Revealing Influencing Factors of Check-in Time in Air Transportation

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Abstract: Air passengers are particularly faced with uncertainty during their travel. Information regarding the expected check-in time is not sufficient enough. In many cases, there is no infrastructure to measure the time of check-in process and to inform passengers. The aim of our research was to elaborate a method based on historical data in order to reveal the influencing factors and their effects on time elements (queuing and service time). We have considered various air-carrier operational types, periods of the year and destinations. The cases of each type and their combinations have been fully investigated. The most important influencing factors are: passenger numbers, baggage to passenger ratio, ratio of wheelchair passengers and the number of open check-in counters. The results serve as input data for prediction of check-in time in a personalized passenger information service.

Keywords: airport check-in; historical data; passenger queues; regression analysis

1 Introduction

Air travel requires more fatiguing preparation and causes more frustration than other modes of transportation due to stochastic process elements. Airport check-in queuing time is the sixth factor that causes discomfort for passengers according to a study [1]. Additionally, queues have negative impact on customers' satisfaction [2] and if the queues are too long, some passengers may even miss their flight [3]. Stress and uncertainty during travel are often caused by lack of information (e.g. about check-in time). These negative effects are more significant in case of incidents as delays, cancellations, long queues at check-in, etc. Passengers expect a smooth door-to-door travel experience during the entire journey [4].

In most of the airports there is no infrastructure to measure the check-in time elements, which is the basis for information provision. However, it would be useful to know, in advance, whether it is necessary to arrive earlier to the airport even if it cannot be measured directly. In accordance with check-in, some studies [5] [6] [7] dealt with the modeling and the optimization of check-in and cumulative diagrams were used in order to model the operation of check-in counters. In [8] different queuing models were analyzed and compared. In [9] it has been found that the service quality is mainly driven by the number of available check-in counters, the dynamic arrival rate of passengers, and the distribution of the service time. According to the study [10] the number of needed check-in counters depends on the average speed of passenger flows through the check-in points and average check-in service time. In [11] the optimal number of check-in counters has been determined. These studies considered the check-in time depending on the available infrastructure but did not deal with the characteristics of flight or the composition of the passengers as influencing factors. Additionally, the study [12] stated that queuing theory is too restricted to predict and calculate queuing times. However, the model of integrated database is available to provide sufficient information for air passengers [13]. Based on the literature review it has been found that airport service time has strong effect on quality of service. Currently, only very few studies regarding check-in time analysis and the revealing of influencing factors are available.

In our research we have elaborated an analysis method (grouping and slicing method), searching for the influencing factors of check-in time. We also produced a correlation analysis for the same database. It is widely used as dependences not only between pairs of variables, but between larger groups of variables can be quantified in this manner [14]. We compared the results of both methods and highlighted those, check-in time, influencing factors that are determined by both methods. The purpose was to identify the basic and specified properties of the flight which influence the check-in time and to determine their effects. The following initial hypotheses were supposed:

Check-in time depends on the properties of the flight, which are the following:

- Basic (static) properties: type of airline, season, destination
- Specific (semi-dynamic) properties: number of passengers, baggage/passenger ratio, ratio of wheelchair passengers, number of used lanes.

According to the revealed correspondences the check-in service and queuing time are to be calculated without any immobile measuring infrastructure using only the flight characteristics. It is useful for both the airports 2-3 days prior to the scheduled flight to allocate the resources (e.g. check-in counters) and for the passengers during their preparation for the journey.

Section 2 summarizes the data collection method and the database structure of the analysis. Section 3 describes the elaborated analysis method. In Section 4 the results, in Section 5 a discussion is provided and the conclusions are drawn in the final section.

2 Data Collection

The airport check-in process has been disaggregated and analyzed. Time of the entire, completed check-in process (t_c) is calculated as a sum (1) of the following time values:

- Queuing time (t_q)
- Service time (t_s)

$$t_c = t_q + t_s \tag{1}$$

At the airport, that provided the sample data (Budapest Airport - BUD), the process of passenger check-in and baggage drop-off are handled together at the same counter. Passengers for a certain flight are standing in a single queue and proceed to the counters immediately before the check-in process. We have focused only on check-in aided by personnel.

2.1 Data Recording Steps

The sample database contained the following items:
Flight data: from Airport Operational Database (AODB), in reference to the check-in process (e.g. number of passengers, number of pieces of baggage, etc.).
Queuing data: recorded check-in time data (e.g. queuing and service time) between January 2013 and August 2016. The data recording was carried out by the employees of BUD through an Android mobile application that registered the arrival and leave to/from the check-in counter. The analyzed database contains 13,400 check-in time records belonging to 424 flights.

One employee registered either one flight or one flight group (in case of common check-in) trough continuous monitoring the dedicated check-in counters. Premium service counters were not included in data collection at Budapest Airport as passengers of first/business classes or frequent flyers are handled in a separate queue. In this way, the method ensured that all the passengers of one flight were standing in a single queue. The person had to monitor only the end of the queue for arriving passengers and all the dedicated check-in counters for leaving passengers. The flow chart of the data recording operations and the display of the application are summarized on Figure 1.

Flight details are uploaded from AODB /1/. The flight resource group /3/ depends on uploaded data, current date and time. Only the flights concerned in the near time window are available for selection. The employee monitors whether any passenger arrives to the queue or leaves from the counter /6/. In case of an arriving passenger, with the ‘Add passenger’ button the timestamp is registered and the queue length is increasing /7/. In the case of a leaving passenger, the button of the number of the check-in counter - from which the passenger is leaving - is pressed and the timestamp is registered /8/. A new counter can be opened with the long press of button ’X’ /10/. With the same method, it can be closed (deleted) /11/. If all the passengers have left and all the counters are closed, data are exported to the created database /12/.

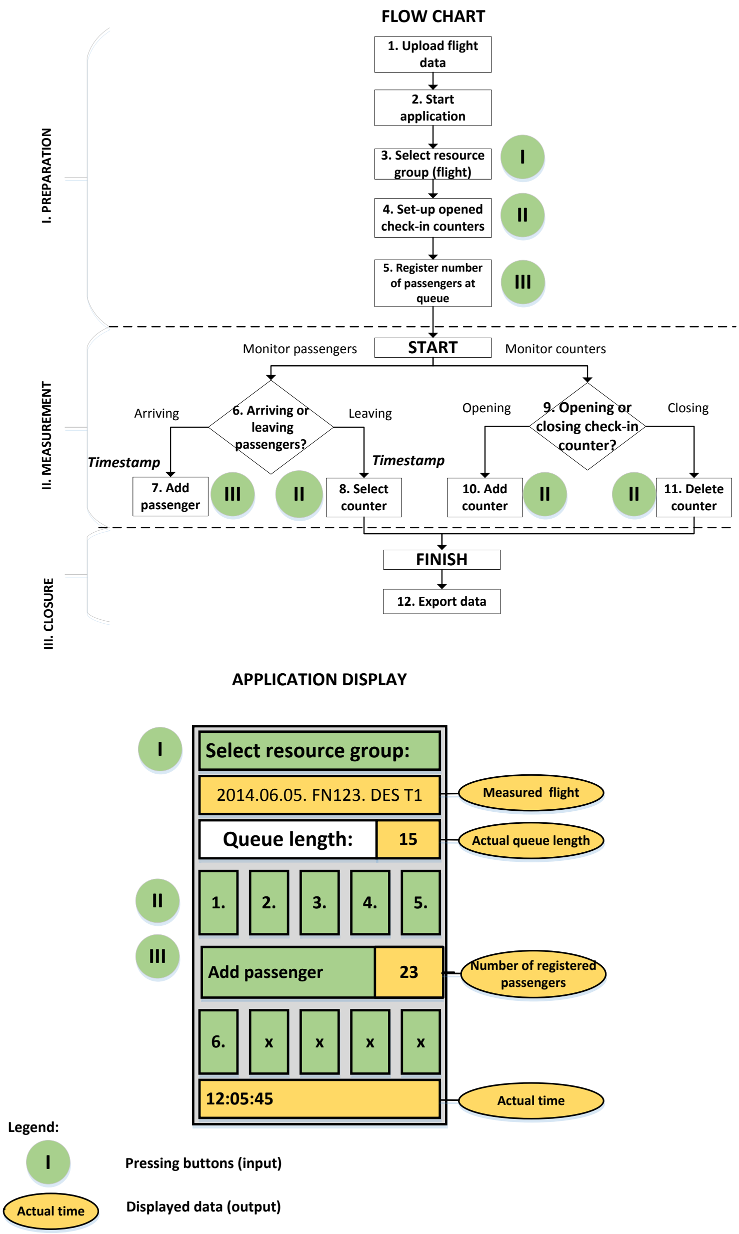

Figure 1
Flow chart of data recording and the application display considering the practice of BUD

2.2 Database Structure

Figure 2 illustrates the simplified database structure.

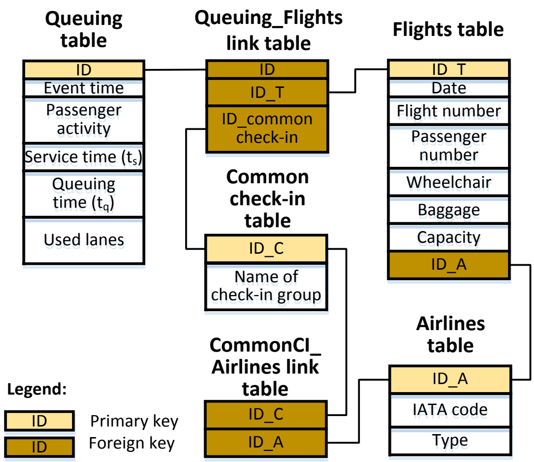

Figure 2

Simplified structure of the database considering the practice of BUD

The model contains only the attributes that are necessary to understand the analysis method. Table 1, 2 and 3 contains the explanation and data type of attributes with an example for better understanding.

Table 1

Structure of Queuing table

Name of attribute	Explanation	Data type	Example
ID	ID of recording	counter	136
Event time	Date and time of event	date	2013.02.12. 18:38
Passenger activity	Arriving (A) to queue or departing (D) from check-in counter	text	D
Service time (t_s)	(in seconds)	numeric	152
Queuing time (t_q)	(in seconds)	numeric	205
Used lanes	Number of opened counters	numeric	3

Table 2
Structure of Flights table

Name of attribute	Explanation	Data type	Example
ID_T	ID of traditional check-in	counter	1
Date	Scheduled date	date	2013.01.11.
Flight number	Master flight number	text	FN123
Passenger number	Number of passengers	numeric	147
Wheelchair	Number of passengers with reduced mobility	numeric	2
Baggage	Number of pieces of baggage	numeric	80
Capacity	Seat capacity	numeric	150

Table 3
Structure of Common check-in table

Name of attribute	Explanation	Data type	Example
ID_C	ID of common check-in	counter	1
Name of check-in group	Fictitious name for airline groups using common check-in	text	GROUP1

The 'Queuing' table contains the measured data, whereas 'Flights' Table contains the specific characteristics of flights. The 'Airlines' table contains the IATA codes and the type of airline (low-cost or traditional). Grouping of airlines was based on their business model (as airline type).

3 Analysis Method

We have elaborated an analysis method in order to reveal the influencing factors of check-in time.

1. We introduced a grouping and slicing method according to the static and semi-dynamic properties of a flight.
2. The introduced method was adapted for BUD. We calculated the statistical properties (minimum/maximum values, medians, quartiles, mean values) of each sub-group in order to identify the influencing factors.
3. We carried out correlation and regression analysis regarding all the basic and semi-dynamic properties of flights. The results of correlation and regression analysis as well as the results of slicing method have been compared.

3.1 Grouping and Slicing Method

The marking system of statistical values (e.g. mean value) has been introduced as in Figure 3.

Left upper index:
grouping aspects of flight specific (semi-dynamic) properties

$${}^{b_1,\dots,b_m}_{a_1,\dots,a_k}\bar{t}_x$$

Left lower index:
grouping aspects of basic (static) properties

Right lower index:
type of time

c: check-in time
q: queueing time
s: service time

Figure 3
Marking system of statistical values

The basic (static) and specific (semi-dynamic) properties of the flights have been classified in Table 4. It summarizes the notation as well. Both the number of grouping aspects (k, m) and the number of categories in case of aspects (l_k, n_m) can be extended. In this way a flexible method has been created. The presented grouping aspects and the categories are based on the available types in a middle-sized airport. Grouping aspects are independent.

In cells of the grouping aspect the corresponsive database table and column names are also indicated by italic. The grouping is to be performed by these columns either directly or by logical implications / calculated expressions.

Baggage/passenger ratio reflects the amount of pieces of baggage per person. The number and intervals of categories have been determined by our practical experience.

Table 4
Variables and their values used during grouping

	Vari-able	Grouping aspect/table-column	Values	Meaning of values (groups)
Basic (static) properties	**a_1**	type of airline/ *Airlines-Type*	**0**	all airlines
			1	traditional airline
			2	low-cost airline
			l_1	...
	a_2	type of destination /*Flights-Flight number*	**0**	all destination
			1	Europe
			2	not-Europe
			l_2	...
	a_3	season / *Queuing-*	**0**	all seasons

		Event time	**1**	winter
			2	summer
			l_3	...
	a_k	k. grouping aspect	l_k	…
Specific (semi-dynamic) properties	b_1	passenger number / *Flights-Passenger number*	**0**	all data
			1	0-50 passenger
			...	...
			4	150-200 passengers
			n_1	...
	b_2	baggage/ passenger ratio /*Flights-Baggage* and *Passenger number*	**0**	all data
			1	0-0.25
			...	...
			8	1.75-2
			n_2	...
	b_3	ratio of wheelchair passengers / *Flights-Wheelchair*	**0**	all data
			1	0-1%
			...	...
			7	10%
			n_3	...
	b_4	Used lanes (check-in counters) / *Queuing – Used lanes*	**0**	all data
			1	1
			…	…
			5	5
			n_4	…
	b_m	m.grouping aspect	n_m	…

3.2 Adaptation of Grouping and Slicing Method for BUD

In the case of BUD k=3 and m=4. Accordingly, number of 'dimensions' as grouping aspects are 3 and 4. The number of options (as different data elements) are l_k and n_m.

Several statistical values regarding check-in service and queuing time have been calculated for the sub-groups according to basic (static) properties. Mean values have been calculated for the sub-groups according to specific (semi-dynamic) properties.

3.3 Correlation and Regression Analysis

The same variables (a_k, b_m) have been used for the correlation and regression analysis as in grouping and slicing method. Qualitative variables (a_1, a_2, a_3) are indicated as dummy variables based on Table 5. Final results are presented in this paper. The results of the regression analysis can be applied for prediction method regarding check-in time.

Table 5

Dummy variables

a_1	type of airline	traditional	1	Dummy 1
		low-cost	0	
a_2	type of destination	Europe	1	Dummy 2
		not-Europe	0	
a_3	season	winter	1	Dummy 3
		summer	0	

4 Results

4.1 Results of Grouping and Slicing Method

Influence of Basic (Static) Properties

Statistical values (minimum, maximum, median, first quartile, third quartile) have been calculated for all the combinations of basic properties and the results (in seconds) are summarized in Table 6, Figure 4 and 5. Results are provided only for the data and its sub-groups that are available in the recorded sample database. The calculated statistical values were examined and compared in group-pairs in order to determine dependency. Based on this comparison t_s depends on a_1 ,a_2, b_2, b_3 variables, whereas t_q depends on a_2, a_3, b_1, b_2, b_3 variables. The minimum and maximum values show which airline type, destination type and season performs as the best and the worst.

Table 6

Mean values according to basic (static) properties

Type of time	**All data**	**Min**		**Max**	
$\mathbf{t_q}$	678.53	$\mathbf{t_q}{}_{111}^{000}$	395.58	$\mathbf{t_q}{}_{122}^{000}$	946.32
$\mathbf{t_s}$	88.3	$\mathbf{t_s}{}_{212}^{000}$	62.21	$\mathbf{t_s}{}_{121}^{000}$	120.76
$\mathbf{t_c}$	766.83	$\mathbf{t_c}{}_{111}^{000}$	484.96	$\mathbf{t_c}{}_{122}^{000}$	1057.12

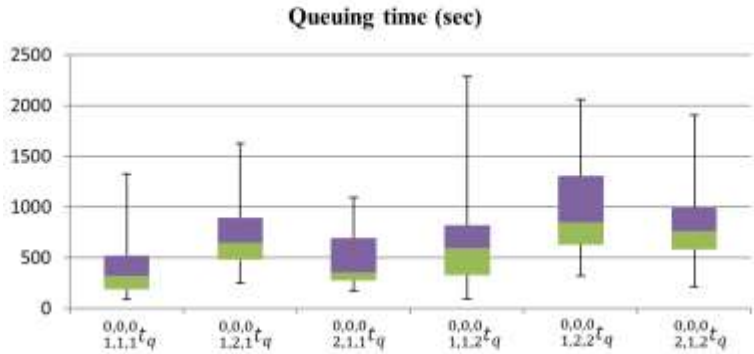

Figure 4
Statistical values for queuing time

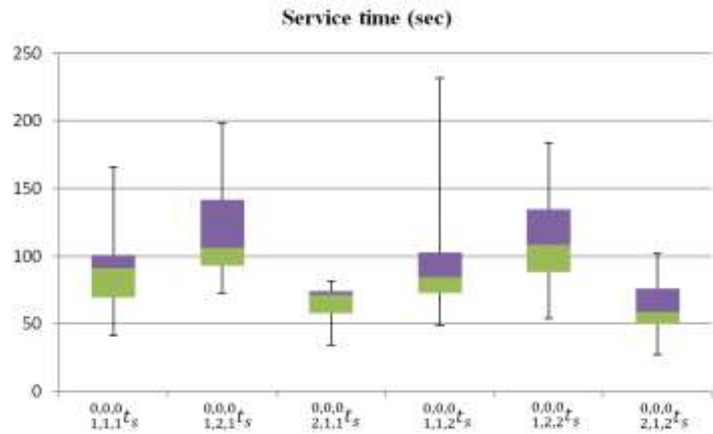

Figure 5
Statistical values for service time

Influence of Flight-specific (Semi-dynamic) Properties

Average values have been calculated for the semi-dynamic properties of the flights and the results (in seconds) are summarized in Figure 6 and 7. The values belonging to certain grouping aspects are indicated as independent variables on the horizontal axis of the diagrams. The functions of polynomial trend lines are also presented on the figures.

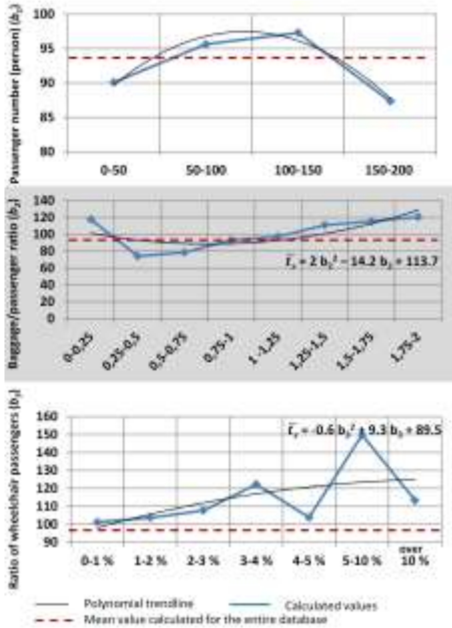

Figure 6
Mean values of service times

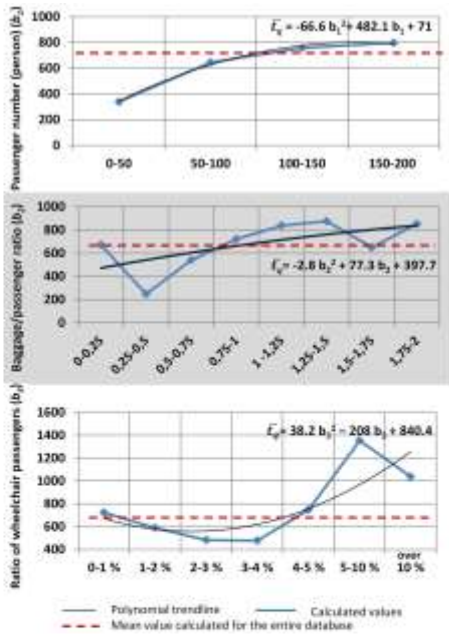

Figure 7
Mean values of queuing times

4.2 Results of Correlation and Regression Analysis

The result of correlation analysis in case of service and queuing time are summarized in Table 7.

Table 7

Correlation results

	t_s	t_q	a_1	a_2	a_3	b_1	b_2	b_3	b_4
t_s	1								
a_1	0.286	-0.200	1						
a_2	-0.234	-0.402	0.169	1					
a_3	0.069	-0.194	0.114	0.053	1				
b_1	-0.155	0.434	-0.450	-0.197	-0.113	1			
b_2	0.378	0.341	0.108	-0.384	-0.071	0.079	1		
b_3	0.150	0.083	0.073	0.013	0.005	0.180	0.067	1	
b_4	0.210	0.191	0.015	-0.267	-0.077	0.688	0.235	0.191	1

highlighted background: medium correlation (absolute value >0.3)

Table 8

Regression statistics

	Service time	Queuing time
r	0.58	0.66
r^2	0.34	0.43
Adjusted r^2	0.32	0.42
Standard error	21.56	301.59

According to the value of adjusted r^2, the reliability of the results is medium-strength both in case of service and queuing time calculation.

After removing those variables that have no or very weak influence, we recalculated the results. Final results are summarized in Table 9 and 10, where the elements of the equation are highlighted with cultured background**.**

Table 9

Results of statistical analysis (service time)

		Coefficients	**Standard error**	**t value**	**p value**
Intercept	**Name of variable**	74.33	6.93	10.73	$1.83*10^{-22}$
a_2	type of destination	-7.42	3.47	-2.14	0.034
b_1	passenger number	-0.31	0.043	-7.68	$3.18*10^{-13}$

b_2	baggage/ passenger ratio	21.17	4.6435	4.56	$7.83*10^{-6}$
b_3	ratio of wheelchair passengers	563.96	204.99	2.75	0.006
b_4	used lanes	11.44	1.8	6.36	$8.86*10^{-10}$

Based on the calculations the service time can be predicted according to the equation (2):

$$t_s=74.33 - 7.42*a_2 - 0.31*b_1 + 21.17*b_2 + 563.96*b_3 + 11.44*b_4 \quad (2)$$

Table 10

Results of statistical analysis (queuing time)

		Coefficients	**Standard error**	**t value**	**p value**
Intercept	**Name of variable**	287.51	122.11	2.35	0.019
a1	type of airline	303.41	110.48	2.75	0.006
a2	type of destination	-310.23	54.46	-5.7	$3.3*10^{-8}$
a3	season	-150.56	52.84	-2.85	0.005
b1	passenger number	6.51	0.72	8.98	$5.7*10^{-17}$
b2	baggage/ passenger ratio	300.96	65.6	4.59	$7*10^{-6}$
b4	used lanes	-181.53	29.14	-6.23	$1.9*10^{-9}$

Queuing time can be predicted according to the equation (3):

$$t_q=287.52 +303.41*a_1-310.3*a_2-150.56*a_3+6.51*b_1+300.96*b_2- 81.53*b_4 \quad (3)$$

4.3 Comparison of the Results

We compared the results of the two methods (grouping and slicing method vs. correlation analysis) in Table 11. In the case of the grouping and slicing method the calculated statistical values were examined and compared in group-pairs. In case of connection between the queuing/service time and the variables, ✓mark is displayed. The strength of the connections has been revealed by correlation analysis. In the table, strong or medium connection has been marked with ✓and weak or very weak connection has been marked with X. A green background shows that both methods resulted in the same dependency, while light green shows if the variable has no influence and dark green if it has. Accordingly, these influencing factors have to be taken into consideration in for a prediction method.

Table 11
Dependencies of times on variables

	Name of variable	Service time (t_s)		Queuing time (t_q)	
		Grouping and slicing	**Correlation analysis**	**Grouping and slicing**	**Correlation analysis**
a_1	type of airline	✓	X	X	X
a_2	type of destination	✓	X	✓	✓
a_3	season	X	X	✓	X
b_1	passenger number	X	X	✓	✓
b_2	baggage/passenger ratio	✓	✓	✓	✓
b_3	ratio of wheelchair passengers	✓	X	✓	X
b_4	used lanes	N.A.	X	N.A.	X

✓: dependency
X: non-dependency
green background: same dependency in both methods
light green: variable has no influence
dark green: variable has influence

5 Discussion

Based on the results of the applied two methods the following have been found:

- Service time (t_s) of low cost airlines is 30-40% lower than in case of the traditional airlines (due to the lower number of check-in baggage and the higher number of prepared boarding passes).
- Queuing time (t_q) does not depend on the type of airline (a_1), but does on the type of destination (a_2).
- Service time (t_s) does not, but the queuing time (t_q) depends on the number of passengers on flight (b_1): the higher is the number of passengers the higher is the queuing time (4).

$$\overline{t_q} = -66.6 * b_1^2 + 482,1 * b_1 + 71 \tag{4}$$

- The higher is the baggage/passenger ratio (b_2) the higher is the service time (t_s) and the queuing time (t_q) (5), (6).

$$\overline{t_s} = 2 * b_2^2 - 14.2 * b_2 + 113.7 \tag{5}$$

$$\overline{t_q} = -2.8 * b_2^2 + 77.3 * b_2 + 397.7 \tag{6}$$

According to the results obtained from capacity analysis model [7], 76 passengers pass with 118 pieces of luggage through one check-in counter per hour. In this case $\overline{t_s}$ =47.4 sec/passenger. However, we found that in the case of BUD, according to (5), $\overline{t_s}$ = 96.5 sec/passenger belongs to the same baggage/passenger ratio.

Deviation between the two values could be that in case of [7], the results are calculated by fuzzy logic model, while in our case it is a real measured data, where service time could depend on the passengers' behavior. Additionally, BUD handles significant through – check-in requirements as well.

- According to correlation analysis it has been found that there is very weak correlation between check-in time (t_c) and ratio of wheelchair passengers (b_3) on the flight, however the grouping method showed an increased tendency. The false result is the consequence of the small sample (only 10% of the analyzed flights had wheelchair passengers on board).
- The smallest service-time (t_s) belongs to the low-cost airline, summer period, European destination combination. It is because low-cost airlines try to minimize the cost by forcing passengers to travel with less baggage and with a prepared boarding pass. It reduces the time spent at the check-in counter, in this way airlines have to pay less for the handling companies. Conversely, traditional airlines provide boarding pass printing and baggage check-in at the counters and that takes longer.
- The smallest check-in time (t_c) belongs to the traditional airline, winter period, European destination combination. The result is the consequence of lower queuing time (t_q) of traditional airlines. As the order of magnitude of queuing time is higher than the service time, the huge service time (t_s) does not affect the time of the overall process.
- Non-European destinations require more service and queuing time. An explanation is the baggage/passenger ratio on flight (b_2).

The method is mainly developed for airport operators in order to have a general overview about expected check-in time values. In the case of having information only about the static properties of the flight (e.g. 2 weeks before departure), the average check-in time values calculated by grouping and slicing method can be used for informing passengers. In case of having information about the semi-dynamic properties of flight, using the equations of the regression analysis gives more precise data. With the combination of these two methods, the expected check-in time can be predicted notably. These influencing factors are available from flight schedule and seat reservation system. The calculated results could also serve as input data for passenger information applications (e.g. airport application, airline application or integrated application) on mobile devices to display the expected check-in time for passengers. It would be provided as public information; similarly, like an actual flight schedule. Those who have downloaded the application could check the information from anywhere. Data reliability could be improved by the further analysis of the method and the usage of more historical data. This is our goal in further research.

Conclusion

Our main findings show that the influencing factors of check-in time and their effects are the following:

- Check-in time slightly depends on the basic (static) properties of the flight and mainly the queuing times depend on the type of destination (a_2)
- Check-in time is influenced by specific (semi-dynamic) properties of the flight, mainly by the number of passengers (b_1) and the baggage/passenger ratio (b_2).

Accordingly, these influencing factors have to be taken into consideration for the case of a prediction model.

Based on the result, the proposed measures, in order to decrease time elements are as follows:

- Reducing queuing time is more effective if the entire check-in time is to be reduced
- Proper information provision (about baggage, gate info etc.) for passengers before check-in, in order to avoid long service time at the counters
- Decrease of service time by the initiation of boarding pass pre-printing and the promotion of travelling without baggage
- Reduction of service time by baggage drop-off in the city (e.g. at airport shuttle bus/ train stations or launching baggage delivery service);
- Opening of more check-in counters (or separated queues), for the case of when more than 5% of the total number of passengers are wheelchair passengers
- Better integration of seat reservation system of airlines and airport operational database in order to calculate the necessary numbers of check-in counters more precisely

- Data management with shorter data transmission cycle time (e.g. between seat reservation systems of airlines and airport databases regarding passenger number, baggage number, etc.).

During the research we learned that more precise determination of category intervals (considering several additional factors) resulted in more accurate results. Furthermore, the grouping aspects may vary depending on the characteristics of the dataset (e.g. analysis of check-in process in case of special items on flight: dogs, ski equipment, bikes etc.).

Further research directions are the amendment of calculations using additional grouping aspects and the elaboration of an advanced prediction method of check-in time, based on these analysis method/results and the historical data being available from different sources but mapping the same physical process. Automation in other sectors of transportation alters the conventional processes and researches are increasingly focusing on its impacts [15] [16]. Therefore, the aviation sector should be prepared for similar challenges. The autonomous airports, in the future, need more precise prediction information concerning check-in time elements, in order to plan their capacity more perfectly. The integration of passenger handling functions (check-in, baggage drop-off, security check, passport control) needs further analysis of the time elements. As a research goal, we are going to build these time elements into an elaborated method. As a future opportunity, the model will be further developed to measure and optimally minimize the security lines at the airport.

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