INVESTIGATION OF AIRPORT TERMINAL RESILIENCE BY SIMULATION MODELING

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ABSTRACT

The concept of resilience is present in many research fields today, aiming to understand and optimize a system's behaviour against external disturbances. Yet, no resilience framework has been developed for airport terminal systems. This paper aims at transferring the resilience concept to airport terminal systems. Furthermore, resilience will be used to quantify the impact of disturbances on terminal systems with simulation modeling. The goal is here to obtain a basis for understanding and improving the performance at disruptive events. A resilience framework for airport terminal systems will be defined based on current literature about resilience definition and quantification. Moreover, a simplified terminal model will be set up in a simulation tool. With the model, different disturbance scenarios concerning the duration and the affected process station will be tested. At the same time, the general applicability of the simulation tool for resilience investigations will be verified and an input parameter sensitivity analysis will be conducted. Based on the simulation results, the reaction of the terminal system on external disruptions will be analyzed and basic insights about airport terminal resilience will be gained for the simplified terminal system. The simulations can later be extended to complex generic or real-world terminal systems in order to derive specific recommendations for action.

Keywords: Resilience, Airport terminal system, Simulation modeling, Discrete event simulation

1. INTRODUCTION

Infrastructure systems are often operating close to their maximum capacity (Mattsson and Jenelius 2015). This also holds for the airport infrastructure, as there is a high growth rate in aviation, while runway or terminal extensions at airports have to fulfill strict regulations and need to be planned long in advance (ICAO 2016). Incidents such as system failures or staff strikes therefore lead to high delays and understanding the behaviour of the airport terminal system during and after those disturbing events builds a desirable goal. This includes, for example, knowing after which intensity or duration of the disturbing event the airport can still return to normal operation.

The resilience of a system provides information on how a system reacts on an external disturbance. The research about the term "resilience of systems" has been growing over the past years, just as the number of papers dealing with resilience has increased (Hosseini et al. 2016). Application areas vary from ecology, psychology or material science to infrastructure systems. Most of the studies in the field of resilience engineering deal with the definition of resilience (Righi et al. 2015). For stated reasons, understanding the reaction of an airport terminal system to disturbing events with the goal of improving the resilience of the system has a clear motivation today. Therefore, this paper aims at establishing a resilience framework for airport terminal systems including a definition of resilience and measures to quantify resilience. Moreover, basic experiments about the airport terminal resilience will be conducted in simulations with a basic terminal model.

The paper is structured as follows. In Section 2, definitions of the term resilience as well as metrics quantifying resilience will be specified based on a literature review. In Section 3, a resilience framework including a definition and appropriate metrics will be developed for airport terminal systems. A discrete event simulation of the airport terminal resilience with a basic terminal model will be described in Section 4. The analysis of the results in Section 5 and the conclusion in Section 6 complete the paper.

2. LITERATURE REVIEW

The term resilience is defined in various disciplines such as psychology, material science, ecology, economics or engineering. The review of definitions in current literature will include those various disciplines. The focus for resilience measures will lie on engineering disciplines in order to obtain a suitable basis for the definition of key resilience indicators for the airport terminal system.

2.1. Definition of Resilience

The word resilience originates from the Latin word "resiliere", which can be translated by "bounce back". The online dictionary "Duden" defines resilience as psychological resistance or strength to survive difficult life situations without continuous impairments. According to (Grotberg 1997), psychological resilience is the universal capability to refrain from, minimize and overcome negative external influences.

In material science, resilience describes the physical property of a material to be elastic and return to the initial shape after having transformed due to stress application (Hoffman 1948). (Moench 2009) distinguishes between soft and hard resilience. Hard resilience is defined as the strength or hardness of a material or structure under applied pressure. Soft resilience is defined as the capability to absorb and regenerate from a disturbance. In that sense, soft resilience corresponds to the flexibility of a system. (Schultze 1996) defines ecological resilience as the strength of a disturbance which can be absorbed by a system without any structural changes of the system itself. The essence of economic resilience implies the mitigation of the effects caused by a disturbance to prevent losses (Rose and Liao 2005). A resilient social or ecological system is furthermore characterized by the ability to withstand large disruptions through “adaptation and evolution”. Properties of resilient systems therefore include diversity, efficiency, adaptability and cohesion. Those properties can be specified more closely for economic systems or ecosystems. (Fiksel 2003) For (Li and Lence 2007) the resilience of infrastructures is defined as the ratio between failure and recovery probability.

In the following, generally applicable definitions for the resilience of a “system” independent of the aforementioned disciplines will be reviewed. According to (Hollnagel 2006), resilience is the capability of a an organization or a system to maintain its function prior to, during or after a disturbing event. (Woods 2009) sets resilience as an adaptive capacity, which means that a system has the potential to adapt to changes. A system in general operates in an equilibrium and behaves in a certain way under normal conditions. A disturbing event unbalances the system and the performance is reduced. In this context, resilience is the ability of a system to minimize or reduce the amount and the duration of the performance loss after the disruption. (Proag 2014) The resilience of a system is furthermore defined by certain properties of the system. On the one hand, robustness is the ability of a system to withstand a disruption without a function loss. On the other hand, the redundancy of a system describes if and to what extent a system can be replaced in order to maintain functionality. Furthermore, the resourcefulness provides information on whether physical, technological or monetary funds are available. Finally, rapidity implies the ability of a system to return to the original performance level after a disturbance. (Bruneau and Reinhorn 2006) The absorptive, adaptive and restorative capability as a characteristic ability concerning resilience are introduced by (Nan and Sansavini 2017). The absorptive capacity implies the ability to reduce negative exterior impact and minimize the negative consequences for the system. This ability resembles the robustness referenced above. The adaptive capability describes the ability to adapt to the disturbance while the restorative capability, similar to the above mentioned rapidity, describes the ability to return to the original state after the disturbance.

The definition of static and dynamic resilience also comprises the terms robustness and rapidity. While static resilience implies the ability to maintain functions during a disturbance, dynamic resilience is characterized by the time till recovery of the original state. (Rose 2007)

As the environment of a system can change over time, new disturbances can appear and the resilience of a system has to be assessed in regular intervals. In a system of systems, a network of independent, complex systems, reactive and proactive resilience are defined. Reactive resilience comprises the compensation of other systems in case one system fails. Proactive resilience implies a new system configuration before a system can fail. This is achieved by a reduction of the overall system performance. (Uday and Marais 2013)

The disturbance or failure itself is defined as root or reason for the change in the system performance, while the stress or perturbation marks the effect or consequences of the disturbance. The disturbance is characterized by type, frequency, intensity and duration. The perturbation is the answer of the system on the disturbance and can be transient or permanent, which means that the system can return to the original state or not. In this context, a resilient system will return to the reference state and show transient behaviour. (Gluchshenko and Foerster 2013)

Concerning airport systems, there are only a few studies about resilience in current literature. The resilience of an airport is defined as the ability to stay operational with an appropriate security level (Chen and Miller-Hooks 2012). Furthermore, resilience is defined as the capability to withstand a disturbance and show a transient perturbation (Gluchshenko and Foerster 2013).

As there are various definitions of resilience in literature, it is difficult to stress one uniform definition. (Woods 2015) groups the resilience concepts in literature into four main categories. The first category implicates the general return from a trauma respectively the return to the equilibrium situation. The second category puts resilience on a level with robustness, defined as the capability to absorb disturbances. Furthermore, resilience can be seen as an opposite to brittleness, comprising an elastic or flexible behaviour in borderline situations. The fourth category includes resilience as a network architecture which is able to adapt to new conditions. (Hosseini et al. 2016) stress that there are similarities between the definitions concerning the capability to absorb, adapt to and recover from disturbances.

As it has been shown, resilience is compared to or equated with the terms of redundancy, robustness, rapidity or flexibility. It can be summarized that there are two dominating aspects, defining the resilience of a system dependent on the magnitude and the duration of the performance loss induced by a disturbance. The consequences on this definition on possible resilience measures will be discussed in the following subsection.

2.2. Quantification of Resilience

As stated above, the ability to reduce the performance loss after a disturbing event as well as the ability to quickly recover to the original state are both relevant for the resilience of a system. While the first aspect is often referred to as robustness, the latter can described with the term rapidity. The quantification of resilience can accordingly follow those two main definitions or combine both of them.

In the following, the time dependent system performance is described with $p(t)$. The original system performance at the time t_0 is p_0 and the start time of the disturbing event is t_s. The minimum performance of the system after the disturbing event is p_{min}. The time after which the system starts to recover from the disturbance is t_r and the time at which the system reaches a new stable state is t_0'. The performance at the new stable state is p_0' and can be equal to, lower or higher than p_0. The system performance over time is shown in Figure 1 and can be measured either as a performance function such as throughput of passengers in an airport or cars in a road network over time. In this case, the performance curve drops after the disruptive event. The system performance can furthermore be characterized by a delay function such as queue length for passengers or cars, the delay time for aircraft or trains or the queuing time for the system users over time. In this case, the curve of $p(t)$ increases after the disruptive event. If not stated otherwise, the system performance in this section will be represented by the performance function. (Nan and Sansavini 2017; Henry and Emmanuel Ramirez-Marquez 2012)

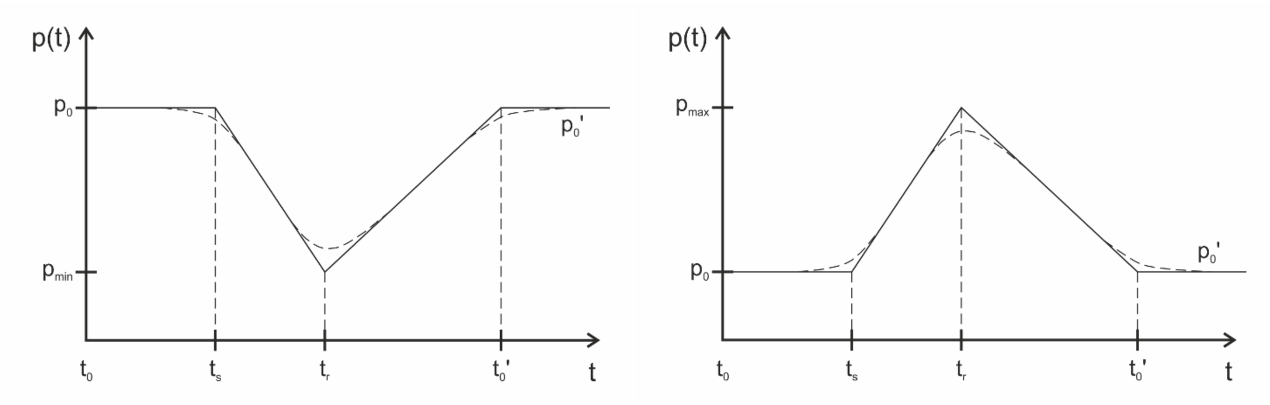

Figure 1: System performance as performance (left) and delay function (right) before, during and after disturbance (adapted from (Nan and Sansavini 2017))

The transition between the performance levels p_0, p_{min} and p_o' might also be stepwise. The recovery starting at t_r can be induced either by actions or strategies pursued after the disturbance or by an internal systemic relaxation after the disturbance.

As stated above, one measure for the system resilience is the robustness, which is equal to the minimum performance p_{min} of the system after the disruption (see Equation (2-1)) (Nan and

Sansavini 2017). In order to quantify the resilience of a system by its robustness, the "resilience efficiency" $R^{(1)}$ is defined in Equation (2-2) as the ratio of the minimum performance p_{min} due to the disturbance and the normal system performance p_0 (Proag 2014).

$$Robustness = p_{min} \tag{2-1}$$

$$R^{(1)} = \frac{p_{min}}{p_0} \tag{2-2}$$

However, those definitions do not consider the system performance over time. It is neither recorded whether original performance is recovered at any time nor it is included how quickly the system can recover. In order to capture those two aspects of resilience, other measures need to be considered.

Resilience as the ratio between recovered performance and performance loss after the disturbance ($R^{(2)}$, see Equation (2-3)) forms another measure of resilience. The resilience $R^{(2)}$ consequently takes values between 0 and 1. According to this definition, a system is resilient if it is able to fully recover from the disturbance (resilience value 1). The system is not resilient if it stays at the disturbed state where $p(t)$ equals p_{min} (resilience value 0). (Gama Dessavre et al. 2016)

$$R^{(2)}(t) = \frac{p(t) - p_{\min}}{p_o - p_{\min}} \tag{2-3}$$

The gradient of the performance curve between the time of the minimum performance t_r and the time of the return to a stable state t_0' is a measure for the rapidity of the system to recover from the disturbance (Bruneau and Reinhorn 2006). The rapidity as the average gradient of the performance curve during the performance drop (see Equation (2-4)) and recovery (see Equation (2-5)) can be defined as follows.

$$Rapidity^{(drop)} = \frac{p(t_s) - p(t_r)}{t_r - t_s} \tag{2-4}$$

$$Rapidity^{(recover)} = \frac{p(t_0') - p(t_r)}{t_0' - t_r} \tag{2-5}$$

The rapidity of the system can also be measured by the time interval the system needs to recover. The time of deviation is defined as the time interval between the deviation from the initial performance at t_s and the minimum system performance at t_r. In a highly resilient system, the time of deviation is significantly higher than the time of recovery. Accordingly, in a system with low resilience, the time of deviation is significantly lower than the time of recovery. A possible measure of resilience then comprises the ratio between the time of deviation and the time of recovery ($R^{(3)}$, see Equation (2-6)) or the sum of both as the time of perturbation ($R^{(4)}$, see Equation (2-7)). (Gluchshenko and Foerster 2013)

$$R^{(3)} = \frac{t_r - t_s}{t_0' - t_r} \tag{2-6}$$

$$R^{(4)} = t_0' - t_s \tag{2-7}$$

Another possibility to include the function behaviour over time is comparing the area under the performance curve after the disruptive event and the area under a performance curve without any disruption, which is also referred to as "resilience quality" ($R^{(5)}$, see Equation (2-8)). This metric takes values between 0 and 1. (Proag 2014)

$$R^{(5)} = \frac{\int_{t_s}^{t_0'} p(t)\, dt}{\int_{t_s}^{t_0'} p_0\, dt} \tag{2-8}$$

Similar to this approach, (Bruneau and Reinhorn 2006) define the resilience of an infrastructure as integral of the deviation from normal performance over time ($R^{(6)}$, see Equation (2-9)). This metric can be extended by including several consecutive disturbing events (Zobel and Khansa 2014).

$$R^{(6)}(t_{end}) = \int_{t_0}^{t_{end}} 1 - \frac{p(t)}{p_0}\, dt \qquad (2\text{-}9)$$

The latter approaches combine the rapidity and the robustness aspect. The resilience measure itself, however, does not distinguish between systems with a high robustness and low rapidity and vice versa, as the area functions might lead to the same resilience value, see Figure 2. Consequently, for an integral examination of the resilience of a system, further measures need to be included.

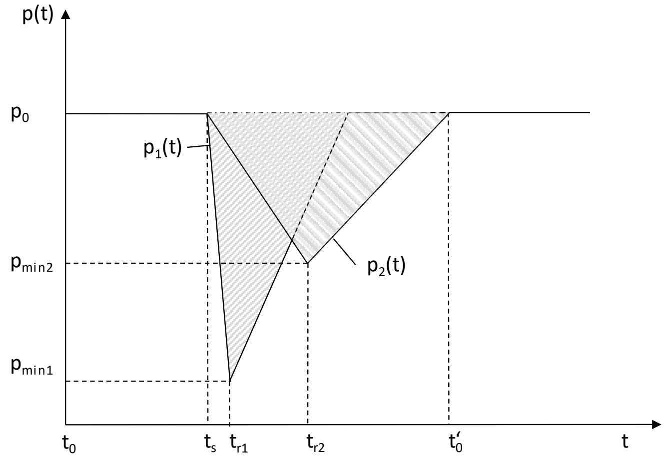

Figure 2: Performance function of two systems with equal resilience quality but different robustness and rapidity

Dynamic resilience (R^{dyn}, see Equation (2-10)) as a measure for the absorptive, restorative and adaptive capacity of the system is introduced by (Francis and Bekera 2014). The adsorptive respectively the adaptive capacity is defined as the ratio of the system performance at the minimum level respectively the recovered state compared to the original state. The restorative capacity is defined as the "speed of recovery" v_r. The speed of recovery depends on the time of final recovery and is approximated by an exponential function. The value of the dynamic resilience is not necessarily between 0 and 1.

$$R^{dyn} = \left(\frac{p_{min}}{p_0}\right)\left(\frac{p_0'}{p_0}\right) v_r \qquad (2\text{-}10)$$

In order to quantify the resilience of a network, the importance of single network components can be quantified. (Barker et al. 2013) define vulnerability and recoverability as main drivers for the network resilience, similar to robustness and rapidity which have already been identified. They also define two component importance measures to quantify the influence of one network element on the resilience of the whole network. The ratio between the performance loss caused by a certain link failure and the maximum performance loss caused by any link failure, multiplied with the time to full recovery, describes one component importance measure. The other component importance measure is defined as the positive effect if one certain link cannot be disrupted.

A metric including the robustness, the rapidity, the performance loss and the recovery ability is developed by (Nan and Sansavini 2017). The robustness and the rapidity have already been defined in the Equations (2-1), (2-4) and (2-5). The absolute performance loss equals Equation (2-9) multiplied with the original state performance p_0.The integration limits can here be adapted to the disruptive phase where $t_s \le t \le t_r$ and to the recovery phase where $t_r \le t \le t_0'$. The integral according to Equation (2-9) with the integration limits of t_s and t_0' and scaled by the duration of the time interval $(t_s - t_0')$ defines the time averaged performance loss, "$TAPL$". The recovery ability is defined as $R^{(2)}(t_0')$ according to Equation (2-3). The overall resilience metric "$R^{(combined)}$"merging the described factors results in the Equation (2-11).

$$R^{(combined)} = Robustness \cdot \frac{Rapidity^{recover}}{Rapidity^{drop}} \cdot \left(\frac{R^{(6)}(t_0') \cdot p_0}{t_0' - t_s}\right)^{-1} \cdot R^{(2)}(t_0') \qquad (2\text{-}11)$$

This resilience indicator is dimensionless and takes positive values. A high robustness, high recovery ability and high recoverability increase the resilience. At the same time, a high performance loss and a high rapidity during the disruptive phase reduce the resilience.

Various metrics defined in literature have been presented. On the one hand, there are static metrics linked to the robustness which do not depend on time (Equations (2-1), (2-2)). On the other hand, there are dynamic metrics, which can be calculated at any specific time (Equations (2-3), (2-9)). There are also metrics which can only be calculated after a new steady state is reached (Equations (2-5)-(2-8), (2-10), (2-11)). Some metrics only take values between 0 and 1 and therefore allow a direct assessment about whether the resilience is high or low (Equations (2-2), (2-8)). Others do take values above 1 depending on the chosen performance function. In this case, an evaluation of the resilience value is limited to comparisons with other equally scaled resilience values.

3. RESILIENCE FRAMEWORK FOR AIRPORT TERMINAL SYSTEMS

Based on the definitions and metrics for resilience extracted from literature (see Section 2), a framework for airport terminal systems will be set up in this section. In order to do so, the system boundaries and the performance indicators have to be determined.

A system is defined as a group of interconnected single components, which form a complex entity (Meyer and Miller 2001). The airport terminal system is physically separated from the environment by the buildings' walls. The throughput of the terminal can be measured by the passenger flow. Departing passengers enter the terminal, proceed through various process stations and leave the building boarding the aircraft. Arriving passengers deboard the aircraft, enter the terminal and leave the terminal after also passing different process stations. Baggage, staff and goods are also entering and leaving the terminal area but shall not be considered here. Instead, for now only departing passenger flows shall be considered. The departure flow includes several process stations the passengers need to pass in order to proceed to their gate and board their flight. The monitoring starts when passengers enter the terminal building and ends when they leave the building. The process stations considered in the basic terminal model will be specified in Section 4. While some process stations in the terminal like the check-in kiosk and the check-in desks can be traversed in parallel, most of the process stations like the boarding pass control and the security control have to be concluded one after the other. Consequently, if one process station breaks down, this failure is interrupting the whole passenger flow. Performance indicators for the terminal system are the passenger throughput in a certain time as well as the average or absolute time one passenger needs from entering to leaving the terminal area (referred to as system time), but also passenger-specific delay or queuing times. The throughput forms a performance function which would decrease after a disruptive event. The passengers' system time, queuing time or delay would imply delay functions increasing after a disruptive event. All presented performance indicators, except for the system time, can be assessed for a single process station in the terminal or for the overall terminal system.

Referring to the generic definitions of resilience in Section 2.1, the resilience of an airport terminal system can be defined as the ability of the terminal system to absorb, adapt to and recover from external disturbances. Electronic system failures, power outages, staff strikes or terroristic attacks are examples of external disturbance influencing the processes in the terminal area. Moreover, scenarios affecting the arrival and departure of passengers like traffic jams, public transport delays or major flight delays can affect the internal airport terminal procedures. A resilient terminal system shows robustness and rapidity in order to be able to minimize and withstand those external disturbances. This implies for example that if one or several process stations fail for a certain time, the passenger throughput does not drop "too far" and reaches a stable level again after a preferable short time, or that the queuing times rise at the affected station but decrease again as soon as possible.

As the metrics presented in Section 2.2 are generic depending on the systems performance indicator, all of them are theoretically applicable on an airport terminal system. In the following, selected metrics will be combined to enable a comprehensive resilience evaluation for airport terminal systems.

In order to consider the robustness as well as the rapidity of the terminal system, and in order to be able to distinguish between both capabilities, three resilience metrics (R^{t1}, R^{t2} and R^{t3}) will be defined. To capture the maximum performance loss of the terminal system, the absolute robustness R^{t1}_{abs} (see Equation(3-1)) as well as the relative robustness R^{t1}_{rel} ("resilience efficiency", similar to Equation (2-2)) form the first metric. In case the passengers' queuing time or system time are set as performance function, the absolute robustness equals p_{max} and the relative robustness equals the inverse of Equation (3-2). The relative robustness takes values between 0 and 1.

$$R^{t1}_{abs} = p_{min} \tag{3-1}$$

$$R^{t1}_{rel} = \frac{p_{min}}{p_0} \tag{3-2}$$

As a measure for the rapidity of the system, the time of disturbance is set into relation with the time of recovery (R^{t2}, see Equation (3-3)). It is assumed that a disturbance like a system failure or a strike is not a timely isolated event, but a continuing stress starting at $t_{s,start}$ and ending at $t_{s,end}$. This metric consequently is not applicable for isolated events such as a terroristic attack and takes values between 0 and 1. If the system recovers instantly once the disturbance ends, the resilience corresponds to 1. The longer the time of recovery continues, the lower the resilience. An infinite time of recovery, which means that there is no recovery, corresponds to a resilience of 0.

$$R^{t2} = \frac{t_{s,end} - t_{s,start}}{t'_0 - t_{s,start}} \tag{3-3}$$

The third metric R^{t3} combines both aspects of robustness and rapidity and corresponds to the resilience quality (see Equation (2-8)). As integration limits, the investigated time interval limits are chosen. In case a delay function is chosen as performance indicator, the inverse needs to be calculated in Equation (3-4). The resilience quality takes values between 0 and 1.

$$R^{t3} = \frac{\int_{t_0}^{t_{end}} p(t)\, dt}{\int_{t_0}^{t_{end}} p_0\, dt} \tag{3-4}$$

For the assessment of the resilience of an airport terminal system, three metrics have been described. For an overall resilience evaluation, those metrics can be combined to one resilience indicator R^t, see Equation (3-5). The resilience indicator R^t takes values between 0 and 1, as R^{t1}_{rel}, R^{t2} and R^{t3}also take values between 0 and 1. The value of 1 corresponds to a high resilience while the value of 0 corresponds to a low resilience.

$$R^t = R^{t1}_{rel} \cdot R^{t2} \cdot R^{t3} \tag{3-5}$$

In order to define and quantify resilience, possible failures and their type, frequency, intensity and duration also need to be defined. For the purpose of starting basic experiments in this paper, the complete failure of one process station at a certain time during the day will be assumed in Section 4. The duration will be varied.

If no internal actions, such as reserve staffing or redundant system substitutes, are started and a system operates at 100% of the theoretical capacity, delays following the disturbance cannot be compensated respectively caught up by the system. The system cannot recover and stays at a reduced performance level. In this case, the metrics R^{t2} equals 0. The combined metric also equals 0 and the system is not resilient. In this context, all resilience investigations in Section 4 need to be evaluated according to the capacity utilization rate of the terminal system, which gives information about how close to the capacity limit the system is operating.

4. SIMULATION OF THE AIRPORT TERMINAL RESILIENCE

While simple models might still be solved analytically, more complex terminal systems require simulation modeling. Queuing theory for example forms a mathematical discipline to analytically solve queuing systems. However, this approach is limited to exponentially distributed service times and reaches a limit after a certain level of complexity. (Borshchev 2013) As the presented simple terminal model is supposed to be further enlarged and modified to a complex generic terminal model, the investigations here are conducted with a simulation tool and not analytically.

4.1. Model Setup

A deterministic, discrete event simulation model is set up in AnyLogic (The AnyLogic Company 2019). While the deterministic character facilitates reproducible results, the discrete event modeling method is appropriate to model "a sequence of operations being performed across entities". (Borshchev 2013)

The basic terminal model consists of two check-in process stations, one boarding pass control and one security control. The structure of the model is shown in Figure 3. Walking times are not considered. The purpose is yet not to map the complete, complex terminal system but to show the applicability of the simulation tool and to gain basic insights about the resilience of a terminal system. As performance indicator, the system time is chosen. The current passenger system time can be measured as a function over time. One day of operations is simulated. The absolute robustness of the disturbed system therefore equals the maximum system time during the day. The relative robustness corresponds to the ratio of the maximum system time without and with disturbance and will be referred to as R^{t1} in the following. The rapidity is defined in Equation (3-3). The metric R^{t3} equals the ratio of the sum of the system time over all departing passengers during the day without and with disturbance. Consequently, the metric R^{t3} corresponds to the ratio of the average passenger system time during the day without and with disturbance.

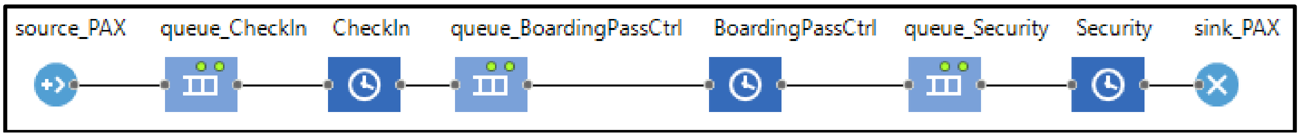

Figure 3: Simulation model in AnyLogic

As the processing times are dependent on the passenger type, the number of bags or the travel experience of the passenger, this parameter can take values in a certain range depending on the simulated airport. In this case, there is no specific airport providing information from historical data or existing predictions. The process times for the check-in counters, the boarding pass control and the security control are therefore defined based on values found in literature. In this case, the processing times used in the baseline scenario of the Eurocontrol CDM landside modeling (Kohse and Roeher 2007) are selected as initial values.

Concerning the flight plan, two different passenger arrival patterns are modelled. One pattern equals the simplest case of a constant passenger arrival rate and the other equals a normal distribution, which is applied to a flight plan of one hourly departing flight. The normal distribution complies with the effect that passengers arrive with a pattern depending on their flight departure time (Alodhaibi et al. 2019). The number of passengers per hour is equal for both rates. For a variation of the occupancy at a process station, the process time and the passenger arrival rate have to be adjusted relative to each other. An in- or decrease of the process time at a service station leads to an in- or decrease in occupancy, assuming the passenger arrival rate stays the same. An in- or decrease of the passenger arrival rate at a service station leads to an in- or decrease in occupancy, assuming the process time stays the same. Consequently, in a sensitivity analysis of the input parameters processing time, passenger arrival rate and capacity utilization, the correlation between those parameters always needs to be considered.

The capacity utilization of the overall terminal system is determined by the bottleneck of the system, which is the process station with the highest occupancy. Assuming that all passengers pass the check-in, the boarding pass control and the security control in this order and considering the maximum processing time of 120 seconds at the check-in, the maximum capacity of the system is 60 passengers (PAX) per hour. Consequently, a 100% occupancy equals a passenger arrival rate of 60 PAX/hour, while a 50% occupancy equals a passenger arrival rate of 30 PAX/hour.

An overview of all input- and output parameters is shown in Figure 4. To assess the sensitivity of the model on the named input parameters, several simulations are conducted. The simulated parameter variations are described in the following subchapter.

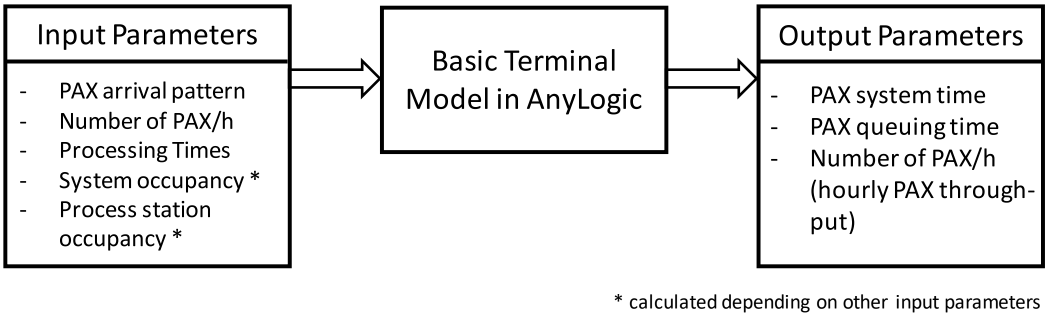

Figure 4: Model input and output parameters

4.2. Parameter Variation

As explained in Section 4.1, the passenger arrival rate as well as the processing time and occupancy of the service stations will be varied in the simulations. A modification of the occupancy of the check-in process stations (and consequently the whole terminal system) implies a change in the passenger arrival rate or the process time, as described in Section 4.1. In this case, the passenger arrival rate will be modified. The arrival rate at the security control depends on the service rate of the check-in and boarding pass station and is consequently not modifiable without changing the other process stations properties. Consequently, the occupancy of the security control is changed by modifying the process time of the security control. Moreover, different disturbance events are modelled. In order to characterize those events, the duration of the disturbance and the affected process station are varied. In this context, the failure of the check-in process station as well as the security control is simulated, in each case with the duration of 0.5, 1, 2 and 4 hours. The varied parameters and the range of values are listed in Table 1.

Table 1: Simulated parameters and range of values

Parameter	*Range*
Occupancy at process station/terminal system [%]	{50; 60; 70; 80; 90; 100}
Passenger arrival rate [PAX/h]	{30; 36; 42; 48; 54; 60}
Duration of disturbance [h]	{0.5; 1; 2; 4}
Affected process station	check-in; security
Processing times at check-in, boarding pass control, security control [sec]	120; 6; {30; 35; 36; 42; 48; 54; 60}
Passenger arrival pattern	constant rate; normal distribution

5. RESULTS

5.1. Disturbance at the Check-in Process Station

The resilience indicators R^{t1}, R^{t2}, R^{t3} and R^{t} of the system with the simulated occupancies and passenger arrival rates of the system as well as different durations of disturbance at the check-in are shown in Figure 5. With a constant passenger arrival rate, the metric R^{t1}, which is a measure for the robustness, does not depend on the occupancy of the system. The minimum value for R^{t1} equals 0.011 at the highest simulated duration of disturbance (4 h) and the maximum value equals 0.082 at the lowest simulated duration of disturbance (0.5 h). Consequently, R^{t1} and the robustness of the system strongly depend on the duration of the disturbance. With a normally distributed passenger arrival rate, the value of R^{t1} is dependent on the occupancy and increases starting at the occupancy of 80%. This can be explained by the fact that the maximum system time without a disruption increases with the normal distribution starting at the occupancy of 80%. The passenger arrival rate is not constant anymore and there are times with a comparably higher arrival rate and comparably higher queuing times. Therefore, the minimum value for R^{t1} with the normally distributed rate equals 0.011 at the highest simulated duration of disturbance (4 h) and the maximum value equals 0.182 at the lowest simulated duration of disturbance (0.5 h). If robustness is determined by the maximum system time, a highly balanced system with low maximum system time is less robust in the simulated experiment as the maximum system time is increasing with a higher percentage. For a constant arrival rate, the indicator R^{t1} does not depend on the overall system occupancy, for a normally distributed arrival rate it does.

The indicator for rapidity, R^{t2}, does not depend on the duration of the disturbance for the constant arrival rate. Moreover, a linear correlation between R^{t2} and the occupancy can be observed. The only exception for this forms the value at 90% occupancy with a disruption of 4 hours, which equals 0 as the steady state is not reached again during the considered time interval. The minimum value for R^{t2} equals 0 at the occupancy of 100% independent of the duration of the disruption and at the occupancy of 90% in combination with a disruption of 4 hours. In this case, the system time does not reach the value before the disruption during the considered time interval. The maximum value equals 0.5 and is reached at the occupancy of 50% independent of the duration of the disruption. The observation that R^{t2} linearly depends on the occupation can be explained as follows. The more spare capacity the system has, the more accumulated queuing people can be processed per hour and the quicker the system time is reduced after the disruption ends. The normally distributed arrival rate shows a very similar curve concerning R^{t2}. Therefore, the arrival rate does not show a significant influence on the indicator R^{t2} in the simulated experiments.

The resilience indicator R^{t3} combines both the rapidity and the robustness of the system. As shown in Figure 5, R^{t3} depends on the occupancy as well as on the duration of the disturbance for both simulated arrival rates. Consequently, R^{t3} takes comparably higher values for low occupancies and low durations of disturbance. The maximum value for R^{t3} with the constant rate equals 0.808 at the lowest simulated duration of disturbance (0.5 h) and the lowest occupancy (50%). The minimum value equals 0.012 at the highest simulated duration of disturbance (4 h) and the highest occupancy (100%). While the curve of R^{t2} has a linear shape, the curve of R^{t3} has a parabolic shape rapidly decreasing at high occupancies. The values of R^{t3} for the normally distributed arrival rate are slightly higher compared to the constant rate. This might be explained by the fact that the normally distributed rate is lower at the end of the disturbance. From that follows that directly after the end of the disturbance, more accumulated waiting passengers can be processed and the time of recovery is shorter. However, the deviations are very small with a maximum of 0.054 at an occupancy of 100% and a duration of disturbance of 0.5 hours.

The resilience indicator R^t is the product of the three indicators R^{t1}, R^{t2} and R^{t3}. Consequently, R^t depends on the occupancy of the system and the duration of the disturbance, see Figure 5. The maximum value for R^t with the constant rate equals 0.033 at the lowest simulated duration of disturbance (0.5 h) and the lowest occupancy (50%). The minimum value equals 0 at the highest simulated duration of disturbance (4 h) and the highest occupancy (100%). The maximum values for the normally distributed arrival rate are equal to those for the constant rate. There is a slight deviation between the curves of the constant rate and the normally distributed rate, especially for a disturbance of 0.5 hours. The shape of the curves is not linear, as the curves have a comparably higher gradient at small occupancies.

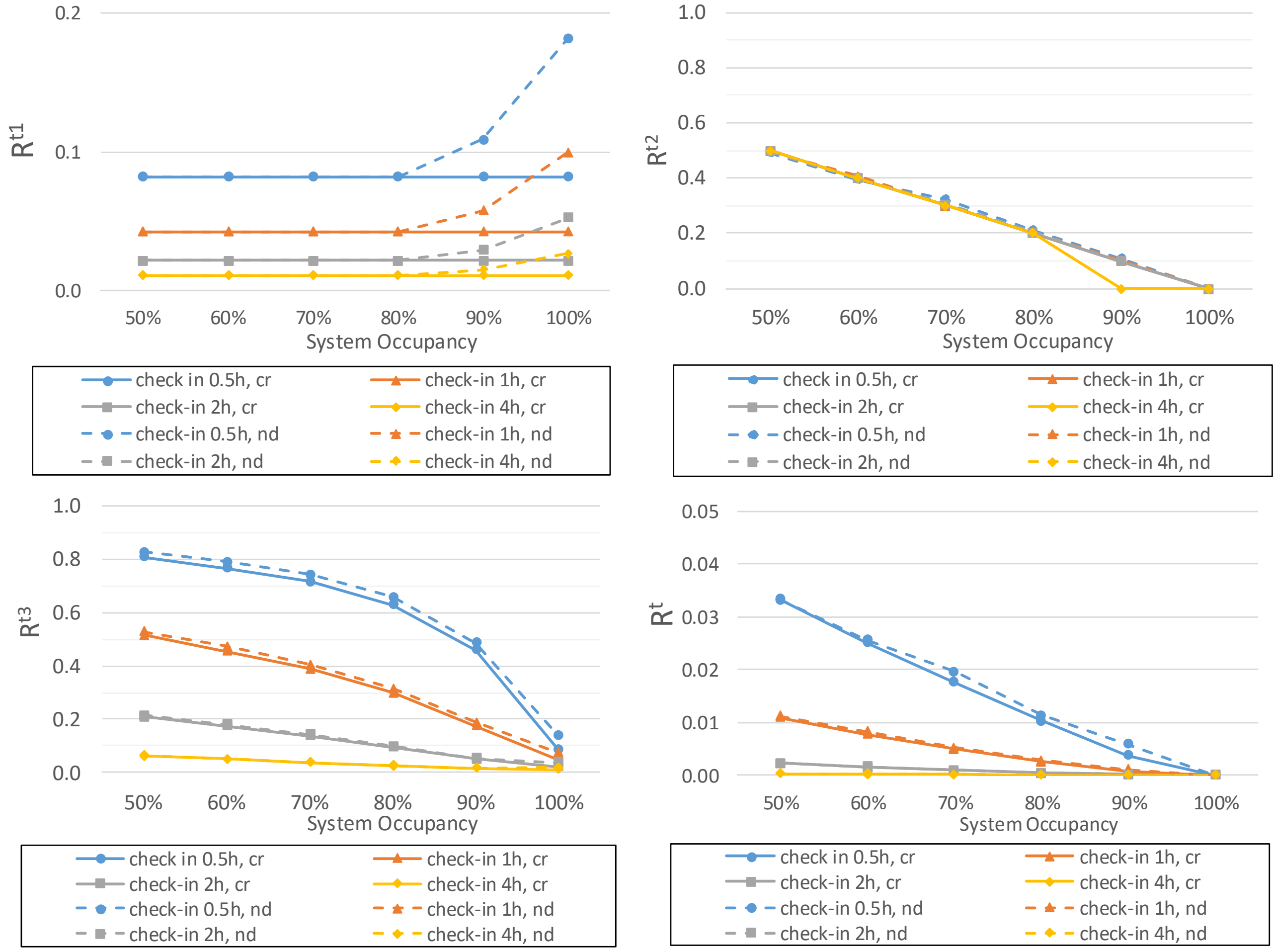

Figure 5: Resilience indicators for check-in process station with constant (cr) and normal distributed (nd) passenger arrival rate

5.2. Disturbance at the Security Process Station

The resilience indicators of the system with the simulated system occupancies and passenger arrival rates as well as different durations of disturbance at the security control are shown in Figure 6. While the occupancy of the check-in station is equal to the overall system occupancy, the occupancy of the security here is not directly affected by the passenger arrival rate but determined by the processing time of 35 seconds and therefore stays constant at a level of 58.3%. The results of a varied occupancy of the security control are shown in Figure 7 and will be discussed in Subsection 5.3. The results shown in Figure 6 typify the disturbance of a process station which is, in contrast to the check-in discussed above, not the bottleneck of the system. Therefore, even at the maximum system occupancy of 100%, there are spare capacities at the affected process station.

As observed for the check-in process station, the metric R^{t1}does not depend on the occupancy of the system when a constant arrival rate is applied. The minimum and maximum value for R^{t1} equal the respective values for the disturbance at the check-in station. Consequently, the robustness does not depend on the affected process station in the simulated experiments with the constant arrival rate. With a normally distributed passenger arrival rate, the value of R^{t1} increases starting at the occupancy of 80%. This effect was already observed for the check-in process station. The minimum value for R^{t1} with the normally distributed rate equals 0.011 at the highest simulated duration of disturbance (4 h) and the maximum value equals 0.188 at the lowest simulated duration of disturbance (0.5 h). The metric R^{t1} consequently is slightly higher for high occupancies and a normally distributed arrival rate compared to the results for the disturbed check-in station.

The indicator R^{t2} does again show very similar curves for different durations of the disturbance at a constant arrival rate. As in Subsection 5.1, a linear correlation between R^{t2} and the occupancy can be observed. The main difference is the higher level of the values of R^{t2}. This higher level, which is equal to lower times of recovery, can be explained by the spare capacities at the security control due to the constant occupancy of 58.3%.The minimum value for R^{t2} equals 0.415 (and not 0) at the occupancy of 100% independent of the duration of the disruption. The system time does reach the respective value before the disruption during the considered time interval for all considered occupancies and durations of disturbance. The maximum value equals 0.704 (and not 0.5) and is reached at the occupancy of 50% and a disruption of 4 hours. As in 5.1, the normally distributed arrival rate shows a very similar curve concerning R^{t2}. However, the values for a 100% occupancy of the system are lower compared to the constant rate, especially for 0.5 and 1 hour of disturbance. The minimum value equals 0.284 at 1 hour of disturbance and an occupancy of 100%. Consequently, with increasing system occupancy the arrival rate has an influence on R^{t2}, especially for the occupancy of 100%.

The resilience indicator R^{t3} shows a strong dependency on the duration of disturbance, but not on the occupancy. For the constant arrival rate, the curves have a slight negative gradient with a maximum value of 0.854 at a disturbance of 0.5 hours with an occupancy of 50% and a minimum value of 0.053 at a disturbance of 4 hours with an occupancy of 100%. Those values are slightly higher than the values in Subsection 5.1. For the normally distributed arrival rate, the curves are very similar with one exception, which concerns the values at a 100% occupancy. As this parameter already led to a comparably high robustness and a low maximum system time, also the average system time does not increase as much compared to the scenario without disturbance. One conclusion might again be that a highly balanced system with low average system time without a disruption is less resilient in the simulated experiment as the average system time with a disruption is increasing with a higher percentage.

For the constant arrival rate, the combined resilience indicator R^{t} shows a decreasing trend with increasing occupancy or increasing duration of disturbance. The maximum value for R^{t} with the constant rate equals 0.047 at the lowest simulated duration of disturbance (0.5 h) and the lowest occupancy (50%). The minimum value equals 0 at the highest simulated duration of disturbance (4 h) and the highest occupancy (100%). The values of R^{t} are consequently higher than the values in Subsection 5.1. For the normally distributed arrival rate, the maximum of R^{t} equals 0.051 at an occupancy of 100% and a disturbance of 0.5 hours. The respective maximum for each duration of disturbance is found at 100% occupancy. This follows from the maxima of the indicators R^{t1} and R^{t3} at this occupancy

In general, the influence if the system occupancy is clearly reduced when the security control is affected. Moreover, the passenger arrival rate has a clear influence on the resilience indicators, especially when the system occupancy equals 100%.

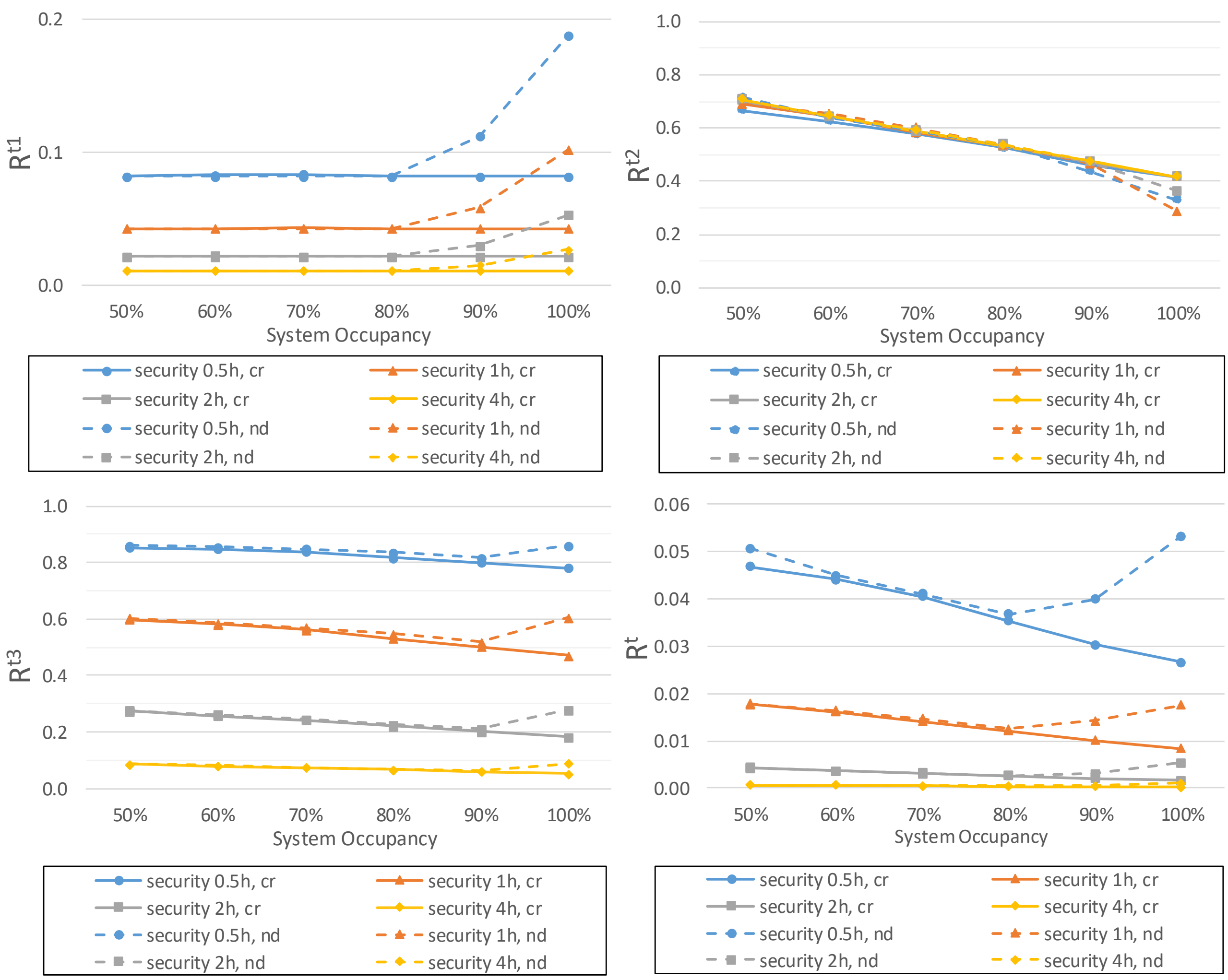

Figure 6: Resilience indicators for security process station with constant (cr) and normal distributed (nd) passenger arrival rate

5.3. Comparison of Disturbance at the Check-in and the Security Process Station

The results of a varied occupancy of the security control and the check-in (see Subsection 5.1) at a constant passenger arrival rate are shown in Figure 7. While the occupancy of the overall system is varied when the occupancy of the check-in is modified, the occupancy of the system stays at 100% when the processing times of the security control and at the same time the occupancy of the security control are varied.

The results for both process stations are very similar. The resilience indicator R^{t1} for the disturbed security control takes values between 0.011 and 0.094 and increases slightly with increased occupancy at the security control. For the 50% occupancy, the simulated values for disturbed security and check-in process station are equal. The curve for the disturbed security control, however, shows a slightly increasing trend for an increasing occupancy of the respective process station while the curve for the disturbed check-in stays constant.

The resilience indicator R^{t2} is equal for both disturbed process stations and therefore, based on the simulation results, does not depend on the affected process station if the station's occupancy is equal.

Considering R^{t3}, for short disturbances (0.5 h, 1h) there are slight deviations between the affected process stations. The maximum deviation is 0.031 at a disturbance of 0.5 hours and an occupations of the respective process station of 90%. If there is a deviation, the R^{t3} values for the affected security control are mostly slightly higher than those of the affected check-in stations, especially for high occupancies.

The comparison of R^t shows that for low occupancies, the indicator for the affected check-in stations is higher while for high occupancies, the indicator for the affected security control has higher values. The maximum deviation between both values is 0.0015 at a disturbance of 0.5 hours and an occupancy of 50%. The differences concerning the occupancy of 100% are nulled as R^{t2} equals 0 in this case.

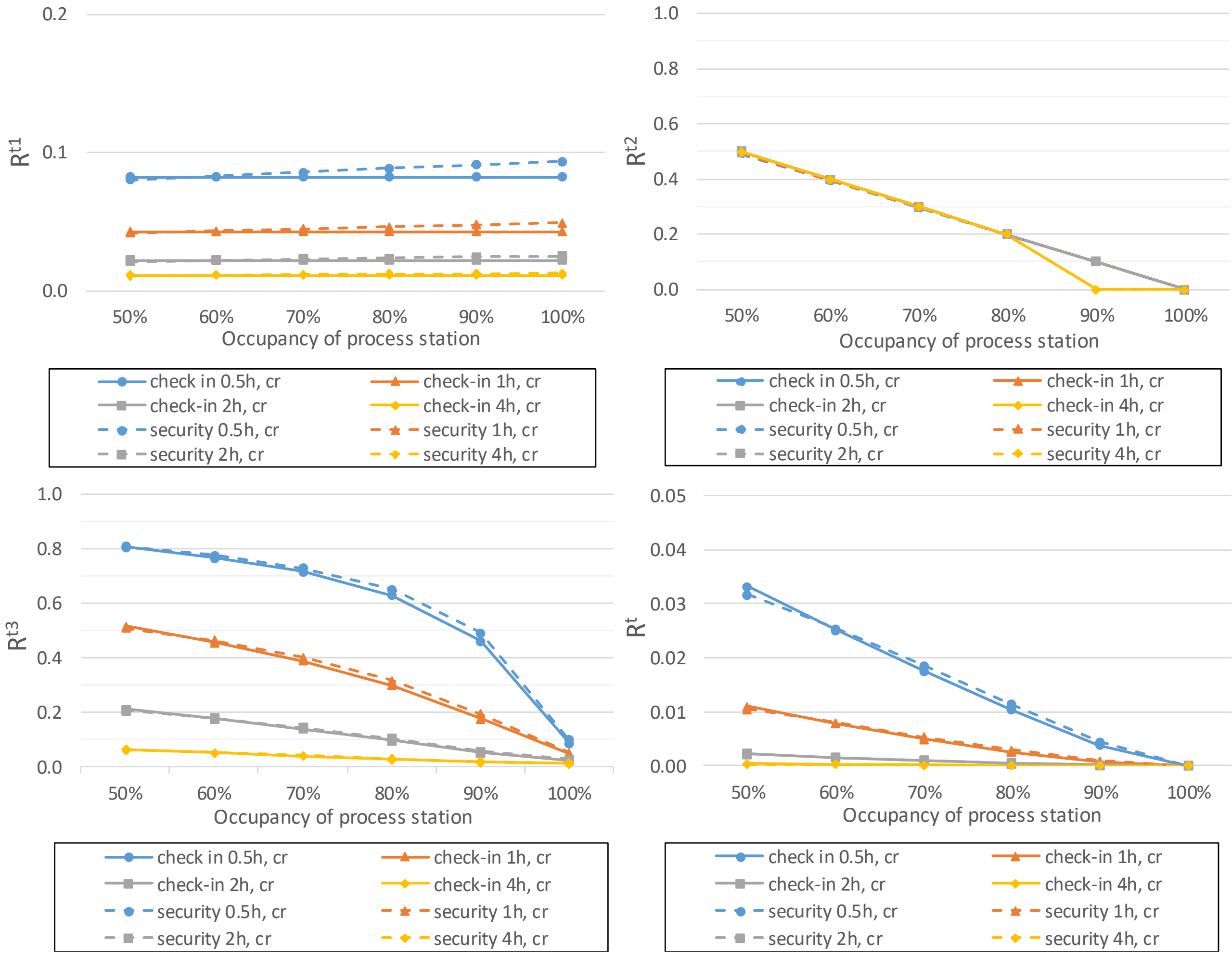

Figure 7: Resilience indicators for check-in and security process station with constant passenger arrival rate (cr) and depending on the occupancy of the respective process station

5.4. Plausibility of the results

In order to prove the plausibility of the results, the maximum system time and the recovery time of the system can be calculated analytically for the constant rate. The maximum system time is the sum of the disruption time and the time the system needs to compensate the queue resulting from the disruption. For example, at a 50% occupancy with a disruption of 0.5 h, the first passenger suffering from the disruption waits 1,800 seconds and otherwise processes the system in 161 seconds (sum of all processing times). The system time without disruption equals 161 seconds, the maximum system time with disruption equals 1,961 seconds. Consequently, the robustness equals 0.082, which was also calculated in the simulations (see Subsection 5.1). Furthermore, the time of recovery is the sum of the time of disruption and the time the system needs to dissolve the assembled queue at the check-in stations. At a 50% occupancy with a disruption of 0.5 h, this would equal the 1,800 seconds of the disruption and additional 1,800 seconds the system needs to process the additional waiting 15 passengers with the spare capacity of 30 passengers per hour. The resulting value of 0.5 for R^{t2} was also determined in the simulations. The results from the simulation therefore equal the results from test calculations and can be regarded as plausible values.

6. CONCLUSION

In this paper, various definitions and measures for resilience have been presented in a literature review. Based on the literature review, a resilience framework for airport terminal systems has been introduced including a definition of resilience as well as four resilience indicators. The resilience indicators include the aspects of robustness, rapidity and a combination of both.

In a discrete event simulation, the resilience framework was applied to a basic terminal model. An input parameter sensitivity analysis was conducted by varying the input parameters "system occupancy", "passenger arrival rate" as well as "processing time". Furthermore, the duration of the disturbance and the affected process station were modified.

The results showed that for a constant arrival rate, the indicator R^{t1} for the robustness of the system was independent of the system occupancy, while the indicator R^{t2} for the rapidity was independent of the duration of the disturbance. Furthermore, for constant arrival rates the other combined indicators R^{t3} and R^{t} were depending on both the occupancy and the duration of the disturbance. The normally distributed arrival rate led to a deviation of the resilience indicators especially concerning a high occupancy and concerning the indicator R^{t1}. Regarding the affected process station, the results for equally varied occupancies at the respective process stations showed similar resilience indicator values. Regarding the comparison at equal system occupancies but different process station occupancies, there were higher deviations, especially for the normally distributed rate in combination with high system occupancies. Moreover, the general applicability of the simulation model could be demonstrated by plausibility calculations.

It can be stated that the combination of timely dependent arrival patterns, high system occupancies and unequal process station occupancies is closest to reality. Consequently, more complex dependencies on occupancy and arrival rate can be expected and further simulations need to be conducted. In order to gain more insights, the model can additionally be enlarged by further process stations like a passport control, a check-in kiosk or a gate control. Furthermore, the intensity of the disruption can be varied or the failure of parallel process stations can be examined. Finally, in order to gain specific recommendations for the operation of airport terminals, a more complex model like a generic terminal model or an airport specific model should be generated.

7. REFERENCES

Alodhaibi, Sultan; Burdett, Robert L.; Yarlagadda, Prasad K.D.V. (2019): Impact of Passenger-Arrival Patterns in Outbound Processes of Airports. In *Procedia Manufacturing* 30, pp. 323–330. DOI: 10.1016/j.promfg.2019.02.046.

Barker, Kash; Ramirez-Marquez, Jose Emmanuel; Rocco, Claudio M. (2013): Resilience-based network component importance measures. In *Reliability Engineering & System Safety* 117, pp. 89–97. DOI: 10.1016/j.ress.2013.03.012.

Borshchev, Andrei (2013): The big book of simulation modeling. Multimethod modeling with AnyLogic 6. Chicago: AnyLogic North America.

Bruneau, Michel; Reinhorn, Andrei (2006): Overview of the Resilience Concept.

Chen, Lichun; Miller-Hooks, Elise (2012): Resilience. An Indicator of Recovery Capability in Intermodal Freight Transport. In *Transportation Science* 46 (1), pp. 109–123. DOI: 10.1287/trsc.1110.0376.

Fiksel, Joseph (2003): Designing Resilient, Sustainable Systems. In *Environ. Sci. Technol.* 37 (23), pp. 5330–5339. DOI: 10.1021/es0344819.

Francis, Royce; Bekera, Behailu (2014): A metric and frameworks for resilience analysis of engineered and infrastructure systems. In *Reliability Engineering & System Safety* 121, pp. 90–103. DOI: 10.1016/j.ress.2013.07.004.

Gama Dessavre, Dante; Ramirez-Marquez, Jose E.; Barker, Kash (2016): Multidimensional approach to complex system resilience analysis. In *Reliability Engineering & System Safety* 149, pp. 34–43. DOI: 10.1016/j.ress.2015.12.009.

Gluchshenko, Olga; Foerster, Peter (2013): Performance based approach to investigate resilience and robustness of an ATM System. In *Air Traffic Management Research and Development Seminar,* checked on 5/15/2018.

Grotberg, Edith H. (1997): The International Resilience Research Project, 1997. Available online at https://files.eric.ed.gov/fulltext/ED417861.pdf.

Henry, Devanandham; Emmanuel Ramirez-Marquez, Jose (2012): Generic metrics and quantitative approaches for system resilience as a function of time. In *Reliability Engineering & System Safety* 99, pp. 114–122. DOI: 10.1016/j.ress.2011.09.002.

Hoffman, R. M. (1948): A Generalized Concept of Resilience. In *Textile Research Journal* 18 (3), pp. 141–148. DOI: 10.1177/004051754801800301.

Hollnagel, Erik (Ed.) (2006): Resilience engineering. Concepts and precepts. Aldershot u.a.: Ashgate.

Hosseini, Seyedmohsen; Barker, Kash; Ramirez-Marquez, Jose E. (2016): A review of definitions and measures of system resilience. In *Reliability Engineering & System Safety* 145, pp. 47–61. DOI: 10.1016/j.ress.2015.08.006.

ICAO (Ed.) (2016): ICAO Long-Term Traffic Forecasts. Passenger and Cargo. Available online at https://www.icao.int/safety/ngap/NGAP8%20Presentations/ICAO-Long-Term-Traffic-Forecasts-July-2016.pdf, checked on 4/28/2019.

Kohse, Uta; Roeher, Ken (2007): CDM LANDSIDE MODELLING - PROJECT PHASE 2: ACARE SCENARIOS. Edited by Eurocontrol.

Li, Yi; Lence, Barbara J. (2007): Estimating resilience for water resources systems. In *Water Resour. Res.* 43 (7), p. 75. DOI: 10.1029/2006WR005636.

Mattsson, Lars-Göran; Jenelius, Erik (2015): Vulnerability and resilience of transport systems – A discussion of recent research. In *Transportation Research Part A: Policy and Practice* 81, pp. 16–34. DOI: 10.1016/j.tra.2015.06.002.

Meyer, M. D.; Miller, E. J. (2001): Urban transportation planning. A decision-oriented approach, 2nd ed. New York: McGraw-Hill.

Moench, Marcus (2009): Adapting to Climate Change and the Risks associated with Other Natural Hazards. Methods for Moving from Concepts to Action. In *The Earthscan Reader on Adaptation to Climate Change*.

Nan, Cen; Sansavini, Giovanni (2017): A quantitative method for assessing resilience of interdependent infrastructures. In *Reliability Engineering & System Safety* 157, pp. 35–53. DOI: 10.1016/j.ress.2016.08.013.

Proag, Virendra (2014): Assessing and Measuring Resilience. In *Procedia Economics and Finance* 18, pp. 222–229. DOI: 10.1016/S2212-5671(14)00934-4.

Righi, Angela Weber; Saurin, Tarcisio Abreu; Wachs, Priscila (2015): A systematic literature review of resilience engineering. Research areas and a research agenda proposal. In *Reliability Engineering & System Safety* 141, pp. 142–152. DOI: 10.1016/j.ress.2015.03.007.

Rose, Adam (2007): Economic resilience to natural and man-made disasters. Multidisciplinary origins and contextual dimensions. In *Environmental Hazards* 7 (4), pp. 383–398. DOI: 10.1016/j.envhaz.2007.10.001.

Rose, Adam; Liao, Shu-Yi (2005): Modeling Regional Economic Resilience to Disasters. A Computable General Equilibrium Analysis of Water Service Disruptions*. In *J Regional Sci* 45 (1), pp. 75–112. DOI: 10.1111/j.0022-4146.2005.00365.x.

Schultze, Peter (Ed.) (1996): Engineering within ecological constraints. National Academy of Engineering. Washington, D.C: National Academy Press. Available online at http://dx.doi.org/10.17226/4919.

The AnyLogic Company (Ed.) (2019). Available online at https://www.anylogic.de/, updated on 4/29/2019.

Uday, Payuna; Marais, Karen (2013): Exploiting Stand-in Redundancy to Improve Resilience in a System-of-Systems (SoS). In *Procedia Computer Science* 16, pp. 532–541. DOI: 10.1016/j.procs.2013.01.056.

Woods, D. D. (2009): Escaping failures of foresight. In *Safety Science* 47 (4), pp. 498–501. DOI: 10.1016/j.ssci.2008.07.030.

Woods, David D. (2015): Four concepts for resilience and the implications for the future of resilience engineering. In *Reliability Engineering & System Safety* 141, pp. 5–9. DOI: 10.1016/j.ress.2015.03.018.

Zobel, Christopher W.; Khansa, Lara (2014): Characterizing multi-event disaster resilience. In *Computers & Operations Research* 42, pp. 83–94. DOI: 10.1016/j.cor.2011.09.024.