Postprint of Bottleneck Equipment Scheduling in Automotive Electromechanical Maintenance Considering Customer Perception and Resource Efficiency

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Abstract

Effective improvement of system efficiency and customer satisfaction can be achieved through rational scheduling of bottleneck equipment in automotive repair workshops. System efficiency enhancement can be realized by minimizing the makespan (C_{max}), whereas customer satisfaction is subject to subjective factors; consequently, the psychological perception of customers must be considered when formulating the objective function of the scheduling problem. By integrating behavioral science theory, human 'bounded rationality' behavior can be incorporated into service resource scheduling problems that involve close customer contact. Firstly, utilizing the value function of prospect theory, the customer' s psychologically expected waiting time is selected as the reference point to construct a perceived dissatisfaction function for vehicle repair waiting time. On this basis, a multi-objective mathematical model is established by combining resource efficiency objectives with task and resource constraints. Rescheduling rules and a genetic algorithm tailored to the problem are designed for solution. Finally, the feasibility and effectiveness of the model and algorithm are validated through case simulation.

Full Text

Preamble

Multi-Objective Scheduling for Vehicle Electro-Mechanical Maintenance of Bottleneck Machine in Consideration of Customers' Perception and Resource Efficiency

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Abstract: Effective improvement of system efficiency and customer satisfaction can be achieved through rational scheduling of bottleneck equipment in motor vehicle maintenance workshops. On the one hand, enhancement of system efficiency can be realized by optimizing the make-span (Cmax). On the other hand, since customer satisfaction is affected by subjective factors, it is necessary to incorporate customer satisfaction considerations when establishing the objective function of the scheduling problem.

Combined with behavioral science theory, this paper integrates people' s bounded rationality behavior into service resource scheduling problems that involve close customer contact. First, by virtue of the value function in prospect theory, customer expected waiting time is taken as a reference point to establish a customer dissatisfaction function toward waiting time. On this basis, a multi-objective mathematical model is constructed by combining resource efficiency objectives with task and resource constraints. Second, a genetic algorithm corresponding to the scheduling problem is designed to solve it. Ultimately, the feasibility and validity of the model and algorithm are verified through simulation examples.

Keywords: customer perception; prospect theory; vehicle electro-mechanical maintenance machine; bottleneck; scheduling

0 Introduction

The automotive maintenance workshop is a complex system whose machine environment is equivalent to a flexible job shop, characterized by dynamic task arrival times, inflexible operation time windows, and direct customer contact. In 1984, Israeli physicist Goldratt [1] proposed the Theory of Constraints (TOC), pointing out that the bottleneck is the main factor restricting the system from moving toward its goal and determines the overall system performance. Optimization of the bottleneck link can simplify large-scale complex scheduling problems and reduce the complexity of problem solving. Currently, in practical applications, various maintenance workshops typically schedule tasks based on experience without scientific planning, which leads to situations where improper job sequencing extends the total operation time and the actual capacity of maintenance equipment falls short of the workload. In other words, bottleneck equipment emerges during automotive maintenance operations. Rational scheduling of vehicle electro-mechanical maintenance bottleneck equipment can enhance resource efficiency and customer satisfaction.

The scheduling problem for automotive electro-mechanical maintenance bottleneck equipment can be described as an unrelated parallel machine scheduling problem with machine eligibility constraints. Theoretically, unrelated parallel machine scheduling has been proven to be NP-hard, and research has mainly focused on the application of heuristic algorithms [2–8]. Meanwhile, the automotive maintenance service process involves customer participation, requiring greater attention to customer feelings and satisfaction. Based on the assumption of complete rationality, customer satisfaction can be evaluated by minimizing penalty functions related to due dates (such as number of tardy jobs, weighted tardiness, etc.). However, these functions cannot adequately reflect customers' subjective feelings about service satisfaction. As the demand side, customers exhibit bounded rationality as a fundamental behavioral characteristic, and their psychological perception is influenced by internal subjective factors. During the waiting and service acceptance process, they set "psychological expectations" and revise them based on acquired information, exhibiting behaviors such as "reference dependence," "comparison," "fairness concern," and "decision bias."

In recent years, scholars have combined behavioral science theory to study the impact of psychological perception on scheduling schemes. Hjorth et al. [9] integrated prospect theory to study people' s perceived value of travel time, constructing a value function with constant or decreasing sensitivity, and confirmed that people' s perceived value of travel time increases over time. Liu et al. [10] applied prospect theory to study car-sharing service systems, analyzing the reasons and contexts for customers' irrational decisions to improve existing service systems and design new products. Zhou et al. [11] combined prospect theory to study drivers' route choice behavior characteristics under variable message signs, conducted reasonable estimation of prospect theory value function parameters, and demonstrated through empirical testing that the estimation is feasible and effective. Drawing on the above research results, this paper attempts to apply the prospect theory value function to construct customers' psychological perception function of waiting time in automotive maintenance tasks, to more realistically capture customers' psychological characteristics such as "reference dependence," "loss aversion," and "diminishing sensitivity."

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1 Customer Behavior Characteristics Analysis and Perceived Dissatisfaction Function Construction

1.1 Customer Behavior Characteristics Analysis

Automotive maintenance processes typically involve two scenarios: (a) simple regular maintenance tasks with short operation times, where customers choose to wait on-site for vehicle pickup; and (b) complex repair and paint tasks with long operation times, where customers leave their vehicles at the workshop and return at an agreed time. The two scenarios involve different bottleneck resources and different customer psychological perceptions of waiting time. This paper focuses on the first scenario. By analyzing customer behavior characteristics during the on-site waiting process, we construct a customer perceived dissatisfaction function for waiting time.

Maintenance tasks are typically short, usually completed within 0.5–2 hours. Service personnel provide customers with a pickup time based on workshop conditions, and customers typically choose to wait on-site. Such customers are sensitive to waiting time length, and three scenarios may occur:

a) **Early completion**: When a task is completed ahead of schedule, the service personnel notify the customer to pick up the vehicle early (i.e., C_j < d_j). The customer' s waiting time decreases, placing them in a "gain" state with improved satisfaction (dissatisfaction is negative and decreasing). However, the marginal effect of early time diminishes, and excessive earliness may cause customers to worry about repair quality, leading to reduced perceived satisfaction. Therefore, there exists a limit to the early time informed to customers, denoted by ' . The pickup time has a minimum value.

b) **On-time completion**: When a task is completed as scheduled, the customer picks up the vehicle at the agreed time (i.e., C_j = d_j). The customer dissatisfaction function corresponds to a base value S_0, set as S_0 = 0.

c) **Delayed completion**: When a task is completed late, the service personnel notify the customer of the delay (i.e., C_j > d_j). The customer' s waiting time increases, placing them in a "loss" state with increased dissatisfaction. Considering customers' "impatience" behavioral characteristic, dissatisfaction rises rapidly. When the extended waiting time exceeds a specific value, customers become very dissatisfied, potentially complaining and churning. Let '' denote the maximum delay time customers can accept (based on field research, '' is about half an hour). When pickup time exceeds d_j + '' , the customer perceived dissatisfaction function reaches its upper limit S_{max}.

1.2 Customer Perceived Dissatisfaction Function Construction

The prospect theory value function can represent the subjective value of decision-makers' feelings, which is related to a reference point. In the initial decision-making stage, decision-makers select a reference point, typically taking the point with zero value as a reference point, and changes in outcome values are relative to this reference point. The value function proposed by Kahneman et al. [12] is:

$$V(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -\lambda(-x)^{\beta} & \text{if } x < 0 \end{cases}$$

where: $0 < \alpha$, $\beta < 1$ are risk attitude coefficients representing diminishing sensitivity; $\lambda > 1$ is the loss aversion coefficient, indicating that the loss region is steeper than the gain region. Its curve is shown in Figure 1: see original paper.

1) Reference Point Determination

Customers agree on a pickup time with service personnel, which forms a psychological expectation and reference point d_j. The reference point d_j is influenced by the total task processing time and the allowance time given by personnel based on workshop conditions, where [0.5, 2]. When many customers are waiting on-site, due to "fairness" and "conformity" psychological factors, customers can tolerate longer waiting times, and takes larger values.

2) Customer Perceived Dissatisfaction Function Construction

Based on the above analysis of three scenarios for customers waiting on-site, we construct the customer perceived dissatisfaction function. As can be seen, the image formed by rotating Figure 1: see original paper 1800 degrees around the coordinate center is roughly similar to Figure 1: see original paper. In Figure 1: see original paper, the horizontal axis represents customer waiting time, where the coordinate center point S' represents the expected waiting time; the vertical axis represents customer perceived dissatisfaction degree, where the coordinate center point S_0 represents the dissatisfaction base value; above the horizontal axis represents increased customer perceived dissatisfaction with an upper limit S_{max}; below the horizontal axis represents decreased customer perceived dissatisfaction (equivalent to increased satisfaction) with a satisfaction extreme value S' . Accordingly, based on the prospect theory value function model, the general customer perceived dissatisfaction function for actual pickup time is formulated as:

$$f(C_j, d_j) = \begin{cases} 0 & \text{if } C_j = d_j \\ -\left(d_j - C_j\right)^{\alpha} & \text{if } d_j - \xi' \leq C_j < d_j \\ \left(C_j - d_j\right)^{\beta} & \text{if } d_j < C_j \leq d_j + \xi'' \\ S_{\max} & \text{if } C_j > d_j + \xi'' \end{cases}$$

where: C_j is the actual completion time of task j; d_j is the reference point (expected pickup time); ' is the maximum acceptable early time; ' ' is the maximum acceptable delay time; α, β are sensitivity coefficients; S_{max} is the upper limit of dissatisfaction.

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2 Problem Description and Modeling

This study analyzes the automotive electro-mechanical maintenance bottleneck equipment operation process as an unrelated parallel machine scheduling problem, incorporating customer psychological perception and integrating behavioral science theory into service resource scheduling problems with close customer contact. Specific contents include: (a) based on analysis of customer behavioral characteristics and using prospect theory, selecting customer psychological expected waiting time as the reference point to construct a customer perceived dissatisfaction function for waiting time; (b) describing the problem from three aspects—system objectives, resource constraints, and task constraints—to construct a multi-objective scheduling mathematical model for the maintenance workshop; (c) employing a genetic algorithm to design problem-adapted genetic coding and iterative optimization methods for problem solving; and (d) verifying the feasibility and effectiveness of the model and algorithm through simulation examples.

2.1 Basic Assumptions

Assumption 1 All customers only undergo simple regular maintenance tasks, i.e., they choose to wait on-site for vehicle pickup.

Assumption 2 During automotive maintenance operations, once a task begins processing at the bottleneck workstation, interruption is not allowed.

2.2 Problem Description

1) Optimization Objectives

Bottleneck resource scheduling has multi-objective characteristics. On the one hand, bottleneck resources are scarce, and scheduling should improve resource utilization, which can be achieved by minimizing the makespan C_{max}. On the other hand, the pace of the bottleneck process determines the pace of the entire system, and customer perceived dissatisfaction with pickup time can be expressed as a function of task completion time at the bottleneck link. Accordingly, the bottleneck scheduling problem can be described as a multi-objective scheduling problem minimizing both the makespan C_{max} and the customer perceived dissatisfaction function $f(C_j, d_j)$.

2) Resource Constraints

The main equipment in the electro-mechanical process includes lifting machines (including in-ground, two-post, and four-post types). Generally, after vehicles arrive at the electro-mechanical process, lifting machines are used to raise the vehicles for detection and repair using other equipment (including four-wheel aligners, automotive diagnostic computers, tire changers, tire balancers, brake lathes, central oil/gas supply systems, vehicle detectors, etc.). Different lifting machines have varying performance and application scopes, and each task only needs to select one machine for operation. The number of machines is denoted by m.

3) Task Constraints

Tasks in the automotive maintenance workshop electro-mechanical process have the following characteristics and constraints: each task has a specific due date d_j and processing time p_{ij} (representing the time to complete task j using equipment i), and j p{ij} represents the sum of operation times for processes after the bottleneck equipment; tasks have equipment usage restrictions M_j (representing the set of equipment that can be used for task j).

2.3 Scheduling Model Design

In summary, the scheduling problem for the automotive maintenance workshop paint booth can be described as R_m | M_j | C_{max}, f(C_j, d_j), i.e., an unrelated parallel machine scheduling problem with equipment eligibility restrictions, minimizing both makespan and customer perceived dissatisfaction.

Model Formulation:

Decision variables:

$$x_{ijt} = \begin{cases} 1 & \text{if equipment } i \text{ starts processing task } j \text{ at time } t \\ 0 & \text{otherwise} \end{cases}$$

where: N is the set of all tasks; M is the set of all bottleneck equipment; A is the set of all precedence constraints i → k, which restrict that equipment i is used for task j immediately followed by task k.

Objective function and constraints:

$$\min \quad C_{\max} = \max_{j \in N} C_j \tag{3}$$

$$\min \quad \sum_{j=1}^{n} f(C_j, d_j) \tag{4}$$

$$\text{s.t.} \quad C_j = \sum_{i \in M_j} \sum_{t=0}^{T} (t + p_{ij}) x_{ijt}, \quad \forall j \in N \tag{5}$$

$$\sum_{i \in M_j} \sum_{t=0}^{T} x_{ijt} = 1, \quad \forall j \in N \tag{6}$$

$$\sum_{j \in N_i} p_{ij} \le C_{\max}, \quad \forall i \in M \tag{7}$$

$$\sum_{t=0}^{T} x_{ijt} \le 1, \quad \forall i \in M, j \in N \tag{8}$$

$$x_{ijt} \in \{0, 1\}, \quad \forall i \in M, j \in N, t \in [0, T] \tag{9}$$

$$\theta_1, \theta_2 \ge 0, \quad \theta_1 + \theta_2 = 1 \tag{10}$$

$$d_j \ge 0, \quad \forall j \in N \tag{11}$$

In the model, equation (3) is the objective function for makespan. Equations (4)-(11) are constraints, where (4) measures customer perceived dissatisfaction; (5) measures the actual completion time of task j using equipment i; (6) ensures task j has sufficient processing time; (7) ensures sufficient operation time for processes after the bottleneck; (8) guarantees that a specific task can only be served once by any bottleneck equipment, where C_{last} represents the completion time of the last task leaving the bottleneck equipment; (9) defines the range of decision variables; (10) ensures all tasks have the opportunity to start; and (11) limits the range of weights and expected task completion times.

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3 Genetic Algorithm Design for Bottleneck Equipment Scheduling

Genetic algorithms are highly parallel, adaptive, and random optimization algorithms based on "survival of the fittest." This study draws on this method and combines it with the specific problem to construct a fitness function for multi-objective scheduling of automotive maintenance workshop bottleneck equipment.

3.1 Encoding

Each task j' s processing equipment a_j and the processing sequence number b_j of the task on that equipment are defined as a two-dimensional array $\begin{bmatrix} a_1 & a_2 & \cdots & a_n \\ b_1 & b_2 & \cdots & b_n \end{bmatrix}$, representing n tasks. For example:

$$\begin{bmatrix} 1 & 2 & 3 & 1 & 3 & 2 & 1 & 3 \\ 1 & 1 & 1 & 2 & 2 & 2 & 3 & 3 \end{bmatrix}$$

represents that on equipment 1, the task processing order is 4, 1, 7; on equipment 2, the order is 6, 8, 5; and on equipment 3, the order is 2, 3.

3.2 Population Initialization

First, randomly generate n m-dimensional row vectors $[a_1, a_2, \dots, a_n]$ as the first row of chromosomes, where $a_j \in M$ (M represents the set of all equipment). Second, determine the total number of processing tasks n_i on each equipment i based on the above random vector. Then, for each chromosome, the elements in the second row corresponding to equipment i are randomly selected as non-repeating natural numbers from $[1, n_i]$ to determine the processing sequence of corresponding tasks on equipment i.

3.3 Individual Fitness Evaluation

Based on the genetic algorithm model and characteristics of the unrelated parallel machine problem, the fitness function is set as:

$$\text{fitness} = \theta_1 \cdot \frac{C_{\max} - C_{\max}^{\min}}{C_{\max}^{\max} - C_{\max}^{\min}} + \theta_2 \cdot \frac{\sum_{j=1}^{n} f(C_j, d_j) - f_{\min}}{f_{\max} - f_{\min}}$$

where θ_1 and θ_2 are weights for the two objectives.

3.4 Crossover Operation

First, perform two-point crossover on the first row gene strings of two parent individuals. Then, apply the following correction principle to the second row gene strings after two-point crossover. Assume that after two-point crossover, the n_i elements corresponding to equipment i in the second row gene string are $[b_{i1}, b_{i2}, \dots, b_{in_i}]$, then assign the smallest value to new gene value 1, the second smallest to 2, and so on. If after crossover there are k identical values corresponding to new gene value v, then randomly select k different values from $[1, n_i]$ as the corrected gene values for the corresponding positions.

For example, assume the parent individuals for crossover are:

$$A = \begin{bmatrix} 1 & 2 & 3 & 1 & 3 & 2 & 1 & 3 \\ 1 & 1 & 1 & 2 & 2 & 2 & 3 & 3 \end{bmatrix}, \quad B = \begin{bmatrix} 3 & 1 & 2 & 2 & 1 & 3 & 2 & 1 \\ 1 & 1 & 1 & 2 & 2 & 2 & 3 & 3 \end{bmatrix}$$

The symbol " " indicates crossover points. After crossover, the individuals become:

$$A' = \begin{bmatrix} 1 & 2 & 3 & 2 & 1 & 3 & 2 & 1 \\ 1 & 1 & 1 & 2 & 2 & 2 & 3 & 3 \end{bmatrix}, \quad B' = \begin{bmatrix} 3 & 1 & 2 & 1 & 3 & 2 & 1 & 3 \\ 1 & 1 & 1 & 2 & 2 & 2 & 3 & 3 \end{bmatrix}$$

where the underlined positions indicate cases where the second row gene strings corresponding to equipment 1 contain identical gene values after crossover, requiring correction. Applying the above principle to correct the second row gene strings yields the new individuals:

$$A'' = \begin{bmatrix} 1 & 2 & 3 & 2 & 1 & 3 & 2 & 1 \\ 1 & 1 & 1 & 2 & 2 & 2 & 3 & 3 \end{bmatrix}, \quad B'' = \begin{bmatrix} 3 & 1 & 2 & 1 & 3 & 2 & 1 & 3 \\ 1 & 1 & 1 & 2 & 2 & 2 & 3 & 3 \end{bmatrix}$$

3.5 Mutation Operation

The mutation operation can be set as follows: for each gene in the first row, randomly select a real number from (0,1). If the number is less than the mutation probability p_m, randomly select a gene a'_j from M to replace a_j. The second row gene strings of chromosomes are not mutated. However, to preserve as much parent information as possible (referring to the processing sequence of jobs on the same machine), after mutating the first row gene strings, a correction scheme similar to the crossover operation is applied. That is, if after mutation the second row gene strings contain identical values corresponding to new gene values, assign the smallest value to 1, the second smallest to 2, and so on. If there are k identical values corresponding to new gene value v, randomly select k different values from $[1, n_i]$ as the corrected gene values for the corresponding positions.

For example, before mutation, an individual is:

$$\begin{bmatrix} 1 & 2 & 3 & 1 & 3 & 2 & 1 & 3 \\ 1 & 1 & 1 & 2 & 2 & 2 & 3 & 3 \end{bmatrix}$$

After mutating the first row gene strings (underlined positions indicate mutation), the individual becomes:

$$\begin{bmatrix} \underline{2} & 2 & 3 & 1 & \underline{2} & 2 & 1 & 3 \\ 1 & 1 & 1 & 2 & 2 & 2 & 3 & 3 \end{bmatrix}$$

3.6 Algorithm Steps

The iterative steps combining the genetic algorithm model with unrelated parallel machine problem characteristics are as follows:

a) Set parameters: population size h, crossover probability p_c, mutation probability p_m, maximum generations H, and initialize generation counter $l = 0$;

b) Evaluate the fitness values of individuals in the initial population;

c) Check termination conditions. If satisfied, output results; otherwise proceed with the following steps;

d) Perform selection operation based on fitness values to select individuals from the current population;

e) If crossover probability p_c is satisfied, execute crossover operation on selected individuals to produce two temporary individuals; otherwise, use the selected parent individuals as temporary individuals;

f) Execute mutation operation on temporary individuals with probability p_m to produce two new individuals;

g) If the number of new individuals is less than h, return to step e); otherwise, set $l = l + 1$ and return to step b).

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4 Case Study

A simulation of one day' s operation at an automotive maintenance workshop bottleneck equipment is conducted, with each group marked by I, and the proposed method is applied for scheduling. The results are compared with the commonly used First-Come-First-Served (FCFS) rule in maintenance workshop operation sequencing.

Through field research, a normally operating automotive maintenance workshop receives between 20 and 100 maintenance tasks daily, with bottleneck equipment quantity ranging from 6 to 12 units. The bottleneck equipment processing time p_{ij} is uniformly distributed in the interval [0.5, 3] hours. Based on statistical data [13], the task arrival time at bottleneck equipment follows a Poisson distribution in the interval [0, 7], and d_j represents the average processing time of tasks on different types of bottleneck equipment.

The following evaluation metrics are adopted. Define a set of problem instances I with the same characteristics, and let $S \in I$ be a given instance. Let $H(S, A)$ be the objective function value obtained by heuristic algorithm A for instance S. Then the optimal solution for this instance across several heuristic algorithms is $BEST(I) = \min_{A\in\Theta}\{H(S, A)\}$. Accordingly, for each problem type I, the relative performance indicator can be calculated as:

$$\rho(I, A) = \frac{BEST(I)}{H(S, A)}$$

The relative performance indicator is a metric for evaluating algorithm superiority, describing how close the results obtained by an algorithm are to the optimal solution across all algorithms. A relative performance indicator equal to 1 means the algorithm is optimal among all algorithms; the closer the indicator is to 1, the better the algorithm' s performance, though not necessarily optimal.

All algorithms are implemented in MATLAB and run on a Pentium dual-core computer with a 1.73 GHz CPU for experimental simulation. The test results are shown in .

TABLE:1 Scheduling Performance Comparison

Scheduling Performance Parameters	100$×8|100×$12	
FCFS Relative Performance	0.88	0.85
GA Relative Performance	0.95	0.93

The data in the table lead to the following conclusions: The simulation results of the model and algorithm used in this paper are significantly superior; as problem scale increases, the performance advantage becomes more pronounced.

5 Conclusion

Addressing the current situation in enterprises where lack of scientific planning leads to excessively long customer waiting times and low equipment utilization, this paper studies the scheduling problem of bottleneck resources in automotive maintenance workshops. Based on analysis of the diminishing marginal effect characteristics of how early or delayed pickup times affect customer perceived dissatisfaction, the value function from prospect theory is introduced to design a customer perceived dissatisfaction function that includes both general and special cases during the vehicle pickup process. Combined with bottleneck resource characteristics, a multi-objective scheduling model considering both customer perceived satisfaction and resource efficiency is constructed, and a problem-adapted genetic algorithm is designed and proposed. Finally, system simulation with case studies demonstrates that the algorithm in this paper has significant advantages in optimizing objective function values.

The research results enable more rational scheduling of bottleneck equipment in automotive maintenance workshops. First, it can shorten customer waiting times for vehicle pickup, improve customer perceived satisfaction, and thereby enhance enterprise core competitiveness. Second, it can standardize automotive maintenance operation processes, improve maintenance equipment operation efficiency, and reduce actual operation costs. Third, for service system scheduling, it provides a research approach for improving service efficiency and reducing service costs.

Since factors affecting human perception and behavior are numerous and complex, how to more accurately capture customers' perceived satisfaction with scheduling schemes requires further in-depth research. Future plans include: first, using empirical methods to study the setting of customer reference points, time sensitivity, and other perception factors under different categories and scenarios; second, further improving the design of customer perceived satisfaction functions and designing matched algorithms for solution; and finally, combining research results with actual cases.

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Note: Figure translations are in progress. See original paper for figures.