maximize the overall measurement of value in the early design stages, Mavris and Kirby proposed a nine-step technology identification, evaluation and selection (TIES) method. In the steps of technology evaluation and selection, GA was employed to acquire the optimal portfolio of alternative technologies [38]. Since long development procedures are required for both aircrafts and vehicles, most of the TIES methods could be employed in the decision-makings of OEMs' vehicle technology combination (TC) design. Montalbo et al. identified a light-weighting TC strategy to optimize net present value in a time horizon of three years for three vehicle models respectively. In this strategy, the best solution was searched in numerous available materials and manufacturing processes by implementing GA [39].

Therefore, the existing studies from the perspective of OEMs have seldom considered complying with FCR standards by choosing a portfolio of fuel-efficient technologies for each vehicle as a combinational optimization problem. Besides, fewer studies have solved this problem with elaborately designed heuristic algorithms. In general, studies focused on one category of fuel-efficient technologies instead of devising a decision-making method with regard to different categories of technologies extensively. Most importantly, to the best of our knowledge, no study has conducted complexity analyses of relevant problems. Substantially, this critical shortfall might result in exaggerating the difficulty of the problem and overdoing the problem with excessively designed algorithms. With the aim of filling such gaps, the contribution of this paper lies in three aspects. Firstly, the mathematical model of the TC problem is constructed and the complexity analysis is conducted in this study. Secondly, an efficient and reliable algorithm is elaborated to solve this problem. Thirdly, results of technology strategy from both the OEM commonly used greedy algorithm and the designed GA are compared, which considers the fuel-efficient technologies extensively.

The whole paper is organized as follows. In the next session, the TC mathematical model is presented with a complexity analysis conducted by restricting the decision problem of TC to the decision problem of 0/1 knapsack problem. Subsequently, a GA is developed and the effectiveness of the GA is examined by solving a selected case. Next, the performance of the designed GA is compared with the TC decision-making method that is commonly used by OEMs in China. The final section draws conclusions based on the entire study.

3. Technology combination problem

In this study, TC problem is defined as selecting the technologies to be implemented on an OEM's vehicle product assortment that can optimize the OEM's targets subject to the constraints of FCR standards, greenhouse gas emissions standards, air pollutants standards, etc. The application of TC is not restricted to automotive industry. The application could be extended to other manufacturing sectors where numerous parameter-related technologies are available for selection and several compulsory requirements should be satisfied. Under the CAFC standards in China, the technologies for selection and combination are fuel efficiency related. In current standards of Phase III and the newly enacted Phase IV, there is no violating penalty provision. The target for most OEMs is to meet the standards while minimizing the technology incremental cost. In this section, TC mathematical model is formulated and complexity analysis is conducted.

3.1. Technology combination problem framework description

Assume an OEM with n vehicle models in the market as well as m feasible fuel-efficient technologies, with the parameters defined in Table 2. The connections among those parameters in the decision making process of OEMs are illustrated in Fig. 2.

The objective is to minimize the technology incremental cost without violating the standards. The framework for TC is formulated as

$$\min \sum_{j=1}^{n} s_j \sum_{i=1}^{m} (x_{ij}-\widetilde{x}_{ij})c_i \tag{1}$$

subject to:

(1) CAFC constraint
(2) FCR limit

Table 2
Parameter notations and descriptions.

Notation	Description
$i \in \mathbb{Q} = \{1,2,...,m\}$	Set of all available fuel-efficient technologies for the OEM
$j \in \mathbb{P} = \{1,2,...,n\}$	Set of all vehicle models of the OEM
$StL(m_j)$	The step function defined by the standards to determine the FCR limits
$StT(m_j)$	The step function defined by the standards to determine the FCR targets
$\mathbf{C} = [c_1,c_2,...c_m]$	c_i is the cost of technology i
$\mathbf{E} = [e_1,e_2,...e_m]$	e_i is the FCR reduction effect of technology i, $0 \leqslant e_i \leqslant 1$
$\mathbf{F} = [f_1,f_2,...f_n]$	f_j is the FCR of model j after technology implementation
$\mathbf{L} = [l_1,l_2,...l_n]$	l_j is the FCR limit of model j after technology implementation
$\mathbf{M} = [m_1,m_2,...m_n]$	m_j is the curb weight of model j after technology implementation
$\mathbf{S} = [s_1,s_2,...s_n]$	s_j is the projected sales of model j after technology implementation
$\mathbf{T} = [t_1,t_2,...t_n]$	t_j is the FCR target of model j after technology implementation
$\mathbf{W} = [w_1,w_2,...w_n]$	w_j is the CAFC calculation weight[a] of model j after technology implementation
$\mathbf{V} = [v_1,v_2,...v_m]$	v_i is the impact on curb weight after implementing i, $0 \leqslant v_i \leqslant 1$
$\mathbf{X} = [\mathbf{x_1},\mathbf{x_2},...,\mathbf{x_n}]$	$\mathbf{x_j}$ is the decision variable column vector of model j with m elements, $x_{ij} \in \{0,1\}$ is the final state of technology implementation
$\widetilde{\mathbf{F}}, \widetilde{\mathbf{L}}, \widetilde{\mathbf{M}}, \widetilde{\mathbf{S}}, \widetilde{\mathbf{T}}, \widetilde{\mathbf{W}}$	The corresponding parameters before technology implementation
$\widetilde{\mathbf{X}} = [\widetilde{\mathbf{x}}_1,\widetilde{\mathbf{x}}_2,...,\widetilde{\mathbf{x}}_n]$	The initial technology implementation condition, $\widetilde{x}_{ij} \in \{0,1\}$

[a] According to the standards, when a vehicle model's powertrain configuration is battery electric vehicle (BEV), fuel cell vehicle (FCV) or plug-in hybrid electric vehicle (PHEV) and several criterion are met, "super weight" is adopted to calculate the OEM's CAFC. For example, the "super weight" of BEVs is 5, 3, 2 in year 2016 ~ 2017, 2018 ~ 2019, 2020, respectively, while for traditional internal combustion engine (ICE) models, the weight is 1.

(3) Technology compatibility

The constraints stated in Eq. (1) are described as follows:

(1) **CAFC target constraint**: Under China's fuel economy standards, an OEM's CAFC should meet the CAFC target. The constraint is described in Eq. (2).

$$\begin{cases} TCAFC = \dfrac{\sum_{j=1}^{n} s_j t_j}{\sum_{j=1}^{n} s_j} \\ CAFC = \dfrac{\sum_{j=1}^{n} s_j f_j}{\sum_{j=1}^{n} s_j w_j} \\ CAFC \leqslant TCAFC \end{cases} \tag{2}$$

(2) **FCR limit**, which determines the entry of domestic vehicle market. Vehicle models violating this constraint could not acquire the license to sell in China. The constraint is described in Eq. (3).

$$f_j \leqslant StL(m_j) \tag{3}$$

(3) **Technology compatibility**, which means that some technologies could not be implemented concurrently. It is determined by the physical features of fuel-efficient technologies and could be divided into four classes:

(a) Overlapping effect. When several technologies following the same fuel-efficient principle or acting on almost the same part of a vehicle's energy flow are applied together, the effects are extremely overlapped by each other and even less than the impact of the individual technologies [38,40,41]. Therefore, it is not cost-effective to apply HEV technology with any of them together. For example, one main fuel saving principle of HEV is that the internal combustion engine (ICE) could be shut down when the vehicle is stopped or decelerating so that the ICE is adjusted into more economical map zones when it is operating at low load, which is the fuel-efficient principle of engine turbocharging, engine downsizing and cylinder deactivation as well. For two overlapping effect technologies that are available to model j, the constraint is described in Eq. (4).

$$x_{\alpha j} + x_{\beta j} \leqslant 1, \quad \alpha,\beta \in \mathbb{Q} \tag{4}$$

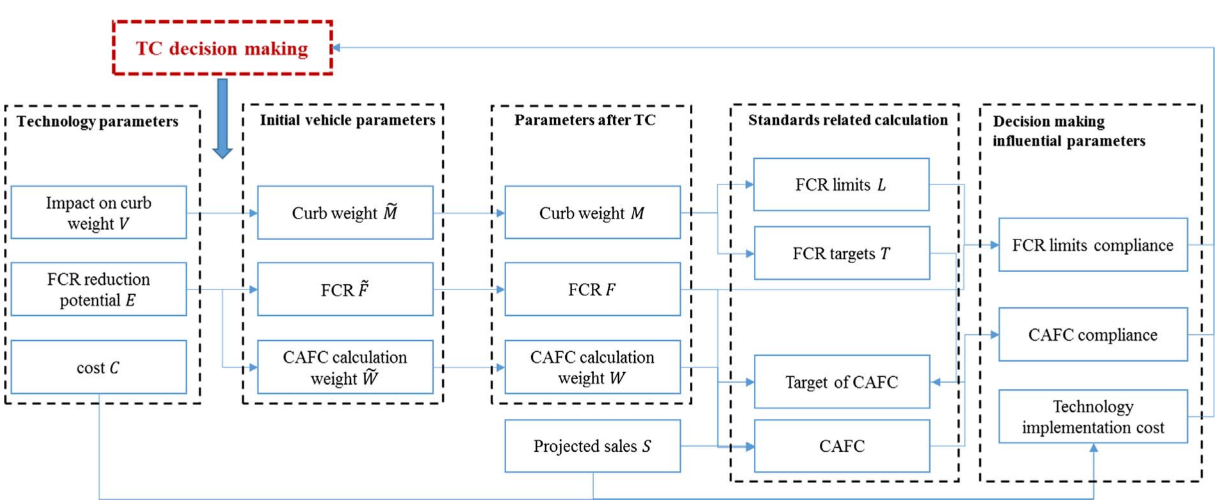

Fig. 2. The connections of parameters in TC.

(b) Same category. Technologies in the same category could not be applied concurrently. For example, duel clutch transmission (DCT) and continuous variable transmission (CVT) could not be additionally equipped on one drivetrain. Let $\{\mathbb{Q}_{c_1},\mathbb{Q}_{c_2},\ldots\mathbb{Q}_{c_\gamma}\}$, $\gamma \in N^+$ be the set of subsets of $\mathbb{Q}$, where each technology could only be used exclusively among the subset. The constraint is described in Eq. (5).

$$\sum_{i\in\mathbb{Q}_{c_\sigma}} x_{ij} \leqslant 1,\quad 1 \leqslant \sigma \leqslant \gamma,\quad \sigma \in N^+ \tag{5}$$

(c) Incompatible powertrains. Technologies which are applicable exclusively to one type of powertrain could not be implemented on other powertrains. For example, gasoline direct injection (GDI) could not be applied to diesel or battery electric vehicle (BEV) powertrains. Let $\{\mathbb{Q}_{p_1},\mathbb{Q}_{p_2},\ldots\mathbb{Q}_{p_\eta}\}$, $\eta \in N^+$ be the set of subsets of $\mathbb{Q}$ that contain technologies applicable exclusively to individual powertrains. The constraint is described in Eq. (6).

$$\sum_{i\in p_\mu} x_{ij} \sum_{i\in\mathbb{Q}_{p_\nu}} x_{ij} = 0,\quad 1 \leqslant \mu < \nu \leqslant \eta,\quad \mu,\nu \in N^+ \tag{6}$$

(d) Preferential FCR targets. Under China's Phase IV CAFC standards, FCR of FCVs and BEVs are counted as zero [12]. Therefore, in terms of complying with the standards, it is not cost-effective to implement other technologies when BEV powertrain has been applied to one model. Let $\mathbb{Q}_{FCV}$ and $\mathbb{Q}_{BEV}$ be the subsets of $\mathbb{Q}$, which contain FCV technologies and BEV technologies respectively. The constraint is described in Eq. (7).

$$\sum_{i\in\mathbb{Q}_{FCV}\cup\mathbb{Q}_{BEV}} x_{ij} \sum_{i\notin\mathbb{Q}_{FCV}\cup\mathbb{Q}_{BEV}} x_{ij} = 0 \tag{7}$$

Partial discrete approximation is an approach most widely used to estimating the synergistic impact of technologies on reducing FCR. In order to avoid overestimating FCR benefits of technological synergistic impact, different approximation methods of PDA are employed under different structures of standards [37,42]. Under the US CAFE standards, the level of fuel economy is measured in mile per gallon (MPG). Let Δ_i be the fuel economy benefit of technology $i \in \mathbb{Q}_j$, where $\mathbb{Q}_j$ is the set of selected technologies to be applied to model j, and $\widetilde{MPG}_j$ be the initial fuel economy of model j. The cumulative fuel economy impact is calculated as Eq. (8). While under the China's CAFC standards, liter per 100 km (L/100 km) is used to measure the FCR. Let δ_i be the FCR reduction effect of technology, and the corresponding impact is calculated as Eq. (9), which is used in this study.

$$MPG_j = \widetilde{MPG}_j(1 + \sum_{i\in\mathbb{Q}_j} \Delta_i) \tag{8}$$

$$f_j = \widetilde{f}_j \prod_{i\in\mathbb{Q}_j} (1-\delta_i) \tag{9}$$

In addition to reducing the chances of overestimating the FCR benefits, another intention of using the two methods above is to estimate the interactions among technologies, which have been accounted for in the Δ_i and δ_i terms [42]. After excluding the concurrent implementation of technologies with considerable overlapping effects, the interactions among technologies have been notably decoupled by the technology compatibility constraints. Therefore, the method in Eq. (10) is suitable as well, which will be used to conduct complexity analysis of TC below.

$$f_j = \widetilde{f}_j (1- \sum_{i\in\mathbb{Q}_j} \delta_i) \tag{10}$$

When applied to one model, the technology's physical weight affects the model's curb weight m_j, additionally affects the curb weight based parameters, the FCR target $t_j = StT(m_j)$ and FCR limit $l_j = StL(m_j)$. The curb weight after technology implementation is calculated as Eq. (11).

$$m_j = \widetilde{m}_j(1 + \sum_{i\in\mathbb{Q}_j} v_i) \tag{11}$$

3.2. Complexity analysis

(1) Assumptions

In this model, the aim is to analyze the complexity of TC and design a metaheuristic algorithm to solve TC, for which economical effects are not taken into consideration. The projected sales is given and does not vary after the implementation of technologies, and hence $\widetilde{S} = S$. Besides, the super weight effects specified by the CAFC standards are disregarded. That is $w_j \equiv 1, j \in \mathbb{P}$. As the FCR targets and limits are determined by step functions of vehicle curb weights, TC could not be described explicitly by using the decision variables. To analyze the complexity of TC, an approximation is made that the FCR targets and limits are determined by linear functions, as Eq. (12) shows.

$$\begin{cases} t_j = k_{t1} m_j + k_{t2} \\ l_j = k_{l1} m_j + k_{l2} \end{cases} \tag{12}$$

where, k_{t1}, k_{t2}, k_{l1} and k_{l2} are the coefficients in approximating the FCR targets and limits.

(2) NP-hardness of TC

Consider the special case of TC where there is only one vehicle model in the OEM's assortment and no fuel-efficient technologies have been implemented on the model. That is $\widetilde{x}_i = 0$. Let the available technologies set of the OEM be $\mathbb{Q}_\tau$, where each technology is compatible with the others. Consequently, the combined FCR reduction could be estimated by Eq. (10). The special case of TC could be written as Eq. (13)

$$\begin{aligned} &\min \quad s \sum_{i\in\mathbb{Q}_\tau} x_i c_i \\ &\text{subject to:} \begin{cases} \dfrac{s\widetilde{f}\,(1 - \sum_{i\in\mathbb{Q}_\tau} x_i e_i)}{s} \leqslant \dfrac{s k_{t1}\widetilde{m}\,(1 + \sum_{i\in\mathbb{Q}_\tau} x_i v_i) + k_{t2}}{s} \\ \widetilde{f}\,(1- \sum_{i\in\mathbb{Q}_\tau} x_i e_i) \leqslant k_{l1}\widetilde{m}\,(1 + \sum_{i\in\mathbb{Q}_\tau} x_i v_i) + k_{l2} \end{cases} \end{aligned} \tag{13}$$

As specified by the standards, the FCR target is more stringent than the FCR limit for one model. The two constraints in Eq. (13) could be simplified to one. Let $(e_i\widetilde{f} + k_{1t} v_i \widetilde{m})$ be d_i and $(\widetilde{f} - k_{1t}\widetilde{m} - k_{2t})$ be b_f, the decision problem of these instances is "given the incremental cost b_c, does a combination of technologies $x_i \in \{0,1\}, i \in \mathbb{Q}_\tau$ exist so that the constraints in Eq. (14) are satisfied?"

$$\begin{cases} \sum_{i\in\mathbb{Q}_\tau} x_i d_i \geqslant b_f \\ \sum_{i\in\mathbb{Q}_\tau} x_i c_i \leqslant b_c \end{cases} \tag{14}$$

Set the cost of the technologies $c_i = b_c d_i / b_f$. The constraints in Eq. (14) are transformed into Eq. (15)

$$\sum_{i\in\mathbb{Q}_\tau} x_i c_i = b_c \tag{15}$$

As the 0/1 knapsack decision problem is described as "given $(a_1,a_2,a_3,\ldots,a_\sigma,b)$, does $\sum_{i=1}^{\sigma} x_i a_i = b$, $x_i \in \{0,1\}$ have a solution? ", the above decision problem of the restrictive special instance of TC is equivalent to the well-known 0/1 knapsack decision problem, which has proven NP-complete [39]. As an optimization problem is NP-hard when it has a version of decision problem which is NP-complete [43], the result can be established that TC is NP-hard even when the problem is basic and several simplifications are made. Therefore, TC is a NP-hard problem. A further introduction of NP-hard problem and related terminology is given in Appendix A.

4. Heuristic algorithm to solve technology combination problem

As proved in the previous section, TC is NP-hard, which indicates that unless $P = NP$, it is unlikely to find an efficient polynomial algorithm to solve it optimally. Moreover, in most instances, there are dozens of feasible fuel-efficient technologies for OEMs. Even for the intermediate volume OEMs in China, the assortments would consist of over 10 vehicle models in general. Therefore, enumeration method which requires significant computation is impractical for most OEMs. In order to acquire the best solution at an acceptable computational cost [35], the application of a heuristic algorithm to TC is necessary. GAs are particularly suitable for complex optimization problems that could be mapped into a set of strings [44]. Since the decision variables of TC are binary, a GA is designed and implemented to solve TC. As a search heuristic, GAs have proven quite effective in exploring the solution domain and finding the optimum [45]. However, in the worst case for an OEM where n fuel-efficient technologies are available without technology incompatibilities and m vehicle models are included in the assortment, the search space of possible solutions is over $2^{m\cdot n}$, which implies an intractable calculation amount. Since the "no free lunch" theorem demonstrates that matching algorithms to specific problems brings better performance [46,47], sufficient prior information of TC should be acquired before developing a suitable GA to solve TC, which includes the provisions of the standards, the feasible fuel-efficient technologies and technology compatibilities among them.

4.1. Case selected and data input

In this study, an intermediate volume OEM in China is selected, whose sales in 2015 is around 580,000 and assortment consists of 8 vehicle models containing 36 vehicle versions. The detailed vehicle parameters are listed in Appendix B. Three determining parameters of fuel efficient technologies that are most related to the compliance of the regulation are selected, which is comprised of FCR reduction potentials, direct manufacturing cost and effects on curb weight. The data of technologies available before 2020 is adapted from fuel-efficient technology assessment reports. The estimations of FCR reduction potentials relied on more than one method, including fundamental technical analyses, literature reviews, full system simulation, vehicle test data, data from automakers and suppliers, experts' opinions and etc. [42,48,49]. Since the FCR reduction potentials, costs and effects on weight for different segments of vehicles are not identical, the data is divided into 2 categories, one consists of the data for A and A0 segments (generally defined as passenger vehicles with wheelbase of under 2.7 m), and another consists of the data for B and above segments (wheelbase of above 2.7 m). 56 technologies classified into 4 categories are selected in this case. As illustrated in Fig. 3, technologies are further classified into sub-categories and the numbers in the brackets represent the amounts of technologies in each category Technology incompatibilities are adapted from the several technology assessments [42,48,50,51]. In addition, with respect to technology implementation within vehicle versions and models, two assumptions are made based on the real world OEM manufacturing and product positioning process. First, vehicle versions under the same vehicle model should be implemented with the same engine and vehicle technologies, for instance, GDI, turbocharging, mass reduction, aerodynamics, etc. Second, accessory, transmission and HEV technologies could be used on vehicle versions within the same vehicle model.

4.2. The design of genetic algorithm

(1) **Coding and constraints**

Considering the objective function of TC in Eq. (1), binary coding, which is the most widely used conventional method in combinatorial optimization problems, is suitable for the calculation process to solve TC. However, binary coding would extend the search space of GAs exponentially where most of the solutions might be infeasible on account of the constraints. This would degrade the algorithm performance considerably. Several coding and constraint handling techniques are applied to the proposed GA so that the search space would be effectively reduced and the algorithm performance would be improved.

(a) Specialized solution structure. Constraints presented in the problem could be hidden by specializing the solution structure [52]. In TC, numerous technology compatibility constraints increase the difficulty of hiding the constraints. Specializing the structure contains four steps, after which all the technology compatibility constraints are eliminated. Firstly, by employing a top-down method, technologies are divided into 4 categories The solution structure for each vehicle version is encoded into a 4-digit integer structure. Secondly, technologies in each category are subdivided into subclasses. The incompatibilities could be defined among subclasses. Thirdly, compatible technologies are combined using a bottom-up method, from the bottom tier to the four main categories. Dominated combinations are eliminated and the dominating combinations are ordered based on cost-effectiveness. As illustrated in Fig. 4. Last, powertrain indicator matrix is established. For each powertrain, the lower and upper bounds of the 4-digit integers are defined, which eliminates the remaining constraints of overlapping effect and preferential FCR targets as discussed above in Section 3.
(b) Decoders. An appropriate decoder could avoid the generation of infeasible solutions [52,53]. In this case, vehicle versions and models are implemented with some fuel efficient technologies initially. Thus the incremental cost and fuel economy are more appropriate while calculating the CAFC related constraints. Decoding integers into binary structure makes the calculation process simple and guarantees the feasibility of solutions.
(c) Penalty functions. Penalty functions provide a method of guiding the search towards feasible solutions [53,54]. A proper penalty factor would compromise between satisfying the constraints and maintaining diversity of the GA population. As the objective function is to minimize the total cost, the penalty function is defined as Eq. (16)

$$P = \begin{cases} +\infty, & \text{if } \mathbf{TCS_j x_j} \leqslant (1,1,\ldots,1)^T \\ TOC + p_{cons1}(CAFC-TCAFC)\tau_0 & \text{else} \\ \quad + p_{cons2}\sum_{j=1}^{n}(f_j-l_j)\tau_j, & \end{cases} \tag{16}$$

where, TOC is the total incremental cost derived in Eq. (1); $\mathbf{TCS}_{\mathbf{j},\sigma_j\times \mathbf{m}}$ is the technology compatibility constraints matrix of vehicle model j, and σ_j is the total number of constraints; p_{cons1} and p_{cons2} are penalty function factors, which are adaptive to the GA process. During the initial generations, the relatively small factors are applied to guarantee the diversity and avoid premature, and larger factors are set afterwards to satisfy the constraints. $\tau \in \{0,1\}$ is a constraint violation indicator. $\tau = 1$ when corresponding constraint is violated. Otherwise, $\tau = 0$. Death penalty [53] is applied when the technology compatibility constraints are not satisfied. The arbitrary penalty of infinity leads to an extremely low fitness.

(2) **Initialization**

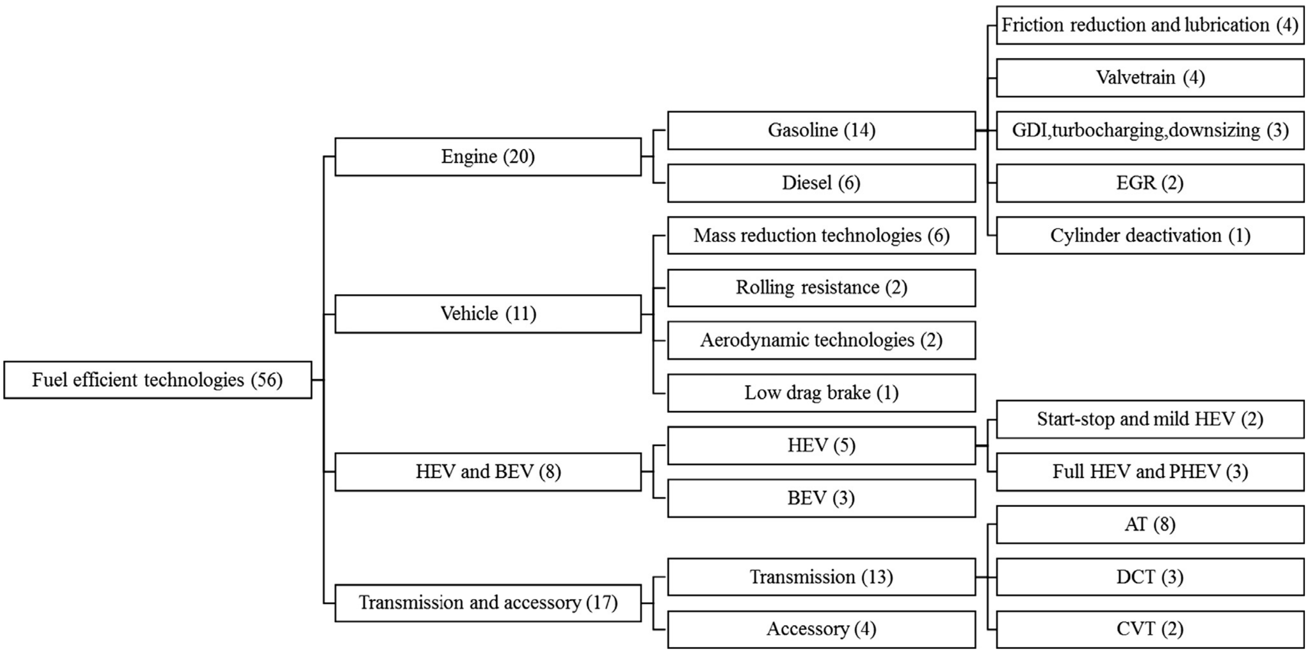

Fig. 3. Selected fuel-efficient technologies.

Population initialization is a crucial task in evolutionary algorithms because it can affect the search space, the convergence speed and also the final solution [55]. To guarantee both the population diversity and the convergence speed, the initial population is generated by two approaches. The major portion is generated with the prerequisite of satisfying all the constraints, other individuals are randomly initialized.

(3) **Fitness evaluation and selection**

As the objective is to minimize the total cost, the penalty function value and the fitness of an individual is negatively correlated, which indicates that a higher penalty represents a lower fitness to survive. Thus the penalty is used to represent an "inverse" fitness. Roulette approach is employed in the process of selection.

(4) **Crossover and offspring generation**

In the process of crossover, two parents are randomly selected to produce two children. In order to avoid the generation of infeasible solutions, powertrain indicator matrix, which records the type of one powertrain (gasoline, diesel, HEV or BEV), is employed to eliminate the infeasibilities while generating offspring. Meanwhile, the elitists that have been recorded in the previous step are transmitted directly into the next generation so that a non-negative evolution process is guaranteed.

(5) **Mutation**

By using the adaptive mutation method, the twin goals of sustaining the capacity of convergence and maintaining the diversity in the population could both be realized [56]. The algorithm stops when the defined number of evolution generation is achieved. The process of the designed GA is illustrated in Fig. 5.

5. Results and discussion

5.1. Simulation results

The GA described above is coded into MATLAB programs and employed in the selected case. As the encoded solution structure contains 144 bits, a sufficient large population size is set to be 20,000. Moreover, the factors of penalty function are tuned in the initial simulations so that feasible solutions could be acquired while maintaining the population diversity. Numerous simulations are conducted to determine the

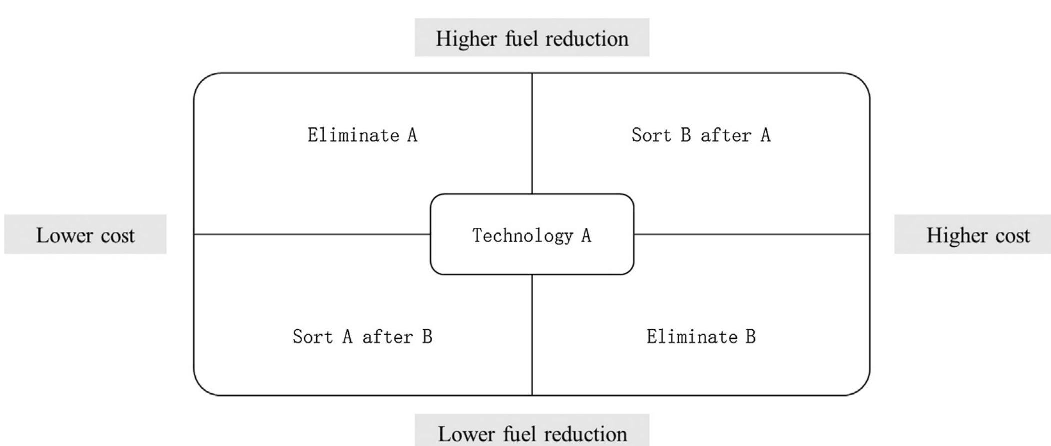

Fig. 4. The comparing matrix of two TCs.

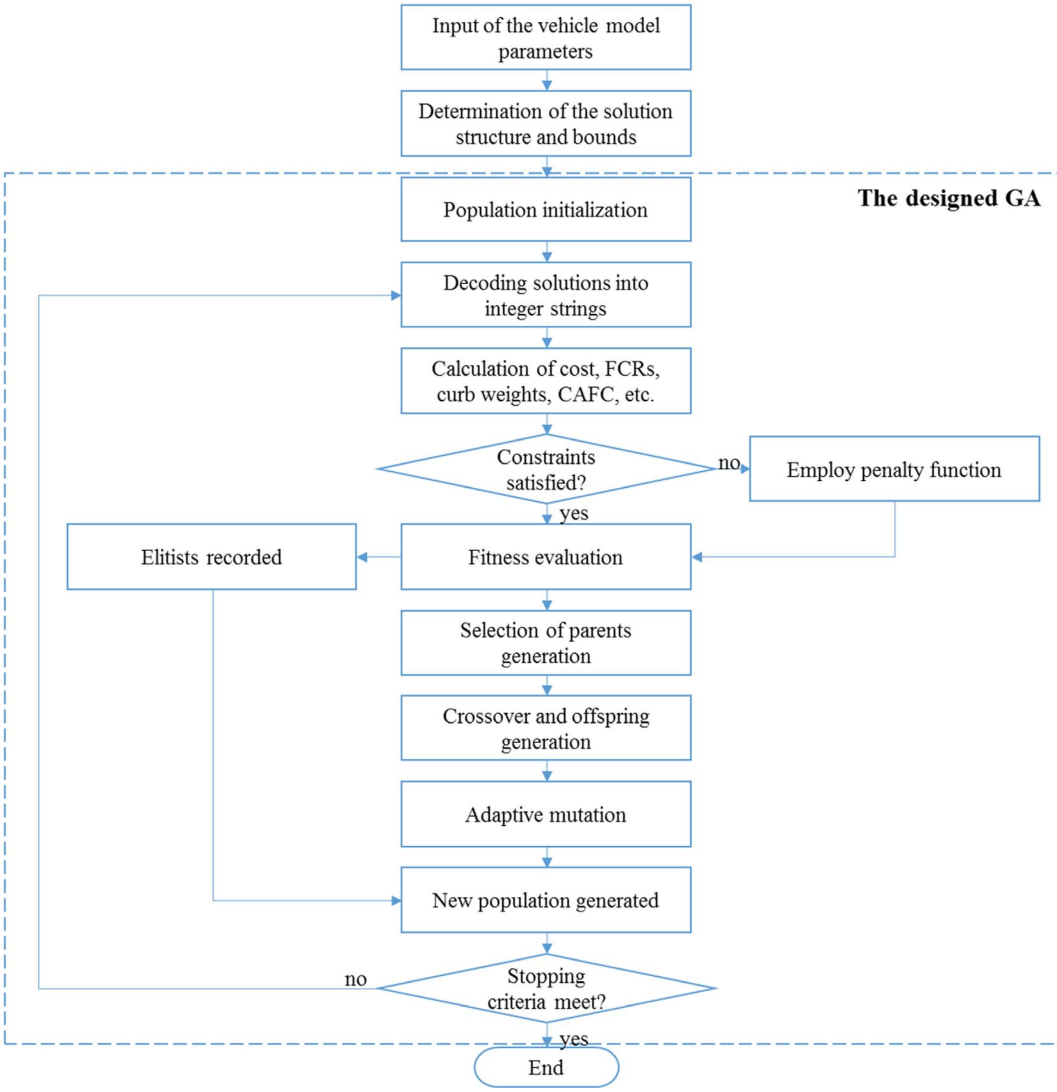

Fig. 5. The iteration process of the designed GA.

technical parameters in the algorithm, as presented in Table 3. Dozens of simulations are conducted and the repeatability of the proposed GA is confirmed. The coefficient of variation of the optimizing objective and the fuel saving contributions from different technology categories are selected to measure the repeatability. The coefficient of variation of the average incremental cost is 0.16%, while the largest coefficient of variation of the fuel saving contributions is 1.9%. For this selected case, the overall running time is around 4 h on an ordinary computer.

The population converges to a feasible solution without violating any constraint constantly. Thus the penalty function value represents the overall fuel-efficient technology implementation cost. Typical convergence history result is shown in Fig. 6. Each red cross[1] stands for the mean penalty function value in each generation, with the blue dot representing the minimum penalty function value. The gap between the two values indicates the diversity of each generation. When the two points coincide, the population becomes homogenous eventually. It is obvious that during the evolutionary process, the best technology implementation cost declines generation by generation, and the gap between the mean and minimum penalty function values narrows. The population becomes increasingly uniform and converges completely when the optimal TC solution is acquired.

[1] For interpretation of color in Fig. 6, the reader is referred to the web version of this article.

Table 3
Technical parameters of the designed GA in this case study.

Parameters	Notation	Value
Population size	N_p	20000
Elitists ratio	R_E	0.0001
Penalty function factor 1	p_{cons1}	10^{10}
Penalty function factor 2	p_{cons2}	10^{8}
Stopping generation number	GN	50

5.2. Comparative analysis between genetic algorithm and the greedy method

To understand how OEMs in China make fuel-efficient TCs to satisfy the standards, several directors of domestic OEMs' technology centers are interviewed. It is found that the method used by OEMs to select technology portfolios for each vehicle model is quite comparable to greedy algorithms, both of which are "quick and dirty" methods. Since greedy algorithms only search a local optimal choice in each step, they could yield solutions for problems with high computational complexity in a reasonable time. For example, in knapsack problem, a greedy algorithm is to put the most valuable item of each step into the "sack" until the remaining space of the "sack" is not sufficient for any of the remaining items. Greedy algorithms could not get a global optimal solution mostly and may even get the worst solution in some extreme

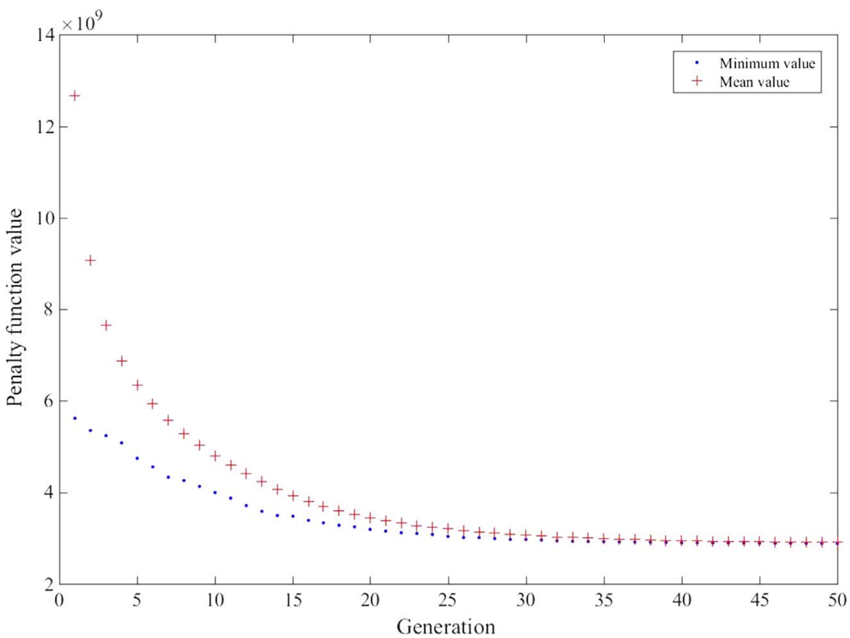

Fig. 6. The designed GA convergence history for TC optimization.

cases.

According to the interview result, a "greedy" algorithm is developed based on the OEMs' decision making process. As illustrated in Fig. 7, an OEM firstly assesses the cost and FCR reduction effect of its reserving fuel-efficient technologies, and lists the available TCs for each vehicle model. Then the listed combinations are sorted by cost-effectiveness, which is defined in Eq. (17)

$$CE_k = \frac{\sum_{i \in \mathbb{Q}_k} c_i}{1-\prod_{i \in \mathbb{Q}_k} (1-e_i)} \tag{17}$$

where, CE_k is the cost-effectiveness of TC k. c_i and e_i, as defined previously, are the cost and FCR reduction effect of technology i. Subsequently, for a vehicle model which does not meet the specified FCR target initially, the TCs are implemented in the cost-effectiveness sequence until the FCR target is satisfied. Several technology implementation states are recorded around the point where one vehicle model exactly satisfies FCR target. By enumerating all possible combinations across the fleet, one solution that both satisfies all constraints and costs the least is selected, which is the determined TC strategy based on the greedy algorithm. To conduct a comparative analysis, the identical case described above is solved by the "greedy" algorithm. The results are compared and analyzed as follows.

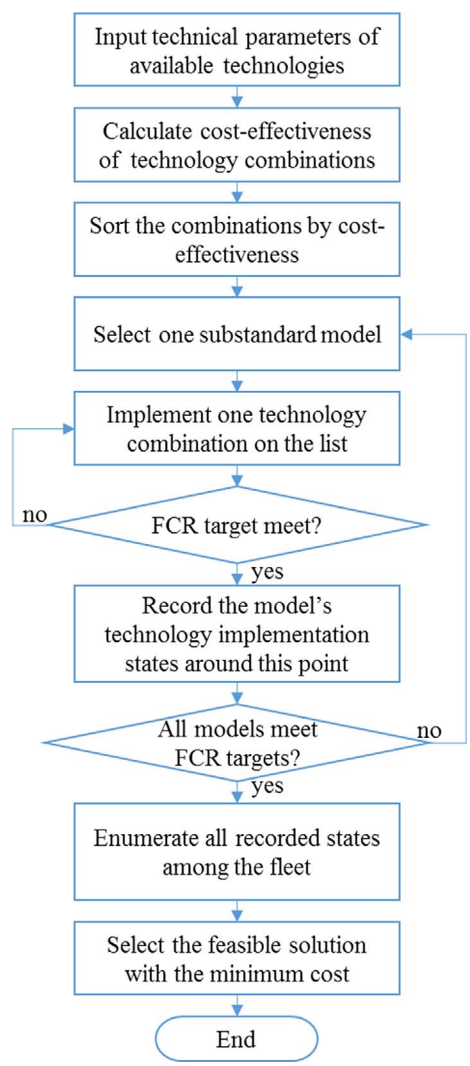

Fig. 7. The "greedy" decision making process.

(1) **Fleet-wide compliance parameters**

The fleet-wide regulation compliance parameters are illustrated in Fig. 8. Both the two methods provide the strategies of technology implementation that fully satisfy the standards constraints. However, under the greedy method, the average incremental cost of complying with CAFC standards is ¥8650 per vehicle, which is 16.4% higher than that under GA. As to the vehicle parameters, 31 out of 36 vehicle versions' curb weight increases, leading to the increase of 19 versions' FCR target, which accounts for 50.3% of the total production. While under greedy algorithm, only 12 vehicle versions' curb weight increases, which accounts for the FCR target increase of 9.7% of the overall vehicle production. The fleet average curb weight under GA is 1352.2kg, 5.5% higher than that under greedy method. Since FCR target is curb weight based in China, a higher average curb weight means a lower CAFC target under GA, as shown in Fig. 8. The detailed vehicle parameters under both GA and greedy methods are presented in Appendix C.

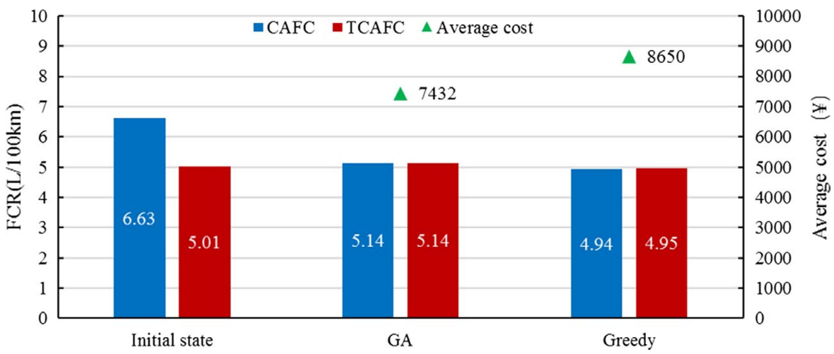

Fig. 8. Result comparison of GA and greedy method.

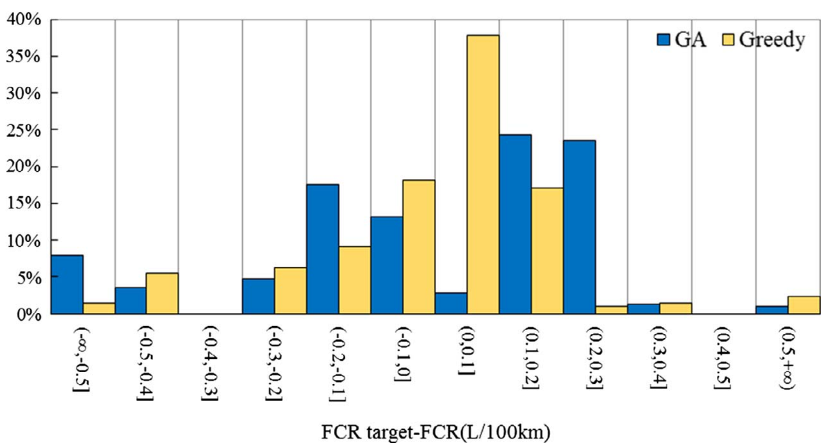

Fig. 9. Histogram of FCR to FCR target gap.

(2) **Fuel consumption rate gap and incremental cost distribution**

Figs. 9 and 10 illustrate the histogram of FCR gaps and incremental costs of vehicle models. In comparison with GA, the main drawback of greedy method is that the solution searching domain is significantly reduced. And each vehicle model could only be implemented with TCs around the point exactly satisfies the standards. This brings two consequences. One is vehicle models are featureless in terms of fuel economy. The FCR of each vehicle model would be around the weight-based FCR target. Since FCR is positively correlated to power and other performance, homogenous vehicles in FCR also results in less diversity of an OEM's the product portfolio in terms of other vehicle attributes. As illustrated in Fig. 9, vehicles' FCR to FCR target under GA is more dispersed than that under greedy method.

Another consequence of this drawback is higher average cost. Reduced searching domain means reduced tolerance of FCR target. Vehicle models have to be made within the specific FCR tolerance which is in fact not compulsory under China's standards. For a model with a wide FCR to FCR target gap, fuel-efficient technologies could be over used to fill it, while this gap could be largely made up by models initially with better FCRs under GA. This consequently brings a higher average cost. As the histogram shows in Fig. 10, the cost distribution under greedy method is more dispersed. The high percentages in (16,000, 18000] and (20,000, + ∞) categories are directly caused by the models with larger FCR to FCR gaps initially.

(3) **Compliance contributions and implementation rates of technologies**

In order to understand the difference of technology strategies under both methods, fuel efficient technologies are divided into 7 categories. The compliance contributions of different technology categories are

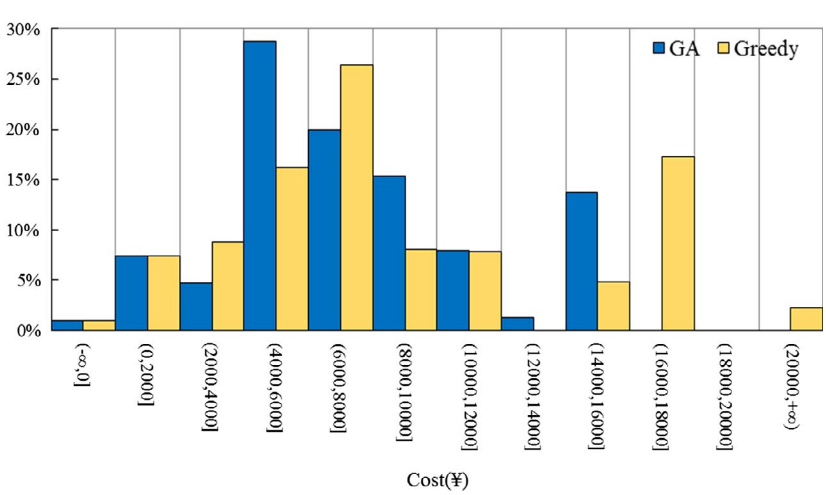

Fig. 10. Histogram of technology incremental cost.

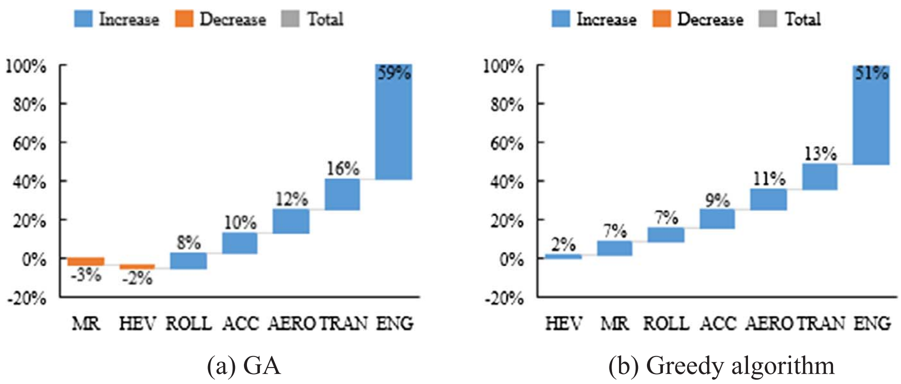

Fig. 11. Compliance contributions of different technologies. [Technology abbreviations in this figure. ACC, accessory technologies. AERO, aerodynamic technologies. CVT, continuously variable transmission. DCT, .dual clutch transmission. EFR, engine friction reduction. ENG, internal combustion engine technologies. EV, electric vehicle. GDI/T/D, gasoline direct injection with turbocharging and engine downsizing. HEV, hybrid electric vehicles. LDB, low drag brakes. MR, mass reduction. PHEV, plug-in electric vehicle. ROLL, rolling resistance reduction. TRAN, transmission technologies. VT, valvetrain technologies.].

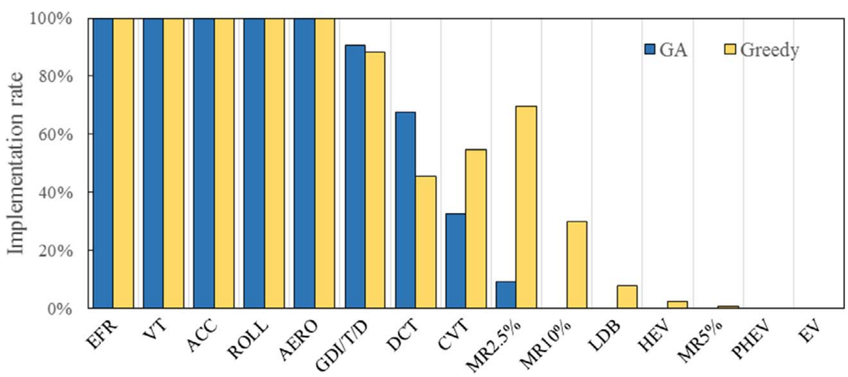

Fig. 12. The implementation rate of fuel efficient technologies. [Technology abbreviations in this figure. ACC, accessory technologies. AERO, aerodynamic technologies. CVT, continuously variable transmission. DCT, .dual clutch transmission. EFR, engine friction reduction. ENG, internal combustion engine technologies. EV, electric vehicle. GDI/T/D, gasoline direct injection with turbocharging and engine downsizing. HEV, hybrid electric vehicles. LDB, low drag brakes. MR, mass reduction. PHEV, plug-in electric vehicle. ROLL, rolling resistance reduction. TRAN, transmission technologies. VT, valvetrain technologies.].

presented in Fig. 11. Note that the negative contributions of technologies are results of removing the existing fuel-efficient technologies. As shown in Fig. 11, the existing HEV and mass reduction technologies are mostly removed under GA, which leads to a total −5% compliance contribution. Both strategy rely mainly on convention engine and drivetrain technologies to satisfy the 2020 CAFC regulation. The contribution of engine and transmission technology account for 75% and 64% over GA and greedy method, respectively. However, there are notable differences in technology categories of mass reduction, HEV and engine technologies. Fig. 12 illustrates the technology implementation rates, which give some insight into the detailed technology strategies. Despite the high implementation rate of conventional engine technologies, under both strategies, rolling resistance reduction, aerodynamics technologies and accessory technologies are highly valued as well. Nevertheless, all vehicle models use various levels of mass reduction technologies under greedy method, while the corresponding proportion under GA is 9.3%. Mass reduction contributes to FCR reduction on one hand. Meanwhile, it also reduces the curb weight and offsets the contribution itself by decreasing the weight-based FCR target on the other hand. As shown in Eq. (17), mass effects of technologies are not considered under greedy method. This results in the overestimation of the priorities of mass reduction technologies. HEV technologies are inferior to most engine technologies in terms of cost-effectiveness. Nevertheless, for a vehicle model with a wider FCR to FCR target gap initially, HEV technologies have to be used to keep the FCR close to FCR target under greedy method. As shown in Fig. 12, 2.3% vehicles use strong HEV technologies under greedy method.

In practical decision making situations, there are still some reasons for OEMs to use the greedy method. Firstly, although an OEM should produce both typically powerful and fuel-efficient vehicle models in its whole product portfolio, it should also guarantee that neither the performance nor fuel economy of each vehicle model is unsatisfactory. The greedy method could improve the fuel economy of all vehicle models to appropriate levels (around the FCR targets) so that no large gap of fuel economy among the models exists. Secondly, technology research and development has always been a critical shortfall for China's automotive industry, especially for China's national OEMs. Thus relatively few fuel-efficient technologies are available for these OEMs, which makes the greedy method seemingly sufficient to make TC strategies. Finally, considering the stringency of the previous phase standards, OEMs could effortlessly comply with the standards by simply making some adjustments or adding one or two fuel-efficient technologies in one or two years, in which situation the cost-effectiveness based greedy method is a simple but efficient choice.

6. Conclusions

Confronted with the annually strengthening vehicle fuel economy regulations in major vehicle markets around the world, automakers have great difficulty searching for optimal technological strategies for their vehicle product assortments. This paper examines a promising heuristic method for technological strategy making by selecting the largest vehicle market China and its current phase fuel economy regulation as a case. Several contributions are made and the results also provide valuable information for both the automakers and policy makers.

Firstly, the mathematical model of TC is established, where physical weight of technology, effects of FCR reduction, incremental cost and most standards scheme parameters are adequately considered. The objective function should satisfy the constraints of fuel economy regulation, vehicle models' FCR targets and incompatibilities among fuel-efficient technologies. By employing the method of restriction, complexity analysis can be performed. The decision problem of TC is identical to the well-known 0/1 knapsack decision problem. TC has been proven to be NP-hard. In other words, it indicates that it is unlikely to identify an efficient polynomial time algorithm to obtain optimal technological strategies. Therefore, automakers should consider using heuristic algorithms for technological strategies making.

Secondly, a heuristic algorithm based on GA is elaborated to solve TC. Simulation results demonstrate that this algorithm could obtain results with fast convergence speed and good repeatability. To evaluate the performance of GA, the strategy making result is compared to that of the commonly used greedy method. In particular, GA can outperform greedy method in terms of the overall technology incremental cost, which can be reduced by 14.1%. Therefore, the overall cost can be effectively reduced by using heuristic algorithms for technological strategies making. The technological strategy details are also compared. Results show that the greedy method may overvalue the cost-effectiveness of mass reduction and HEV technologies. From the perspective of automakers, therefore, lower priorities should be given on these technologies in terms of complying with the regulation.

Thirdly, the comparison results also provide some insight into the technological strategy for regulation compliance. Both methods rely mainly on conventional engine and drivetrain technologies to satisfy regulation by 2020, which account for 75% and 64% of the CAFC reduction. Besides these technologies, rolling resistance reduction, aerodynamics technologies and high efficiency accessory technologies are also high priorities for current phase regulation compliance.

However, making technological strategy optimally by using GA leads to a higher fleet average curb weight and in turn a higher CAFC target for weight-based fuel economy regulation structures. Therefore, automakers' optimization of the compliance cost would have negative effects on the penetration of mass reduction technologies from the perspective of policy makers. As a result, the national energy saving potential would be further diminished. Further modification is needed to make the regulation structure more neutral to mass reduction technologies.

In future studies, it would be interesting to extend the scope of the model to multiple periods and multiple OEMs, which should be a better approach to the real market. Game theory, demand and supply theory as well as utility functions could all be appropriately applied. By considering the future updating of fuel economy regulation, this model could also be used for conducting scenario analysis, which can evaluate the impacts of different schemes. For example, the proposed violation fine, the fuel economy credits system, the carry-over and deficit schemes of credits can be applied to fuel-efficient technologies.

Acknowledgement

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Appendix A. Definitions of P, NP, NP-Complete and NP-hard problems [57]

(1) P problem. Given an optimization problem, if there exists an algorithm A for the optimal solution, a polynomial function $g(x)$, and a constant α, such that Eq. (A.1) holds for all instances of the problem, then the given problem can be solved in polynomial amount of computation time, or polynomial problem. The set of all polynomial problems is **P**.

$$C_A(I) \leqslant \alpha g(l(I)) \tag{A.1}$$

I is an instance. $l(I)$ is the size of the instance. $C_A(I)$ is the computation time for solving instance I.

(2) NP problem. Given a decision problem, if there exists a polynomial function $g(x)$ and a verifier B such that I is a "yes" instance of the decision problem if and only if the following two conditions are satisfied:

(1) there exists a solution string S whose size $l(S) = O(g(l(I)))$
(2) the verifier B can verify S as a "yes" instance of I in a computation time of $O(g(l(I)))$

Then this decision problem is Non-deterministic polynomial, or NP problem. $\mathbf{P} \subseteq \mathbf{NP}$.

(3) NP-Complete. Given a decision problem C if $C \subseteq \mathbf{NP}$ and any NP problem can be transformed into C, then C is called NP-Complete, or NPC. The set of NPC problem is **NPC**.
(4) NP-hard. Given a decision problem C if any NP problem can be transformed into C, then C is called NP-hard, or NPH. $\mathbf{NPC} \subseteq \mathbf{NPH}$

Appendix B. Vehicle parameters in this selected case

The vehicle parameters are listed in Table B.1. Some parameters are used to determine the technology implementation baseline and the availability of each fuel efficient technologies. For example, the V6 indicator is used to determine the engine downsizing potential and cost, and the transmission type is used to determine the transmission technology baseline. Some parameters are used to determine the regulation related parameters. For example, AWD, TRS and AT are binary indicators to determine FCR target and limit for each vehicle version.

Table B.1
Technical parameters of the vehicle models and versions.

Model	Version	Transmission	Displacement (L)	Wheelbase (mm)	Engine power (kW)	Curb weight (kg)	FCR (L/100 km)	DOHC	SOHC	V6	AWD	TRS	AT
Model 1	V1.1	5MT	1.5	2530	96	1058	5.7	1	0	0	0	0	0
	V1.2	CVT	1.5	2530	96	1078	5.3	1	0	0	0	0	1
	V1.3	CVT	1.5	2530	96	1084	5.3	1	0	0	0	0	1
	V1.4	CVT	1.5	2530	96	1105	5.5	1	0	0	0	0	1
	V1.5	CVT	1.5	2530	96	1116	5.4	1	0	0	0	0	1
Model 2	V2.1	5MT	1.5	2600	96	1078	5.6	1	0	0	0	0	0
	V2.2	5MT	1.5	2600	96	1099	5.7	1	0	0	0	0	0
	V2.3	5MT	1.5	2600	96	1114	5.8	1	0	0	0	0	0
	V2.4	CVT	1.5	2600	96	1094	5.4	1	0	0	0	0	1
	V2.5	CVT	1.5	2600	96	1117	5.4	1	0	0	0	0	1
	V2.6	CVT	1.5	2600	96	1136	5.4	1	0	0	0	0	1
Model 3	V3.1	5AT	2.4	2795	145	1715	9.1	1	0	0	0	0	1
	V3.2	6AT	3	2795	193	1870	9.9	1	0	1	0	0	1
Model 4	V4.1	5MT	1.8	2650	102	1240	6.5	0	1	0	0	0	0
	V4.2	5MT	1.8	2650	102	1265	6.5	0	1	0	0	0	0
	V4.3	5AT	1.8	2650	102	1275	6.7	0	1	0	0	0	1
	V4.4	5AT	1.8	2650	102	1300	6.7	0	1	0	0	0	1
	V4.5	5AT	1.8	2650	102	1310	6.7	0	1	0	0	0	1
Model 5	V5.1	CVT	2	2775	114	1495	7.6	0	1	0	0	0	1
	V5.2	CVT	2	2775	114	1510	7.6	0	1	0	0	0	1
	V5.3	CVT	2	2775	114	1520	7.6	0	1	0	0	0	1
	V5.4	CVT	2.4	2775	137	1545	7.7	1	0	0	0	0	1
	V5.5	CVT	2.4	2775	137	1555	7.7	1	0	0	0	0	1
	V5.6	6AT	3	2775	192	1660	8.8	0	1	1	0	0	1
Model 6	V6.1	CVT	2.4	2900	137	1775	7.8	1	0	0	0	1	1
	V6.2	CVT	2.4	2900	137	1815	7.8	1	0	0	0	1	1
	V6.3	CVT	2.4	2900	137	1839	7.8	1	0	0	0	1	1
	V6.4	CVT	2.4	2900	137	1861	7.8	1	0	0	0	1	1
Model 7	V7.1	5AT	1.3	2450	60	1016	6.1	0	1	0	0	0	0
	V7.2	5MT	1.3	2450	60	1056	6.9	0	1	0	0	0	1
Model 8	V8.1	6MT	1.5	2610	96	1200	6.2	1	0	0	0	0	0
	V8.2	CVT	1.5	2610	96	1204	5.9	1	0	0	0	0	1
	V8.3	6MT	1.8	2610	100	1248	7	0	1	0	0	0	0
	V8.4	CVT	1.8	2610	100	1256	6.7	0	1	0	0	0	1
	V8.5	CVT	1.8	2610	100	1302	6.5	0	1	0	0	0	1
	V8.6	CVT	1.8	2610	100	1390	7.1	0	1	0	1	0	1

Appendix C. Vehicle parameters after optimization

(See Tables C.1 and C.2).

Table C.1
Vehicle parameter variance under GAModel.

	Version	Incremental Cost (¥)	FCR target (L/100 km)	FCR limit (L/100 km)	FCR (L/100 km)	Curb weight (kg)	Curb weight due to mass reduction (kg)	Curb weight due to other technologies (kg)
Model 1	V1.1	5538.4	0.0	0.0	−1.0	−1.2	26.5	−27.6
	V1.2	4311.1	0.2	0.4	−0.8	20.1	27.0	−6.8
	V1.3	4311.1	0.2	0.4	−0.8	20.2	27.1	−6.9
	V1.4	4311.1	0.0	0.0	−0.9	20.6	27.6	−7.0
	V1.5	1397.9	0.0	0.0	−0.8	15.1	27.9	−12.8
Model 2	V2.1	2576.5	0.2	0.4	−1.2	36.9	0.0	36.9
	V2.2	2576.5	0.0	0.0	−1.3	37.6	0.0	37.6
	V2.3	3803.8	0.0	0.0	−1.4	15.3	0.0	15.3
	V2.4	1622.4	0.0	0.0	−0.8	4.3	0.0	4.3
	V2.5	1622.4	0.0	0.0	−0.8	4.4	0.0	4.4
	V2.6	−63.4	0.0	0.0	−0.8	−23.7	0.0	−23.7
Model 3	V3.1	12865.3	0.2	0.4	−2.9	55.3	42.9	12.4
	V3.2	10474.2	0.3	0.4	−3.1	41.4	46.8	−5.4
Model 4	V4.1	9391.0	0.0	0.0	−1.8	36.2	31.0	5.2
	V4.2	8163.7	0.2	0.4	−1.7	62.7	31.6	31.1
	V4.3	7714.7	0.2	0.4	−1.6	63.2	31.9	31.3
	V4.4	8942.0	0.2	0.4	−1.7	37.9	32.5	5.4
	V4.5	8942.0	0.2	0.4	−1.7	38.2	32.8	5.5
Model 5	V5.1	14275.3	0.2	0.4	−2.0	45.7	37.4	8.4
	V5.2	10469.2	0.2	0.4	−1.7	31.2	37.8	−6.5
	V5.3	10469.2	0.2	0.4	−1.7	31.4	38.0	−6.6
	V5.4	10232.6	0.0	0.0	−2.0	1.3	38.6	−37.3
	V5.5	10232.6	0.0	0.0	−2.0	1.3	38.9	−37.5
	V5.6	7473.3	0.2	0.4	−2.2	26.7	41.5	−14.8
Model 6	V6.1	6092.2	0.0	0.0	−1.7	27.5	44.4	−16.9
	V6.2	7319.5	0.0	0.0	−1.9	−7.6	45.4	−53.0
	V6.3	9898.3	0.3	0.4	−2.0	46.6	46.0	0.6
	V6.4	6092.2	0.3	0.4	−1.7	28.8	46.5	−17.7
Model 7	V7.1	5482.4	0.0	0.0	−1.4	13.9	0.0	13.9
	V7.2	5504.2	0.2	0.4	−1.7	36.1	0.0	36.1
Model 8	V8.1	7595.3	0.2	0.4	−1.6	22.9	30.0	−7.1
	V8.2	5745.7	0.2	0.4	−1.2	22.5	30.1	−7.6
	V8.3	4379.6	0.0	0.0	−1.5	16.3	31.2	−14.9
	V8.4	3757.3	0.0	0.0	−1.2	−9.0	31.4	−40.4
	V8.5	6336.1	0.2	0.4	−1.3	29.1	32.6	−3.4
	V8.6	4674.7	0.0	0.0	−1.4	−9.9	34.8	−44.7

Table C.2
Vehicle parameter variance under greedy algorithm.

Model	Version	Incremental Cost (¥)	FCR target (L/100 km)	FCR limit (L/100 km)	FCR (L/100 km)	Curb weight (kg)	Curb weight due to mass reduction (kg)	Curb weight due to other technologies (kg)
Model 1	V1.1	4418.4	0.0	0.0	−0.9	−6.4	0.0	−6.4
	V1.2	4418.4	0.0	0.0	−0.9	−6.5	0.0	−6.5
	V1.3	4418.4	0.0	0.0	−0.9	−6.6	0.0	−6.6
	V1.4	4418.4	0.0	0.0	−0.9	−6.7	0.0	−6.7
	V1.5	1505.3	0.0	0.0	−0.8	−12.4	0.0	−12.4
Model 2	V2.1	2078.7	0.2	0.4	−1.2	36.9	0.0	36.9
	V2.2	2078.7	0.0	0.0	−1.2	37.6	0.0	37.6
	V2.3	2078.7	0.0	0.0	−1.2	38.1	0.0	38.1
	V2.4	1124.7	0.0	0.0	−0.7	4.3	0.0	4.3
	V2.5	1124.7	0.0	0.0	−0.7	4.4	0.0	4.4
	V2.6	−1788.5	0.0	0.0	−0.6	−1.3	0.0	−1.3
Model 3	V3.1	28509.4	0.5	0.8	−3.9	191.7	0.0	191.7
	V3.2	33423.2	0.5	0.8	−4.3	188.7	0.0	188.7
Model 4	V4.1	8075.8	0.0	0.0	−1.8	31.1	0.0	31.1
	V4.2	8075.8	0.0	0.0	−1.8	31.8	0.0	31.8
	V4.3	7626.9	0.0	0.0	−1.7	32.0	0.0	32.0
	V4.4	7626.9	0.2	0.4	−1.7	32.6	0.0	32.6
	V4.5	7626.9	0.2	0.4	−1.7	32.9	0.0	32.9
Model 5	V5.1	16112.6	−0.2	−0.4	−2.5	−145.2	−112.1	−33.1
	V5.2	16112.6	−0.2	−0.4	−2.5	−146.7	−113.3	−33.4
	V5.3	16112.6	−0.2	−0.4	−2.5	−147.6	−114.0	−33.6
	V5.4	14346.2	−0.4	−0.8	−2.4	−151.5	−115.9	−35.6
	V5.5	14346.2	−0.4	−0.8	−2.4	−152.4	−116.6	−35.8
	V5.6	15919.9	−0.2	−0.4	−3.1	−130.9	−124.5	−6.4
Model 6	V6.1	10632.8	−0.4	−0.8	−2.3	−182.1	−133.1	−49.0
	V6.2	10632.8	−0.4	−0.8	−2.3	−186.2	−136.1	−50.1
	V6.3	10632.8	−0.4	−0.8	−2.3	−188.7	−137.9	−50.7
	V6.4	10632.8	−0.2	−0.4	−2.3	−190.9	−139.6	−51.3
Model 7	V7.1	7678.2	0.0	0.0	−1.7	−11.0	−25.4	14.4
	V7.2	8127.1	0.0	0.0	−2.1	−11.5	−26.4	14.9
Model 8	V8.1	7204.9	0.0	0.0	−1.5	−7.4	0.0	−7.4
	V8.2	6582.6	0.0	0.0	−1.3	−31.1	0.0	−31.1
	V8.3	4291.7	0.0	0.0	−1.6	−13.8	0.0	−13.8
	V8.4	3669.5	0.0	0.0	−1.3	−38.6	0.0	−38.6
	V8.5	3669.5	0.0	0.0	−1.3	−40.0	0.0	−40.0
	V8.6	3669.5	0.0	0.0	−1.4	−42.8	0.0	−42.8

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