Research Article

A Dish Scheduling Model for Traditional Chinese Restaurants Based on Hybrid Multiple Criteria Decision-Making Algorithms and a Double-Layer Queuing Structure

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Received 29 October 2021; Revised 26 February 2022; Accepted 5 March 2022; Published 30 March 2022

Academic Editor: Yuanchang Liu

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This paper proposes a dish scheduling model for traditional Chinese restaurants based on hybrid multiple criteria decision-making (MCDM) algorithms and a double-layer queuing structure (DLQS). It simulates real-world dish scheduling and may be universally applied. First, several factors that affect the dish ranking were identified, and their weights were determined. Subsequently, a modified Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was used to rank the dishes and enhance the ranking stability after classifying the dishes based on system preset categories. A DLQS was designed to transfer the dishes from the top layer of the queue to the bottom of the queue according to certain rules, so that they could be processed and served in the correct order. The case study indicates that this model may help in the automation of dish scheduling and improve overall customer satisfaction.

1. Introduction

The catering industry is one of the most important branches of the modern service field. Many people eat meals in restaurants every day. In China, as of 2017, there were more than 3.6 million registered catering companies and more than 18 million people working in the industry [1]. To provide fresh and extravagant food for customers, staff in catering companies (i.e., catering managers, chefs, serving personnel, etc.) should take responsibility in their jobs and complete the food processing as soon as possible. With increasing market competition and high customer expectations, catering companies should reasonably plan the dishes’ processing sequence from customers’ orders to obtain the best production efficiency and customer satisfaction. In real-world catering production environments, dishes are usually scheduled by the head chef based on their personal and practical experience. However, dish scheduling in catering companies is quite complex, and manual scheduling may not guarantee both quality and efficiency. Errors by a head chef are more likely to occur as the number of orders and working hours increase. Moreover, chefs usually endure considerable physical and mental pressure, as they are often required to simultaneously maintain the cooking level and respond to customers’ dish processing queries [2]. Recent studies have used algorithms and heuristics to optimize labor use. For instance, Dziurzanski et al. [3] used genetic algorithms to optimize the makespan, energy cost, and cooking quality of dishes for commercial kitchens. In this study, kitchen equipment was assumed to be communal, and several kinds of equipment could be operated simultaneously by one chef. In another study, Sze et al. [4] studied the manpower scheduling for in-flight catering loading operations using an insertion heuristic method. This model attempted to reduce the manpower assignment while ensuring that
catering services were delivered to aircrafts within their transit time at the apron.

Previous studies on dish scheduling have also investigated different strategies to optimize cooking time and dish preparation using various models. Kuo and Nelson [5] used four rules in scheduling dish preparation in a cafeteria. The four rules were as follows: the shortest processing time (SPT), longest processing time (LPT), longest holding and shortest processing time (LHSHP), and the longest holding and longest processing time (LHLSP). Their case study showed that the LHSHP performed best in increasing the labor use and reducing the makespan. Nakabe et al. [6] optimized the cooking procedure with the extended parallelized depth first/implicit heuristic search (PDF/IHS) to reduce the cooking time. Kimura et al. [7] investigated an approach to schedule cooking in a family restaurant. The model was designed based on the slack rule for an oven-baked scenario, where dishes were required to be repeatedly processed. Here, “slack” refers to a job with the least margin until its deadline being given the highest priority. In addition, the authors attempted to develop a preferred schedule, where multiple dishes from an order could be served simultaneously. Dai and Fan [8] developed a scheduling model for takeout restaurants by comparing four scheduling strategies and evaluating them using the rate of completed customer orders. In the study, each scheduling strategy considered one factor such as the dish’s processing time. There were no requirements on the serving order of dishes. Matsushima and Funabiki [9] developed a static model for home cooking to minimize the total cooking time. In this model, the cooking procedure is divided into a sequence of several cooking steps. An exhaustive search was applied to identify the optimal order of cooking for a limited number of dishes, while simulated annealing (SA) was adopted for scenarios involving many dishes.

Several studies have also used computer technologies and robotics to optimize dish production. For instance, Yi et al. [10] adopted a mixed-integer programming (MIP) method to seek the best dish production sequence for a dual-arm robot. Noone and Coulter [11] suggested applying modern robotics to enhance the production efficiency of American quick-service restaurants. They used computer vision technologies to sense the customer flow, so that the production could be effectively planned. Moreover, partial freezers were used for batch production in Japanese cuisine restaurants to improve the production efficiency and quality [2]. Yamakata et al. [12] proposed to use “recipe tree” (a structure similar to workflow) to realize the parallel production. Nonaka et al. [13] pointed out that the serving order of dishes could affect the customer satisfaction, and they proposed to set an extra area for temporary storage to ensure the serving order.

To sum up, these studies searched for the best dish scheduling rule to optimize the cooking time, labor use, and ability to simultaneously provide dishes for a certain type of restaurant cuisine. However, dining habits and preferences vary across cultures and regions. For example, the order in which dishes are served is important in traditional Chinese restaurants. Cold dishes are usually served as the appetizer, and desserts are the final course. In addition, there is a serving interval between dishes. The serving interval should be moderate; otherwise, it may cause customer dissatisfaction or a deterioration in the quality of the dish. Moreover, traditional Chinese restaurants will take the customer priority (CP) and the number of people per table (NPPT) into account in dish scheduling, except for the dishes’ holding or waiting time (WT) and processing time (PT). This can be regarded as a classic multiple criteria decision-making (MCDM) problem.

This study proposes a model based on hybrid MCDM algorithms and a double-layer queuing structure (DLQS) to schedule dishes for traditional Chinese restaurants. The factors that affected the dish’s ranking were surveyed from local catering companies via questionnaires. Their weights were determined using the Analytic Hierarchy Process (AHP). A modified Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was adopted to rank the dishes and enhance the ranking stability after they were classified by the system preset categories. To ensure that the dishes from different categories were served in the correct order, a DLQS was designed, and it was also used to maintain an ideal serving interval between dishes. The case study indicates the model’s feasibility.

The remainder of this study is organized as follows: Section 2 introduces the methodologies that are the established hierarchical structure of the orders and cooking benches, the AHP method, and the modified TOPSIS method. Section 3 introduces the DLQS and the detailed dish scheduling process. The dish scheduling experiment is presented in Section 4, in which a case study is conducted to verify the model’s feasibility. The paper is concluded in Section 5.

2. Methodology

Traditional Chinese restaurants usually set up a few types of posts to process dishes from different categories, such as frying, steaming, and roasting. Each post contains several cooking benches, and every chef works at their designated bench. This structure may help enhance the productivity levels of each chef and ensure optimal dish quality [2]. The dishes from different orders will be assigned to their corresponding production posts after the kitchen receives the orders from customers. A dish should subsequently be selected to have priority processing by considering multiple criteria. In this section, an order’s hierarchical structure and the cooking benches’ layout are presented. Furthermore, the AHP method and the modified TOPSIS method are introduced. They are used to determine the criterion weights and rank the dishes, respectively.

2.1. The Hierarchical Structure of an Order and Cooking Benches. Assume that a catering company sets $n$ kinds of posts, and then the post set $P$ can be denoted as $P = \{p_1, p_2, p_3, \ldots, p_i, \ldots, p_n\}$, where $p_i$ represents the $i^{th}$ post in the post set. A customer order $O$ can be denoted as $O = \{o_{1}, o_{12}, \ldots, o_{nk}, \ldots, o_{np}\}$, where $o_{ik}$ represents the $k^{th}$ dish that should be processed by the $i^{th}$ post.
As shown in Figure 1, there are six dishes in the customer’s order, and they can be classified into three posts. Every dish has its preset category and will be classified to the corresponding post to be processed. \( o_{11} \) and \( o_{12} \) are classified to \( p_1 \), \( o_{21} \) and \( o_{22} \) are classified to \( p_2 \), and so on. In this instance, each post contains three cooking benches. For example, \( p_{11} \), \( p_{11} \) and \( p_{13} \) are cooking benches that belong to \( p_1 \). The number of posts and cooking benches varies according to the production environment. However, the hierarchical structure of an order and the cooking benches may be similar in different traditional Chinese restaurants.

2.2. The AHP Method. The AHP method was proposed by Saaty in 1977 to calculate the weights of a set of alternatives according to their importance relationship [14]. It is a well-known qualitative and quantitative hierarchical analytical method and has been used in many fields for alternative selection and evaluation [15–19]. The alternatives’ weights can be calculated by constructing the hierarchical structure of the target problem and analyzing the importance relationship of the elements in each layer. To ensure the evaluation result’s validity, it is strongly suggested to check each layer’s consistency [19]. Since knowledge of the prior criteria is not required, and the expert experience can be adequately considered, AHP may be more widely accepted by catering managers to determine the weights of the criteria that may influence the dish ranking process. The calculation of criterion weights by the AHP method may be described as follows:

**Step 1.** Assume that there are \( n \) criteria that are needed to determine the importance relationship. These criteria are evaluated by pairwise comparison with a scale of one to nine (as shown in Table 1).

Thus, a pairwise comparison matrix with a size of \( n \times n \) can be obtained as shown in

\[
A = \begin{pmatrix}
    a_{11} & a_{12} & \cdots & a_{1n} \\
    a_{21} & a_{22} & \cdots & a_{2n} \\
    \vdots & \vdots & \ddots & \vdots \\
    a_{n1} & a_{n2} & \cdots & a_{nn}
\end{pmatrix}_{n \times n}
\]

Denote \( a_{ij} \) as the element of \( i^{th} \) row and \( j^{th} \) column in \( A \), \( a_{ij} \) meets \( a_{ij} = 1/a_{ji} \), \( i = 1, 2, 3, \ldots, n \), \( j = 1, 2, 3, \ldots, n \). It is clear that \( a_{ii} = 1 \) when \( i \) is equal to \( j \).

**Step 2.** Compute the weight vector \( W \) using the row geometric mean method (RGMM) [20, 21]. The criterion weights can be obtained from

\[
w_i = \left( \prod_{j=1}^{n} a_{ij} \right)^{1/n}, \quad i = 1, 2, 3, \ldots, n.
\]

**Step 3.** The largest eigenvalue of \( A \) can be computed as

\[
\lambda_{\text{max}} = \frac{1}{n} \sum_{j=1}^{n} \left( AW \right)_j/w_i
\]

**Step 4.** Compute the consistency index (CI) using

\[
CI = \frac{\lambda_{\text{max}} - n}{n - 1}
\]

**Step 5.** Compute the consistency ratio (CR) of the pairwise comparison matrix using

\[
CR = \frac{CI}{RI}
\]

where \( RI \) is the random index defined by Saaty [22]. It is related to the scale of the pairwise comparison matrix (see Table 2). The consistency check can be passed if \( RI < 0.1 \).

2.3. The Modified TOPSIS Method. TOPSIS was proposed by Hwang and Yoon [23] and further developed by Yoon [24] and Hwang et al. [25]. It is a famous MCDM algorithm that has many advantages. The advantages include a logical framework, a fully utilizable original alternative information, and basic programming implementation [26–28]. Thus, it has been widely implemented in many fields [29]. The simplicity and high computational performance of TOPSIS are in demand in dynamic and large-scale dish scheduling environments. In addition, TOPSIS has been a practical and popular MCDM algorithm when combined with AHP for alternative ranking [30–32]. Salabun et al. [33] undertook an attempt to benchmark multiple MCDM algorithms. The experimental results showed that TOPSIS was well correlated with other MCDM algorithms such as PROMETHEE II [34] and COPRAS [35, 36].
However, there may be a rank reversal when using TOPSIS. This means that the order of alternatives may change when an alternative is added or deleted [37, 38]. Rank reversal exists not only in TOPSIS, but also in many other MCDM algorithms. These include AHP, VIKOR, and PROMETHEE [39, 40]. The conventional vectorial normalization method of TOPSIS is believed to be the main cause of rank reversal because it will affect the alternatives’ independence in a calculation [37, 41–43]. A modified TOPSIS proposed by Aires and Ferreira [41] was adopted to help improve the stable ranking in this study. We adopted the Max-Method recommended by the authors for criterion normalization, since it performs well in similarity and dispersion with conventional TOPSIS [41].

We assumed that there was an alternative set with \( n \) alternatives for decision-making (ranking). \( X_i \) was the \( i \)th alternative in the set, \( i = 1, 2, 3, \ldots, n \). The number of criteria was \( m \) and the criterion set was denoted as \( C = \{ c_1, c_2, \ldots, c_m \} \). Criterion \( c_j \)’s weight is \( w_j \) and \( c_j \)’s data that belonged to alternative \( X_i \) is \( x_{ij} \), \( j = 1, 2, 3, \ldots, m \). \( n_{ij} \) and \( r_{ij} \) denoted the normalized data and weighted normalized data of \( x_{ij} \), respectively. Thus, the implementation steps of the modified TOPSIS for alternative ranking could be described as follows:

**Step 1.** Calculate the normalized decision-making matrix \( (n_{ij}) \).

In the conventional TOPSIS, the vectorial normalization method is used, which is indicated by

\[
n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}}, \quad i = 1, 2, 3, \ldots, n, \quad j = 1, 2, 3, \ldots, m.
\]

To improve ranking stability, the Max-Method is recommended to normalize the criterion data as

\[
n_{ij} = \frac{x_{ij}}{\max(c_j)}, \quad i = 1, 2, 3, \ldots, n, \quad j = 1, 2, 3, \ldots, m,
\]

where \( \max(c_j) \) is the possible maximum of \( c_j \).

**Step 2.** Calculate the weighted normalized matrix \( (r_{ij}) \) from

\[
r_{ij} = w_j \cdot n_{ij}, \quad i = 1, 2, 3, \ldots, n, \quad j = 1, 2, 3, \ldots, m.
\]

**Step 3.** Obtain the positive ideal solution (PIS) and negative ideal solution (NIS). In the conventional TOPSIS, PIS and NIS can be obtained as equations (9) and (10), respectively:

\[
PIS = \{r_{1^*}^+, r_{2^*}^+, \ldots, r_{j^*}^+, \ldots, r_{m^*}^+\}
\]

\[
r_{j^*}^+ = \begin{cases} \max(r_{ij}|i = 1, 2, \ldots, n), & \text{if } c_j \in BC \end{cases}
\]

\[
PIS = \{r_{1^-}, r_{2^-}^-, \ldots, r_{j^-}^-, \ldots, r_{m^-}\},
\]

\[
r_{j^-} = \begin{cases} \min(r_{ij}|i = 1, 2, \ldots, n), & \text{if } c_j \in CC \end{cases}
\]

In the modified TOPSIS, they can be calculated using (11) and (12):

\[
PIS = \{r_{1^*}^+, r_{2^*}^+, \ldots, r_{j^*}^+, \ldots, r_{m^*}^+\},
\]

\[
r_{j^*}^+ = \begin{cases} w_j, & \text{if } c_j \in BC \\
\frac{\min(c_j)}{\max(c_j)}, & \text{if } c_j \in CC \end{cases}
\]

\[
PIS = \{r_{1^-}, r_{2^-}^-, \ldots, r_{j^-}^-, \ldots, r_{m^-}\},
\]

\[
r_{j^-} = \begin{cases} \frac{\min(c_j)}{\max(c_j)} w_j, & \text{if } c_j \in BC \\
w_j, & \text{if } c_j \in CC \end{cases}
\]

where \( \min(c_j) \) is the possible minimum of \( c_j \). BC refers to the "Benefit Criterion," and CC refers to the "Cost Criterion."

**Step 4.** Calculate the distance from alternative \( t_b \) to \( t_d \) and \( t_i \) as equations (13) and (14), respectively:

\[
D_i^+ = \sqrt{\sum_{j=1}^{m} (r_{ij} - r_j^+)^2}, \quad i = 1, 2, 3, \ldots, n.
\]

\[
D_i^- = \sqrt{\sum_{j=1}^{m} (r_{ij} - r_j^-)^2}, \quad i = 1, 2, 3, \ldots, n.
\]

**Step 5.** Calculate the closeness coefficient of alternative \( X_i \):

\[
f_i = \frac{D_i^-}{D_i^- + D_i^+}, \quad i = 1, 2, 3, \ldots, n.
\]

**Step 6.** Rank the alternatives in a descending order of their closeness coefficients.

### 3. Applied Approach

#### 3.1. Double-Layer Queuing Structure

As mentioned in Section 1, traditional Chinese restaurants should serve dishes in the correct order. For example, fried dishes are
often served after the cold dishes and soups, while desserts should be served at the end. This is the convention that catering managers should follow and what customers in China expect. Hence, it is optimal to process dishes from different categories in a rigorous order.

In addition, the serving frequency should be set to improve the customer’s dining experience. From the questionnaires with catering managers of local catering companies, we can confirm that a serving interval of between two to ten minutes is preferable in traditional Chinese restaurants. To meet the above requirements, a DLQS was designed for each post, in which the bottom layer of the queue was executed according to the order placed in the queue. All dishes in the top layer of the queue were ranked, so that a list of ready dishes could be obtained. The time that a ready dish took to arrive at the bottom layer of the queue was determined by its priority, PT, the expected completion time of the preceding dish, and so on. The overall DLQS is shown in Figure 2.

3.2. Criteria for Dish Ranking. By surveying local catering companies, four independent factors were obtained as the criteria that should be taken into consideration in dish ranking decision-making. These are the dish’s WT, CP, NPPT, and PT. It is noteworthy that these four criteria can be classified into the benefit and cost types. Regarding the benefit type, the larger the criterion is, the better it is regarded to be. The opposite is true for the cost type, such that the larger the criterion is, the worse it is regarded to be. Generally, the dish’s WT, CP, and NPPT are a part of the benefit type, while the dish’s PT is part of the cost type.

Based on the above, the application objectives may be divided into two levels when using AHP. These are the general scheduling objective and its subobjectives. The hierarchy of the objectives is shown in Figure 3. The subobjectives are composed of four elements: (1) the shortest WT, (2) the best response to CP, (3) the highest balance of the tables, and (4) the most efficient production. They correspond to the four criteria mentioned above. The highest balance of the tables indicates that the dishes from the order (table) with more people should be given priority to be processed. In addition, the most efficient production means that the dishes with shorter processing times should be processed earlier, and so on.

3.3. Dish Scheduling Process. The dish scheduling process with DLQS can be outlined as follows:

**Step 1.** Classify all newly added dishes to the top layer of the queue of their corresponding posts. Dishes’ corresponding posts and PTs should be set as default parameters in advance.

**Step 2.** Rank all the dishes in the top layer of the queue for each post. A dish with the highest ranking will be the ready dish that belongs to this post from one customer’s order. The list of ready dishes can be obtained from Figure 2.

**Step 3.** Based on the priorities and preset processing order of the different posts, dishes in the same order are linked. Therefore, every dish except the first one has its preceding dish.

**Step 4.** Dynamically calculate all the unprocessed dishes’ expected completion times. Thereafter, determine whether the ready dishes have met the waiting requirements to join the bottom of the queue.

An unprocessed dish will be preallocated to a bench where the total PT is minimal. We assumed that the selected bench’s total PT was $t_b$ and that the dish’s default PT was $t_d$. Thereafter, the dish’s ideal expected completion time $t_i$ may be calculated as (without considering the delivering time)

$$t_i = t_b + t_d.$$  \hspace{1cm} (16)

We set an ideal serving interval $s$. $s$ should be 0 if the dish was the first one in the customer’s order. We assumed that if the expected completion time of a dish’s preceding dish was $t_p$, then the ideal serving time of this dish $t_s$ should be

$$t_s = t_p + s.$$  \hspace{1cm} (17)

A dish from high to low priority in the top layer of the queue can be preallocated to a bench with the following rules: if it is $t_i \geq t_s$, it means that the dish may exceed the ideal serving time. The current bench may be immediately preallocated to this dish, and its expected completion time will be $t_i$. Moreover, the dish meets the waiting requirements to join the bottom of the queue if it is a ready dish. When there is no dish matching the above condition, the bench will be preallocated to the dish that has the minimum value of $(t_s - t_i)$ among the prior dishes from different orders. The dish’s expected completion time will be $t_s$.

**Step 5.** Ready dishes will not join the bottom of the queue until they meet the waiting requirements. This serves to ensure orderly processing and ideal serving interval between dishes from the same order. If the number of ready dishes that meet the requirements is more than the number of vacant seats in the bottom of the queue, the ready dishes will be transferred from a high to a low priority.

The overall flowchart of dish scheduling can be seen in Figure 4.

4. The Dish Scheduling Experiment

The calculation process of the weights of the four criteria by the AHP method is presented in this section. In addition, a dish ranking experiment is performed to verify the ranking difference using the conventional and modified TOPSIS. Moreover, an indicator called the “mean weighted tardiness” is defined, and a case study is conducted to test the proposed model’s performance.
4.1. Criterion Weighting. An experienced catering manager was invited to score the importance relationship between the four criteria mentioned in Section 3.2 using a nine-point scale (see Table 1). The pairwise comparison matrix can be constructed in Table 3. The weight vector can be obtained as \( W = [0.5562, 0.2699, 0.1091, 0.0648] \) by equation (2). The largest eigenvalue of the pairwise comparison matrix \( \lambda_{\text{max}} \) can be calculated as 4.0931.

The consistency index (CI) can be calculated as

\[
CI = \frac{\lambda_{\text{max}} - n}{n - 1}
\]

\[
= \frac{4.0931 - 4}{4} = \frac{0.0931}{4} = 0.0310,
\]

Figure 2: A post’s double-layer queuing structure.

Figure 3: The evaluation factors for dish selection.

Figure 4: Overall flowchart of dish scheduling.
where \( n \) represents the scale of the pairwise comparison matrix.

The corresponding random index (RI) can be found in Table 2. It allows us to review the consistency of the pairwise comparison matrix to determine whether the comparative result is reasonable. The consistency ratio (CR) can be calculated as

\[
CR = \frac{CI}{RI} = \frac{0.0310}{0.9} = 0.0344 < 0.1.
\]

Thus, the consistency examination can be passed, and the criterion weights are reliable.

4.2. Dish Ranking. We simulated the procedure of dish ranking for a certain post as an example. There are six dishes waiting to be cooked, namely, C1–C6, and the corresponding WTs, CPs (small number means low priority), NPPTs, and PTs are indicated in Table 4.

The dishes were ranked using four MCDM algorithms, which were the modified TOPSIS, the conventional TOPSIS, PROMETHEE II, and COPRAS. The V-shape preference function was chosen when using PROMETHEE II, so that the differences between criteria can be adequately considered in the decision-making process. Table 5 shows the ranking results. We note that the possible maximums of the criteria for normalization should be larger or equal to all real criterion data when using the modified TOPSIS, or the normalized data may be larger than one.

Spearman’s rank correlation coefficient [33, 44] was calculated to assess the similarity of the rankings. The calculated coefficients are shown in Table 6. The results show that the ranking with the modified TOPSIS is well correlated with that of the other three MCDM algorithms in this example.

### 4.3. Scheduling Performance Indicator

In the manufacturing industry, the mean flow time, tardiness, and cost are usually set as indicators for evaluating the scheduling methods [45–49]. Sometimes, it is necessary to conduct the evaluation with multiple factors. In the catering industry, it is more suitable to select the overall customer satisfaction as the indicator. The overall customer satisfaction is related to the tardiness of the orders, the CP, the NPPT, and so on. Although the weighted sum method [48, 50, 51] is proposed to be effective for a comprehensive evaluation, it is not recommended in the dish scheduling environment. This is because the factors mentioned above are significantly different in terms of their nature and dimensions. This study proposes mean weighted tardiness to represent the overall customer satisfaction with a catering company. This is calculated by multiplying the above factors where each factor has a corresponding coefficient. The mean weighted tardiness is a form of simple calculation based on the weighted tardiness of each order.

As we assumed that there were \( m \) orders in the system, and the \( i^{th} \) order included \( n \) dishes. The weighted tardiness of the \( j^{th} \) dish \( t_{wt}(j) \) can be calculated as (20):

\[
t_{wt}(j) = [t_{rc}(j) - t_{sd}(j)] \cdot \left\{1 + [CP(i) - CPM] \cdot W_{CP}\right\} \cdot \left\{1 + [NP(i) - NPM] \cdot W_{NP}\right\},
\]

where \( t_{sd}(j) \) denoted the ideal completion time of \( j^{th} \) dish and \( t_{rc}(j) \) denoted its real completion time. They were recorded in minutes. \( CP(i) \) was the CP and \( NP(i) \) was the NPPT of the \( i^{th} \) order. The system’s minimum CP was \( CPM \) and the minimum NPPT was \( NPM \). The coefficient of CP was \( W_{CP} \) and that of NPPT was \( W_{NP} \). Note that \( t_{wt}(j) \) should be zero if the calculation result is below 0.

Thus, the weighted tardiness of \( i^{th} \) order \( T_{wt}(i) \) and the mean weighted tardiness \( T_{mwt} \) can be calculated as (21) and (22):

\[
T_{wt}(i) = \sum_{k=1}^{n} t_{wt}(k), i = 1, 2, 3, \ldots, m,
\]

\[
T_{mwt} = \frac{1}{m} \sum_{k=1}^{m} T_{wt}(k), i = 1, 2, 3, \ldots, m.
\]

4.4. Case Study and Discussion

Fifty-four of the most popular dishes were selected from a local traditional Chinese restaurant that has been in business for over a decade. They were numbered and classified into five categories. The dish set and post information are depicted in Table 7.

To maintain the correct order of the dishes to be served, DLQS is retained in the experiment. The dishes are ranked based on four rules including AHP combined with Modified TOPSIS (ACMT), First Come First Serve (FCFS), SPT, and LPT. The performance of the four ranking rules was tested in different conditions, that is, while the number of orders varied from 10 to 50, and the order creation interval varied from 10 to three minutes accordingly. We attempted to develop a simulation environment that closely corresponded
to the real world. One-fifth of the simulated orders had a random priority from two to five, while the priorities of the other orders were one. The ideal serving interval between the dishes in the same order was two minutes. The detailed rules for creating an order are indicated in Table 8. Dishes were randomly selected from the dish set, and the number of dishes was in proportion to the number of people placing the order.

We conducted 10 repeated experiments for each tested production environment with a limited number of orders. The orders were prepared according to the rules listed in Table 8. CPM was set to one, and NPM was set to five. $W_{CP}$ and $W_{NP}$ were constants 0.2 and 0.02, respectively. We ranked the dishes with the four rules mentioned earlier and scheduled them with the DLQS. Each dish’s tardiness can be recorded, so that the weighted tardiness of the different orders and the mean weighted tardiness may be calculated. Figure 5 shows the ranking results of these four rules regarding the mean weighted tardiness, while the exact calculation value is indicated in Tables 9–11.

As indicated in Figure 5, ACMT performs best in reducing the mean weighted tardiness, followed by the FCFS, SPT, and LPT. ACMT achieves this optimization because it can consider the MCDM process. It is beneficial to process these dishes with the SPT rule when there are a limited number of orders because the labor is sufficient, and all dishes can be processed in a timely manner. This is consistent with the conclusions of scheduling theory, in which the job with the SPT should be completed first [52]. SPT may be adopted in such scenarios. In contrast, with the increase in customer orders, it is possible that the processing ability may not satisfy the production requirements. Due to the strict processing order of the dishes from the different categories, scheduling by SPT means that the dishes with the LPTs will be processed at the end of each post. Thus, an unplanned delay of other posts may occur.
Table 9: Mean weighted tardiness with 10 orders.

| ACMT  | Rank of ACMT | FCFS  | Rank of FCFS | LPT   | Rank of LPT | SPT   | Rank of SPT |
|-------|--------------|-------|--------------|-------|-------------|-------|-------------|
| 237.2 | 3            | 229.4 | 2            | 305.8 | 4           | 173.4 | 1           |
| 91.2  | 1            | 121.7 | 3            | 124.5 | 4           | 91.5  | 2           |
| 140.5 | 1            | 159.4 | 4            | 142.0 | 3           | 140.5 | 2           |
| 141.3 | 2            | 140.1 | 1            | 166.8 | 4           | 145.4 | 3           |
| 92.2  | 1            | 96.9  | 4            | 95.7  | 3           | 93.1  | 2           |
| 213.2 | 1            | 251.9 | 4            | 234.2 | 3           | 213.5 | 2           |
| 203.4 | 4            | 201.8 | 2            | 196.9 | 1           | 202.2 | 3           |
| 173.5 | 3            | 175.8 | 4            | 164.2 | 1           | 171.8 | 2           |
| 168.5 | 2            | 147.8 | 1            | 200.5 | 4           | 173.3 | 3           |
| 118.5 | 3            | 118.2 | 2            | 119.6 | 4           | 113.5 | 1           |

Table 10: Mean weighted tardiness with 20 orders.

| ACMT  | Rank of ACMT | FCFS  | Rank of FCFS | LPT   | Rank of LPT | SPT   | Rank of SPT |
|-------|--------------|-------|--------------|-------|-------------|-------|-------------|
| 637.5 | 2            | 621.3 | 1            | 1141.8| 4           | 702.4 | 3           |
| 801.8 | 1            | 859.0 | 2            | 1259.9| 4           | 927.4 | 3           |
| 727.2 | 1            | 747.5 | 2            | 1307.9| 4           | 943.3 | 3           |
| 766.4 | 2            | 760.9 | 1            | 1096.9| 4           | 927.4 | 3           |
| 662.3 | 1            | 752.0 | 3            | 1030.9| 4           | 674.1 | 2           |
| 629.2 | 2            | 610.9 | 1            | 871.7 | 4           | 729.4 | 3           |
| 1066.6| 1            | 1079.7| 2            | 2167.7| 4           | 1435.5| 3           |
| 660.3 | 2            | 662.9 | 3            | 897.6 | 4           | 625.7 | 1           |
| 655.7 | 1            | 670.6 | 2            | 1088.1| 4           | 816.2 | 3           |
| 558.3 | 1            | 566.5 | 2            | 754.9 | 4           | 572.0 | 3           |

Table 11: Mean weighted tardiness with 50 orders.

| ACMT  | Rank of ACMT | FCFS  | Rank of FCFS | LPT   | Rank of LPT | SPT   | Rank of SPT |
|-------|--------------|-------|--------------|-------|-------------|-------|-------------|
| 2765.6| 1            | 3085.5| 2            | 5394.0| 4           | 3570.0| 3           |
| 2220.8| 2            | 2154.4| 1            | 3461.1| 4           | 2657.8| 3           |
| 2921.6| 1            | 2942.5| 2            | 6481.8| 4           | 3434.1| 3           |
| 2612.9| 1            | 2794.6| 2            | 4477.7| 4           | 3033.8| 3           |
| 3242.6| 2            | 3188.8| 1            | 5542.9| 4           | 4018.3| 3           |
| 2566.1| 1            | 2589.3| 2            | 3958.2| 4           | 2686.5| 3           |
| 1888.6| 2            | 1710.1| 1            | 5291.9| 4           | 2425.9| 3           |
| 2162.2| 1            | 2609.5| 2            | 4353.9| 4           | 2946.3| 3           |
| 3163.8| 1            | 3456.8| 2            | 6705.0| 4           | 4073.7| 3           |
| 2506.0| 1            | 2932.3| 2            | 5389.8| 4           | 3187.1| 3           |
and impact the production efficiency. Moreover, it should be noted that, in real-world production environments, the dish with a longer WT is given a higher priority. FCPS can be considered as a suitable scheduling solution in busy scenarios, which is consistent with the above analysis. However, it is not recommended to be adopted when there are a limited number of dishes because the dishes with shorter processing times have fewer advantages. LPT is not the optimal solution to reducing the mean weighted tardiness. Generally, ACMT can be trusted in both quiet and busy scenarios.

Notably, the DLQS designed in this study performed robustly for the processing and serving of dishes from different categories in the correct order in the experiment. Furthermore, the performance of different ranking rules was tested further by adjusting $W_{CP}$ and $W_{NP}$. $W_{NP}$ was adjusted from 0.01 to 0.04, and $W_{CP}$ was adjusted from 0.1 to 0.4. The result showed that ACMT remained optimal.

5. Conclusions

This paper proposes a dish scheduling model for traditional Chinese restaurants using hybrid MCDM algorithms and DLQS. The model may be universally applied. AHP was adopted to determine the factors’ weights, which may affect the dish scheduling. A modified TOPSIS was used to rank the dishes after they were classified to their corresponding posts. This paper also designed a DLQS to ensure that dishes from different categories were processed and served in the correct order. It was robust in the experiment. To test the proposed model’s performance, mean weighted tardiness was defined to indicate the overall customer satisfaction. It was calculated from the orders’ tardiness, the CP and NPPT. The case study indicates this model’s feasibility.

Meanwhile, the model’s performance may vary slightly with the production environment. It is beneficial to analyze and establish the relationship between ranking rules and order characteristics to choose the optimal scheduling model for dish production. Although the automation of dish scheduling is convenient for catering companies, the flexibility should be maintained. For example, it is common to adjust the priorities of different customers in the dish processing period to address customers that may have special demands. The working efficiency may be further improved by permitting the same dishes from different orders to be processed simultaneously. In the present study, the results of the modified TOPSIS method did not show rank reversal, but this may occur in other studies. These limitations should be acknowledged and considered in future work. Moreover, the model proposed in this study remains to be integrated into the real-world production systems, such as catering companies, for further testing.

Data Availability

All data generated during the study are included in this article.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

The authors would like to thank Taizhou Wanglin Hotel and Taizhou Xiaobao Hotel for the detailed description of the problem, providing production information and helping them to evaluate the research results.

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