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Sustainable operations-oriented painting process optimisation in automobile maintenance service

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ABSTRACT

Building a more sustainable society is an urgent requirement for today's service-oriented manufacturing enterprises, such as automobile maintenance firms. In automobile maintenance service, traditional painting process scheduling scheme usually only considers the profits of enterprises, ignoring the requirements of customers or other stakeholders. To address this gap and achieve sustainable operations of enterprises in the long term, this paper concentrated on the vehicle scheduling of painting process problem with the concern of the demands of managers, workers, customers, governments and non-government environmental protection organisations. This problem was formulated as a nonlinear 0–1 integer programming model to minimise makespan (MP), total pollutant emissions (TPE) and total customers' perceived dissatisfaction (TCPDS). A genetic algorithm was designed to solve the model, and a practical case using data from both the information system and the survey was performed to test the performance of the proposed model and algorithm. Computational results revealed that the genetic algorithm performed well in terms of validity and stability. Pareto solutions demonstrated that optimising task sequences helped increase customers' perceived satisfaction while improving the makespan of vehicle painting, decreased paint waste, and reduced worker health and safety risks. Some of the increases in the percentage of well-timed customer service reservations were catalysed by the method that combined tiered pricing, related to delivery times, the automobile painting efficiency, which improved customers' perceived satisfaction. This paper also further guides managers to incorporate sustainable development into operations in service-oriented manufacturing enterprises.

1. Introduction

To improve the sustainability of enterprises, it is necessary for managers to improve operational strategies to make progress in achieving their economic, environmental and social, sometimes also called the triple-bottom-line (TBL) objectives from the perspective of diverse stakeholders. Operations management based on the TBL perspective is a new and promising topic (Jaehn, 2016; Cao et al., 2017). The challenge is how to define the TBL goals and monitor progress in achieving them through improved operations management from multiple stakeholders' perspectives (Simeoni et al., 2019). In service-oriented manufacturing, painting process scheduling in automobile painting service is a challenge for improving operations management. The painting process has undesirable impacts on the environment, making governmental and non-governmental environmental protection organisations pay close attention to painting facilities' gaseous and liquid pollution emissions (Giampier et al., 2019). Significantly, managers devote much time to improving production efficiency as optimisation of scheduling of automobile painting is an illustrative challenge. For customers, their perception as an indicator in service-oriented manufacturing requires more attention (Cao et al., 2016).

The authors of this paper comprehensively considered ways to improve the efficiency and customers' perceived satisfaction by optimising the scheduling of the painting timetables and delivering top quality vehicle painting. Moreover, it had been simultaneously regarded

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to improve the work environment and worker health by decreasing gaseous and liquid pollutant emissions into the air or water, thereby making progress toward more sustainable societal service delivery.

The economic goal is a key focus of enterprise managers because they are always limited to financial constraints (Chen et al., 2019). One of the economic objectives is to realise the virtuous circle of capital turnover, which often focused upon the ways to improve equipment utilisation and reducing costs (Cantele and Zardini., 2018). The painting process with high output value plays an indispensable role in automobile maintenance service. Some researchers have focused on improving efficiency from a technical perspective by updating the equipment and improving operational strategies (Oliveira et al., 2018; Cavalcante et al., 2020). Effective job scheduling can help optimise utilising the limited resources without increasing costs (Mokhtari et al., 2017). For the workshop, the equipment and other hardware resources are expensive and limited, which is economically unfeasible to allocate separate painting equipment for each colour of the automobile. The authors used a mathematical programming method to schedule the automobile painting process to improve the efficiency of using the limited painting equipment while improving customer satisfaction, reducing costs and making progress toward achieving the enterprises' economic goals.

It is apparent that governmental organisations provide regulatory guidelines that must be met for achieving environmental goals. Additionally, non-governmental environmental protection organisations, customers and other public citizens are increasingly important and concerned stakeholders. With the frequent occurrence of serious pollution events, people have become very concerned about ecological and environmental issues, and almost all countries have introduced environmental protection policies (Dong et al., 2011). The Chinese government has developed and enforces more stringent water environmental regulations to reduce water pollution (She et al., 2020). Compared with the other production stages, a large number of pollutant emissions will inevitably be produced during the automobile painting, such as volatile organic compounds, liquid wastes, and particulate matter (Isabella et al., 2020). Most scholars are mainly devoted to reducing environmental pollution by improving paint materials and technological processes for spraying and capturing volatile and liquid emissions (Antonaia et al., 2016; Nelson et al., 2016). Effective painting process scheduling schemes can decrease the cleaning frequency of painting equipment, thereby reducing some pollutants and helping the companies progress toward achieving their environmental goals for the painting workshop.

Regarding the social dimensions, the customers with bounded rationality are one of the key stakeholders. Automobile maintenance service belongs to service-oriented manufacturing, with dual characteristics as a customer service industry and part of the original manufacturing industry. The Handbook for Implementers of ISO 260001 (2011) demonstrated that customers' perceived satisfaction could be used as one measure of making progress on the social dimension of sustainability. Most authors who have addressed improvements in this sector have mainly focused on economic and environmental indicators to provide automobile painting process services (Salihoglu, 2016). In addition to the fact that the painting process scheduling only focuses upon optimisation of equipment utilisation efficiency and emission reductions, the focus upon the complex psychological behaviour of customers and the improvement of customers' perceived satisfaction must be added as an essential objective in service-oriented vehicle painting. Thereby, this helps enterprises to make progress in seeking to fulfil their social dimension of the TBL.

In summary, some studies have focused on painting scheduling problems, but the literature on helping achieve the TBL is limited (Xu et al., 2013; Kolakowska et al., 2014; and Oliveira et al., 2018). The TBL is highlighted as a method to measure progress toward sustainable performance (Gimenez et al., 2012; Sarkis and Dhavale, 2015). However, traditional scheduling models purely focus on one or two objectives (Shim and Park, 2016; Lee et al., 2016; and Moradzadeh and Tomsovic, 2013). In this sense, the authors of this paper concluded that integrating the painting process scheduling with TBL goals by developing and testing a suitable solution algorithm and providing a balanced scheme should be addressed. According to a review of different dimensions, although researchers have made significant progress in this area, the following questions are unsolved:

1. How to design the sustainability-based operational strategies regarding painting process scheduling in service-oriented enterprises?
2. How to measure the TBL objectives from different stakeholders of the painting process scheduling?
3. How to formulate and test a tri-objective mathematical programming model for the painting process scheduling problem with the consideration of unrelated machines in parallel, due dates, release times, sequence-dependent setup times?
4. What is the optimal scheduling scheme? What are the TBL trade-offs of sustainability for the painting process scheduling problem?

To underscore the above questions, the authors of this paper described, characterised, and modelled painting process scheduling problems in the presence of task assignments, switching times, and sequencing. Task assignment affects the balance of tasks on equipment and affects efficiency. Task switching times influence emissions, which have negative impacts on the environment and society. Task sequencing affects the delivery times of vehicles and directly influences customers' perceived satisfaction. Accordingly, the authors formulated a multi-objective optimisation model regarding the painting process scheduling problem. Shortening the makespan, reducing the total pollutant emissions and increasing the customers' perceived satisfaction were the described objectives. Due to the high efficiency and applicability to solve practical cases, the genetic algorithm has been proven to have potential advantages in solving combinatorial optimisation problems (Alcan and BaşLıGil, 2012). The authors employed a genetic algorithm to solve the proposed model. The trade-offs and the influences among the three objectives were discussed to help design a sustainable strategy in service-oriented enterprises.

The novelty of this paper included addressing the following three points. Firstly, different from the previous literature focussed upon two TBL dimensions (Choi and Ng, 2011), the authors of this paper concerned all three of the TBL dimensions of the painting process scheduling from the perspective of multiple stakeholders and provided insights for more sustainable operations of service-oriented vehicle painting enterprises. Secondly, the authors used prospect theory to capture the TCPDS regarding task completion times and quantify the customer's incomplete rationality characteristics. A multi-objective nonlinear programming model was proposed to measure the needs of multiple stakeholders in the painting process scheduling problem, among which the social objective was measured by TCPDS. Thirdly, the authors did a case study and found that merely improving vehicle painting task sequencing was insufficient to sustainedly optimise multi-dimensional goals, including reducing waste volumes and improving system efficiency and service time perception. Even though the wastes were reduced through task sequencing, it was still necessary to implement additional customer-oriented tactics to facilitate the interests of customers and the other stakeholders, such as encouraging customers to make reservations and providing tiered pricing related to delivery time.

The remainder of this paper is structured as follows. A literature review on this issue is provided in the following section. A problem description is delineated in section 3, mainly the involved resources, tasks and multi-dimensional objectives regarding the painting process scheduling problem. Section 4 presents a novel multi-objective programming model to formulate the painting process scheduling problem. Section 5 includes details of the Pareto-optimal scheduling and sensitivity analysis based on a practical case. Section 6 provides managerial insights and future research directions.

2. Literature review

In recent decades, the combination of sustainable development and traditional operations management have been discussed. This section presents the gaps of this paper and the existing literature. A summary of the literature on the scheduling problem is shown in Table 1.

2.1. Sustainable operations

In 1987, the World Commission on Environment and Development (WCED) defined sustainability as: "Development that meets the needs of the present without compromising the ability of future generations to meet their needs". Such definition was gradually integrated into academic researches, thus obtaining some achievements. For example, Liam and Philip (2010) portrayed that sustainability was a fundamental principle of natural resource management, and all factors (operational efficiency, minimising environmental impacts and socio-economic considerations) were interdependent. Khalili (2011) emphasised that sustainable development was a vision built around the relationships among the economy, environment and society. Theoretical studies showed that the sustainable development of manufacturing systems was an urgent requirement for today's manufacturing companies (Giret et al., 2015). A similar viewpoint also can be found in service systems. The three Ps (profit, planet and people) were recognised as three critical elements that contribute to sustainable operations, which was increasingly concerned by academics and practitioners. In summary, scholars in different fields proposed different interpretations of the definition of sustainability, and the insights of Liam and Philip (2010) regarding sustainability we mentioned above was adopted here. In terms of sustainable operations management, it incorporated the stakeholders and environmental impacts into traditional operations management, which was profit- and efficiency-oriented (Paul et al., 2005). In this sense, it is evident that the decisions in operations management would strongly influence multi-dimensional sustainability performance.

2.2. Job-shop scheduling problem with different features

Since studies on painting process scheduling problems can only be found in the limited literature, this section extends the related works to the job-shop scheduling problem. Most of the relevant literature primarily dealt with the economic objective in the job-shop scheduling problem. For instance, Low et al. (2010) dealt with single equipment scheduling problems with availability restrictions to minimise makespan. Sun et al. (2012) studied multi-type flow shop scheduling

Table 1
Summary of the literature on the scheduling problem.

Reference	Year	Topic		Sus.[c]	Problem characteristics			Model features				Solution method
		Cat.[a]	Sub.[b]		Due.[d]	Rel.[e]	Seq.[f]	Obj.[g]	Main obj.[h]	Type: Integer	Type: Linearity	
Pan et al.	2008	1	FFc.	–	–	r_j.	S_{jk}.	Multi.	1	Mixed	Nonlinear	Particle Swarm Optimisation
Low et al.	2010	1	Single	–	–	r_j.	S_{jk}.	Single	1	Pure	Linear	First-fit Algorithm
Han et al.	2010	1	Pm.	–	–	r_j.	S_{jk}.	Multi.	1,3	Mixed	Linear	Genetic Algorithm
Zhang et al.	2011	1	FJc.	–	–	r_j.	–	Single	1	Pure	Linear	Genetic Algorithm
Wang et al.	2011	1	Pm.	–	–	r_j.	–	Single	1	Pure	Linear	Polynomial-time Algorithm
Kan et al.	2011	1	Fm.	–	–	r_j.	–	Multi.	1,2	Mixed	Linear	Priority-list Algorithm
Fang et al.	2011	1	Fm.	–	–	r_j.	S_{jk}.	Multi.	1,2	Mixed	Linear	Priority-list Algorithm
Sun et al.	2012	1	Fm.	–	d_j.	–	–	Single	1	Mixed	Linear	Polynomial-time Algorithm
Hao et al.	2013	1	Fm.	–	–	r_j.	S_{jk}.	Multi.	1,2	Mixed	Nonlinear	List Schedule Algorithm
Subramanian et al.	2014	1	Single	–	–	–	S_{jk}.	Single	1	Pure	Linear	Iterated Local Search
Liu et al.	2014	1	Jm.	–	d_j.	r_j.	–	Multi.	1,2	Pure	Linear	Genetic Algorithm
Shrouf et al.	2014	1	Single	–	–	r_j.	S_{jk}.	Single	1,2	Mixed	Linear	Genetic Algorithm
Liu and Huang	2014	1	Fm.	–	–	r_j.	S_{jk}.	Multi.	1,2	Mixed	Linear	Genetic Algorithm
Ding et al.	2016a	1	Fm.	–	–	r_j.	–	Multi.	1,2	Mixed	Linear	MONEH Algorithm
Ding et al.	2016b	1	Rm.	–	–	r_j.	–	Multi.	1,4	Mixed	Linear	MONEH Algorithm
Zhang	2017a	1	Jm.	–	–	–	S_{jk}.	Multi.	1,2	Mixed	Linear	Particle Swarm Optimisation
Güçdemir and Selim	2017	1	Jm.	–	d_j.	r_j.	S_{jk}.	Single	4	Pure	Linear	Simulated annealing
Coca et al.	2019	1	FJc.	1,2,3	–	r_j.	S_{jk}.	Multi.	1,2,3	Mixed	Linear	NSGA-II and –III methods
Deng et al.	2011	2	Workforce	–	–	r_j.	S_{jk}.	Single	1	Mixed	Nonlinear	Ant Colony Optimisation
Moradzadeh and Tomsovic	2013	2	Energy	–	d_j.	–	–	Multi.	1,3	Pure	Linear	Pricing Algorithm
Zakariazadeh et al.	2014	2	Transport	–	–	–	–	Multi.	1,2	Mixed	Linear	Augmented ε-constraint
Ramos et al.	2014	2	Transport	1,2,3	–	–	–	Multi.	1,2,3	Mixed	Linear	Augmented ε-constraint
Cao et al.	2018	2	Emergency	3	–	–	–	Multi.	3	Mixed	Nonlinear	Genetic Algorithm
Chamandoust et al.	2019	2	Energy	1,2	d_j.	–	–	Multi.	1,2,4	Mixed	Nonlinear	Fuzzy approach
Gao and Cao	2020	2	Emergency	1,2,3	–	–	–	Single	1,2,3	Pure	Nonlinear	Augmented ε-constraint
Cao et al.	2021	2	Emergency	1,2,3	–	–	–	Multi.	1,2,3	Mixed	Nonlinear	Primal-dual Algorithm
Liu et al.	2020	3	Workforce	–	–	–	–	Single	4	Mixed	Linear	Decomposition-based heuristic
Li et al.	2020	3	Fm.	–	–	–	S_{jk}.	Multi.	4	Mixed	Linear	Ant Colony Optimisation
This paper		3	Rm.	1,2,3	d_j.	r_j.	S_{jk}.	Multi.	1,2,3	Pure	Nonlinear	Genetic Algorithm

[a] Three categories are 1. Scheduling in manufacturing. 2. Scheduling in service. 3. Scheduling in service-oriented manufacturing.

[b] It represents the machine environments or service subjects under each category. Notably, 'Pm.' denotes the identical machines in parallel; 'Qm.' denotes machines in parallel with different speeds; 'Rm.' denotes the unrelated machines in parallel; 'Fm.' denotes flow shop; 'FFc.' denotes the flexible flow shop; 'Jm.' denotes the job shop; 'FJc.' denotes the flexible job shop.

[c] It indicates whether three dimensions of sustainability are explicitly considered into the scheduling problem, which 1. Economic, 2. Environmental, 3. Social. Note that '-' means the dimensions of sustainability are not considered.

[d] This column states whether the scheduling problem has a due date. Note that '-' means this constrain is not mentioned clearly in the text.

[e] This column states whether the scheduling problem has a release date. Note that '-' means this constrain is not mentioned clearly in the text.

[f] This column states whether the scheduling problem has the sequence-dependent setup time. Note that '-' means this constraint is not mentioned clearly in the text.

[g] The established model has single or multiple objectives.

[h] It demonstrates which concerns are considered into the main objective(s). 1. Economic. 2. Environmental. 3. Social. 4. Others.

problems with the consideration of deteriorating tasks and minimum makespan. Subramanian et al. (2014) discussed the single equipment scheduling problem with the concern of total weighted tardiness and the sequence-dependent setup times. The studies mentioned above indicated that many authors only took into account economic objective, yet environmental one was rarely considered into the job-shop scheduling problem. With growing awareness of environmental protection, different types of emissions and energy-related factors were incorporated into such issues. For example, Fang et al. (2011) addressed the flow shop scheduling problem considering the makespan, energy consumption and associated carbon footprints. Liu et al. (2014) investigated a hybrid flow shop scheduling problem with energy-related criteria and the total weighted tardiness objective. Liu and Huang (2014) considered two multi-objective production scheduling problems involving economic- and environmentally-related criteria. Zhang (2017a) investigated paint shops' environmentally aware production scheduling in automobile manufacturing to minimise the total pollutant emissions and the total weighted tardiness. Shrouf et al. (2014) achieved energy savings by optimising operations management in the factory scheduling problem. However, by comparing with economic and environmental dimensions of sustainability, studies seldom focused on the social objective for production scheduling problems, which recently attracted some scholars' attention. For instance, Coca et al. (2019) focused on the sustainable evaluation of flexible job shop scheduling systems, in which the social sustainability performance in an industrial case was measured by workstations, noise, ambient temperature, etc.

2.3. Multi-objective optimisation model formulation and its solution strategies

Painting process scheduling has some of the same goals as other processes scheduling in the workshop. It aims to improve efficiency, energy conservation and emission reduction and improve stakeholders' perceived satisfaction. No one can turn a blind eye on the fact that the scheduling of the painting process would balance different conflicting objectives from different stakeholders. The multi-objective optimisation approach is very prevalent in both flow and job shop scheduling problems. For instance, Zhang et al. (2011) portrayed a flexible task-shop scheduling problem to minimise the makespan and applied the genetic algorithm to solve the developed model. Kan et al. (2011) used a multi-objective mixed-integer programming model to describe a flow shop scheduling problem aiming to reduce power consumption and carbon footprint. Hao et al. (2013) proposed a new ant colony metaheuristic algorithm based on the multi-objective optimisation model to solve the mixed flow shop scheduling problem. Ding et al. (2016a) studied a permutation flow shop scheduling problem to minimise the total carbon emissions and the makespan and designed two heuristic algorithms to solve this issue. Ding et al. (2016b) established a mixed-integer linear programming model to formulate a parallel machine scheduling problem, and a column generation heuristic was provided to approximately solve the reformulated model.

2.4. Summary

Based on a sustainable operations perspective, the authors of this paper analysed the literature presented in Table 1. The following conclusions were made.

(1) The relevant literature mainly focused on one or two but all dimensions of sustainability for scheduling problems in manufacturing, service, and service-oriented manufacturing. Few publications simultaneously considered three dimensions of sustainability, indicating that this topic was still in its early stage and needed further study. Given the above research background combined with the triple-bottom-line framework, the authors of this paper addressed all three TBL dimensions and expected to develop an operational strategy to achieve sustainable painting process scheduling in automobile maintenance services based on a multi-stakeholder perspective.

(2) Automobile painting services which are part of service-oriented manufacturing, have dual characteristics of the service industry and manufacturing one. Differing from some studies, the painting process scheduling problem in automobile maintenance services with the constraints of the sequence-dependent setup times, due dates, and release dates was investigated by the authors of this paper. Such a problem is NP-hard due to the combinations of assignments, switching times and sequencing. It is necessary to seek a proper heuristic algorithm to solve this problem.

(3) The TBL optimisation objectives have been addressed in the existing literature. The following points can be obtained from Table 1. Economic sustainability was characterised by efficiency. Minimising MP, which could be regarded as optimal utilisation of equipment, was the most common economic objective. In terms of the environmental dimension of sustainability, energy consumption and pollution emissions were the main objectives. It seemed that reducing pollution emissions was a critical path to make progress toward environmental sustainability. For the social dimension, human perception received increasing attention from academics in this field. Therefore, minimising MP, TPE and TCPDS are portrayed as indicators that can measure relative progress toward achieving sustainable objectives. Some authors used the Pareto optimisation to study the interactions among multiple objectives, which helped them conduct meaningful explorations on the trade-offs among the TBL objectives.

(4) The authors of this paper formulated the painting process scheduling problem as a nonlinear 0–1 integer programming model to optimise objectives from the perspective of different stakeholders. Human perception is one element of the social dimension of sustainability (Chou et al., 2015). Different from some literature (Li et al., 2020; Güçdemir and Selim, 2017), the authors measured social sustainability using the nonlinear TCPDS. Wang et al. (2017) clarified that humans were usually bounded rationally under risk and uncertainty, whose psychological behaviours were significant in decision-making. Few authors combined human psychological and behavioural characteristics to analyse and quantify customers' perception. The value function of prospect theory was adopted to describe customer behaviour and characterise customers' perception to address this gap.

(5) Most of the relevant literature adopted a heuristic algorithm to solve scheduling problems (Han et al., 2010; Cao et al., 2018). Cao et al. (2018) clarified that the heuristic algorithm was a popular approach to solve complex mathematical programming models, especially for solving large-scale combinatorial optimisation problems, which are also NP-hard. In standard heuristic algorithms, a genetic algorithm that is more robust to solve complex problems provided a general framework. The authors of this paper focussed on modelling a practical case and designing a heuristic algorithm to find a satisfactory scheme for scheduling vehicle painting times. According to Cao et al. (2018), a genetic algorithm was chosen, and the coding and parameters were modified to obtain feasible solutions for the proposed model.

3. Problem description

The customers send damaged vehicles needing to be painted to automobile maintenance service enterprises. Each damaged vehicle is equivalent to a painting task. Various information needs to be considered to shorten MP, reduce TPE, and decrease TCPDS, such as the vehicle, equipment, and customers. Economic, environmental and social objectives are used as a decision-making basis to assign different painting tasks to limited integrated equipment and further determine task sequence. The painting scheduling process is shown in Fig. 1. Furthermore, to make a clear statement for readers, the necessary notations of the model are defined in Table A.1 of Appendix A.

3.1. Resource environment

There are m pieces of painting equipment in parallel, and each one includes multiple integrated pieces of equipment. The integrated equipment contains a painting booth, spray gun, cleaning equipment, and so on. The number of painting tasks is n. Owing to the high cost of the painting equipment, m is assumed to be much smaller than n (that is, $m \ll n$) for enterprises. Simultaneously, the painting task j requires a single operation, and anyone of m pieces of equipment can process it.

3.2. Task constraints

Tasks for the painting process in automobile maintenance service are provided with the following characteristics and constraints.

① Release time $r_j^{'}$ presents the earliest time that damaged vehicles can begin the painting process, which refers to the time that vehicles reach the spray booth. Due to the uncertainty of the time that customers deliver their damaged vehicles to automobile maintenance service enterprises, the release time for the painting task j is not stable. However, release time $r_j^{'}$ can be shown as uniform distribution via the enterprises' effective management and scheduling.

② Sequence-dependent setup time s_{jk}^{i} describes the sequence-dependent setup time between the painting task j and k, which includes task replacement time and equipment purification time; s_{0k}^{i} denotes the setup time for k if k is the first in the sequence of the painting equipment i. Meanwhile, s_{j0}^{i} indicates the clean-up time after j if j is last in the sequence of i. When switching to

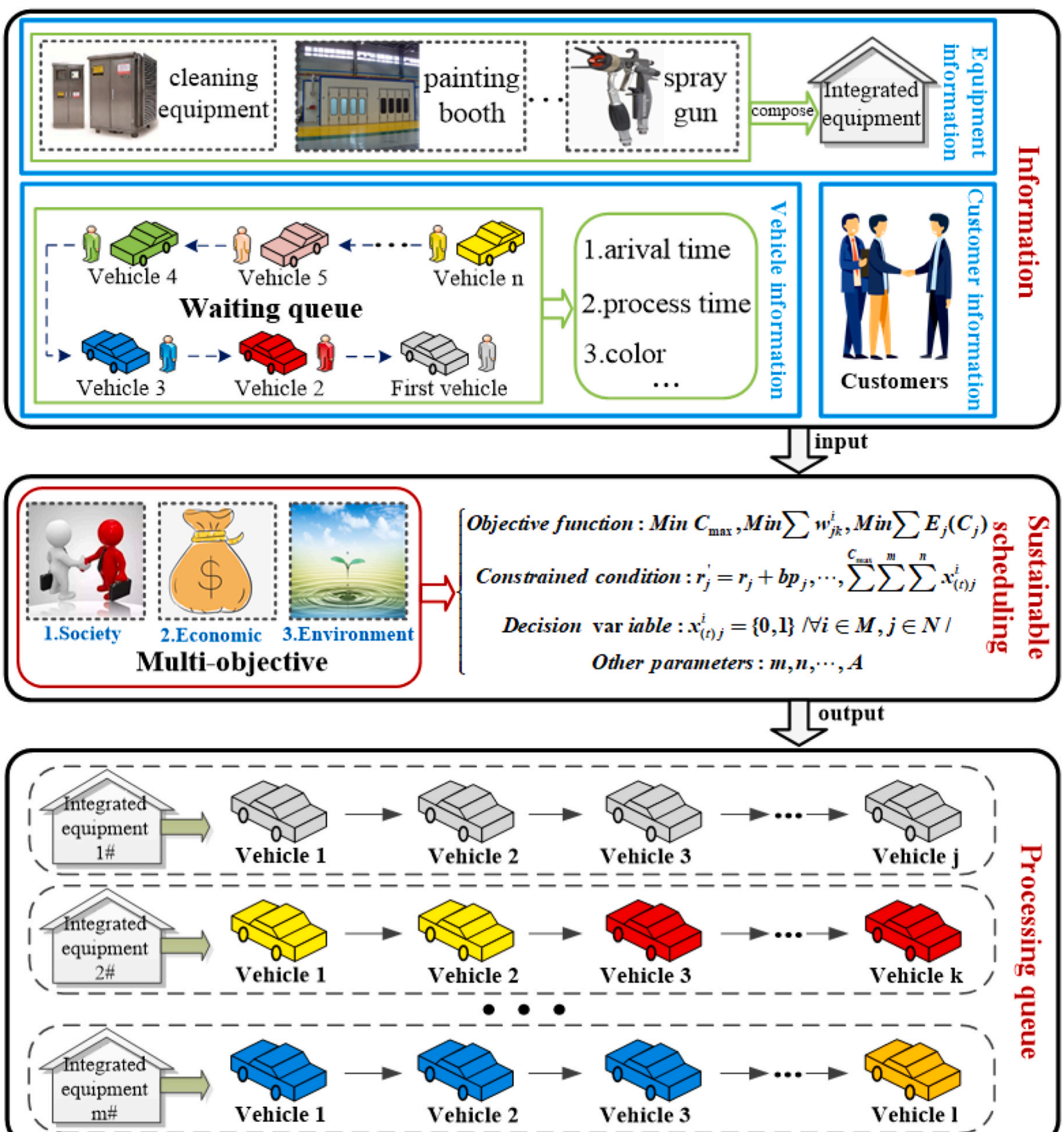

Fig. 1. Scheduling system for the painting process.

vehicles of different colours, cleaning the relevant equipment (such as spray guns) is essential, which leads to more setup time and produces pollution emissions.

③ Processing time p_j^i illustrates the processing time of the painting task j on painting equipment i. It depends on the degree of the vehicle's damage. The discrepancy in equipment performance can also make processing time on the same task using different equipment unequal.

④ The negotiated pick-up time d_j delineates the pick-up time that service staff negotiates with customers. Enough work time for the subsequent operations (such as vehicle washing and inspection) needs to be reserved, including task grace time.

3.3. Optimisation objectives

Painting process scheduling in automobile maintenance service has multi-objective characteristics from a relatively more sustainable operations perspective. System efficiency can be improved by optimising task combination and task sequences on different equipment, manifested by shortening MP (economic dimension) and reducing pollution emissions (environmental dimension). The approach can also decrease customers' perceived dissatisfaction (social dimension based on customers' perspective) to a certain extent. The previous two aspects can be measured by quantitative indicators, the last one involving subjective feelings of customers, which needs to be analysed in detail.

3.3.1. Economic objective

The economic objective is to improve the efficiency of painting equipment, which can be expressed by minimising MP ($C_{\max}$). As painting equipment configured in enterprises is expensive and limited, it is necessary to enhance the overall utilisation of scheduling resources. During the operational process, the differences in task processing time result in various task combinations and unequal equipment workloads, further reducing system efficiency. Switching the painting colour requires additional equipment for cleaning time. To improve economic profitability of the company, it is essential to minimise MP to balance task loads on different painting equipment.

3.3.2. Environmental objective

The environmental objective is to reduce pollution emissions and contributes to improving environmental sustainability, and the objective can be expressed by minimising TPE ($\sum w_{jk}^i$) in the painting process scheduling problem. The colour of the next vehicle determines whether pollution is generated, and the pollution here refers to waste paint and the solvent used to clean the spray equipment. When switching vehicles to the same colour system, cleaning the equipment (such as spray guns) is unnecessary, so the pollution emissions volume is 0. In contrast, it is necessary to clean the spray gun as vehicles of different colour systems are switched, resulting in pollution. In terms of environmental impacts, a more optimal task sequence can decrease the cleaning times for switching between different vehicles of different colour systems, thereby cutting down TPE. Under the conditions of different colours, the inconsistent arrival time of vehicles and limited painting equipment, it is important to consider the combination and sequencing of equipment for reducing pollution emissions and wasted time.

3.3.3. Social objective

The social objective involves customers' subjective feelings. The authors of this paper measured customers' perception by TCPDS ($\sum E_j(C_j)$). According to the pick-up time that service staff negotiated with customers, tasks have a time restriction. Whether tasks can be completed before the negotiated pick-up time may determine if the customers can pick up their vehicles on time, hence directly impacting customers' perception. In different scenarios, customers have different perception of waiting-time variations, which needs further analysis. Due to the long duration of the painting process, customers bring vehicles to automobile maintenance service enterprises and negotiate the time for picking up their painted vehicles. Three situations that may occur are described the customers' perception function establishment, and details corresponding to each situation are presented in Appendix B.

① Picking up vehicles in advance. Customers receive pick-up notice from service staff in advance and arrange the time to pick up their vehicles according to their wishes. If the customer's arrangement can be more flexible, their satisfaction indeed increases. If customers have made plans according to the negotiated pick-up time, their perceived satisfaction may increase slightly.

② Picking up vehicles on time. When reaching the negotiated pick-up time, customers can pick up their vehicle on time so that they are satisfied with the maintenance services.

③ Delaying picking up vehicles. Abnormal interference factors (such as sudden shortage of materials, task surge, equipment malfunction or chromatic aberrations) may cause scheduling changes. Task delay time becomes longer. Before the negotiated pick-up time, service staff contacts customers, explains the situation and arranges a new pick-up time. Sometimes it may be difficult for the customers to modify their plans. They may be dissatisfied with the maintenance services. Simultaneously, their psychological perception and expectations may be changed.

4. Model formulation for the painting process scheduling

In this section, the painting process scheduling problem in automobile maintenance service is designed as a nonlinear 0–1 integer programming model with multi-objective functions. More details can be found in section 4.2. Based on the advantages of the genetic algorithm on solution quality and computation time, it is recommended as the most suitable algorithm to solve the painting process scheduling problem, as explained in section 4.3.

4.1. Assumptions

(1) Each painting task is handled once by the painting equipment.
(2) At any time, one piece of painting equipment can be utilised for one painting task at the most.
(3) Painting equipment is not allowed to be interrupted once a painting task begins.
(4) The number of painting equipment is m, the amount of painting tasks that need to be completed is n. Additionally, m is far less than n ($m \ll n$).
(5) All painting tasks are inspected at the same quality level.

4.2. Nonlinear 0–1 integer programming model formulation

The painting process scheduling problem in automobile maintenance service is formulated as a nonlinear 0–1 integer programming model. To optimise economic (efficiency), environmental (pollution emissions) and social (customers' perceived dissatisfaction) objectives, the corresponding formulations are as follows.

$$\text{Min } C_{\max} \tag{1}$$

$$\text{Min } \sum w_{jk}^i \tag{2}$$

$$\text{Min } \sum E_j(C_j) \tag{3}$$

Subject to

$$r_j' = r_j + bp_j \tag{4}$$

$$d_j = r_j' + \sum \overline{p}_j + \varepsilon_j \tag{5}$$

$$s^i_{jk} = rtime + ctime(co_j, co_k) \quad \Big/ \forall[(i,k) \rightarrow (i,j)] \in A,\ i \in M,\quad j,k \in N \Big/ \tag{6}$$

$$C^i_j = \left(C^i_k + S^i_{jk} + P^i_j\right) \cdot x^i_j \quad \Big/ \forall[(i,k) \rightarrow (i,j)] \in A,\ i \in M,\quad j,k \in N \Big/ \tag{7}$$

$$C^i_j - P^i_j \geq r'_j \quad \Big/ \forall[(i,k) \rightarrow (i,j)] \in A,\ i \in M,\quad j,k \in N \Big/ \tag{8}$$

$$C_{max} = \max\left(C^i_1, C^i_2, \ldots, C^i_n\right) \tag{9}$$

$$w^i_{jk} = water(co_j, co_k) \cdot x^i_j \quad \Big/ \forall[(i,k) \rightarrow (i,j)] \in A,\ i \in M,\quad j,k \in N \Big/ \tag{10}$$

$$\sum_{j=1}^{n} x^i_j \leq n \quad \Big/ \forall i \in M \Big/ \tag{11}$$

$$\sum_{i=1}^{m} \sum_{j=1}^{n} x^i_j = n \tag{12}$$

$$x^i_j = \{0, 1\} \quad \Big/ \forall i \in M,\ j \in N \Big/ \tag{13}$$

$$d_j \geq 0 \quad /\forall j \in N/ \tag{14}$$

Herein, Eqs. (1)–(3) present objective functions in the nonlinear 0–1 integer programming model. Eq. (1) is to minimise MP in the economic dimension. Eq. (2) aims to minimise TPE in the environmental dimension. Eq. (3) is to minimise TCPDS in the social dimension.

Eqs. (4)-(14) depict all constraints. Constraint (4) delineates the release time of a task in the painting process, that is, the start time of the task in that state. Constraint (5) elaborates the pick-up time that service staff negotiated with customers. Constraint (6) measures the setup time required by equipment i from completing the painting task k to the initiation of the painting task j, which is equal to the sum of the task replacement time and purification time. Therein, the purification time is related to the colour of front-and-rear vehicles. Constraint (7) defines that C^i_j is a positive number when task j is completed on equipment i; otherwise, $C^i_j = 0$. Constraint (8) ensures that when the task j reaches the painting booth, there is enough time to process it. That is, the completion time is no less than the processing time of task j on equipment i. Constraint (9) defines the MP for the whole system, which denotes the completion time of the last task j on the painting equipment i in automobile maintenance services. Constraint (10) highlights the pollution generated by cleaning equipment between tasks j and k on equipment i, connected with the colour of front-and-rear vehicles. Constraint (11) defines that the number of tasks assigned to any one piece of equipment is no more than n. Constraint (12) guarantees that all tasks can be processed by one piece of painting equipment. Constraint (13) defines the binary decision variable. Constraint (14) gives the non-negative restriction on the negotiated pick-up time.

4.3. Solution strategy

Marandi et al. (2014) indicated that most of the combinatorial optimisation problems were NP-hard. Yu et al. (2004) clarified that if each task had a different ‘delay’, then the problem became NP-hard. The scheduling problem of n tasks on m parallel machines is also NP-hard in the ordinary sense. The painting process scheduling problem in automobile maintenance service is formulated as a nonlinear integer programming model in this paper, which naturally belongs to a combinatorial optimisation problem for parallel machines and NP-hard.

To solve the proposed model, this paper devises a strategy incorporating genetic algorithm and Pareto optimality approach. In terms of the former, the genetic algorithm becomes more prevalent because it seeks optimum solutions for complex optimisation problems, i.e., painting process scheduling, through directional random searches (Akgündüz et al., 2011). For instance, Min and Cheng (1999) proposed a genetic algorithm to solve the model of minimising the MP. Vallada and Ruiz (2011) presented a genetic algorithm to solve the parallel machine scheduling problem that considered machine and task sequence-dependent setup times. The authors of this paper leverage their insights to employ a genetic algorithm to obtain a satisfactory scheme concerning painting process scheduling. With regard to the latter, the Pareto optimality approach is used to obtain a set of efficient solutions regarding painting process scheduling, thus helping managers choose the most suitable scheme based on actual conditions. Fig. 2 presents the procedure to solve this problem discussed here.

5. Case study

To illustrate the proposed model and algorithm, a practical case of the painting process scheduling problem at a 4S maintenance service centre for Toyota in China was used to simulate the operations of painting equipment for one day. A real-world case was used. Some parameters involved in the model are determined from statistical data, i.e., statistical data from practical cases is used to determine the range of some parameters, thus simulating the situation in the future. According to the enterprise’s information system, the observation statistics, interviews, and questionnaire are conducted in 2018 (see Table 2). It can be found that the daily number of tasks painted ranges from 7 to 20 in an enterprise with two pieces of painting equipment. It is equipped with purification equipment which is shared by the two spray booths. The time that customers send their vehicles to the automobile maintenance service enterprise has a Poisson distribution. After completing the pre-order maintenance task, the painting process can be performed. The enterprise can eliminate the uncertainty of vehicles’ arrival time at the spray booth through effective management and scheduling, which makes the time at interval $[0h, 8h]$ according to the uniform distribution. The prominent colours of vehicles to be repaired are white, black, champagne, grey and red, of which white vehicles account for 50%. This may be related to customer preferences. There will be chromatic aberrations in vehicles of the same colour due to unequal usage time, but it has little effect on processing time. The processing time of white vehicles in the painting process distributes at interval $[3h, 4.5h]$, and the

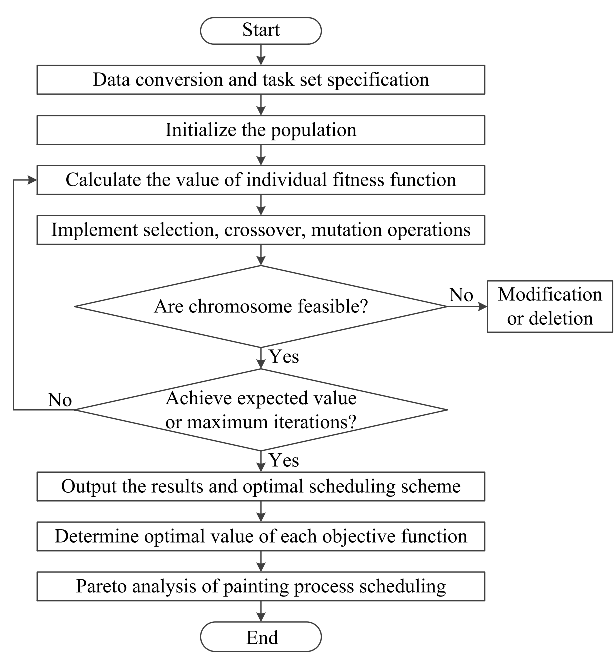

Fig. 2. Flow chart of solution strategy.

Table 2
Survey data

Category	Data	Colour	Quantity percentage	Processing time
m	2	white	50%	$[3\text{h}, 4.5\text{h}]$
n	$[7, 20]$	black	12%	$[1\text{h}, 1.5\text{h}]$
r_j'	$[0\text{h}, 8\text{h}]$	champagne	12%	$[1\text{h}, 1.5\text{h}]$
τ	2h	grey	20%	$[1\text{h}, 1.5\text{h}]$
ξ'	$[0.5\text{h}, 3\text{h}]$	red	6%	$[1\text{h}, 1.5\text{h}]$

remaining colour vehicles are in the range of [1h,1.5h]. The grace time of task j can be expressed as $\varepsilon_j = k\overline{p}_j$, where the value of k ranges from [0,6]. During processing, if two vehicles are processed in turn, the spray gun must be cleaned before switching, then more pollution is generated. Since wastewater yield per unit time is determined, the pollution emissions volume is positively correlated with the cleaning time. The survey revealed that cleaning the spray gun once produces 0.2t of pollution (see Table 3). The maximum waiting time τ that customers can bear is 2h. The time that customers pick up vehicles can be advanced when ξ' is at interval $[0.5\text{h}, 3\text{h}]$. Besides, $\alpha = \beta = 0.88, \lambda_1 = 2.25$ are defined by Tversky and Kahneman (1992).

5.1. Computational results obtained by genetic algorithm

The genetic algorithm operators are selected as follows, population size: 600; maximal iterations: 100; crossover probability: 0.8; and mutation probability: 0.1. All experiments were conducted using MATLAB (2018a) on the server machine with Intel Core i5 3rd gen CPU 1.8 GHz and 4 GB RAM. Computational results are as follows. The value of the MP function approximately converged at the 17th iteration, and the average CPU time was 25s. The value of the TPE function approximately converged at the 6th iteration, and the average CPU time was 4s. The value of the TCPDS function approximately converged at the 26th iteration, and the average CPU time was 35s. The convergent maps are shown in Fig. 3.

In Fig. 3a, the value of the initial solution was 1518, and the optimal solution was 1397, MP decreased 7.9% by optimisation. Through balancing the number of tasks on different equipment and optimising task sequencing continually, the MP can be reduced to a minimum which means the system efficiency has been maximised, and the optimal economic objective was achieved.

In Fig. 3b, the value of the initial solution was 1.6, and the optimal solution was 1, and TPE decreased 37.5% by optimisation. The painting sequence of vehicles in the same colour system was arranged together as much as possible, reducing cleaning times. Pollution emissions were reduced, and environmental performance improvements were achieved. Thereby, progress in improving the environmental sustainability performance of automobile maintenance services can be achieved.

In Fig. 3c, the value of the initial solution was 1420, and the optimal solution was −814, and TCPDS decreased 157.3% by optimisation. Through effective scheduling of painting sequences, the situation can be avoided when customers are informed to pick up their vehicles beyond the negotiated, which means that customers' perceived satisfaction has been increased significantly.

Table 3
Pollution emissions matrix generated by cleaning equipment/10^{-1} t.

	white	black	champagne	grey	red
white	0	2	2	2	2
black	2	0	2	2	2
champagne	2	2	0	2	2
grey	2	2	2	0	2
red	2	2	2	2	0

5.2. Pareto-optimal scheduling

A schedule is called Pareto-optimal if it is impossible to decrease the value of one objective without increasing the value of the other (Pinedo, 2002). Under the multi-objective optimisation framework, the algorithm was designed to generate a set of efficient solutions (in the Pareto-optimal sense) with an extensive distribution (different trade-offs among three objectives) so that the decision-maker can choose the most suitable solution based on practical conditions (Zhang, 2017b). Suppose there are three objectives, γ_1, γ_2 and γ_3. All Pareto-optimal solutions can be represented by a set of points in the $(\gamma_1, \gamma_2, \gamma_3)$ space. This set of points illustrates the trade-offs among the three objectives. The authors of this paper portrayed these three objectives as $C_{\max}$, $\sum w_{jk}^i$ and $\sum E_j(C_j)$. Environmental issues are receiving increasing attention from enterprises. Thus, the authors of this paper mainly focused on the trade-offs between environmental and other objectives.

5.2.1. Determining trade-offs among the three objectives

Step 1: Determine the coordinate system. The X-axis represents MP ($C_{\max}$) objective value, Y-axis represents TCPDS ($T = \sum E_j(C_j)$) objective value and Z-axis represents TPE ($W = \sum w_{jk}^i$) objective value.

Step 2: Determine the optimal value of each objective in the case where a single objective is considered. The minimum values of MP, TPE and TCPDS are 1397, 1 and −814, respectively.

Step 3: Select TPE as a benchmark and determine the range and step size. TPE unites with the MP, MP is regarded as the primary objective, and the secondary one is TPE. When $MP = 1397$, the optimal solution for TPE_1 is 1.8. Similarly, when $TCPDS = -814$, the optimal solution for TPE_2 is 2.8. Since $TPE_1 < TPE_2$, Pareto-optimal solutions of the TPE have a value range of $[1, 2.8]$ in the case of considering the three-dimensional objective comprehensively. The authors of this paper focused on the interactions of environmental objectives and others by developing a two-dimensional Pareto graph. The TPE was used to divide the three-dimensional figure, thus obtaining the MP-TCPDS Pareto graph. MP-TCPDS was divided into ten layers with a minimum increment of TPE (that is 0.2).

Step 4: The system drew the MP-TCPDS Pareto graph for each layer. It determined the step size of the MP in each layer. As the range of the MP was small, it was determined easily. The step size was set based on MP, and Pareto-optimal solutions of each layer of MP-TCPDS were respectively plotted in steps of 70, 10, 70, 30, 40, 5, 40, 25, 25, and 10. The relevant data are presented in Table 4. The points are connected, in turn, to obtain a three-dimensional Pareto graph, as shown in Fig. 4.

Step 5: Connect two Pareto frontiers separately. The optimal points of MP in each layer of MP-TCPDS were connected to obtain a Pareto frontier TPE-MP-TCPDS, as shown in Fig. 5a. Similarly, the optimal points of TCPDS in each layer of MP-TCPDS were connected to obtain a Pareto frontier TPE-TCPDS-MP, as shown in Fig. 5b.

5.2.2. Pareto frontier analysis

5.2.2.1. Analysis of pareto frontier TPE-MP-TCPDS. The Pareto frontier TPE-MP-TCPDS reflects the trade-off between TPE and MP. It can be seen from Fig. 5a that as TPE increases, MP first drops and then remains stable. The falling part can be divided into two stages: The TPE increased by 20% from 1 to 1.2, whereas MP decreased by 27.2% from 2027 to 1475; The TPE increased by 50% from 1.2 to 1.8, while MP decreased by 5.3% from 1475 to 1397. Overall, appropriate relaxation of TPE can impose a significant decrease on MP based on the former stage, so considering the trade-off between the TPE and MP in combination with practical demands is necessary. In the latter stage, even if the requirements for the MP are relaxed, there is little improvement in

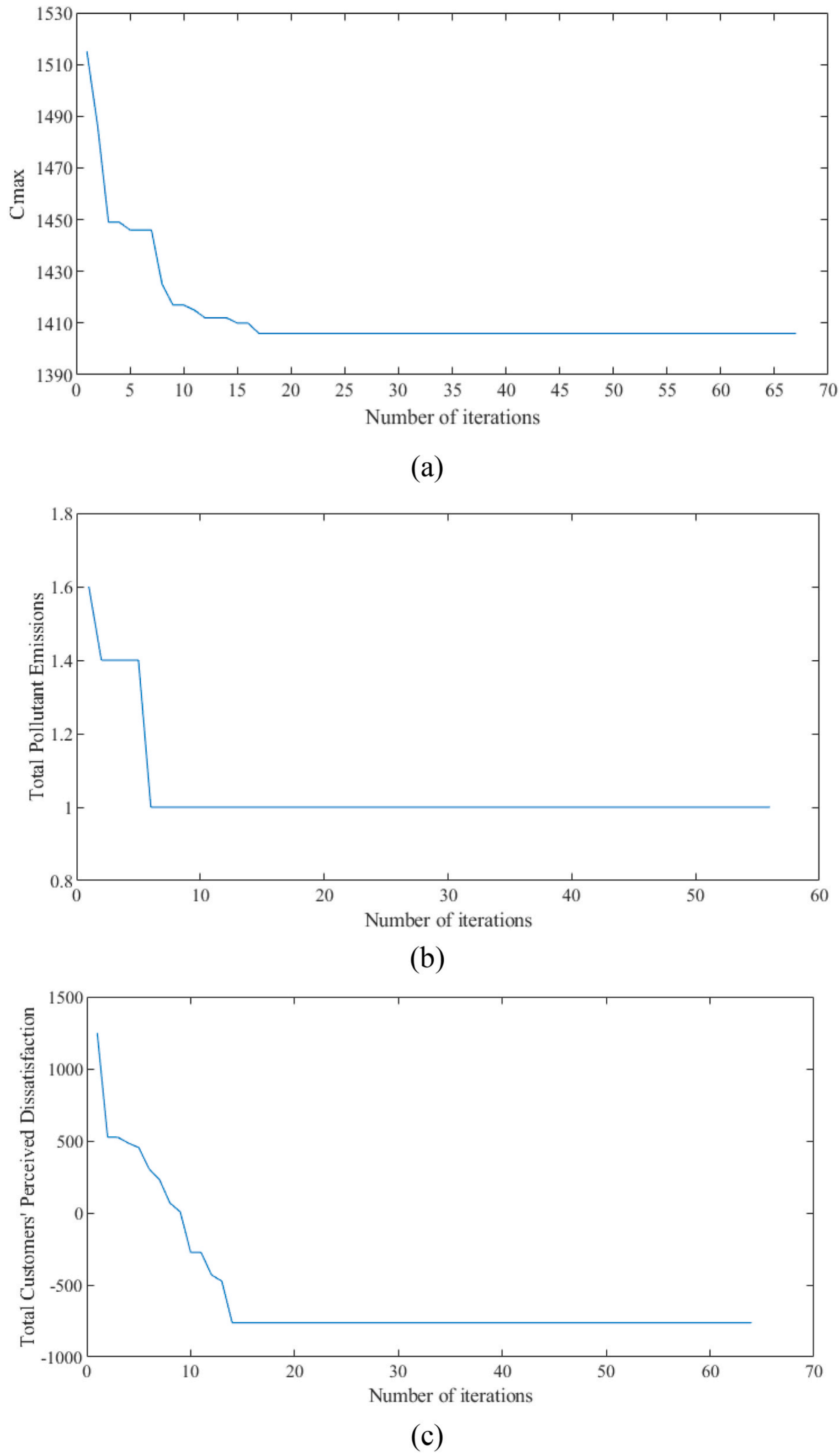

Fig. 3. Convergent map regarding makespan, total pollutant emissions and total customers' perceived dissatisfaction.

equipment efficiency, so the TPE should be emphasised to optimise with consideration of more interaction with customers at this stage.

5.2.2.2. Analysis of the pareto frontier TPE-TCPDS-MP. The Pareto frontier TPE-TCPDS-MP reflects the trade-off between the TPE and TCPDS. It can be seen from Fig. 5b that as TPE increases, TCPDS shows a downward trend, and the slope changes significantly. The decline can be divided into two stages: Firstly, as TPE increases, TCPDS has little change. When $TPE \in [1.6, 1.8]$ and $TPE \in [2.2, 2.4]$ respectively, TPE increased by 20%, whereas TCPDS decreased by 0.5% and 0.6%.

Secondly, TCPDS decreased significantly with the increase of TPE. When $TPE \in [1, 1.2]$, $TPE \in [1.2, 1.6]$, $TPE \in [1.8, 2.2]$ and $TPE \in [2.4, 2.8]$,

Table 4
Computational results.

Value of TPE	Value of MP-TCPDS, which is denoted as $(C_{\max}, \sum E_j(C_j))$					
1.0	(2027, 2978)	(2096, 2402)	(2100, 2254)			
1.2	(1475, 1098)	(1485, 838)	(1490, 620)			
1.4	(1451, 488)	(1529, 443)	(1570, 443)	(1656, 415)		
1.6	(1437, 554)	(1439, 503)	(1495, 130)	(1527, 15)		
1.8	(1397, 1420)	(1398, 814)	(1442, 27)	(1497, 1)		
2.0	(1397, 1420)	(1398, 158)	(1406, −204)			
2.2	(1397, 1420)	(1406, −204)	(1466, −350)			
2.4	(1397, 1420)	(1400, −138)	(1447, −248)	(1453, −368)		
2.6	(1397, 1420)	(1429, −237)	(1447, −471)	(1473, −471)	(1506, −582)	
2.8	(1397, 1420)	(1409, −391)	(1419, −781)	(1429, −781)	(1439, −790)	(1442, −814)

TCPDS decreased by 53.3%, 19.7%, 11.4%, and 14.5% respectively. Overall, when $TPE \in [1.6, 1.8]$ and $TPE \in [2.2, 2.4]$, even if the requirements for the TPE are relaxed, TCPDS only has a slight reduction, so the TPE should be emphasised to optimise at this stage.

When $TPE \in [1, 1.2]$, $TPE \in [1.2, 1.6]$, $TPE \in [1.8, 2.2]$ and $TPE \in [2.4, 2.8]$ respectively, the appropriate relaxation of TPE can pose a significant increase in terms of the TCPDS. Therefore, it is necessary to consider the trade-off between the TPE and TCPDS combined with realistic demands.

5.2.2.3. Layer analysis. The purpose of the layer analysis was to analyse the trade-offs between the MP and TCPDS under the TPE constraint. It can be seen from Fig. 4 and Table 4 that the MP and TCPDS are challenging to be optimised under strict TPE constraints. If the TPE constraint is moderately relaxed, the optimal solution of TCPDS can be obtained under a particular MP. When $TPE = 1$, the values of MP and TCPDS are large. TCPDS is difficult to be optimised. In the case of appropriate relaxation of TPE, both MP and TCPDS can get more optimisation when $TPE \in [1.2, 1.6]$, and the trade-offs among them can be sought. By proceeding with the relaxation of TPE, the MP can achieve the optimal results when $TPE = 1.8$. However, when $TPE \in (1.8, 2.8]$, MP has little change, and TCPDS has an extensive range of variations in the equalisation scheme of the former and latter. Consequently, the

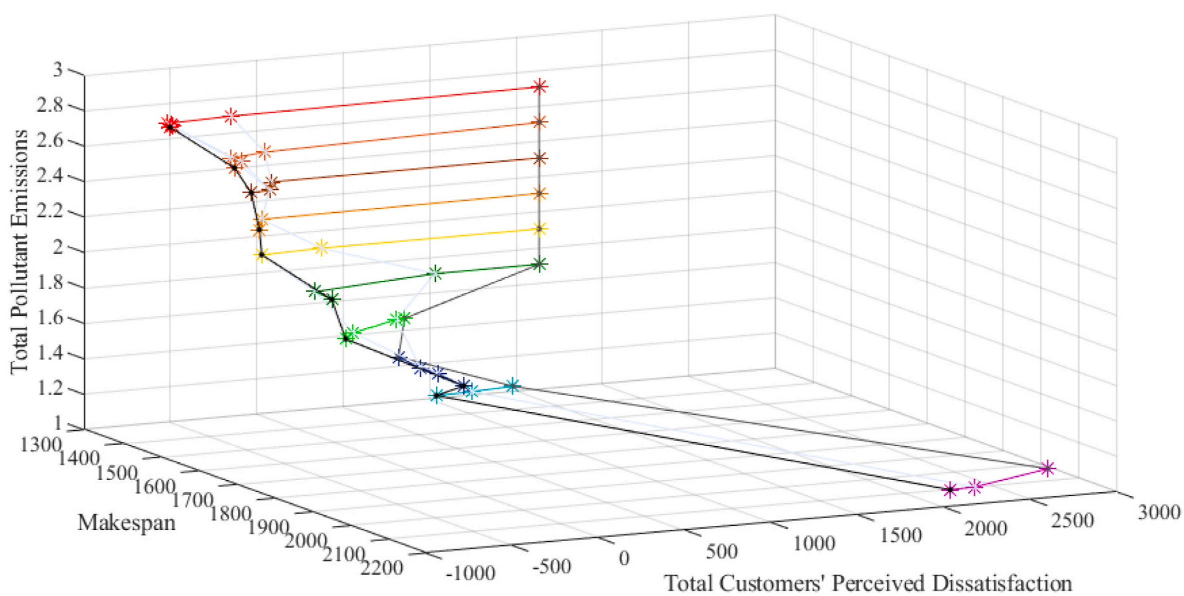

Fig. 4. Pareto graph regarding three objectives when the number of tasks is 18.

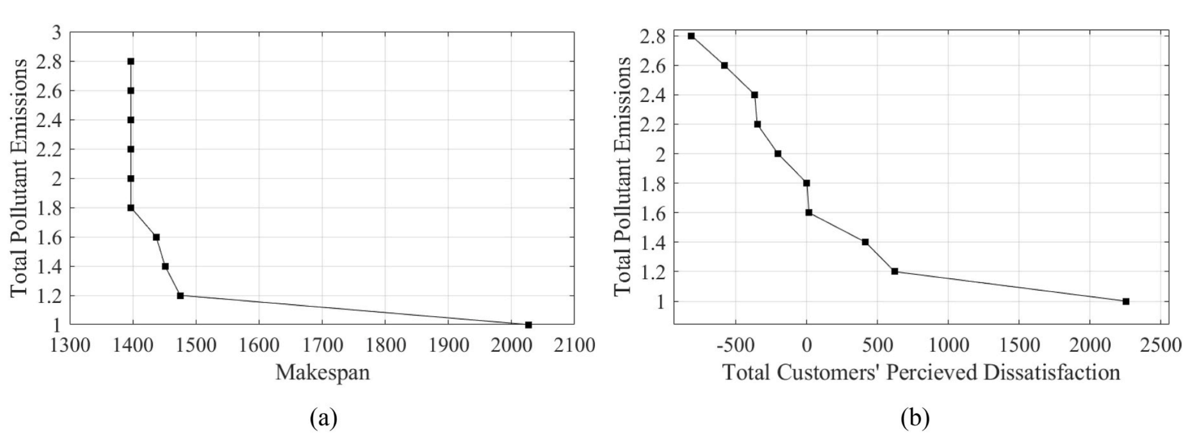

Fig. 5. Pareto frontier regarding makespan, total pollutant emissions and total customers' perceived dissatisfaction.

optimisation of the TCPDS may be emphasised when selecting an equalisation scheme.

5.3. Sensitivity analysis

Sensitivity analysis is an uncertainty analysis method. The extent to which the change of relevant parameters affects the optimisation objective is known as ‘so-called sensitivity’. If a tiny change in a parameter can significantly change the objective function, it is called the sensitivity parameter of scheduling schemes, which needs to be managed.

To achieve the objective of designing a sustainable strategy for service-oriented manufacturing enterprises, the sensitivity parameters under different objectives need to be found to optimise the scheme further. Many parameters affect the scheduling scheme, but only a few principal parameters can be chosen to analyse their influence on every objective. The number of factors is usually selected in the sensitivity analysis. Overholts et al. (2009) used sensitivity analysis to determine the impact of the number of security patrol areas on the quality of daily maintenance schedules and personnel usage. Differing from previous literature, in addition to the number of tasks (NT), the other two factors considered and selected by the authors of this paper were the proportion of the white vehicles (PW) and the proportion of auto fast-service (PF).

Fig. 6a, b and 6c are the sensitivity analysis regarding MP, TPE and TCPDS with PW, NT varying within ±30% and PF changing from 0% to 30%.

The following conclusions can be gained based on Fig. 6:

① For MP, NT and PW have a positive correlation with $C_{\max}$, NT is more sensitive than PW. There is a negative correlation between PF and $C_{\max}$, and $C_{\max}$ is extremely sensitive to the change of PF.

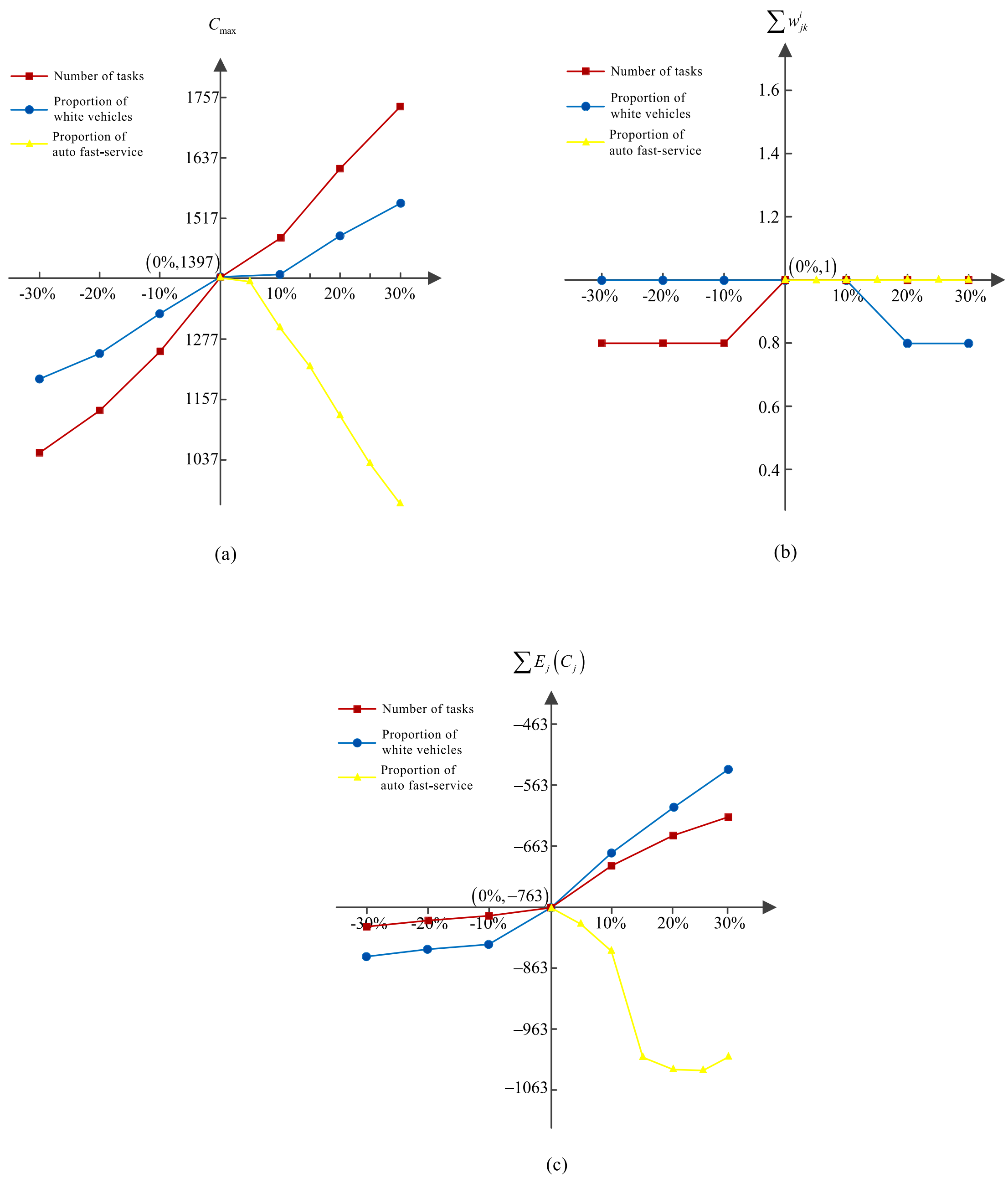

Fig. 6. The sensitivity analysis regarding makespan, total pollutant emissions and total customers’ perceived dissatisfaction.

② For TPE, when PW increases 10% based on survey data, that is PW = 55%, PW is more sensitive to $\sum w_{jk}^{i}$. When PW is lower than survey data, PW has no significant impact on $\sum w_{jk}^{i}$, yet NT affects it. PF does not affect $\sum w_{jk}^{i}$.

③ For TCPDS, PW has a significant positive effect on $\sum E_j(C_j)$ while PF has a prominent negative effect. As PF increases by 15%, the sharp changes in $\sum E_j(C_j)$ begin to flatten out.

5.4. Managerial insights

Differing from traditional sustainable operations of enterprises, the authors of this paper focused upon the interactions among economic, environmental, and social objectives by using a practical case to provide a reasonable scheduling strategy. The corresponding management suggestions based on the results of Pareto-optimal scheduling and sensitivity analysis were proposed as:

(1) In the production scheduling problem, from ignoring pollution emissions to introducing emission reduction objectives, optimising task sequences can obtain a larger reduction of pollutants with a smaller decrease in system efficiency and customers' perception. If the TPE has excessive restrictions, for instance, when $TPE < 1.2$, the MP and TCPDS will suffer significant losses. Overall, improving task sequences can optimise multi-dimensional objectives to some extent. Once the TPE restrictions are strict, it is hard to obtain the trade-offs of multiple objectives by only relying on this approach. In this context, various methods need to be integrated to actualise the trade-offs of multiple objectives better, such as optimising task sequences, purchasing more cleaning equipment, using tiered pricing related to delivery times, customer reservations in advance, etc.

(2) A tiered pricing strategy was adopted to optimise the short supply situation during operation activities, which can affect the reference point of negotiated pick-up times. Customers can choose maintenance speed, such as urgent or normal. When choosing the former, the reference point will be put forward appropriately, the customer waiting time will be shortened. More money needs to be paid because the vehicles have a priority for being serviced. If vehicles are not delivered to customers before their reference points, customers' perception can be respected by reducing the vehicle maintenance price (that is the price the customers have to pay is decreased). In summary, a tiered pricing strategy can effectively decrease TCPDS of the social dimension.

(3) Strengthening and improving the reservation system enables tasks to be better arranged. Under this system, service staff can schedule maintenance tasks more reasonably based on the actual processing situation. The vehicles' arrival times are shown as a uniform distribution, ensuring the consistency of NT in different periods. When the system is busy, it first processes prebooked customers' vehicles. Compared with temporary maintenance services, reservations can reduce uncertainty, shorten waiting times to a certain extent, guarantee that TCPDS is at a lower level. The reservation system can act as a tool to optimise TCPDS by affecting the reference point of the pick-up time.

(4) For different objectives, there may be inconsistent sensitivity parameters. Traditionally, NT and the number of equipment are regarded as pivotal parameters that affect system efficiency. Besides the economic (MP), environmental (TPE), and social objectives (TCPDS) have been added in this paper. Thus, more parameters should be considered. Through sensitivity analyses, it was found that PW and PF significantly affected the achievement of the objectives. It explains the proportion of colour systems most vehicles belong to, and the proportion of auto fast-service are also sensitivity parameters. With the increasing concern for the environment and customer-oriented sustainable operations, managers should focus on NT, PW, and PF to optimise the painting process scheduling to realise the trade-offs among multiple objectives.

6. Conclusions and future work

The authors proposed a multi-objective nonlinear 0–1 integer programming model for sustainable painting process scheduling in automobile maintenance services. Demands from diverse stakeholders were considered and balanced by economic-environmental-social objectives. Specifically, improving equipment utilisation reflects economic goals for managers. Pollutant emissions that measure environmental goals can be achieved by optimising task switching times. Furthermore, customers' perception towards the delivery time of their repainted vehicles is adopted to realise social goals. Thus, task completion time which can be shortened by task sequence is linked with quantifying the subjective behaviour characteristics of customers. In the context of satisfying different stakeholders, the optimal scheduling scheme is conducive to upgrading the performance of production and service operations.

Several insights can be provided based on the results of this study. In practice, customer information, including perception, vehicle colour, and expected pick-up time, are usually unknown before arriving. Obtaining information in advance helps to form a better combination and sequence of painting equipment. A reservation system can reduce uncertainty and shorten their waiting time, thus decreasing emissions and improving customer satisfaction within a relatively reasonable cost-efficiency range. In addition, the results indicated that, through effective scheduling of painting sequences, the situation could be avoided when customers are informed to pick up their vehicles beyond the negotiation. Particularly, the tiered pricing strategy distinctly affects the reference point of negotiated pick-up time. In this sense, customers can choose to pay more expenses for prioritised maintenance services, thus decreasing customers' perceived dissatisfaction effectively and increasing enterprise profits.

This paper also highlighted the trade-offs among economic, environmental, and social objectives, which was different from the previous literature focusing on one or two dimensions. In the case of appropriate relaxation of TPE, both MP and TCPDS can be better. However, as governments and non-government environmental protection organisations put forward more stringent requirements on pollution discharge, TPE is under strict constraint, making TCPDS challenging to optimise by merely relying on improving task sequencing. It should be emphasised for managers to achieve optimal schemes considering practical demands through effective interaction with customers. The authors of this paper enriched the indicators to capture the sustainable performance of service-oriented manufacturing enterprises, especially in terms of environmental and social dimensions.

The proposed model and solution strategies might furnish valuable decision support for managers in practice. One of the main reasons is that it is an important module of the enterprise's information system. In reality, the 4S maintenance service centre the authors took in the study was awarded the 'National Excellent Dealer' award for two consecutive years from 2019 to 2020, with the customers' perceived satisfaction index of 98.7%. However, it was designed only to help managers make decisions, not to substitute the practitioners fully. This paper aimed to evaluate the proposed model from theoretical and practical aspects and highlight the importance and urge of incorporating the philosophies of sustainable operations into service-oriented manufacturing enterprises.

This research paid more attention to the effluent, while other pollutants such as gas and solid waste were ignored. By combining technology with management, further improvements can help decision-makers make production cleaner and make service provision more sustainable. Another topic is to improve the design of the customers' perception function in ways such as describing the performance measurement of social objectives, integrating the quality of the painting, or other quality criteria into the customers' perception function. The authors addressed the connectivity between customers' perception and time, yet quantifying customers' perception requires multi-dimensional evaluation indicators, which are uncertain and fuzzy. Therefore, comprehensive integration of the prospect theory and fuzzy decision-making theory should be used to measure customers' incomplete rational judgment towards waiting times in the future. This helps to increase the achievement of social goals for service-oriented enterprises in the long term.

CRediT authorship contribution statement

Qin Yang: Supervision, Conceptualization, Investigation, Interview, Writing – review & editing. **Xin Meng:** Data curation, Software, Writing – original draft. **Huan Zhao:** Methodology, Data collection, Software. **Cejun Cao:** Supervision, Conceptualization, Validation, Writing – review & editing. **Yang Liu:** Supervision, Conceptualization, Validation, Writing – review & editing. **Donald Huisingh:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Notations

Table A.1
table of notations

Notation	Description
M	Set of painting equipment, indexed by i, where $M = \{1, 2, \cdots, m\}$
N	Set of painting tasks, indexed by j, where $N = \{1, 2, \cdots, n\}$
A	Set of all constraints regarding processing paths or routes $(i,k)\rightarrow(i,j)$, and it indicates that j is processed after k on i
r_j	The time customers send j to automobile maintenance service enterprises
$r_j^{'}$	The earliest time at which j can start the painting processing
p_j^i	The processing time of j on i
s_{jk}^i	The setup time between j and k on i
w_{jk}^i	The pollution generated by cleaning i between j and k
d_j	The pick-up time service staff negotiates with customers
C_j	The practical completion time of j
E	The CPDS
bp_j	The total time required to complete the pre-order process of j
ap_j	The total time required to complete the post-order process of j
$\sum \overline{p}_j$	The sum of average processing time of j in each process on a parallel machine
ε_j	The grace time of j, which contains ap_j
co_j	The colour of the vehicle corresponding to j
$water(co_j, co_k)$	The pollution generated by cleaning equipment in the process of spraying different colours co_j and co_k
$ctime(co_j, co_k)$	The time generated by cleaning i in the process of spraying different colours co_j and co_k
$rtime$	The time replacing vehicles on the painting equipment
x_j^i	The binary variable, 1 if j is processed on i, 0 otherwise

Appendix B. Customers' perception

1. Customers' perception function

In the next section, combining with the value function of the prospect theory (Kahneman and Tversky, 1987), the customers' perception function regarding task completion time is constructed through setting a reference point and comparing profit and loss in different scenarios.

2. Determination of reference point

The negotiated pick-up time of the task denoted as d_j is treated as a reference point, vehicles can be delivered on time or in advance with the following two requirements being met simultaneously. One requirement is that the painting process is accomplished before the negotiated pick-up time. The other is that enough work time for the subsequent operations (such as vehicle washing, inspection) needs to be reserved, including task grace time.

3. Formulation of the customers' perception function

Customers' perception is analysed with the value function of the prospect theory, which is shown in Fig. B.1 and Eq. (B.1). In this figure, the abscissa C_j expresses task completion time; the ordinate $E_j(C_j)$ portrays CPDS.

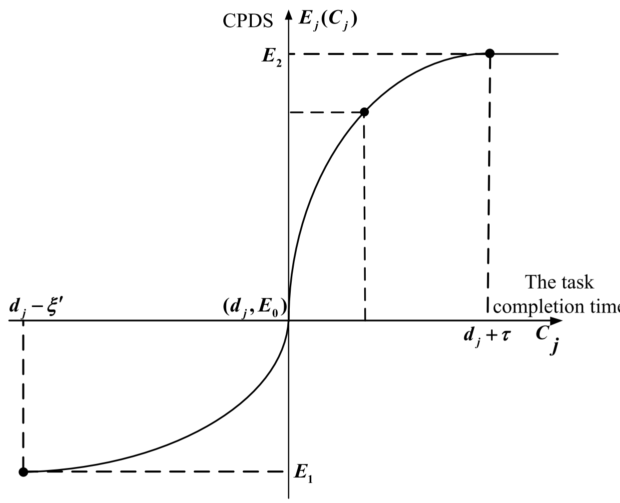

Fig. B.1. The CPDS curve regarding task completion time

$$E_j(C_j)=\begin{cases}E_2 & C_j\geq d_j+\tau\\ \lambda_1(C_j-d_j)^{\beta}+E_0 & d_j\leq C_j<d_j+\tau\\ -(d_j-C_j)^{\alpha}+E_0 & d_j-\xi'<C_j<d_j\\ E_1 & C_j=d_j-\xi'\end{cases} \tag{B.1}$$

① The origin (the reference point) measures customers' perception about picking up vehicles on time. In this context, $C_j = d_j, E_j = E_0$, in which the perceptual base is $E_0 = 0$.
② The first quadrant (loss curve) addresses a situation in which customers' perception is in a lost state. Once task completion time is later than the negotiated pick-up time, customers will feel dissatisfied. The above behaviour is guided by the psychological characteristic of 'loss aversion', which generates a loss aversion coefficient λ_1. With the increasing completion time, customers pick up their vehicles later, the uptrend of the loss curve has a gradual slowdown, guided by the feature of 'sensitivity diminishing'. In the phase, a risk attitude coefficient β is generated, and $\beta<1$. As task completion time reaches the customer's maximum waiting time τ, that is, customers have not picked up their vehicles until this moment, then CPDS reaches the upper limit E_2.
③ The third quadrant (yield curve) discusses the situation whereby customers' perception is in the income state when they pick up vehicles in advance. If painting and other processes for damaged vehicles can be completed before the negotiated pick-up time, the service staff temporarily informs customers that their vehicles can be picked up from now on. Consequently, customers have more choices and a more flexible time to pick up their vehicles. In this context, customers feel satisfied, CPDS becomes a negative value. Customers have planned activities based on the negotiated pick-up time, which are not sensitive to the choice of picking up vehicles in advance and presenting a psychological feature of 'indifference'. This status is manifested as a gentle decrease in the CPDS curve. According to the 'sensitivity diminishing' feature, another new risk attitude coefficient α is generated, where $\alpha<1$. If the advance time reaches extremum ξ', CPDS arrives at the lower limit E_1.

References

Akgündüz, O.S., Tunalı, S., 2011. A review of the current applications of genetic algorithms in mixed-model assembly line sequencing. Int. J. Prod. Res. 49, 4483–4503.
Alcan, P., BaşLıGil, H.S., 2012. A genetic algorithm application using fuzzy processing times in non-identical parallel machine scheduling problem. Adv. Eng. Software 45, 272–280.
Antonaia, A., Ascione, F., Castaldo, A., D'Angleo, A., Masi, R.F.D., Ferrara, M., Vanoli, G. P., Vitiello, G., 2016. Cool materials for reducing summer energy consumptions in Mediterranean climate: in-lab experiments and numerical analysis of a new coating based on acrylic paint. Appl. Therm. Eng. 91–107.
Cantele, S., Zardini, A., 2018. Is sustainability a competitive advantage for small businesses? An empirical analysis of possible mediators in the sustainability–financial performance relationship. J. Clean. Prod. 182, 166–176.
Cao, C., Li, C., Yang, Q., Liu, Y., Qu, T., 2018. A novel multi-objective programming model of relief distribution for sustainable disaster supply chain in large-scale natural disasters. J. Clean. Prod. 174, 1422–1435.
Cao, C., Li, C., Yang, Q., Zhang, F., 2017. Multi-objective optimisation model of emergency organisation allocation for sustainable disaster supply chain. Sustainability 9 (11), 2103.
Cao, C., Liu, Y., Tang, O., Gao, X., 2021. A fuzzy bi-level optimisation model for multi-period post-disaster relief distribution in sustainable humanitarian supply chains. Int. J. Prod. Econ. 235, 108081.
Cao, J., Jiang, Z., Wang, K., 2016. Customer demand prediction of service-oriented manufacturing incorporating customer satisfaction. Int. J. Prod. Res. 54, 1303–1321.
Cavalcante, E.S., Vasconcelos, L., Neto, G., Ramos, W.B., Brito, R.P., 2020. Automotive painting process: minimising energy consumption by using adjusted convective heat transfer coefficients. Prog. Org. Coating 140, 105479.
Chamandoust, H., Derakhshan, G., Hakimi, S.M., Bahramara, S., 2019. Tri-objective optimal scheduling of smart energy hub system with schedulable loads. J. Clean. Prod. 236, 117584.
Chen, L., Luo, S., Zhao, T., 2019. Financial constraints, trade mode transition, and global value chain upgrading of Chinese firms. Sustainability 11, 4527.
Choi, S., Ng, A., 2011. Environmental and economic dimensions of sustainability and price effects on consumer responses. J. Bus. Ethics 104, 269–282.
Chou, C.J., Chen, C.W., Conley, C., 2015. An approach to assessing sustainable product-service systems. J. Clean. Prod. 86, 277–284.

Coca, G., Castrillón, O.D., Ruiz, S., Mateo-Sanz, J.M., Jiménez, L., 2019. Sustainable evaluation of environmental and occupational risks scheduling flexible job shop manufacturing systems. J. Clean. Prod. 209, 146–168.
Deng, G.F., Lin, W.T., 2011. Ant colony optimisation-based algorithm for airline crew scheduling problem. Expert Syst. Appl. 38, 5787–5793.
Ding, J.Y., Song, S., Wu, C., 2016a. Carbon-efficient scheduling of flow shops by multi-objective optimisation. Eur. J. Oper. Res. 248, 758–771.
Ding, J.Y., Song, S., Zhang, R., Chiong, R., Wu, C., 2016b. Parallel machine scheduling under time-of-use electricity prices: new models and optimisation approaches. IEEE Trans. Autom. Sci. Eng. 13, 1138–1154.
Dong, Y., Ishikawa, M., Liu, X., Hamori, S., 2011. The determinants of citizen complaints on environmental pollution: an empirical study from China. J. Clean. Prod. 19, 1306–1314.
Fang, K., Uhan, N., Zhao, F., Sutherland, J.W., 2011. A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction. J. Manuf. Syst. 30, 234–240.
Gao, X., Cao, C., 2020. A novel multi-objective scenario-based optimisation model for sustainable reverse logistics supply chain network redesign considering facility reconstruction. J. Clean. Prod. 270, 122405.
Giampieri, A., Ling-Chin, J., Taylor, W., Smallbone, A., Roskilly, A.P., 2019. Moving towards low-carbon manufacturing in the UK automotive industry. Energy Proc 158, 3381–3386.
Gimenez, C., Sierra, V., Rodon, J., 2012. Sustainable operations: their impact on the triple bottom line. Int. J. Prod. Econ. 140, 149–159.
Giret, A., Trentesaux, D., Prabhu, V., 2015. Sustainability in manufacturing operations scheduling: a state of the art review. J. Manuf. Syst. 37, 126–140.
Güçdemir, H., Selim, H., 2017. Customer centric production planning and control in job shops: a simulation optimisation approach. J. Manuf. Syst. 43, 100–116.
Han, X.L., Lu, Z.Q., Xi, L.F., 2010. A proactive approach for simultaneous berth and quay crane scheduling problem with stochastic arrival and handling time. Eur. J. Oper. Res. 207, 1327–1340.
Hao, L., Du, B., Huang, G.Q., Chen, H., Li, X., 2013. Hybrid flow shop scheduling considering machine electricity consumption cost. Int. J. Prod. Econ. 146, 423–439.
Isabella, B., Deborah, P., Gian, A.B., Maurizio, O., Mariachiara, Z., 2020. Inventory and life cycle assessment of an Italian automotive painting process. Clean. Technol. Envir. 22, 247–258.
Jaehn, F., 2016. Sustainable operations. Eur. J. Oper. Res. 253, 243–264.
Kahneman, D., Tversky, A., 1987. Prospect theory: an analysis of decision under risk. Estudios De Psicología Stud. Psychol. 8, 95–124.
Kan, F.A., Nu, A., Fu, Z.B., Jws, B., 2011. A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction-Science Direct. J. Manuf. Syst. 30, 234–240.
Khalili, N.R., 2011. Theory and concept of sustainability and sustainable development. In: Practical Sustainability, pp. 1–22.
Kolakowska, E., Smith, S.F., Kristiansen, M., 2014. Constraint optimisation model of a scheduling problem for a robotic arm in automatic systems. Robot. Autonom. Syst. 62, 267–280.
Lee, W.C., Wang, J.Y., Lin, M.C., 2016. A branch-and-bound algorithm for minimising the total weighted completion time on parallel identical machines with two competing agents. Knowledge-based. Syst. 105, 68–82.
Li, F., Liao, W., Cai, W., Zhang, L., 2020. Multitask scheduling in consideration of fuzzy uncertainty of multiple criteria in service-oriented manufacturing. IEEE Trans. Fuzzy Syst. 1-1.
Liam, B., Philip, O., 2010. Biofuels from microalgae—a review of technologies for production, processing, and extractions of biofuels and co-products. Renew. Sustain. Energy Rev. 14, 557–577.
Liu, C.H., Huang, D.H., 2014. Reduction of power consumption and carbon footprints by applying multi-objective optimisation via genetic algorithms. Int. J. Prod. Res. 52, 337–352.
Liu, M., Liu, X., Chu, F., Zhang, E., Chu, C., 2020. Service-oriented robust worker scheduling with motivation effects. Int. J. Prod. Res. 1730998.
Liu, Y., Dong, H., Lohse, N., Petrovic, S., Gindy, N., 2014. An investigation into minimising total energy consumption and total weighted tardiness in job shops. J. Clean. Prod. 65, 87–96.
Low, C., Ji, M., Hsu, C.J., Hsu, C.J., Su, C.T., 2010. Minimising the makespan in a single machine scheduling problem with flexible and periodic maintenance. Appl. Math. Model. 34, 334–342.
Marandi, A., Wang, Z., Takata, K., Byer, R.L., Yamamoto, Y., 2014. Network of time-multiplexed optical parametric oscillators as a coherent Ising machine. Nat. Photonics 8, 937.
Min, L., Cheng, W., 1999. A genetic algorithm for minimising the makespan in the case of scheduling identical parallel machines. Artif. Intell. Eng. 13, 399–403.
Mokhtari, H., Hasani, A., 2017. An energy-efficient multi-objective optimisation for flexible job-shop scheduling problem. Comput. Chem. Eng. 104, 339–352.
Moradzadeh, B., Tomsovic, K., 2013. Two-stage residential energy management considering network operational constraints. IEEE. T. Smart. Grid. 4, 2339–2346.
Nelson, A., Sadegh, P., Ahmad, S., Gabriela, P., Kevin, L., Kozo, S., 2016. Evolution of the automotive body coating process—a review. Coatings 6, 24.
Oliveira, M., Fontes, D.B.M.M., Pereira, T., 2018. Evaluating vehicle painting plans in an automobile assembly plant using an integrated AHP-PROMETHEE approach. Int. Trans. Oper. Res. 25, 1383–1406.
Overholts II, D.L., Bell, J.E., Arostegui, M.A., 2009. A location analysis approach for military maintenance scheduling with geographically dispersed service areas. J. Omega. 37, 838–852.
Pan, Q.K., Tasgetiren, M.F., Liang, Y.C., 2008. A discrete particle swarm optimisation algorithm for the no-wait flowshop scheduling problem. Comput. Oper. Res. 35, 2807–2839.
Paul, R.K., Kalyan, S., Luk, N.V., 2005. Sustainable operations management. Prod. Oper. Manag. 14, 482–492.
Pinedo, M., 2002. Scheduling: Theory, Algorithms and Systems, second ed. 2003.
Ramos, T., Gomes, M.I., Barbosa-Póvoa, A.P., 2014. Planning a sustainable reverse logistics system: balancing costs with environmental and social concerns. Omega 48, 60–74.
Salihoglu, G., Salihoglu, N.K., 2016. A review on paint sludge from automotive industries: generation, characteristics and management. J. Environ. Manag. 169, 223–235.
Sarkis, J., Dhavale, D.G., 2015. Supplier selection for sustainable operations: a triple-bottom-line approach using a Bayesian framework. Int. J. Prod. Econ. 166, 177–191.
She, Y., Liu, Y., Deng, Y., Jiang, L., 2020. Can China's government-oriented environmental regulation reduce water pollution? Evidence from water pollution intensive firms. Sustainability 12, 7841.
Shim, S.O., Park, K.B., 2016. Technology for production scheduling of jobs for open innovation and sustainability with fixed processing property on parallel machines. Sustainability 8, 904.
Shrouf, F., Ordieres-Meré, J., García-Sánchez, A., Ortega-Mier, M., 2014. Optimising the production scheduling of a single machine to minimise total energy consumption costs. J. Clean. Prod. 67, 197–207.
Simeoni, P., Ciotti, G., Cottes, M., Meneghetti, A., 2019. Integrating industrial waste heat recovery into sustainable smart energy systems. Energy 175, 941–951.
Subramanian, A., Battarra, M., Potts, C.N., 2014. An Iterated Local Search heuristic for the single machine total weighted tardiness scheduling problem with sequence dependent setup times. Int. J. Prod. Res. 52, 2729–2742.
Sun, L.H., Sun, L.Y., Wang, M.Z., Wang, J.B., 2012. Flow shop makespan minimisation scheduling with deteriorating jobs under dominating machines. Int. J. Prod. Econ. 138, 195–200.
Tversky, A., Kahneman, D., 1992. Advances in prospect theory: cumulative representation of uncertainty. J. Risk Uncertain. 5, 297–323.
Vallada, E., Ruiz, R., 2011. A genetic algorithm for the unrelated parallel machine scheduling problem with sequence dependent setup times. Eur. J. Oper. Res. 211, 612–622.
Wang, J.J., Wang, J.B., Liu, F., 2011. Parallel machines scheduling with a deteriorating maintenance activity. J. Oper. Res. Soc. 62, 1898–1902.
Wang, L., Wang, Y.M., Martínez, L., 2017. A group decision method based on prospect theory for emergency situations. Inf. Sci. 418, 119–135.
Xu, Z., Jia, Q.S., Guan, X., Shen, J., 2013. Smart management of multiple energy systems in automotive painting shop. IEEE Trans. Autom. Sci. Eng. 10, 603–614.
Yu, W., Hoogeveen, H., Lenstra, J.K., 2004. Minimising makespan in a two-machine flow shop with delays and unit-time operations is NP-hard. J. Sched. 7, 333–348.
Zakariazadeh, A., Jadid, S., Siano, P., 2014. Multi-objective scheduling of electric vehicles in smart distribution system. Energy Convers. Manag. 79, 43–53.
Zhang, G., Gao, L., Shi, Y., 2011. An effective genetic algorithm for the flexible job-shop scheduling problem. Expert Syst. Appl. 38, 3563–3573.
Zhang, R., 2017a. Environment-aware production scheduling for paint shops in automobile manufacturing: a multi-objective optimisation approach. Int. J. Environ. Res. Publ. Health 15, 32.
Zhang, R., 2017b. Sustainable scheduling of cloth production processes by multi-objective genetic algorithm with Tabu-enhanced local search. Sustainability 9, 1754.