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Development of a rating system assessing the quality of the service provided by drivers in a taxi aggregator company

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Abstract

This paper deals with the problem of quantitative description and improvement of the quality of the service provided by taxi aggregator companies working on the Russian market. This problem seems to be insufficiently addressed in open research publications due to its high specificity, though some research aiming at searching the quality metrics have been conducted for some companies worldwide. The goal of the current research is mathematical formalization of a rating system assessing the driver service quality that allows one to design a parametrically tunable model. The proposed mathematical model of the rating system is described by means of a state graph where the transition from a vertex to another happens when the explicitly written conditions are satisfied. We show that the rating evaluation for a driver remaining in the active can be carried out by means of linear filtration performed as digital signal processing of the time series consisting of the scores which are given to the driver by their passengers. The type and waveform of the filter impulse response is suggested. The A/B-test conducted for the group of drivers working with a taxi aggregator proved the fact that the integral metric of service quality is sensitive to changes in the parameters of the proposed rating system; this eventually led to a decrease in the rate of taxi rides accompanied with a negative client experience. The rating system model developed can be utilized to increase the quality of the service provided by the taxi aggregator by means of more effective differentiation of the drivers, while the subsequent optimization of the rating system parameters can serve as a tool for achieving indicators supporting the strategic goals of the company.

Keywords: taxi aggregator, driver rating, rating system, digital signal processing, linear filtering, state graph

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Introduction

The service industry of a modern megalopolis exists and evolves in an environment of robust competition for customers. Companies have to carefully monitor the sentiment and customer preferences of active and potential client groups, react to changes quickly, constantly monitor the quality of services provided, search for growth directions and seek to increase consumer value of their products. The automobile passenger market or, to put it simply, passenger taxi market is quite large, diverse by client segments and has its own history. Since the beginning of the 2000s, the advancing taxi aggregator companies inexorably push aside and gradually supersede classic taxi companies with a taxi depot and phone operator. Undoubtedly, the cause of this phenomenon is the advancement of digital technology resulting in universal availability of mobile Internet in cities. Historically, the first taxi aggregator in Russia was Uber, which entered the market in 2009; then Yandex.Taxi and Gett-taxi appeared in 2011. Over the course of the following ten years, the Russian taxi aggregator market has been continuously expanding; new companies have appeared, including regional and local ones.

Broadly speaking, a taxi aggregator is a platform that provides services by arranging taxi rides based on a two-way mobile application connecting passenger demand with driver supply [1], in other words, an aggregator company provides communication between passengers and drivers.

A typical aggregator company should seek to maintain the positive value of its brand among customers and to improve the quality of services provided, thus facilitating an increase in brand loyalty and retention of customers for as long as possible. The specific aspect of the taxi aggregator business is the fact that it is important for a company to maintain loyalty of both passengers and drivers at the same time so as to accommodate the interests of both groups. Drivers are one of the key profit-generating resources in the business model of taxi aggregators. Due to increasing demand of core customers, the companies study and test various methods to attract qualified drivers (i.e. those who provide good quality service to passengers) and to subsequently retain them in the company. A rating system (RS) is one of the methods used to evaluate quality and promote the company's attractiveness for drivers. For most taxi aggregators, RS is the main method of quality control over drivers' service to customers. The score in such RS directly affects the driver's income and ability to continue working with the platform in general, so it becomes the key factor for most of the drivers. In study [2], it is noted that taxi aggregators use a rating system as a tool to motivate drivers to maintain the quality service level standardized by companies. Note that the scores are given not by the company's own experts, but by its clients (passengers).

Considering the importance of the rating system for formation of driver and passenger loyalty, attraction, retention and motivation of drivers, we may set the task to develop a driver RS from the perspective of most parties concerned. The drivers would like to get a transparent and comprehensible RS, which would be sensitive to factors that depend on the drivers' own efforts. The passengers would like to get an illustrative RS to be able to pre-evaluate the quality of drivers offered to them. An aggregator would like to get an RS that increases driver motivation by rewarding their actions aimed at service improvement or by punishing them for their breach of safety and quality rules. Also, RS should be able to provide the aggregator with interpretable and quantifiable feedback signals from passengers which may be used, after processing, for preparation and implementation of changes in the aggregator's terms of service.

The RS that would be almost ideal for all parties concerned should meet the following requirements:

- it should influence the driver as a motivating factor: rewards and punishments;
- it should provide a scalar value, which is calculated on a comprehensible basis with substantive rationale;
- it should feature functions of parameterization and configuration;
- it should provide a special starting period allowing drivers to adapt to the system;
- it should provide for comprehensible feedback to the platform in order to make further modifications;
- it should be sensitive to changes in the driver's behavior: if a driver changes his or her behavior pattern, the RS should detect such a change within a short period of time.

RS improvements may potentially improve the quality of service provided by the aggregator as well as the effectiveness of driver differentiation, and also promote formation of a comfortable working environment for drivers.

The purpose of RS development as part of the current task is to improve the effectiveness of driver differentiation by quality of services provided during rides, and, as a result, to improve the quality of service and customer satisfaction.

It is important to note that the problem of developing an RS for taxi aggregators receive little attention in scientific literature. This is due to the quite narrow focus of such a research subject. Thus, studies [3, 4] address selection of indicators for sensitive qualitative evaluation of passenger preferences in taxi service quality evaluation. In study [5], a selection of metrics is proposed for evaluation of service quality based on entropy, and study [6] contains a discussion of the influence of the service quality indicators used on passenger behavior. Particular attention should be given to analysis of regional passenger markets in a megalopolis in the Middle East [7].

The main source of information for this study is the research [8] done by one of the coauthors of this study which provides a comprehensive analysis of the problem of RS development for the benefit one of the taxi aggregators in Russian market. The informational background provided by the abovementioned research was used in this study in depersonalized form.

1. Taxi aggregator service quality

Since one of the strategic goals of most companies conducting business in a highly competitive environment is to increase its market share, each aggregator company is interested in looking for effective ways to attract and retain new drivers and passengers, i.e. to uphold their satisfaction and loyalty. At least once a year, a typical aggregator company conducts comprehensive research of brand loyalty through online interviews of clients.

To measure brand loyalty, one of the most simple and common methods is used, the *Net Promoter Score* (*NPS*). *NPS* determines a loyalty index: the intention of users to recommend the platform, readiness to convey their personal experience of interaction with the company to new clients. Respondents are asked to evaluate their readiness to recommend the platform to other people on a score from 0 to 10 (where 0 means "not ready to recommend," and 10 means "ready to recommend"). After that, respondents are separated into three categories: 1) promoters (score 9–10); 2) neutrals (score 7–8); 3) and detractors (score 0–6). Then the *NPS* index is calculated according to a formula (1):

$$NPS = P_p - P_c, \tag{1}$$

where P_p is the percentage of promoters in the total number of respondents;

P_c is the percentage of detractors in the total number of respondents.

NPS values are distributed in the [–100%, 100%] range, and the higher the *NPS* value is, the more loyal the audience is and the more ready it is to recommend the platform.

The success of this metric is defined by its simplicity (users are asked only one question and offered an intuitive evaluation scale) and correlation with long-term growth of the company [9], which allows one to set measurable KPIs for increasing brand loyalty.

The designated metric for measurements of customer satisfaction is the *Customer Satisfaction Index* (*CSI*). This index defines the degree to which the platform meets the requirements and expectations of the market and the degree of customers' satisfaction from interaction with the company. The calculation takes account of certain company-defined attributes such as: the company's goodwill, customer value, expectations, perceived quality, which affect the consumer satisfaction and, as a result, consumer loyalty to the company. Each attribute has its weight, i.e. importance among all attributes according to respondent's opinion, and a rating, which are both given by respondents on a 1 to 5 scale. The calculation algorithm can be described with the following formula:

$$CSI = \frac{100\%}{K} \sum_{i=1}^{k} W_i \cdot P_i, \tag{2}$$

where K is the number of analyzed attributes;

W_i is attribute weight;

P_i is attribute rating.

CSI values are distributed in [0%, 100%] range; the higher *CSI* value is, the more satisfied the customers are by interaction with the company.

For comprehensive research of customers' loyalty to a brand, *NPS* and *CSI* values are considered in conjunction. There are two types of *NPS* and *CSI*: by market and by own base. *NPS* and *CSI* by market are calculated based on data received from all customers who were interviewed via a pre-selected Internet platform, and then the company's position among competitors is identified. *NPS* and *CSI* by own base are calculated based on responses of customers of a particular service, and such values demonstrate the change of the company's attractiveness among the most active audience.

Survey among own base of drivers has shown that the *CSI* index of market leaders, i.e. companies working under such brands as Yandex. Taxi, Uber, City-Mobil, showed almost no change during the six months from December 2020 to June 2021 and remained within 40–50% range, as shown in *Fig. 1*. The latter six months of 2021 have shown a certain decline of Uber and City-Mobil indices as compared to Yandex.Taxi as the leading aggregator.

Figure 2 compares the dynamics of *NPS* by own base for drivers of City-Mobil, Uber, Yandex.Taxi for the period from December 2020 to December 2021. On the diagram, it can be observed that the *NPS* index of Yandex and Uber is much higher than City-Mobil, which is indicative of a low satisfaction of City-Mobil drivers from interaction with the aggregator. City-Mobil drivers point out the following downsides: low fares (and therefore low income), problems with supervision and

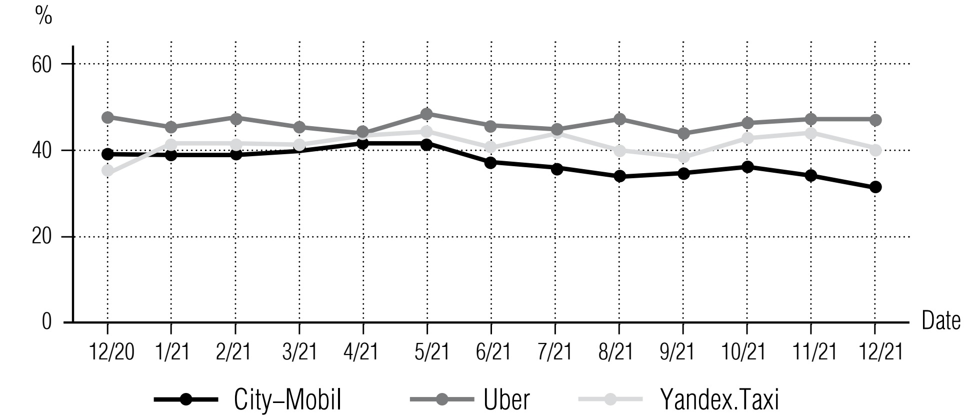

Fig. 1. Dynamics of passenger CSI by own base
for City–Mobil, Uber, Yandex.Taxi (December 2020 – December 2021).

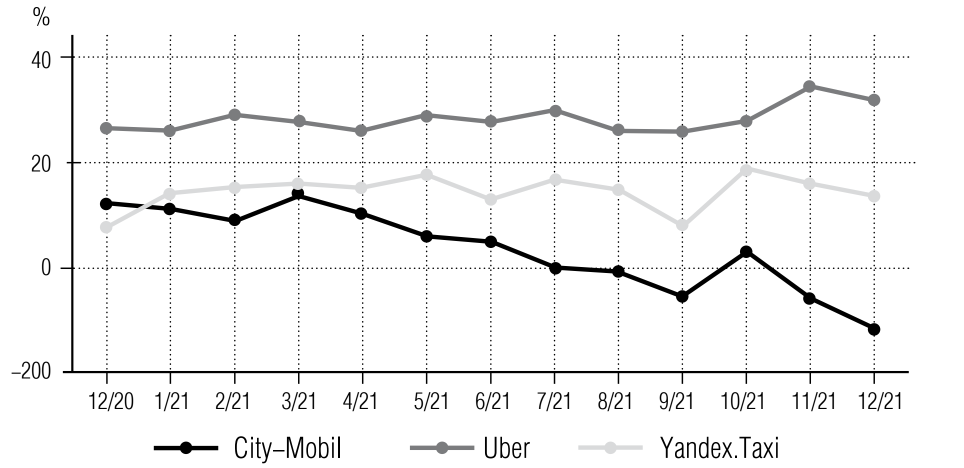

Fig. 2. Dynamics of NPS by own base for drivers
of City–Mobil, Uber and Yandex.Taxi (December 2020 – December 2021). Source: City–Mobil.

low number of orders in general (compared to Yandex.Taxi and Uber).

The above-mentioned indices are designed to evaluate the perceived quality of platforms based on one-time passenger surveys carried out by taxi aggregators. Apparently, the formula of service quality evaluation for a company should be defined in a more strict way and calculated on dynamically obtained data, to which the company would have access at any time.

After each ride, a passenger is invited to rate the ride in the aggregator's client mobile app on a scale from 1 to 5 stars. Customers can put a rating immediately after the ride, or they can get back to it after a while. The passenger may also select tags from the list provided or write his or her own comment to substantiate the rating. Depending on the rating given, the offered tags are changed: examples of tags for different ratings are shown in *Fig. 4*.

The quality of service over time by days or by weeks may be evaluated by a *Bad Trips Rate* (*BTR*) value, which is calculated using the formula:

$$BTR = P_{BT}, \qquad (3)$$

where P_{BT} is the percentage of bad rides from the total number of rides.

Bad rides include all rides, where: 1) the passenger has put a rating of 1–3 (such scores are perceived as a signal of unsatisfactory platform use experience); 2) the passenger has contacted customer support with a problem from "Quality Standard Violations" and/or "Safety Standards Violations." Categories "Quality Standard Violations" and "Safety Standards Violations" include all problems related to drivers' behavior and skills (rudeness, smoking in the vehicle, aggression, traffic violation, illness, inadvertence, etc.), vehicle condition (dirtiness inside the vehicle, bad smell, technical issues, etc.) or order procedures (monetary cheating of the client, no ride given, failure to pay change in cash, etc.)

Unfortunately, this metric should not be used as a quality indicator for a certain driver, because additional research has shown that it depends strongly on the driver's number of rides: the more rides, the lower *BTR* value.

In order to evaluate quality of a certain driver without reference to the number of rides, one more special metric can be used: *CAD* (*Conversion after Driver*), which is customer conversion to another ride after a ride with a certain driver. *CAD* is calculated according to the formula:

$$CAD = \frac{ns_d}{N_d} \cdot 100\%, \qquad (4)$$

where ns_d is the number of passengers who took another ride within less than 60 days after a ride with driver *d*;

N_d is the number of passengers who took a ride with driver *d*.

The results of analysis of this metric can be used to categorize drivers into two groups with maximum difference in their influence on passenger loyalty.

The first group consists of drivers with high conversion rate $CAD \in [80\%, 100\%]$. Such drivers take orders with high rates, work fewer hours per day on average (6 or less), are highly discriminative in ride selection. But the main thing is that they do rides of higher quality. Also, such drivers work longer with the aggregator.

The second group consists of drivers with low conversion rate: $CAD \in [0\%, 20\%]$. Such drivers have lower income, work more hours per day on average (seven or more), are less discriminative in ride selection, but do rides of lower quality according to feedback and ratings given by passengers. Such drivers remain with the aggregator for a shorter period of time.

Driver rating can be called the quality indicator of service provided by the driver with regard to satisfaction of passengers from the services provided. That's why for a passenger, driver rating is a signal of how well a certain driver can satisfy a ride request in terms of safety and comfort. When making an order, passengers pay attention to the rating and would likely reject the ride with a driver who has a low rating (according to their value judgment).

Research of drivers' attitudes towards ratings [8] has shown that around 60% of drivers check their rating on a daily basis, since they realize its importance for successful work. They intend to maintain a high rating by keeping the vehicle clean both inside and outside, keeping smells in the normal range, by politeness and proper conduct, careful driving and passenger care. Research has also shown that drivers are often unable to find out why they got a bad rating, so they treat the idea of a rating system negatively and think that some passengers use it to humiliate and discriminate against drivers. As a result, a drop in their rating spoils their mood and doesn't motivate them to improve their quality of service.

2. Rating system model

Currently, all major companies in the Russian taxi aggregator market have their own driver rating system which makes calculations based on classical approaches of time series analysis.

Time series is a collection of observations generated sequentially over time [10]. Thus, ratings of a certain driver d obtained from passengers are a random value which forms a discrete random time series that can be denoted as: $\{r_d[t]\}$, where $r_d \in \{1, 2, 3, 4, 5\}$. The time series $\{r_d[t]\}$ can be treated as an implementation of a certain random process quantified by the driver's ratings $r_d[t]$ generated by a hidden probabilistic mechanism. In this study, we do not make assumptions on the nature of the process under consideration, in particular regarding its stationary or a more complex non-stationary behavior [11, 12].

Let us define the axis of discrete running time t, integer values of which will mean sequence numbers of rides done by drivers. Let us denote the rating of driver d at the moment of time t as $R_d[t]$. Value $R_d[t]$ is formed on the basis of processing a time series of $r_d[t]$ ratings with account taken of the following variables:
$S_d[t]$ means the driver's state in RS;

$Am_d[t]$ means the number of the drivers' amnesties at the moment of time t;

TH is the threshold value $R_d[t]$, at which the driver is allowed to work with the platform;

$TA_d[t]$ is the moment of the driver's latest amnesty since the decrease of his/her rating below the threshold value;

MA means the maximum number of amnesties for a driver;

NA means the duration of adaptation and recovery period;

RN means a novice's rating during the adaptation period;

RA means the driver's rating immediately after amnesty, which is valid during the recovery period.

2.1. Monitoring of driver state within the platform

The variable describing the driver state monitored by RS assumes values from a finite alphabet $\{N, A, B, C\}$:

N (*newbie*) – the driver works with the platform and has a newbie status;

A (*active*) – the driver works with the platform in rating calculation mode;

B (*blocked*) – the driver is blocked: this state appears when $R_d[t] < TH$ on a certain step;

C (*correction*) – the driver works with the platform in a recovery period, i.e. within a certain period after amnesty.

Figure 3 demonstrates a finite state machine graph implementing the driver's transition between the states. The square brackets contain the conditions for transition to another state. If neither of the transition conditions is met, the driver's state remains the same: $S_d[t] = S_d[t-1]$.

$\{N, A, C\}$ forms a subset of states, in which the driver is allowed to do rides, and time t increases by one with every ride. States in this subset differentiate by rating calculation method and time duration measured by the number of rides during which the driver can remain in every state. The driver may potentially stay in active state A for an infinite period of time, unless and until an exit condition is triggered due to a low rating. At the start of work of each unique driver d, the system performs initialization: $Am_d[t] = 0$, $TA_d[t] = 0$. The accepting state of the graph is state B, in which the driver loses the ability to do rides if the number of amnesties received by him/her has not exceeded the maximum number of amnesties MA set in the system. If the number of amnesties received by the driver does not exceed MA, then the driver may leave this state if he makes an amnesty request. $REQA$ denotes a Boolean variable assuming 'true' value when a driver makes such a request. After that, the driver usually has to undergo additional training provided by the aggregator in order to get the amnesty officially, and only after that he/she would be able to work with the platform again. However, the process of such training will not be reviewed in this study, and the state graph actually demonstrates this event as continuation of the driver's work in state C after the amnesty.

2.2. Linear rating calculation model

Linear digital filtration is a simple but effective way to process the time series of ratings given by passengers to a driver. Such a procedure allows for effective smoothing of a sequence of ratings by generating an average value. This provides an opportunity to reduce the influence of random situational factors on the overall driver rating.

The formula for calculation of the current value of rating $R_d[t]$ depends on the driver's state $S_d[t]$, as shown in (5):

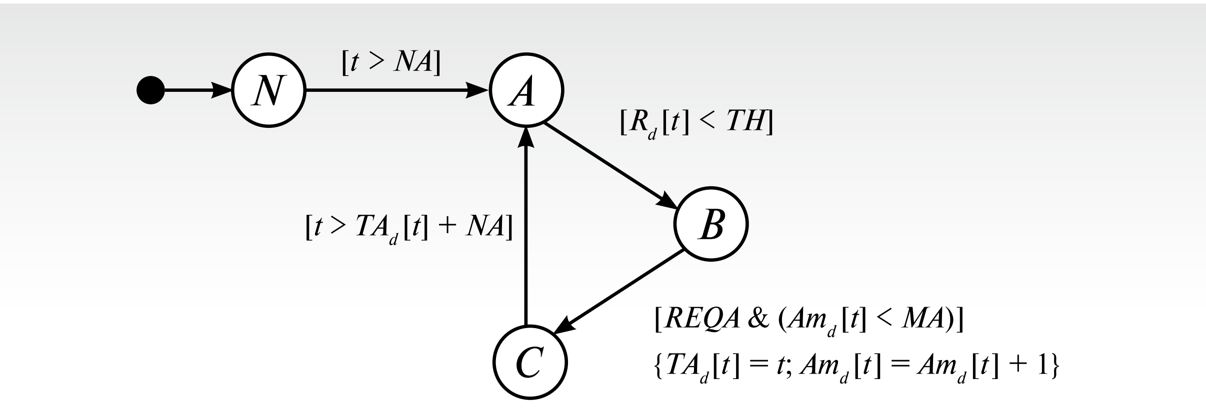

Fig. 3. Driver state graph in the rating system.

$$R_d[t]=\begin{cases}\sum_{n=-\infty}^{+\infty} w[n]r_d[t-n],\\ (S_d[t]=A)\vee(S_d[t]=B);\\ RN,\ NS_d[t]=N;\\ RA,\ S_d[t]=C;\end{cases} \tag{5}$$

where $w[n]$ are the ratios of a weighing function, which, taken together, comprise an impulse response function (*IRF*) of an equivalent linear time-invariant (*LTI*) filter [13] that converts the input digital signal $r_d[t]$ into output signal $R_d[t]$ by linear digital convolution.

The choice of *IRF* $w[n]$ completely defines the *LTI* filter's behavior, and in certain situations, in case of quite general qualitative description of the desired conversion, it happens to be possible to set requirements for *IRF*. Since, in order to form the driver rating $R_d[t]$ in active state (*A*) based on observation over his/her ratings $r_d[t]$ for a certain preceding period of time, the *LTI* filter responsible for such formation must perform a smoothing conversion. In this case, the following requirements apply to its *IRF*.

Firstly, the applied *LTI* filter must be a causal system [14], i.e. at $n < 0$: $w[n] = 0$, which is due to the impossibility of knowing the values of the input signal in future moments of time when calculating the output value in the current moment of time.

Secondly, *IRF* readings must be non-negative: $\forall n: w[n]\geq 0$, which is due to the semantic content of overall rating as a result of accumulation of a time series of rating values.

The third requirement for the filter's *IRF* is the condition of its norming:

$$\sum_{n=-\infty}^{+\infty} w[n]=1, \tag{6}$$

which allows one to receive values of rating $R_d[t]$ within the range of rating values $r_d[t]$.

The simplest selection of *IRF* for calculation and semantic interpretation is an *IRF* implementing a smoothing filter of a simple moving average, *SMA*, calculated based on the last W readings of the input signal:

$$w[n]=SMA_W[n]=\begin{cases}\frac{1}{W},\ 0\leq n\leq W-1,\\ 0,\ n\geq W.\end{cases} \tag{7}$$

Table 1 shows driver rating calculation methods used by major taxi aggregators present in the Russian market as of January 2022.

Table 1.

Rating calculation by major aggregators in the Russian market in January 2022

Aggregator company	Smoothening method	Averaging window width *W*	Threshold value *TH*	Adaptation period *NA*
Yandex.Taxi [16]	Weighted moving average	150	4.4	50
Uber [17]	Simple moving average	500	4.6	100
Gett [18]	Simple moving average	150	4.6	50
City–Mobil [19]	Simple moving average	200	4.6	30

3. Example of a driver's rating evaluation

As an example, let us consider the following parameters of a rating system: we use a simple moving average window (7) with parameter $W = 200$, threshold value $TH = 4.6$, adaptation period duration $NA = 30$ and maximum number of amnesties $MA = 3$. *Figure 4* shows the rating time series of a driver from the group with high conversion rate. It can be noted that such a driver's rating has never decreased to less than the threshold value marked by the dashed line on the diagram. The initial section of continuous rating 4.9 is due to the adaptation period. In addition, the diagram shows the value of the estimated rating which can be obtained by using the first line of formula (5) without regard to the driver's actual state in the system.

Figure 5 shows the rating time series of a driver from the group with a low conversion rate. It can be noted that such a driver's actual rating has never decreased below the threshold value marked by the dashed line on the diagram, immediately upon expiration of the adaptation period. After an amnesty, the recovery period has started, during which the driver's rating was set equal to $RA = 4.7$.

4. Estimation of rating system effectiveness

A/B test carried out in February 2022 [15] provided an opportunity to check whether or not the theoretical evaluation of the effect of implementing the new rating system is confirmed by actual changes of service quality metrics.

The A/B test was carried out on a group of drivers who had done at least 250 rides in City-Mobil for the period from November 2021 to January 2022 in St. Petersburg [8]. The test was carried out during five weeks, since in that period drivers were getting enough ratings for calculation of overall rating in various ways. In

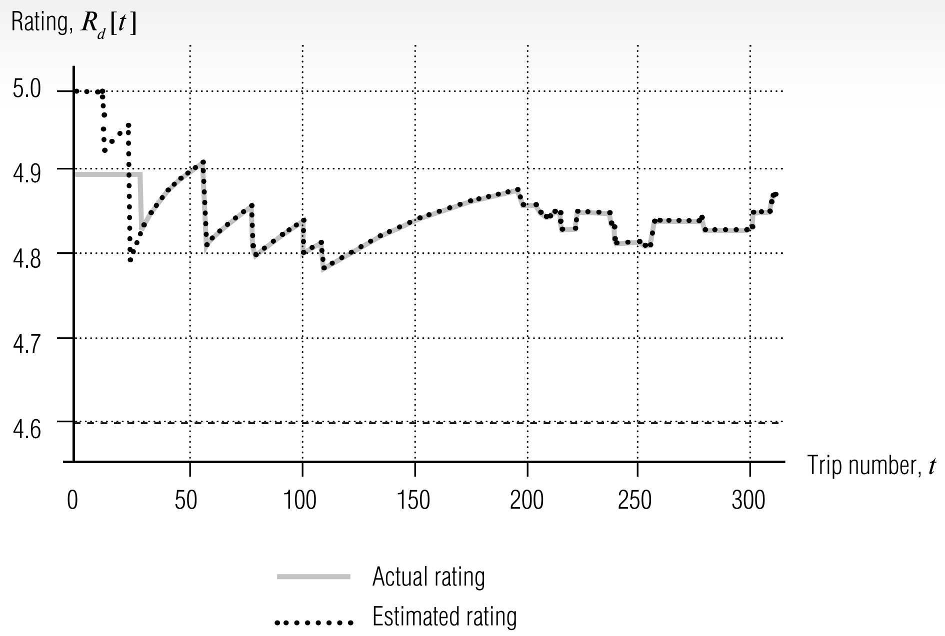

Fig. 4. Variation of rating of a driver with high conversion rate.

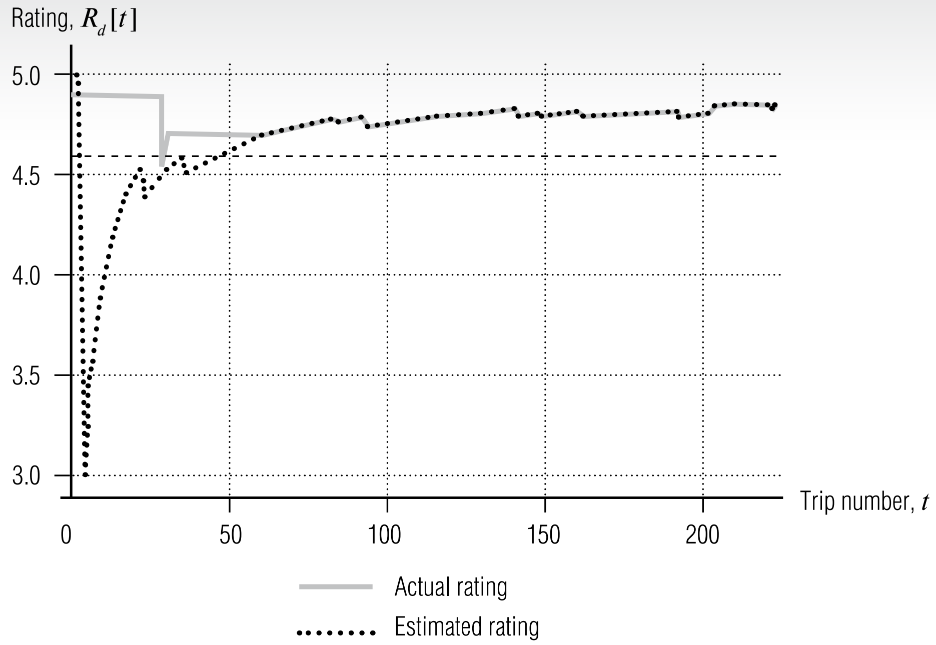

Fig. 5. Variation of rating of a driver with low conversion rate.

that period, a sufficient quantity of observations was accumulated for evaluation of statistical significance.

For test group A, the rating was calculated with the use of an RS having the following parameters: $W = 100$, $T = 4.6$, $A = 2$. For test group B, the rating was calculated with the use of preselected parameters: $W = 200$, $T = 4.6$, $A = 3$. The main metric that was checked for variation was the driver's *BTR*. Such a choice is due to the fact that the drivers selected for testing had almost an equal number of rides. The hypothesis for the A/B test was formulated as follows: the *BTR* value in a test group would undergo statistically significant reduction, because the rating would become more sensitive due to the reduction of moving average window width, and drivers would monitor the quality of service provided better, while the main parameters of drivers, such as a driver's number of rides per day, percentage of accepted orders from the total number of orders, do not change.

The selected drivers were randomly split into groups A and B in 50/50 percentage. Five weeks later, the results were analyzed. The metric in test group A turned out to be 23.52% less than in test group B, while the main parameters showed almost no change. The values obtained for the main metric for the groups are shown in *Fig. 6.*

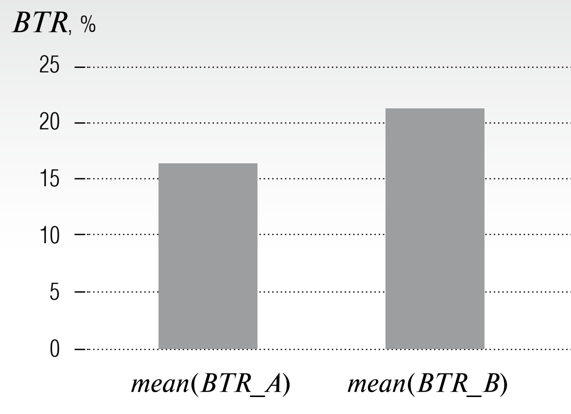

Fig. 6. Comparison of average *BTR* values of two groups of drivers.

Nevertheless, it is also important to check the statistical significance of the observed variation in order to make sure that it was not caused by a mere accident. It was required to check null hypothesis H_0 about equality of average distributions $\{BTR\}_A$ and $\{BTR\}_B$, i.e. H_0: $mean(BTR_A) = mean(BTR_B)$. In this case, a parametric test was used for hypothesis check – Student's t-test. As a result, the estimated value $p = 0.034$ attests to the fact that the null hypothesis is rejected when choosing typical significance level $\alpha = 0.05$, since $p < \alpha$.

Therefore, variations in the metric by groups may be deemed statistically significant, while $mean(BTR_A) > mean(BTR_B)$. This allows us to conclude that the approach reviewed in this study provides an opportunity to build a rating system in which variation of parameters can have a statistically significant influence on the quality of service provided by the taxi aggregator.

Conclusion

The rating system model proposed in this study is built upon the driver state graph, which implements the driver's transition between states upon fulfillment of expressly defined conditions. The method of driver rating calculation depends on the driver's current state. It was shown that for the basic active state of the driver, the task can be formalized as a task to determine a digital filter described by its impulse response function. The basis of digital filtering of a time series of ratings is formed by a smoothing procedure intended to form a value which would integrally reflect the quality of service provided by the driver within a certain period of time. This provides an opportunity to reduce the influence of random and situational factors on the overall driver rating. The advantage of the resulting rating system model is that its adaptation can be achieved by using a limited set of parameters that define its operation: the form and duration of impulse response function of a digital filter, threshold value of rating, permitted number of amnesties, duration of periods of driver's adaptation and recovery after amnesty.

The results of effectiveness analysis of the proposed rating system performed on actual data through an A/B-test on a group of drivers have shown that the new rating system would allow a company to improve service quality indicators by at least 5% due to selection of other parameters of the rating system. This may potentially improve such an indicator as lasting value of a company due to the attraction of new drivers and passengers. It is important to note that development of a mathematically formalizable model of a rating system is an important step that opens up opportunities for further research in this direction, and specifically for optimization of rating system parameters in order to obtain quality indicators ensuring the achievement of strategic business goals of a taxi aggregator company. ■

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