

# Robustness of Complex Adaptive Logistics Systems: Effects of Autonomously Controlled Heuristics in a Real-World Car Terminal

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**Abstract** Logistics systems have to cope with different challenges like unforeseeable machine failures leading to an increase of dynamics and complexity. Accordingly, a system's robustness (i.e. the ability to resist against a number of endangering environmental influences and the ability to restore its operational reliability after being damaged) might be decreased. Thus, this paper aims to answer the following research question: How do selected exemplarily heuristics (Minimum Queue-length Estimation, Minimum Cumulative Processing, Simple Rule-based, Holonic, Ant Pheromone, and Neural Net) contribute to a real world Hamburg Harbour Car Terminal's robustness? Thereby, the research focus in this investigation is on throughput time. As a main result it could be shown that all selected heuristics could contribute to a positive development of the system's robustness in case of machine failures. Thus, from a practical view potentials for the improvement of real-world scenarios might be assumed.

**Keywords** Complex adaptive logistics systems · Robustness of logistics systems · Autonomous control

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# 1 Introduction

Robustness of logistics systems—i.e. the quality to remain effective for all plausible futures [1]—is widely accepted as one performance measure to value sustainable returns in a perturbed business environment [1–3]. Evidence from different industries emphasizes this need for robust systems that are exposed to many potential threats such as equipment failures or supplier discontinuities. Moreover, recent events have shown even higher risks arising from disruptions [4, 5]. Thus, it is desirable to maintain or increase a system’s performance by increasing its robustness.

One approach to increase a logistics system’s robustness is the concept of complex adaptive logistics systems (CALs), since [6] mention a high robustness as one key feature of CALs. Thereby, the higher robustness is achieved by the CALs concept through an autonomous reaction to complex and changing environments whereas a company strives for being successful in highly competitive and fast changing markets [6]. However, since the effects of the CALs concept on robustness has been investigated most prominently from a theoretical perspective, the corresponding research question of this paper is: How does the CALs approach contribute to the robustness of a real-world scenario? Hence, the paper implements one design option of a CALs according to [7] in a Hamburg harbour car terminal to investigate the effects on the system’s robustness. In order to estimate the performance of the design option, five autonomously-controlled benchmark control heuristics are applied. The following goals are subject of the investigation:

The descriptive goals are to describe logistics systems as CALs, to introduce the relevant key performance indicator (KPI) throughput time, to describe the five heuristics and the CALs design option and finally to sketch the scenario. The analytical goals depict the timely effects of the five heuristics and the CALs design option towards robustness. This includes the effects on the average total throughput time (indicator 1) as well as the effects on the duration the system needs to restore the former system state after an incident (indicator 2). The pragmatic goal is to identify the most efficient approach related to the indicators mentioned above. In order to achieve these goals, the paper proceeds as follows: [Sect. 1](#) starts with an introduction to the research field. In [Sect. 2](#), system robustness as a challenge of CALs is introduced followed by a description of logistics systems as CALs. In [Sect. 3](#), the underlying scenario including potential incidents is introduced comprehending the heuristics and the CALs design option. In [Sect. 4](#), the results are presented, interpreted and critically discussed in a logistics context. [Section 5](#) exhibits the conclusion and hints for further research.

## 2 Robustness in Complex Adaptive Logistics Systems

### 2.1 *The Need for Robustness in Logistics Systems*

The trend of logistics companies to become global players [8] leads to the progressive development of logistics systems from linear chains to international networks [9]. In consequence, they are part of global acting International Supply Networks, which are confronted with higher complexity (through number of actors) and dynamics (through the rate of change) [10]. Thus, logistics companies have to differentiate from competitors and simultaneously to cope with the increasing complexity and dynamics in a successful manner. In other words, they have to establish robust structures and processes. But what does robustness mean in the context of logistics systems?

The term robustness can be explained from different perspectives: According to Wycisk et al., robustness is the ability of the system to restore itself after being damaged [6]. Meepetchdee & Shah call a system robust if it is able to cope with complexity and dynamics in a way that an optimal target fulfilment can be achieved [11]. This paper focuses on the overall target achievement as well as on the restoring ability of the system as the research variables, since the robustness shall be understood as the optimization of logistics processes in terms of quality, time, and cost through optimal target fulfilment and restoring ability. However, the question occurs: How can this robustness be increased?

### 2.2 *Logistics Systems as Complex Adaptive Logistics Systems*

One approach being discussed for the achievement of higher robustness in logistics systems is the concept of Autonomous Control (AC) [12–14]. AC originates from the concept of self-organization and is enabled by the combination of software applications, sensor networks and new communication technologies (e.g. RFID). AC aims for an increased robustness of the overall logistics system through the improved ability to cope with complexity and dynamics [15]. However, how exactly can AC contribute to robustness?

Current research has already originated some findings regarding this question: Hülsmann et al. demonstrated that AC enlarges the robustness of logistics systems through a higher capacity for information processing [16]. Moreover, the contribution of AC to the robustness of logistics systems was researched through the analysis of AC's constitutional characteristics on the flexibility and stability and therewith on the adaptivity of the overall system [17]. While research was done on the effects of AC on the robustness of logistics systems, there is a lack of an empirical evaluation and findings. Thus, an approach to establish AC in a real-world scenario is required in order to research effects on robustness.

Wycisk et al. propose their CALS concept to realise a higher degree of AC in a logistics system [6]. They define logistics systems as Complex Adaptive Systems (CAS), since they identified various common properties between supply chains and CAS like heterogeneous agents or interaction. Thereby, they observed a higher adaptivity, positive emergence, and flexibility as CALS characteristics. In turn they also detected a vulnerability of CALS to all no-linear extreme dynamics respectively so called bullwhip-effects [6]. CAS in turn exhibit a certain degree of AC and thus can serve as an enabler of AC in a logistics system. As one major outcome of CALS is a higher system robustness [6], this concept shall be applied to the underlying scenario. However, based on the implications stated above the question occurs: How can the concept of CALS contribute to the robustness of a logistics system?

For the evaluation the throughput time will be the indicator 1, since it was shown that the throughput time rises with increasing the complexity level of logistics systems [13]. Thus, it constitutes an indicator of the logistics system's ability to cope with complexity and dynamics. Indicator 2 holds which AC heuristic features the best performance in restoring the system after a system breakdown. This constitutes an adequate indicator, since robustness beside others describes the system's ability to restore itself after a breakdown (see above). For answering these questions, control heuristics and a CALS design option for a real-world scenario are introduced next.

### **3 A Real-World Scenario for Investigating Effects of Autonomous Control Heuristics on Robustness**

#### ***3.1 The Hamburg Harbour Car Terminal***

In order to investigate the research question, an appropriate scenario is required that can adequately represent a CALS. The real-world car terminal is chosen, since it can be modelled as a CALS as it exhibits clearly distinguishable logistics objects (cars) [18] that can be equipped with CALS characteristics which are e.g. autonomy or interaction [6]. Hence, by implementing a CALS design option the model becomes a real CALS. Consequently, the car terminal can be utilized to estimate effects on the system's robustness through the CALS concept.

In addition to the suitability the terminal is readily described and has a flexible production sequence, a large amount of available real-world data and various changes and flexibilities in the car-flow process [19]. In a nutshell: the scenario exhibits a high degree of complexity and dynamics, system breakdowns can be modelled properly and it is adequately representable in a model. Hence, a subsequent simulation and thus concrete effects of different AC heuristics and the CALS design option on the scenario's robustness can be identified and investigated.

### 3.2 *The Simulation Environment*

The simulation model of this paper builds from a prior simulation developed by Windt et al. (2010b), since it is already operational and correctly represents the real world in the harbour context. The model contains information about e.g. number of cars per year, various routings of car flows in and out of parking, or various ways available to speed as many cars through the Terminal as possible. The information was decomposed into the ‘boxes’ shown in Fig. 1. Then, the means and standard deviations were calculated for the time each of 46,574 cars took to travel on the roads, to go through the required treatment queues and stations and then through the various subsequent stations, as required.

Cars arrive at the incoming parking area (I) (in Fig. 1). They are tagged with a parking order and then driven to a parking area (P1, P2, ..., P9).<sup>1</sup> At DP1 one of several heuristics (we describe these below) is applied to determine which treatment-station queue to drive the car to. If incoming cars lack a parking tag they are immediately driven to the next decision point (DP1). Next, they are temporarily stored in the TPA parking area, or are driven directly to the queue of some treatment station (T1 to T7 in Fig. 1)—if a treatment order is shown. Otherwise, they are driven directly to the exit (O). Available treatment stations are (1) gasoline station; (2) diesel station; (3) de-waxing; (4) car-body repair; (5) car wash; (6) paint shop; and (7) final inspection. Each car entering the Terminal comes with pre-defined orders, which can be divided into treatment and parking orders. Treatment orders call for from one up to six treatment steps; some of the treatment steps have sequence constraints (e.g., removal of transport protection (de-waxing) needs to come before washing and painting). After all treatments are finished cars are driven to the exit O (and are out of the simulation).

### 3.3 *Implemented Incidents in the Car Terminal*

In order to investigate effects of the CALS concept on the robustness of the chosen scenario, some kind of disturbances need to be added. Therewith, effects on throughput time as well as information about restoring capability of the system can be created. There are numerous sources for supply chain (SC) deficiencies that have prominently been investigated in recent research [20–23]. Several categories of SC risks were elaborated [24, 25] and extended lists of risk drivers were identified [20, 26].

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<sup>1</sup> For this baseline simulation accuracy (docking) test and application of the NN model, we ignore all parking waiting times except parking queues directly affecting the car-flows through specific treatment stations, since none of the heuristics involve any parking waits before cars get to DP1.

This paper focuses on internal machine failures, since the model and the real world data offers most adequate information for these issues. In that context, the question of whether the system's robustness can be increased can be investigated: Firstly, the effects on logistics processes in terms of throughput time can be analysed (indicator 1). Secondly, the capability of the system to restore itself after an incident (i.e. a machine failure) can be estimated (indicator 2). Thus, the paper answers the research question by investigating how the different heuristics react to these incidents and keep the whole scenario effective as well as how the heuristics are able to restore the former system state after being exposed to an unforeseen incident.

If a machine breakdowns occurs, the respective machine cannot perform the required treatment for one time of its expected treatment time. Breakdowns are put into the scenario once at a particular date and for three machines in a way that each car is affected. Thus, a visible effect over the whole simulation time can be created and different effects of capacity bottlenecks on the scenario can be investigated for the applied heuristics as well as for the baseline scenario.

### ***3.4 The Applied Car-flow Routing-Heuristics and a CALS Design Option***

Ideally, each car-routing decision should attempt to minimise car-flow time. Thus it is possible that for any given car, the waiting time before entering into any particular station is constantly changing because of the routing effects of the queue-waits and station-processing speeds, say, of the 10 cars ahead of it in the various queues. To navigate the cars through the terminal, five AC heuristics—beside the Standard Method (i.e. the real-world situation in the terminal)—are applied in the simulation: The 'Minimum Queue-length Estimation Heuristic', 'Minimum Cumulative Processing Heuristic', 'Simple Rule-based Heuristic', 'Ant Pheromone Heuristic', and the 'Holonc Heuristic'. These five heuristics are used as benchmarks in order to estimate the performance of the CALS design option 'Neural Net'<sup>2</sup> towards the system's robustness. This selection of the five benchmark heuristics is based on a literature search covering the current state of AC methods applied to logistics [18].

The Standard's Method is a pre-determined ordering of how cars are sent through the treatment stations, as follows: (1) incoming delivery; (2) gas or diesel refuelling; (3) de-waxing; (4) car-body repair; (5) car wash; (6) painting; (7) final inspection; (8) outgoing delivery [18].

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<sup>2</sup> The Design Option 'Neural Net' is selected, since it is the first CALS design option of a bunch of consecutive design options, that require all the preceding design options [7].

The Minimum Queue Length Estimation Heuristic gives top priority to the station with the fewest number of cars in its queue [27]. If all queues have equal length, a random selection is made.

The Minimum Cumulative Processing Heuristic sends the car to the station that shows the lowest ‘QP time’, where  $QP = (\text{station processing time} \times (\text{car in station} + \text{number of cars in station queue}))$ . This ignores driving times and possible overnight times [18].

The Simple Rule-based Heuristic compares estimated waiting times at station-queue points based on the processing time of the previous ten cars. This Heuristic proceeds as follows: (1) When a car leaves a station it transfers information about its processing time to a central location where it is collected and stored; (2) the information from the most recent ten cars is averaged; (3) the next car is sent to the treatment-station queue showing the quickest total treatment time (driving + queue waiting + treatment) based on the averaged times of the previous ten cars [28].

The Ant Pheromone Heuristic starts from how ants gather food: Cars following this heuristic leave virtual (pheromone) marks at each station when they leave. The more marks a station accumulates over a specific number of hours, the more likely it is that a subsequent car is sent to this station [29].

The Holonic Heuristic sends a car to the treatment station offering the shortest total time (based on driving + station-queue waiting + treatment times) gets the car. If several stations have the same queue length (delay), the car showing a quicker final release time is chosen. Whereas the Simple Rule Heuristic focuses on the average time of the previous ten cars, the Holonic Heuristic focuses on which next station is available the quickest (with soonest release time used to break ties) [30, 31].

The CALS design option<sup>3</sup> ‘Neural Net’ [7] sends the car to the next station based on six internal rules and according weightings. These rules define the optimal next station based on current information (e.g. utilization) as well as on information available from the last 50 cars that went through the station. Thus, the neural net not only considers the current state but also considers past developments and can thus identify potential problems in the system.

To benchmark the effects of the introduced heuristics with the CALS design option on the system’s robustness, Sect. 4 presents the obtained results in terms of throughput times in the standard scenario and the scenario with machine failures as well as the effects on the time the system needs to restore after these incidents. These indicators were chosen for the evaluation since ‘time’ constitutes one main success factor for car terminals caused by the importance of customer orientation (delivery times are perceived as one major quality indicator) [32]. However, also other indicators (e.g. utilization) might be feasible for the evaluation of suchlike scenarios and remain still subject to further investigations in the underlying scenario.

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<sup>3</sup> For an overview of further design options of CALS beside the Neural Net see [7].

**Table 1** Average throughput times in scenario without machine failures

Heuristic	$\Delta$ [%] Standard scenario	$\Delta$ [%] Machine failures	p-Value <sup>a</sup> ( <i>t</i> test)
Standard method	Reference method		
Ant pheromone	+6.53	-15.64	$P < 0.001$
Holonic	-4.02	-19.85	$P < 0.001$
Minimum buffer	-8.71	-21.54	$P < 0.001$
Neural net	-12.73	-24.32	$P < 0.001$
Queue-length Estimation	-6.22	-18.39	$P < 0.001$
Simple rule-based	-8.32	-12.73	$P < 0.001$

<sup>a</sup> Since the sample size exceeds 46,000 cars, we assume normal distributions and thus the *t* test is applicable

## 4 Evaluation of the Performance Indicators

### 4.1 Results of the Simulation Runs

The simulation was implemented and executed in the simulation software Tecnomatix Plant Simulation (v.9) from the Siemens AG. Based on the simulations, the succeeding results in Table 1 for the total average throughput times in the standard scenario (column 2) and the total average throughput times in the scenario with machine breakdowns (column 3) were obtained. Additionally, in order to check for the fit between the model and the real world, the p-Values for every heuristic based on a *t* test between the Standard Method and each particular heuristic was accomplished for both scenarios.

Table 1 demonstrates that every heuristic except the Ant Pheromone Heuristic reduces the total average throughput time in the standard scenario. The Ant Pheromone Heuristic increases the total average throughput time by 6.53 % whereas the reductions are in the interval between -4.02 % (Holonic) and -12.73 % (Neural Net). In the scenario with machine failures (column 3), all heuristics reduce throughput time. Thereby, the reductions of the single heuristics are different. They range between the standard scenario and the scenario with machine failures from ~4 % (Simple Rule-Based: -8.32 to -12.73 %) up to ~22 % (Ant Pheromone: +6.53 to -15.64 %). The *t* test additionally presents a fit between the model and the real world (all *p* Values < 0.001).

Figure 1 contains the days during (Feb 29th to Mar 3rd) and right after (Mar 4th onwards) machine disturbances and the average buffer level of the heuristics in comparison to the buffer level of the Design Option ‘Neural Net’ in the standard scenario. This depicts the time the different heuristics require to restore the former system state (see Standard Method representing stable system state) (Fig. 2).

The figure displays relatively high buffer levels of the heuristics (between 25 and 30 % from Feb 29th to Mar 3rd) in comparison to the average utilization in a stable system state (~4 %). Contrariwise, the figure shows low fill levels after all machines are restored on March 4th.



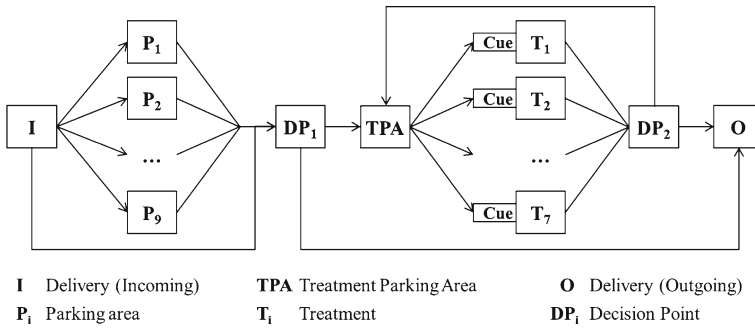


Fig. 1 Schematic representation of the model

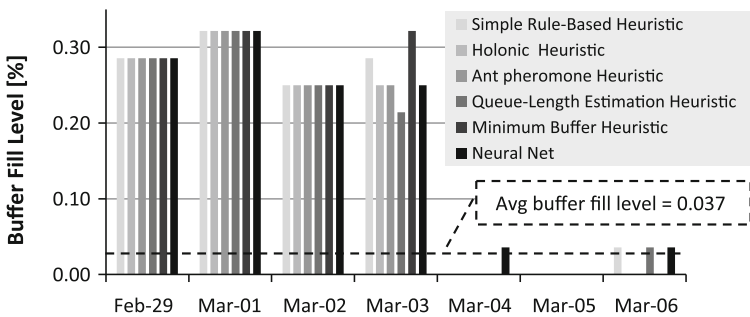


Fig. 2 System restore time after machine failures

### 4.2 Discussion of the Results

In order to evaluate the final results of the real world scenario simulation it has to be discussed how the heuristics effect the two indicators outlined in the research question. Thus, it has to be revealed how the average total throughput times (indicator 1) as well as the time for restoring the system after a machine failure (indicator 2) are influenced.

With regard to the average total throughput time (**indicator 1**) it can be stated that in the standard scenario all heuristics beside one (Ant Pheromone) could improve the throughput times. Thus, it is implied that through the implementation of suchlike heuristics cars can better navigate through the terminal. This finally leads to a better achievement of logistics goals like throughput time as well as due date reliability—as cars are routed faster through the terminal more due dates can be matched. This ultimately leads to a higher robustness in the standard scenario, since the whole system has more reserves due to a higher efficiency and is thus enabled to react more flexible to unexpected incidents finally increasing robustness.

For the machine failure scenario it can be observed that all heuristics generate a decreased throughput time in comparison to the reference heuristics. Thus, for all

heuristics a logistics target achievement and therewith a higher robustness of the overall system through the heuristics' implementation can be assumed. From a practitioners point of view it can be stated that implementing suchlike heuristics can mitigate the negative effects of machine failures like jams and therewith potentially more missed due dates, which might happen in real-world working processes.

However, comparing the AC heuristics with the CALS design option shows that the design option features the highest performance, since it improves the throughput time in the standard scenario ( $-12.73\%$ ) as well as the throughput time in case of machine failures ( $-24.32\%$ ) with the best overall value. Consequently, following the assumption that an increased logistics target achievement leads to higher system robustness and having the result described above it can be stated that designing the underlying scenario as a CALS leads to the highest robustness for the overall system.

However, it has to be addressed that the improvements of single heuristics from the standard scenario to the machine failure scenario are highly volatile. Although a clear improvement trend can be observed, it has to be considered that also small scenario changes (e.g. more or less machine failures in combination with the number of cars) can create huge differences in the results like it can be seen in the case. This results from the AC characteristic emergence leading to non-predictability of the overall system [6]. Thus, it also has to be mentioned that the results are not assignable to every real world scenario—other scenarios might lead to completely different results for the heuristics.

According to the duration the system needs to restore itself after an incident (**indicator 2**) it could first be observed, that all heuristics were able to restore the system within one day after the machine failure. However, differences occurred regarding the time needed for the restoring. In comparison to the first indicator the CALS design option does not constitute the best solution approach. Thus, it can be mentioned that from a practical perspective all heuristics provide the restoring ability for the system after a breakdown. However, since the neural net does not deliver the best results here the question remains how to improve the neural net in order to improve also the restoring ability of this CALS design option. In this specific investigation a recommendation for the overall scenario considering both indicators cannot be given for one specific heuristic—the final decision has to be made based on the individual goal settings (which goals are the most important ones) or rather based on practical goal experiences (e.g. probabilities for machine failures in specific real world scenarios).

Finally, this leads to the conclusion that in sum all heuristics are able to increase the system's robustness in the scenario with machine failures, since they exhibit a lower total average throughput time than the Standard Method (keep system effective) and are able to restore the system after a failure. Thus, this case indicates that having the right circumstances in a real-world scenario (e.g. high complexity and dynamics, lots of options and entities) the selected AC heuristics can improve the system's robustness. Additionally, the CALS design option 'Neural Net' features in both scenarios the best throughput time. On the other hand, the time to

restore is not as short as with the other heuristics. This shows that the CALS design option might feature additional potential to improve a system's robustness but in contrast to other heuristics the design option needs more time to restore the system. Thus, the total performance of the Neural Net in contrast to the other heuristics has to be evaluated in more detail and both indicators have to be weighed against each other depending on their economic impact as well as on the particular context.

## 5 Conclusion

This paper intended to give an idea about how the CALS approach contributes to the robustness of a real-world scenario in comparison to existing control heuristics. The main outcome is that in a scenario with high complexity and dynamics and in combination with machine failures all selected heuristics and the CALS design option can contribute to a positive development of the system's robustness. Additionally, from a practitioners perspective one can see that in real-world scenarios there is potential for improvements in system flows and AC heuristics can be one way to realize this potential.

However, this research features some limitations. First, it does not cover all relevant logistics KPIs—which are partially conflicting like low work in progress and high utilization [32]. Then, the introduced heuristics are complicated to apply in a real-world scenario. The reason is, that AC heuristics as well as the introduced design option 'Neural Net' demand for a complicated set of technological and computer components (e.g. sensor networks, communication interfaces), which also have to meet the organizational and structural requirements of the given institution [33]. Moreover, these components are in sum expensive, what can lead to financial risks resulting from the implementation [34]. Since a testing of the system's outcome is nearly impossible—due to the characteristics of AC like emergence [35]—it might be hard to convince investors of an acceptable return of their investment into the required technologies. Finally, people might avoid suchlike concepts due to their loss of control that comes along with the system's self-organization.

Further research should focus on the given limitations. Hence, additional logistics KPIs could be included in further research as well as a transfer of the gained insights to other simulation scenarios. Moreover, since the research also shows only very little differences between the particular heuristics the investigation horizon and the input parameters should be adapted in order to generate more detailed findings for the different approaches.

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