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A Novel Cancellation Protection Service in Online Reservation System

ZHALEH SADREDDINI
Department of Computer Engineering, Istanbul Arel University, Istanbul, Turkey (e-mail: zhalehsadreddini@arel.edu.tr)
Corresponding author: Zhaleh Sadreddini (e-mail: zhalehsadreddini@arel.edu.tr).

ABSTRACT Web-based systems are frequently used by the customers as well as travel agencies for online flight reservation and booking. In general, customers prefer to plan their trips as early as possible to take advantage of affordable booking opportunities as the price of flight tickets increases over time. However, changing the flight plan may lead to high penalties for the customers which may turn their profits into a loss in promotion tickets. Motivated by this, in this research work, quality of experience (QoE)-based approach is proposed to support user satisfaction in the aforementioned scenario. A cancellation protection service (CPS) is developed to provide assurance for early booking while establishing a balance between user satisfaction and the profit of the service provider (SP). Furthermore, three different CPS functions, namely Fixed CPS, QoE-based CPS, and Flexible CPS are modeled. In our proposed QoE-based CPS method, Analytic Hierarchy Process (AHP) is adopted to assign appropriate weights to different criteria. The proposed CPS approach can enable the customers to have a refund under certain terms if they decide to cancel their tickets. The proposed method is analyzed with real-world data from an airline reservation system which shows the customer transactions in a 6 months-period. The results indicate the effects of the fixed CPS, flexible CPS, and QoE-based CPS methods in the SP's profit points of view. Last but not least, the proposed QoE-based CPS method provides a balance between both the SP profit and user satisfaction.

INDEX TERMS Airline industry, Data analysis, Decision making, Quality of Experience, Online reservation system, Revenue management, Reservation cancellation.

I. INTRODUCTION

THE desire for constant improvement acts as a catalyst that triggers advancements in all industries and the airline industry is not an exemption. Airline reservation systems were first introduced in the late 1950s as relatively simple standalone systems to control flight inventory, maintain flight schedules, seat assignments and aircraft loading [1]. Today, modern airline reservation systems are comprehensive suites of products providing solutions that assist with a large variety of airline management services, from initial reservation to completion of the flight. The Internet has become a major resource for online airline reservation systems while removing the hassle of meeting travel agents. These online reservation systems ensure that the reservations are not only generated and maintained by the airline's own staff but also, they can be managed by travel agents, or other airlines (that have a multilateral Interline Traffic Agreement) using a Global Distribution System [1]. To this end, there is a great interest in research towards designing a modern, flexible online reservation system. These systems include but are not limited to, call centers, travel agencies, internet engines, and global distribution systems. Many are further interested in designing an optimal online reservation system that facilitates online booking and flight schedule with a focus on the service quality. Nowadays, Quality of Experience (QoE) has become one of the most important indicators measuring customers' actual satisfaction with the service received. Consequently, QoE can be regarded as a user-centric characterization of service quality [2].

In the airline industry, as the price of flight tickets increases over time, customers prefer to plan their trips as early as possible to take advantage of affordable booking opportunities. However, changing the flight plan may lead to high penalties for the customers which may turn their profits into a loss. Motivated by this, some airline companies and agencies propose the *cancel for any reason* insurance. This coverage provides a fixed percentage of customers' total trip costs if they have to cancel their trip within 24 hours of buying the ticket for any reason not listed in the standard coverage. The author in [3] shows that how much coverage each company

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provides for the canceled trip. In this study, a QoE-based cancellation guarantee approach is proposed which allows users to cancel their flight ticket up to 2 hours before the flight departure (instead of 24 hours) where 90% refund of their ticket price is guaranteed. The proposed system has several features:

- **Points to Flight**: it allows customers to purchase flight tickets using the points in their credit cards.
- **Flight Price Chart**: this allows customers to buy flight tickets from different airlines, assisting them in comparing real-time ticket prices.
- **Cancellation Protection Service (CPS)**: this is one of the pivotal features to keep the customers satisfied (e.g., high QoE), as using this feature, customers can buy their tickets without worrying about the cancellation of their tickets. This service can be purchased at the booking stage while buying a flight ticket. The rules and conditions of the *cancel for any reason* are described in [4].

The main topic of this study is to design an efficient CPS that is based on the user's experience when things do not go as planned. In order to design a more flexible CPS, decision based data analysis in the centralized online reservation system is applied [4]. After data collection, decision-making method is used to analyze the customer transaction process, categorizing them as *cancel* or *flight*. Then, three different CPS methods are presented such as Fixed CPS, QoE-based CPS, and Flexible CPS, which calculate a CPS fee in each ticket purchasing transaction under the multi criteria decision making methods.

In the CPS implementation section, the proposed Fixed CPS considers two main criteria based on the ticket type (e.g., promotion or flexible) and the flight type (e.g., domestic or international). Although the proposed Fixed CPS method is simple, it can not meet customers' expectations in case of considering their history based on the total ticket cancellation with or without CPS. For instance, suppose that there are two customers, one of which has 10 bookings with CPS and without any cancellation, and the other one is the new customer without any booking history. Both of them will pay the same CPS fee via the Fixed CPS method. To overcome this situation, we propose the QoE-based CPS. This method uses the Analytical Hierarchy Process (AHP) for taking appropriate decisions enhancing user satisfaction based on the customer's criteria. AHP is one of the most inclusive systems that make decisions using multiple criteria [5]. The proposed utility function is modeled in regard to the optimal importance degree of each customer's criterion under the consistency ratio (CR). Finally, the Flexible CPS method is designed based on the user history but not as comprehensive as QoE-based CPS method. While the Flexible CPS method eliminates the deficiencies of the Fixed CPS method, it shows that the QoE-based CPS method based on different criteria is more efficient. The main aim of implementing the flexible CPS is to present the advantages of using different customer criteria employed in QoE-base CPS method, which leads to user satisfaction through the calculation of a more appropriate CPS fee in relation to the customer history. In Section III, 4 different scenarios are analyzed in order to show the performance of the proposed CPS schemes. Finally, in the simulation section, customer transactions are considered in conjunction with the real data which are gathered by the real-world data center of Turna.com [4]. The data analysis highlights the CPS usage ratio, where the proposed QoE-based CPS method provides a balance between both the SP profit and user satisfaction.

A. RELATED WORKS

In the airline business, in order to increase the QoE, and consequently, to maximize the SP's revenue, an accurate estimation of the number of no-show passengers is analyzed in [6]. Another study [7] investigates how competition influences profitability and equilibrium choice of refund policies. In [8], the authors describe that customers with a confirmed booking may cancel their reservation at any given time or become a no-show. These customers are provided with different probabilities and different refunds. The authors formulated the problem as a discrete-time Markov Decision Process (MDP) and used dynamic programming to analyze it. Author in [9] proposed a novel Optimal airfare Ticket Purchase decision-support Service (OTPS) which suggests the best ticket purchase time before the departure time.

Regarding the decision aid approach, in [10], the AHP method is used in the selection of the aircraft type. Authors in [11], propose Fuzzy AHP (FAHP) as an effective solution for resolving the uncertainty and imprecision in the evaluation of airlines' competitiveness. In [12], the authors apply the FAHP method in order to systematically rank the importance degree of the airport selection criteria.

Authors in [13] studied the pricing strategies of the hotel's online reservation system and hotel revenue management using game theory. They presented cancellation strategies by comparing the hotel's profits under different types of cancellation policies. In addition, data mining based cancellation forecasting for revenue management is proposed in [15]. The authors examined the performance of the existing cancellation forecasting models and proposed new promising ones based on Support Vector Machines (SVM). Authors in [16] combined the data from 8 hotels' property management systems with data from several sources and used machine learning algorithms to develop booking cancellation prediction models for the hotels.

By exposing cancellation drivers, models help hoteliers to develop efficient cancellation policies and overbooking tactics. Authors in [18] proposed a dynamic discrete choice model for ticket cancellation and exchange with an application in the context of railway ticket purchase. Their model did not account for fare correlation among adjacent departure times and assumed that fares are not dependent on the demand. In [19], an inter-temporal pricing model with service cancellation is developed by incorporating customer value

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TABLE 1. Comparison of related works

References	QoE	Cancellation service	Data mining	Decision aid	AHP	Arline industry	Revenue management
[6]	✓	-	✓	-	-	✓	✓
[7], [8]	-	✓	-	-	-	✓	✓
[9]	✓	-	-	✓	-	✓	✓
[10], [11], [12]	-	-	-	✓	✓	✓	✓
[13], [14]	-	✓	-	-	-	-	✓
[15], [16], [17]	-	✓	✓	-	-	-	✓
[18], [19]	-	✓	-	✓	-	-	✓
[20], [21]	-	✓	-	-	-	✓	✓
[22], [23]	✓	-	-	-	-	-	✓
This work	✓	✓	-	✓	✓	✓	✓

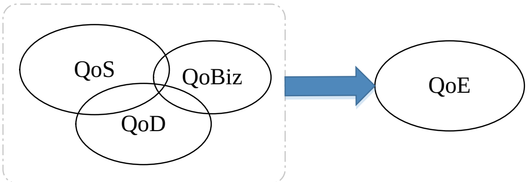

FIGURE 1. The relationship between the sets of attributes while evaluating the quality of web-based services [22].

uncertain and service cancellation. The results illustrated that these parameters affect the optimal inter-temporal pricing strategy, and the seller can benefit from the refund for service cancellation under certain conditions.

To mitigate the effect of cancellations, hotels implement rigid cancellation policies and overbooking strategies, which in turn can have a negative impact on revenue and the hotel's reputation. To reduce this impact, in [17], a machine learning-based system prototype is developed. The prototype, deployed in a production environment in two hotels which also enables the measurement of the impact of actions taken to act upon bookings predicted as *likely to cancel.* Moreover, overbooking is allowed with corresponding penalties determined by an overbooking penalty-cost function. A revenue management model is proposed in [14] that takes cancellations into account in addition to customer choice behavior.

Regarding the online reservation system, there are facilities for ticket cancellation processes made by airlines. One of them allows for ticket cancellation 7 or more days before departure [20]. The refund amount after cancellation is depending on the route and class of passengers. Another airline has its own cancellation protection rules which allows users to cancel their flight ticket up to 12 hours before the flight departure [21]. However, in both airlines, economy tickets are non-refundable and users are not eligible for any refund after cancellation. As can be seen in the aforementioned studies, there are several limitations in refund rules and customers are not eligible to cancel their tickets for any reason. Therefore, the QoE metric should be considered in order to increase user satisfaction.

Regarding user satisfaction, there are metrics for estimating the quality and the customer perception of web-based services such as Quality of Service (QoS) and QoE, which represent objective and subjective assessments correspondingly [22], [23]. The Quality of Business (QoBiz) is rather different from QoS and QoE, where it deals with the financial aspects of service provisioning and refers to those all parameters that are expressed in monetary units. Another specific metric Quality of Design (QoD) can be interpreted as the quality of interaction between end-user and client application. Fig. 1 depicts all of these quality terms assumed to be incorporated into the much broader and generic concept of QoE. They are the integral parts of a service level agreement (SLA), which can be contracted between two SPs or a SP and a user [22], [23]. In this work, a centralized QoE-based online reservation system is implemented in consideration with the real-world data which helps to analyze the proposed CPS schemes and their benefits in terms of the SP's revenue and QoE. The related works are summarised in Table 1.

B. MOTIVATION AND CONTRIBUTIONS

In this paper, we build and generalize our proposed QoE based online reservation system to capture the trade-off between the customer satisfaction and the customer experience. Our goal is to minimize the CPS fee with the least impact on the SP's revenue. We concisely summarize our contributions as:

- We propose a new customer experience based CPS method by considering customers' criteria. In the proposed model, senior customers who have huge amount of transactions such as high flight ratio will have an opportunity to pay less CPS fee when they want to buy a new ticket. This idea does not only satisfy the senior customers but also persuade new users to use the same online reservation system in order to get the chance of paying less CPS payment even for the promotion tickets.
- We propose the weight-based approach to assign appropriate weights to the objectives using the Analytic Hierarchy Process (AHP) method [5].
- We further propose the CR paradigm which compares the Consistency Index (CI) with Random Consistency Index (RI) of the AHP. CR examines the consistency of the evaluation by Eigenvalue and captures the trade-off among different criteria to make a fair decision while assigning the degree of each criterion based on the peak or off-peak time intervals of the year.

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- We use real-world data [4] at different time intervals to understand the customer's behavior at different times of the year. The data analysis proves that there is an increase in the rate of both ticket purchase and cancellation with CPS.
- We carry out extensive simulations driven by real-world data with considering different use cases to show the enhanced performance of our proposed mechanism.

The rest of the paper is organized as follows. The system model and the proposed method are presented in Section II. Performance evaluation is given in Section III. Finally, Section IV concludes the paper.

II. SYSTEM MODEL

In this section, the architecture of the proposed framework is discussed. First, user categories are introduced in sub-section A. Then, data collection techniques used to calculate the ticket price and CPS fee are shown in sub-section B. Later customer transaction is illustrated in sub-section C and finally, the proposed method used to calculate the optimized CPS fee is presented in sub-section D.

A. USER CATEGORY

Users are classified into 4 main membership categories as follows:

- **Normal**: a customer is assigned to this category when he signs up to the online reservation system. A Normal customer earns points (*Points to Flight*) for each purchase ticket.
- **Elite**: a customer is raised to the Elite category when he spends points he had earned earlier.
- **Elite+**: a customer is elevated to an Elite+ category if he earns 1000 points within one year. In this category, a customer earns *Points to Flight* much faster compared to Normal or Elite customer.
- **Premium**: a customer is called a Premium category customer when he earns 2500 points in one year. In addition to the aforementioned advantages, 500 extra *Points to Flight* are loaded to the customer's account.

B. DATA COLLECTION

This sub-section explains how membership flight information can be used, analyzed and overlaid with other data sets to obtain characteristics of the customers and what drives them to buy a CPS-enabled ticket. The centralized control system called data center is designed to gather accurate information making it possible to provide further features for customers. Fig. 2 is a visual representation of the customer flow and how various data sources play a role in calculating real-time predictive metrics to present the right offer at the right time to the customer.

The proposed data center collects the data from different areas as follows:

- **Third-party data**: government, hotels, industry, and online travel agencies. Information that is gathered from these sources helps to suggest appropriate offers based on, cities that customers frequently go, and airlines that operate close to the customers' favorite hotels, etc.
- **Social data**: Twitter, Facebook, and LinkedIn. These sources yield information that helps the system to predict which places are favorite and possible companions from friends and/or family that a customer might like to travel with.
- **Airline data**: future reservations, reservation history, and business or promotion ticket information. These sources of information are the most important ones as they can help to estimate the budget that customers allocate for flight tickets, how early they purchase their ticket, or how many times may they cancel their flights. Thus, the most appropriate CPS can be offered once this information is extracted.
- **User data**: frequent flyer data, account activity ratio, network info, and web/mobile application usage ratio. In this category, the proposed method focuses on the application type that customers use.

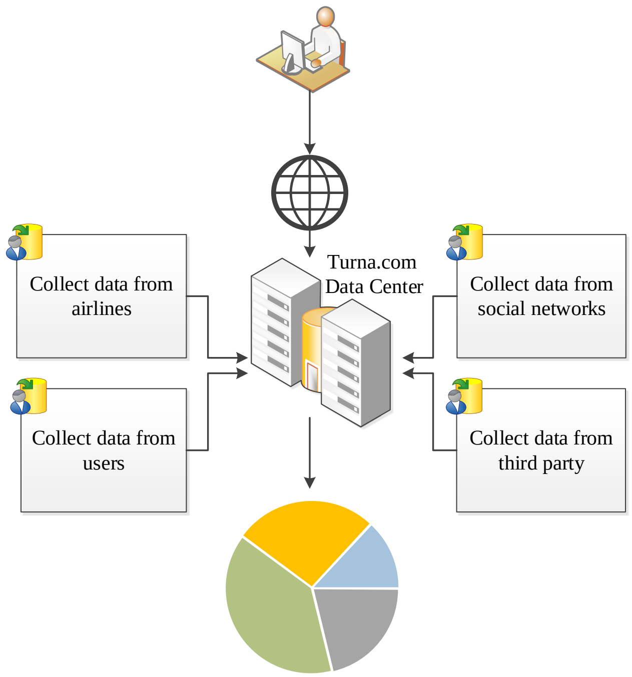

FIGURE 2. Turna.com data center.

In this work, the collected data from Turna.com data center includes 112825 flight tickets which the information of each transaction is presented in Table 2. In the proposed model, for each user, different criteria are extracted from the information in the data set. These extracted criteria which are used in the proposed AHP hierarchical decision tree are explained in sub-section D. After data collection, customer transactions will be analyzed.

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TABLE 2. The collected data from Turna.com data center

Parameters	Description
CustomerId	Customer ID
MembershipDate	Customer's membership date
Gender	Female/Male
BirthDate	Customer's birth date
TicketId	Allocated ID to the bought ticket
BookingDate	Ticket booking date
TicketStatus	Ticket status: Booking/Refund
CancellationAssuranceSelected	Ticket with CPS is shown by 1 and without CPS is shown by 0
SaleAirlineTotal	The total ticket price plus taxes
SaleSC	Service fee for the ticket
SaleDiscount	Discount amount in special cases
SaleTotal	The total ticket price without CPS fee: SaleTotal= SaleAirlineTotal + SaleSC - SaleDiscount
RefundAirlineTotal	The total amount of ticket price plus taxes returned by the airline.
RefundSC	The returned service fee
RefundDiscount	The returned discount
RefundTotal	The total refund amount to the customer in case of any cancellation which does not include CPS fee: RefundTotal= RefundAirlineTotal + RefundSC - RefundDiscount
SaleCancellationFee	CPS fee paid by the customer
RefundCancellationFee	CPS fee returned when the ticket is canceled
CancellationMaxAssurance	The maximum refund amount for the ticket with CPS

C. CUSTOMER TRANSACTIONS

In this sub-section, the proposed CPS based decision tree which is illustrated in Fig. 3 is used to show the customer transaction process. At first, a customer can book or purchase a ticket. Then, there are two categories as follows:

- **Cancel**: customers cancel their ticket. In case of paying CPS fee for the purchased ticket, the SP should pay the refund cancellation fee denoted by $MaxA_F(t_i) = \gamma \cdot S_T(t_i)$. Here, γ is a flexible coefficient based on the ticket type and $S_T(t_i)$ is the total ticket sale price for the ith purchased ticket for each customer as

$$S_T(t_i) = S_A(t_i) + S_C(t_i) - S_D(t_i), \qquad (1)$$

where $S_A(t_i)$ shows the airline ticket price, $S_C(t_i)$ shows the sale cost such as tax and services fee, and $S_D(t_i)$ is the discount value which is due to *Points to Flight*. In the case without CPS payment, cancellation will be diverted to the airlines and refund fee called as $R_T(t_i)$ will be paid based on the airline contract as

$$R_T(t_i) = R_A(t_i) + R_C(t_i), \qquad (2)$$

where $R_A(t_i)$ is refund value by the airline, and $R_C(t_i)$ is the refund cost for the ith purchased ticket which is canceled by customer.
- **Flight**: customers will gain points based on their category and they can use these *Points to Flight* in the next flight as a discount. The discount calculation is described in the following sub-section.

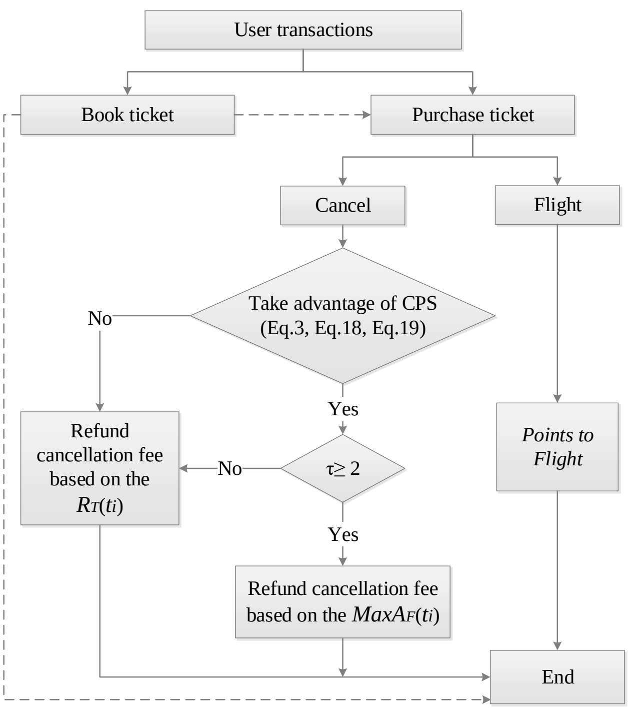

FIGURE 3. Decision tree of customer transactions based on the CPS.

D. CANCELLATION PROTECTION SERVICE (CPS)

CPS allows the customer to cancel their flight ticket up to 2 hours prior to the flight and get γ percentage of their ticket price. CPS can be purchased during a booking process. The rules and conditions of CPS are described in [4]. In this sub-section, three different models are presented as Fixed CPS, QoE-based CPS, and Flexible CPS to calculate the CPS fee.

1) Fixed CPS

This method calculates the CPS fee at each ticket purchase via fixed parameters as given in (3).

$$CPS_F(t_i) = S_T \cdot \alpha + \beta, 0.08 < \alpha \leqslant 0.2, 4.8 < \beta \leqslant 9.8, \qquad (3)$$

where S_T is the total ticket sale price, α is a ratio with the range of $0.08 < \alpha \leqslant 0.2$. A selected value for α is related

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to a promotion (P), or a flexible or normal (N) ticket [1]. On the other hand, the selected α value depends on the domestic or international flight. Thus, there are 2^2 different states for the value of α in the range of $0.08 < \alpha \leqslant 0.2$. β is constant and has a fixed range based on the P and N type ticket. These constant values are determined according to the airline refund instruction. Moreover, t_i shows the ith purchased ticket for each customer.

2) QoE-based CPS

In this sub-section, the proposed QoE-based CPS is introduced to calculate an optimal CPS fee based on the trade-off between the available SP's revenue and customer satisfaction.

We propose the use of the AHP [5] approach to systematically determine the optimized weights for the different objectives. The benefit of using AHP is that it allows effective assignment of weights to objective functions. Instead of assigning weights while relying on heuristic knowledge of the problem domain, AHP relies on the rigor of statistical analysis. The proposed solution comprises three main levels in the hierarchy of the problem. Fig. 4 illustrates the established hierarchy in three different levels.

- **Level 1:** shows the aim of the work; minimizing the CPS fee. This goal is achieved by maximizing the CPS discount $D_{\eta_{ID}}$ where η_{ID} shows customer ID.
- **Level 2:** this level determines the criteria and sub-criteria for each customer.
- **Level 3:** all customers ($Customer_1$ to $Customer_m$) are defined as alternatives in the 3rd level of the AHP hierarchy.

Regarding the AHP infrastructure, for each criterion, the benefit or cost type should be analyzed. In this work, min-max normalization is used [5]. Here, the criteria and their sub-criteria are introduced as follows:

Criterion 1: Ticket Cancellation Ratio (TCR) shows the total ticket cancellation ratio of the customer which has three sub-criteria as follows:

Sub-criterion 1-1: Flexible Ticket Cancellation Ratio with CPS (FTCR) shows the total number of ticket cancellation amongst the flexible tickets bought with CPS payment. In this case, the airline refunds the ticket price due to the refund policy of the flexible ticket type. This is beneficial to the SP provided cancellation was requested within the policy time threshold. Otherwise, it becomes costly as the airlines will not return the refund ticket price to the SP due to the late cancellation. Regarding the FTCR, total gain or loss is calculated using both SP point of view, $SP_F(t_i)$, and user point of view, $C_F(t_i)$, are shown in (4) and (5). The total gain or loss is defined based on the difference between the cancellation time, denoted by t_r and the flight time, denoted by t_f. Typically, when $t_f - t_r < 2$ the airline refunds the ticket price to the SP. When this threshold is violated, no refund will be paid by the SP. The gain or loss of the SP in case of ticket cancellation event is the difference between the total income and total penalty for that particular ticket, which is given as follows

$$SP_F(t_i) = \begin{cases} S_T(t_i) + \vartheta(t_i) + R_T(t_i) \\ \quad - (\phi(t_i) + MaxA_F(t_i)), & \tau \geqslant 2, \\ S_T(t_i) + \vartheta(t_i) + R_T(t_i) - \phi(t_i), & \tau < 2, \end{cases} \tag{4}$$

where $SP_F(t_i)$ shows the SP gain or loss (SPGL) status for each canceled flexible ticket with CPS, where t_i shows the ith purchased ticket for each customer. $S_T(t_i)$ is defined in (1). $\vartheta(t_i)$ shows the CPS fee that was paid by the customer while booking a flight ticket which mentioned as a sale cancellation fee in Turna.com data center. $R_T(t_i)$ is defined in (2). $\phi(t_i)$ is the fee which the SP should pay to the airline based on the contract for each sold ticket, $MaxA_F(t_i) = \gamma \cdot S_T(t_i)$ shows the Cancellation Maximum Assurance paid by the SP for the ith ticket cancellation where $\tau = t_f - t_r$ and γ is a flexible coefficient based on the ticket type.

From the point of view of the user, gain or loss (CGL) status for each canceled flexible ticket with CPS is calculated via $C_F(t_i)$ as shown in (5).

$$C_F(t_i) = \begin{cases} S_T(t_i) + \vartheta(t_i) - MaxA_F(t_i), & \tau \geqslant 2, \\ S_T(t_i) + \vartheta(t_i) - R_T(t_i), & \tau < 2. \end{cases} \tag{5}$$

Please note that, when $\tau \geqslant 2$, the condition in (6) has a high probability where CPS payment is an extra cost for the user since $S_T(t_i) \cong R_T(t_i)$. Thus, the customer loss or gain depends on τ and the airplane rules and conditions.

$$S_T(t_i) + \vartheta(t_i) - MaxA_F(t_i) \geqslant S_T(t_i) - R_T(t_i). \tag{6}$$

To conclude, in the case of CPS payment, the higher the $R_T(t_i)$, the greater the price loss for the customer. Consequently, $0 \leq \frac{S_T(t_i) - R_T(t_i)}{S_T(t_i) + \vartheta(t_i) - MaxA_F(t_i)} < 1$ shows the customer loss.

Sub-criterion 1-2: Promotion Ticket Cancellation Ratio with CPS (PTCR) shows the total number of cancelled promotion tickets for which the CPS fee has been paid. In this case, cancellations and refunds are not permitted by most of the airlines. Therefore, the SP must pay $MaxA_F(t_i)$ by itself. This is where the cost is incurred by the SP but is highly lucrative for the customer based on the CGL. The customer CGL status for the promotion ticket cancellation with CPS, $C_P(t_i)$, is shown as

$$C_P(t_i) = \begin{cases} S_T(t_i) + \vartheta(t_i) - MaxA_F(t_i), & \tau \geqslant 2, \\ S_T(t_i) + \vartheta(t_i). & \tau < 2. \end{cases} \tag{7}$$

The SPGL for the PTCR, $SP_P(t_i)$, can be calculated as a cost function for promotion tickets similar to (4) where the only difference is eliminating $R_T(t_i)$ since $R_T(t_i) \cong 0$ for the PTCR. Note that, in case of high PTCR, $SPGL \leqslant 0$

[1] A flexible or normal ticket is an airline ticket that allows users to make changes to the date and time of their flight before departure [4], [20], [21]. In this work, the terms flexible and normal are used interchangeably.

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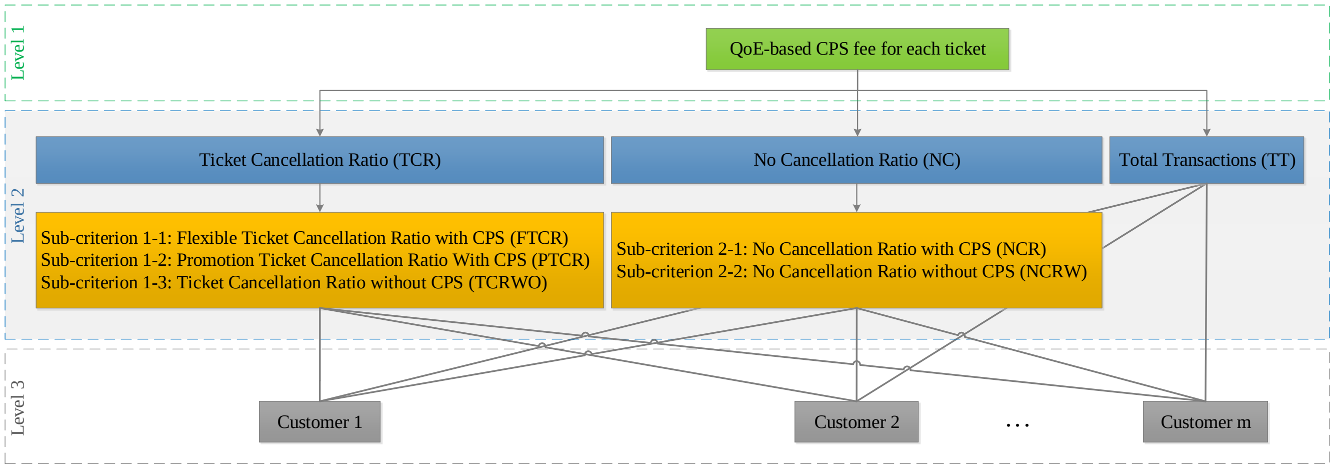

FIGURE 4. AHP hierarchical decision tree based on the system requirements.

which shows the SP's loss where the refund value must be paid by the SP rather than the airline. This loss is calculated via Cancellation Assurance (CA) as

$$CA(t_i) = S_T(t_i) + \vartheta(t_i) + R_T(t_i) - \phi(t_i) - MaxA_F(t_i). \tag{8}$$

Sub-criterion 1-3: Ticket Cancellation Ratio without CPS (TCRWO) shows the total number of canceled tickets without CPS payment. Using this criterion, customer loss is analyzed. Note that, TCRWO is not classified for Flexible and Promotion tickets because in both cases customer loss has occurred and is sufficient to give a CPS discount. This discount motivates the customer to pay the CPS fee for their next flights. The CGL is as follows

$$C_{TC}(t_i) = \begin{cases} S_T(t_i) - R_T(t_i), & \tau \geqslant 2, \\ S_T(t_i), & \tau < 2, \end{cases} \tag{9}$$

where $C_{TC}(t_i)$ shows the CGL for each canceled ticket (N or P) without CPS. For the promotion ticket, $R_T(t_i) \cong 0$ so the total cost is $S_T(t_i)$. For both ticket types, SPGL for the canceled ticket without CPS is $SP_{TC}(t_i) = S_T(t_i) - \phi(t_i)$.

Criterion 2: No Cancellation Ratio (NC) shows all transactions without cancellations. This criterion is divided to the following two sub-criteria:

Sub-criterion 2-1: No Cancellation Ratio with CPS (NCR) shows the SP's revenue where all CPS payments are reserved for the SP. The SPGL is as follows

$$SP_N(t_i) = S_T(t_i) - \phi(t_i) + \vartheta(t_i), \tag{10}$$

where $SP_N(t_i)$ shows SPGL for the NCR. The CGL for each flight, $C_N(t_i)$, is $C_N(t_i) = S_T(t_i)$. In other words, there is no gain (expect the *Points to Flight* as shown in Fig. 3) for users who catch their flight. The more NCR, the more loss for the customer but the refund guaranty still remains.

Sub-criterion 2-2: No Cancellation Ratio without CPS (NCRW) presents benefit for the SP because the more satisfied customers using QoE-based CPS, the higher its reputation. In addition, this criterion helps to increase the discount value for the CPS which motivates the customer to pay CPS fee in future flights. Therefore, there is no gain or loss for customers, $C_{NC}(t_i) = 0$, as flight occurs without any CPS payment and $SP_{NC}(t_i) = S_T(t_i) - \phi(t_i)$.

Criterion 3: Total Transactions (TT) shows the total number of purchased and cancelled tickets which is important to apply priority among customers in order to offer a higher discount for the CPS fee.

In the next step and in order to conduct pair comparison, a questionnaire should be designed and distributed among the respondents (managers, experts, users and, etc.). It is noteworthy that each decision-maker entered their desired amount for each criterion and then individual judgments (of each respondent) have been converted into group judgments (for each of the pair-wise comparison) using their geometrical average. The scale ranges from one to nine where value one implies that the two elements are the same or are equally important. Number nine implies that one element is extremely important compared to the other one in a pair-wise comparison matrix [24]. The pair-wise scale and the importance value attributed to each number are illustrated in Table 3.

Based on the importance degree of the criteria, the data analysis procedure involves the following steps. First the pair-wise comparison matrix called matrix A is extracted. Once built, the value of each row element is calculated as

$$\mathcal{P}_k = \left\{ \prod_{j=1}^{C} A(k,j) \right\}^{1/C}, \forall k = 1,..,C, \tag{11}$$

where C is the number of criterion which is 6 in the proposed method (NCR, NCRW, TT, TCRWO, PTCR, FTCR), k and j are the criteria index in matrix A. After that, sum of the nth-root-of-product values in each row, ζ, is calculated as follows

$$\zeta = \sum_{k=1}^{C} \mathcal{P}_k. \tag{12}$$

The next step is normalizing the aforementioned nth-root-of-products to get the appropriate weights of criteria, ψ_k, as

$$\psi_k = \frac{\mathcal{P}_k}{\zeta}, \quad \forall k = 1, .., C, \tag{13}$$

where $0 < \psi_k < 1$, and $\sum_{k=1}^{C} \psi_k = 1$. The weight of each criterion is gathered in a weight vector as $\mu = [\psi_1, ..., \psi_k]$.

Calculating and checking the Consistency Ratio (CR) of the μ is the final step. In general, the CR is calculated as

$$CR(\mu) = \frac{CI}{RI}, \tag{14}$$

where Random Index, RI is the average value of CI for random matrices using the Saaty scale [24] and CI is the Consistency Index which is calculated as

$$CI = \frac{\lambda - C}{C - 1}, \tag{15}$$

where λ is eigenvalue and is calculated as

$$\lambda = \sum_{k=1}^{C} A(k, j) \times \mu_k. \tag{16}$$

CR can have two statues as follows:

- $CR(\mu) < 0.1$, the decision-maker pair-wise comparisons are relatively consistent.
- $CR(\mu) > 0.1$, the decision-maker should seriously consider re-evaluating the pair-wise comparisons; the source(s) of inconsistency must be identified and resolved and the analysis should be re-done.

In case of $CR(\mu) > 0.1$, the data analysis procedures reconsider with different criterion priority degree till achieving the $CR(\mu) < 0.1$. Next sub-section shows 4 different scenarios in details. After getting the appropriate $CR(\mu)$, μ will be used to calculate the discount ratio which is applied to the CPS for giving the discount to the customer, with an option that allows canceling for any reason. The discount ratio is calculated as

$$D_{\eta_{ID}}(t_i) = \sum_{k=1}^{C} (\psi_k \times nCr_k), \tag{17}$$

where nCr_k shows the normalized value of kth criterion. η_{ID} shows customer ID. In our problem formulation, finding the optimal ψ_k value for each criterion leads to the maximization of discount ratio, $D_{\eta_{ID}}(t_i)$. Consequently, the QoE-Based CPS is calculated as

$$CPS_{QoE}(t_i) = CPS_F(t_i) \times (1 - D_{\eta_{ID}}(t_i)). \tag{18}$$

3) Flexible CPS

This method is designed based on the user history where it eliminates the deficiencies of the Fixed CPS method, but not as comprehensive as QoE-based CPS method. The CPS is calculated as follows

$$CPS_{FL}(t_i) = \begin{cases} CPS_F(t_i) \times \delta, & N, \\ CPS_F(t_i) \times \delta + TCR_{\eta_{ID}}(t_i), & P, \end{cases} \tag{19}$$

where

$$\delta = (1 - N_{\eta_{ID}}(t_i)) \times (1 - NC_{\eta_{ID}}(t_i)), \tag{20}$$

and for each user, the total NCR, $N_{\eta_{ID}}(t_i)$, the total NCRW, $NC_{\eta_{ID}}(t_i)$ and the ticket cancellation ratio, $TCR_{\eta_{ID}}(t_i)$ information are obtained from the data center [4]. The only difference between N and P ticket type CPS is the $TCR_{\eta_{ID}}$ which means the more $TCR_{\eta_{ID}}$, the less $D_{\eta_{ID}}$.

The goal of this method is to pay more attention to CPS calculation based on the customer cancellation history. Although this method is not as comprehensive as the proposed QoE-based CPS, it is more flexible than the Fixed CPS method.

Finally, SPGL and CGL are calculated for each proposed CPS methods for each ticket as follows

$$\begin{aligned} SPGL = & SP_F(t_i) + SP_P(t_i) + \\ & SP_{TC}(t_i) + SP_N(t_i) + SP_{NC}(t_i), \end{aligned} \tag{21}$$

and

$$\begin{aligned} CGL = & C_F(t_i) + C_P(t_i) + \\ & C_{TC}(t_i) + C_N(t_i) + C_{NC}(t_i). \end{aligned} \tag{22}$$

All of the above-mentioned CPS methods are analyzed in Section III based on the real world data.

III. PERFORMANCE EVALUATION

In this section, the importance degree of user criteria is analyzed via 4 different scenarios. Then, the simulation is continued with the most convenient scenario and the importance degree of that scenario are used for QoE-based CPS.

A. IMPORTANCE DEGREE USE CASES

Applying different importance degree for each criterion via 4 different scenarios, AHP can find which scenario is more appropriate based on the $CR(\mu)$ [25]. In each scenario, different degrees of importance of the criterion are considered based on its cost or benefit type [5]. Table 3 shows the cost or benefit type of the criterion from the point of view of the user and the SP. 4 different scenarios are considered based on the criteria detailed in Section II as follows:

Scenario 1: this scenario gives a high importance degree to the PTCR which is the cost type criterion for the SP in case of revenue. For making a balance between benefit and cost type criteria, the second important criterion is the NCR, which is the benefit type criterion from the SP's point of view.

Table 4 shows $CR(\mu) = 0.1655$ which violates the constraint $CR(\mu) < 0.1$. Therefore, this scenario is eliminated automatically as it just focuses on the SP's revenue and does not give any priority to QoE.

Scenario 2: in this scenario, the highest priority is allocated to the NCR. As indicated in Table 4, the value of CR in this scenario is $CR(\mu) = 0.18$ which violates constraint $CR(\mu) < 0.1$. Hence, this scenario is eliminated automatically since a high importance degree for a single criterion, i.e., NCR, to minimize $D_{\eta_{ID}}(t_i)$ is not reasonable.

Scenario 3: TCRWO has the first important criterion. Then NCR after that NCRW. Since there is not an extreme gap between the priority of the criteria in this scenario, hence, $CR(\mu) = 0.07$. Although $CR(\mu) < 0.1$, PTCR is not considered. Hence, this scenario can not have a high performance when the cancellation ratio of promotion tickets is high.

Scenario 4: in this scenario, NCR has the first priority. Then, FTCR is the second important criterion where TCRWO and NCRW have almost the same priority. With respect to these criteria, giving the third and 4th priority cause the discount in CPS fee which can persuade a customer to use CPS. TT is important for giving the CPS discount for the loyal customers with high usage of flight ratio while considering PTCR. Thus, the 4th scenario is the most favorable one since it has the lowest value of $CR(\mu)$, with $CR(\mu) = 0.0476 << 1$. Therefore, the 4th scenario is recommended to be applied for the QoE-Based CPS method. The reason for applying the 4th scenario is explained in more details as follows:

1) ψ_{NCR} = 0.430800: the less ticket cancellation ratio with CPS, the high $D_{\eta_{ID}}$.
2) ψ_{NCRW} = 0.091630: the less ticket cancellation without CPS, the reasonable discount to motivate the customer.
3) ψ_{TT} = 0.061258: the more transactions by customer (booking, flight, cancel), the more advantage for the SP (continues customers). Thus, even with the lowest priority, the online reservation system should consider TT.
4) ψ_{TCRWO} = 0.092255: the less paid CPS fee in a high cancellation ratio, the more monetary loss for the customer. Thus, for preventing the financial loss of the customers and motivate them for paying CPS fee, the SP gives priority to this criterion.
5) ψ_{PTCR} = 0.048065: as customers bought promotion tickets in high ratio, the SP would pay high compensation costs in case of ticket cancellation. Thus, the discount for CPS fee for the next time will be slightly lower. In this case, the proposed method tries to incent customers to buy a flexible ticket with low CPS fee as it depends on the FTCR.
6) ψ_{FTCR} = 0.275989: the more cancellation with CPS, close to the 2 hours before the flight, the more beneficial for the customer. Therefore, the proposed method motivates the customer to pay CPS fee by giving the discount.

Fig. 5 illustrates weights of each criterion, ψ_k, for the above-mentioned scenarios where $0 < \psi_k < 1$, and $\sum_{k=1}^{C} \psi_k = 1, \forall k = 1, .., C$ with $C = 6$. The weight of each criterion is gathered as

$$\mu = [\psi_{NCR}, \psi_{NCRW}, \psi_{TT}, \psi_{TCRWO}, \psi_{PTCR}, \psi_{FTCR}].$$

Table 4 shows the value of vector μ and $CR(\mu)$ for 6 different criterion obtained by the AHP for each scenario.

B. SIMULATION RESULTS

In this section, customer transactions are considered based on the real data which is gathered by Data Center [4] in different months-period of the year 2018. The goal is to calculate the optimal CPS fee based on the customer experience and to analyze its effects in terms of the SP's revenue and user satisfaction. Fig. 6 shows the CA, CPS, and SPGL where customers purchased CPS fee with N type flight ticket booking. The results show that CPS payment is descending till November where July is the first month that Turna.com uses the proposed Fixed CPS. Therefore, the users who purchased the CPS during July and August, their flight time was close to the CPS purchase time. Thus, SP's gain from CPS is high. However, the SP gain is descending till September, while the CPS payment shows slight increase from November to December where the proposed QoE-based CPS method is applied. In September, the SP loses money and in November, there is not any revenue, while there is a very slight gain in

TABLE 3. Cost or benefit criteria type from user and SP points of view

Criteria	Cost/Benefit criteria type	
	From SP's point of view	From user's point of view
FTCR	Benefit	Depends on τ
PTCR	Cost	Benefit
TCRWO	Cost	Depends on τ and ticket type
NCR	Benefit	Cost
NCRW	Benefit	Benefit
TT	Benefit	Benefit

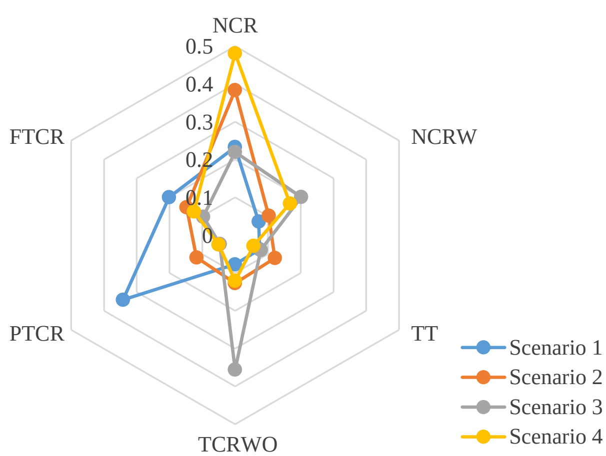

FIGURE 5. Criteria weights for different scenarios.

TABLE 4. Weights of criteria and CR in 4 different scenarios

Scenarios	Decision criteria weights						CR
	ψ_{NCR}	ψ_{NCRW}	ψ_{TT}	ψ_{TCRWO}	ψ_{PTCR}	ψ_{FTCR}	
Scenario 1	0.232928	0.071942	0.074963	0.076971	0.341892	0.201304	0.1655
Scenario 2	0.383255	0.102706	0.121196	0.127148	0.117568	0.148127	0.18
Scenario 3	0.219792	0.201854	0.078549	0.355814	0.046749	0.097242	0.0715
Scenario 4	0.4308	0.09163	0.061259	0.092256	0.048065	0.27599	0.0476

TABLE 5. Data for canceled tickets and cancellation ratio for 6 months-period

Parameters	Months						Average
	July	August	September	October	November	December	
Ticket cancellation request ratio with CPS	0.0423	0.0600	0.0587	0.0713	0.1070	0.0938	0.0722
Accepted ticket cancellation request ratio with CPS	0.0261	0.0174	0.0195	0.0356	0.0826	0.0766	0.0430
Acceptance ratio	0.6190	0.2903	0.3333	0.5000	0.7727	0.8175	0.5555
Number of total tickets with CPS	497	516	664	757	1234	1461	855
Number of total cancellation requests with CPS	21	31	39	54	132	137	69
Number of total accepted cancellation with CPS	13	9	13	27	102	112	46

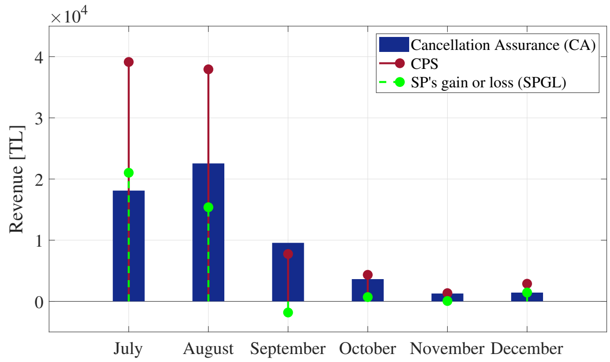

FIGURE 6. SPGL and CA status when CPS is purchased by customers.

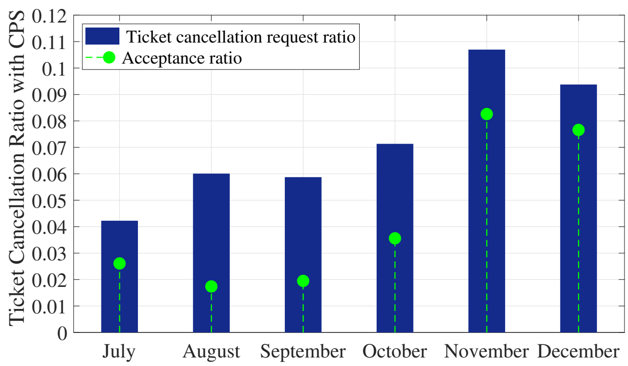

FIGURE 7. Ticket cancellation ratio with CPS for 6 months-period.

October and December. Therefore, it shows that customers are inclined to use CPS and most of the tickets which bought are of the promotion nature or cancellation occurs very close to the flight hour. To show this, customers' canceled tickets with paid CPS is analyzed for 6 months-period in Table 5. In total, there are 5129 tickets with CPS where 414 of them are requested for cancellation and 276 of the cancellation requests are accepted. The number of the total cancellation requests with CPS and their rates, ticket cancellation request ratio with CPS, show that there are 7.22% cancellation request in average where 55.55% of them are accepted which is 4.30% of the total ticket cancellation request. The rest of the requests are rejected because of several reasons which one of them is $\tau < 2$. Fig. 7 illustrates ticket cancellation request ratio and the acceptance percentage for 6 months-period extracted from Table 5. Note that, accepted ratio shows the total PTCR and FTCR (Fig. 4, Level 2: subsection 1-1 and 1-2). Fig. 7 illustrates that the maximum ticket cancellation request ratio is for November with 10.7%. Table 5 shows the analyzed parameters in details. In spite of the fact that there is 5.87% ticket cancellation request ratio in September, $SPGL < 0$ from Fig. 6, where with the 10.7% of ticket cancellation request ratio in November and 9.38% in December, $SPGL \geqslant 0$. It means that although $SPGL$ depends on the ticket type (P or N), CPS payment and the cancellation time (τ), the results at Table 5 show that the appropriate CPS method can affect the SP's gain or loss.

Figs. 8 to 11 show different random customer transactions in detail. Customer history goes back to 2014. In this step, it is assumed that the customer wants to buy a new ticket and the CPS will be calculated with three different methods mentioned earlier. Finally, the proposed QoE-based CPS method is shown to be the best CPS considering customer history. It is assumed that the price of new ticket is $S_T = 100$ during the simulation. At the same time, $CPS_F(t_i)$ calculates the fixed value as 12.8 for flexible tickets and 29.8 for promotion tickets. Note that, the legend is used in Fig. 8 is the same for Figs. 9 to 11.

Fig. 8 shows the customer with $\eta_{ID} = 149394$ transactions that are made up of 85 process, $TT = 85$, with 14 CPS payments, $|\vartheta(t_i)| = 14$, and three cancellations with CPS. For this particular customer, 86.22% of the CPS payment for three cancellations is used for $MaxA_F$. Thus, $SPGL = 93.45 > 0$. In this case $D_{149394} = 0.4485$. Table 6 shows the calculated CPS fee for new ticket with both Flexible and QoE-based CPS methods.

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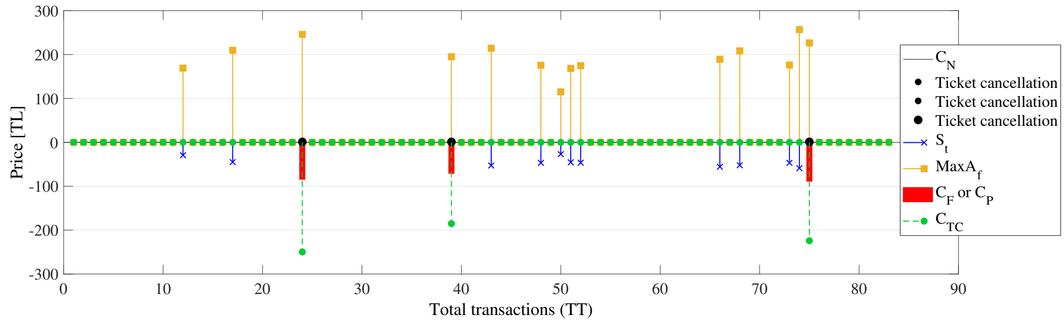

FIGURE 8. Customer transaction for $\eta_{ID} = 149394$.

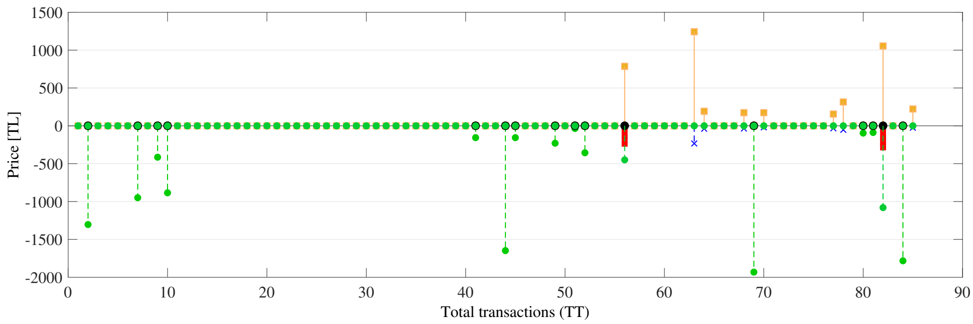

FIGURE 9. Customer transaction for $\eta_{ID} = 150238$.

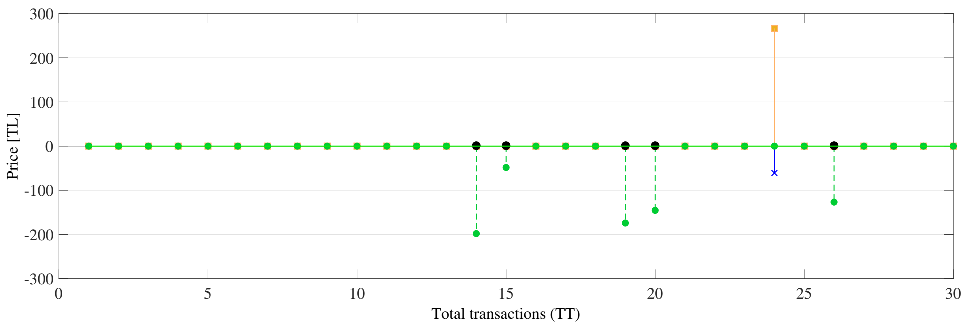

FIGURE 10. Customer transaction for $\eta_{ID} = 152130$.

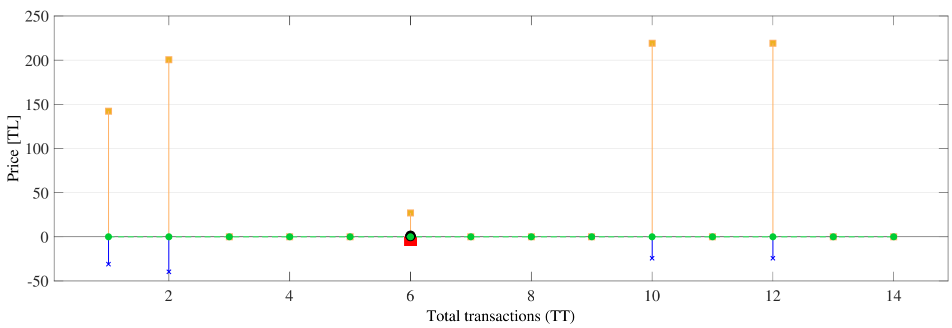

FIGURE 11. Customer transaction for $\eta_{ID} = 260665$.

The results show $CPS_{QoE}(t_i) < CPS_{FL}(t_i)$ for both ticket types. The reason is that the customer paid 14 CPS for all 75 transactions and only 3 flights were actually canceled where the SP merely used 86.22% of CPS payments, consequently, $CA(t_i) < 0$, Fig. 8. This means that the SP has not paid any refund from its own resource. Thus, for this customer, 44.85% CPS discount is considered. However, for the customer with ID $\eta_{ID} = 150238$, Fig.9, the situation is vice versa; a high cancellation ratio with a few CPS payments. Therefore, the new CPS discount should be lower than the discount for the customer $\eta_{ID} = 149394$. These results give $D_{150238} = 25.28$. The value of $SP_P(t_i)$ is -492 which shows the SP loss. Table 7 shows the calculated CPS fee for a new ticket with both Flexible and QoE-based CPS methods. The results show $CPS_{QoE}(t_i) < CPS_{FL}(t_i)$ in both N and P ticket type. The reason is that $SPGL > 0$ which keeps the balance for this customer and hence makes it possible to provide a 25.28% discount.

Fig. 10 shows the customer with ID $\eta_{ID} = 152130$ with 30 transactions, of which 5 cancellations without CPS. Here, there is no CA for any cancellation. The new CPS fee does not change any further in the Flexible method. In this case, Flexible CPS cannot motivate the customer to pay CPS fee. It should be noted that, QoE-based CPS considers the total gain from CPS where $SP_P(t_i) = 60$ (the SP gain 60 Turkish Lira (TL) when customer Refund ticket with CPS) and new CPS fee will be calculated as $D_{152130} = 0.2077$. Table 8 shows the new ticket CPS fee.

In Fig. 11, $TT = 14$, and CPS was paid for 5 of them. As there is not any cancellation without CPS and the SP has revenue from customer $\eta_{ID} = 260665$, the new CPS will be lower than the old one to motivate the customer for paying CPS fee. $SP_P(t_i) = 126$ and $D_{260665}(t_{15}) = 47.64$. Table 9 shows the CPS fees based on Flexible and QoE-based CPS methods.

In all of the analytical results provided above, the goal of the QoE-based method is that although customers pay for CPS in order to guaranty the ticket cancellation, the SP will give a discount possibility with respect to the customer experience with minimal cancellation. In summary:

- The more cancellation, the fewer discounts,
- The more flexible ticket CPS payment, the more discount,
- The more flight, the more discount.

Fig. 12 shows the simulation results for randomly selected customers that wish to buy a ticket. In fact, two different ticket types are simulated as N and P. So, when customers want to buy a ticket, their ticket can be N or P. Fig. 12 (a) shows the case of N type tickets' CPS fees and Fig. 12 (b) shows the estimated CPS fees for P type tickets. As expected, the estimated CPS for promotion tickets is higher than the flexible ones. In both situations, QoE-based CPS does not exceed the Fixed CPS which is inline with the goal of the SP towards user satisfaction. For some customers, Flexible CPS exceeds the Fixed CPS boundary. For instance, the user with ID_1 must pay 29.56 TL for the N type ticket CPS which is almost more than twice the fixed CPS where it is not a suitable amount for the CPS. As a result, QoE-based CPS achieves the goal of the SP towards customers' satisfaction where they will pay less CPS fee based on their behavior in the past. In addition, the proposed QoE-based CPS can make the balance between user satisfaction and SPGL which is shown by Fig. 6. The proposed QoE-based CPS is applied after September to show that even if the CPS fee for the proposed QoE-based is less than the other methods, SPGL is still more than 0, $SPGL > 0$. Consequently, Fig. 13 illustrates the total CPS fee paid by customers for 6 months-period. The average CPS payment in TL for each month is 70.25, 79.11, 81.86, 83.30, 74.24, and 69.21, respectively. It proves that December gives the minimum CPS fee on average. It shows that after September (QoE-based CPS deployment), CPS payment ratio is increasing which shows the customer is eager to pay the CPS fee for both P and N type tickets based on the proposed QoE-based CPS method.

TABLE 6. CPS calculation for the new ticket

Ticket type	CPS method	
	Flexible	*QoE-based*
N	11.04	7.06
P	25.7	16.43

TABLE 7. CPS calculation for the new ticket

Ticket type	CPS method	
	Flexible	*QoE-based*
N	27.24	8.95
P	34.4	20.83

TABLE 8. CPS calculation for the new ticket

Ticket type	CPS method	
	Flexible	*QoE-based*
N	12.29	10.14
P	28.6	23.61

TABLE 9. CPS calculation for the new ticket

Ticket type	CPS method	
	Flexible	*QoE-based*
N	8.86	6.7
P	20.63	15.6

IV. CONCLUSION AND FUTURE WORK

In this paper, we studied the potential limitations of the existing online reservation systems in terms of the SP's revenue and QoE in airline industry. On certain occasions, SPs do not succeed in satisfying all the customers especially the ones that bought promotion tickets earlier and want to change their plans. In this case, ticket cancellation may lead to high penalties for the customers which may turn their profits into a loss in promotion tickets and consequently decreases the SP's revenue. Therefore, we proposed a multi criteria decision-based cancellation protection service (CPS)

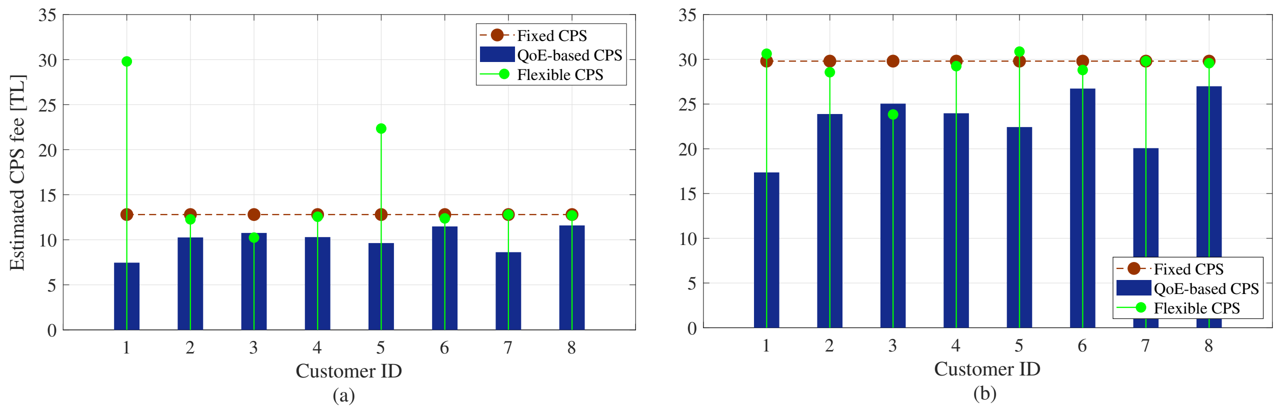

FIGURE 12. Estimated CPS fee for 8 random customers.

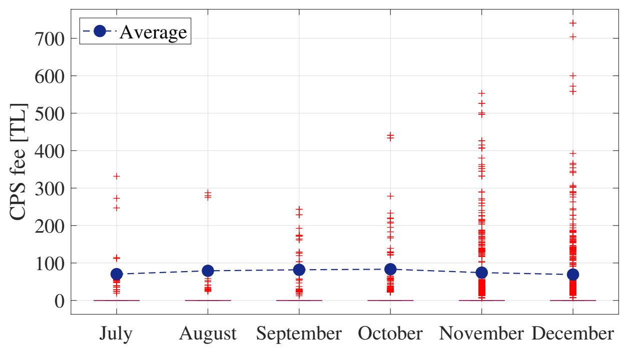

FIGURE 13. Total CPS fee paid by customers during 6 months-period.

solution in online reservation system to capture the trade-off between customer experience and their satisfaction. The proposed scheme helps to calculate the CPS fee based on the customer criteria. We carried out real-world data analysis to demonstrate the performance improvements of the system based on the proposed QoE-based CPS method. Simulation results show that the proposed method calculates more appropriate CPS based on the customers' behavior extracted from the data set which motivates them to pay CPS fee. Last but not least, the proposed QoE-based CPS can be the recommended method for different types of online reservation systems such as online flight, train, bus and even hotel booking systems to provide assurance for early booking.

In the future, we plan to add machine learning techniques to predict customers behavior in order to provide a trade-off between the level of satisfaction of former and senior customers and the SP's revenue.

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NOMENCLATURE

List of Frequently Used Acronyms	Definition
AHP	Analytic Hierarchy Process
CGL	Customer gain or loss
CI	Consistency index
CPS	Cancellation protection service
CR	Consistency ratio
FTCR	Flexible TCR with CPS
N	Normal ticket type
NC	No cancellation ratio
NCR	NC with CPS
NCRW	NC without CPS
P	Promotion ticket type
PTCR	Promotion TCR With CPS
QoE	Quality of Experience
QoS	Quality of Service
SP	Service provider
SPGL	SP's gain or loss
TCR	Ticket cancellation ratio
TCRWO	TCR without CPS
TT	Total transactions

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List of Used Variables	Definition
η_{ID}	Customer ID
S_A	Total ticket price by airline
S_C	Sale cost
S_D	Sale discount
S_T	Total ticket sale price
R_A	Total refund price by airline
R_C	Refund cost
R_D	Refund discount
R_T	Total refund price
ϑ	Sale Cancellation Fee
CA	Cancellation Assurance
$MaxA_F$	Cancellation Maximum Assurance
γ	Flexible coefficient for $MaxA_F$
C_F	Customer gain/loss from FTCR
C_P	Customer gain/loss from PTCR
C_{TC}	Customer gain/loss from TCRWO
C_N	Customer gain/loss from NCR
C_{NC}	Customer gain/loss from NCRW
SP_F	SP gain/loss from FTCR
SP_P	SP gain/loss from PTCR
SP_{TC}	SP gain/loss from TCRWO
SP_N	SP gain/loss from NCR
SP_{NC}	SP gain/loss from NCRW
t_r	Ticket refund time
t_f	Flight time
τ	t_f - t_r
$D_{\eta_{ID}}$	Discount Ratio for CPS
ψ_k	Weight of the criterion
ζ	nth-root-of-product values
λ	Eigenvalue
ϕ	SP payment to the airline for each ticket sale
$\mathcal{P}_k$	Priority vector in AHP
CPS_F	Fixed CPS
CPS_{FL}	Flexible CPS
CPS_{QoE}	QoE-based CPS
α, β	Constant values in the CPS_F

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ZHALEH SADREDDINI received the Ph.D. degree in Computer Engineering, from the Karadeniz Technical University, Turkey, in 2018. She is currently working as an Assist. Prof. Dr. at Istanbul Arel University, Turkey. She had been a visiting researcher funded by Erasmus+ at Brno University of Technology, Czech Republic, in 2016, working on 3GPP Long Term Evolution (LTE) testbed. In addition, she had been a visiting professor at Carleton University, Ottawa, Canada, during summer 2019, collaborating with Prof. Halim Yanikomeroglu on resource allocation in UAV communication. Her primary research interest lies in the area of cognitive radio networks, next-generation cellular networks, routing protocols and network resource management, overbooking, and MCDM techniques. She has been a member of the technical committee of IEEE ICUMT since 2016. She has also been awarded "Best Teaching Assistant" in the Computer Engineering department for the 2015-2016 semester.