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RELOCATION OF RESOURCES IN A HIERARCHICALLY MANAGED TRANSPORTATION SYSTEM UNDER CRITICAL CONDITIONS

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Critical state of operation is reached by a system when it is exposed to an unexpected coincidence of faults (such as periodic rapid increase of the service demand, unavailability of a significant proportion of vehicle operators, simultaneous breakdown of all or a large part of the vehicle fleet). This leads to complete disruption of the transportation system, which persists even after the faults are removed. The duration of critical state of operation is defined as the time needed to resume normal operation after such an incident. It is shown that this time can be predicted using the simulation tools. Furthermore, a contingency plan is proposed, based on relocation of some resources between independent parts of a hierarchically organized transportation system. This contingency plan is analysed to determine the optimal percentage of resources to be relocated and the duration of this relocation.

Keywords: discrete transportation, reliability analysis, simulation tools, risk management

1. Introduction

When designing a discrete transport system, it is essential to take into account the possible faults that may occur during its operation. The dependability (reliability) analysis of such systems lets us determine the level of redundancy that ensures continuity of service at an economically justified level of assurance. There are a lot of techniques that support this type of analysis [1, 3, 9, 10].

Dependability analysis ensures that all the faults are considered proportionately to the probability of their occurrence. Thus, the analysis tends to underemphasize the events that are very improbable, such as the simultaneous breakdowns of all or almost all system components. Such situations are addressed by the techniques of risk analysis, which consider the probability of risk occurrence and their effects [2, 4, 5, 6, 8]. The paper analyses these situations, specifically as applied to the discrete transportation.

It should be noted that it is rarely justifiable to try to prevent these improbable faults by increasing redundancy of the transport resources – it would be a gross waste of those resources. Instead, an important aspect of the risk management is to propose contingency plans in case such an unlikely event occurs. The effects of the event may persist for a long time after its passing, if the system is left without an intervention. The system is said to operate under critical conditions when it is exposed to such an event and while its effect still persists.

It is proposed to demote this problem, by temporarily relocating some of the transport resources from an unaffected part of the system. Thus, the time of critical operation is reduced at the cost of increasing its extent. It is clearly an important aspect of contingency planning to predict the consequences of the critical state of operation in case of the alternate management plans. This is addressed by using the simulation tools developed for the dependability analysis, slightly modified to deal with the critical conditions.

2. Model of the Transport System

We consider a class of discrete transport systems (DTS) organized hierarchically, i.e. having a number of independently run regional distribution centres (RDC) and a central system interconnecting them. The model is inspired by the organization of the Polish Postal Service, though it is in no way limited to it [3, 9]. The basic assumptions are as follows:

- the distribution of cargo is realized in discrete quantities (containers carried by vehicles),
- each regional centre is completely independent of the others, having its own fleet of vehicles, its own human resources (vehicle drivers) and organization,
- the flow of cargo, to be distributed, cannot be regulated: the distribution centre has to accept all the incoming volume of cargo, regardless its current capabilities to handle it.

In the presented model we concentrate on the operation of a single RDC, a limited segment of the system typically used to distribute goods locally. The system consists of nodes (locations from which goods are collected and to which they are carried) and vehicles travelling between the nodes. The vehicles are manned by the human drivers, who may be allocated to different vehicles. The RDC is modelled as a collection of:

- the set of nodes X, in which a central node $x_0 \in X$ is distinguished (the local distribution centre),
- the set of routes between the nodes R,
- the set of vehicles V,
- the set of assignments Z, which determines the volume of cargo to be transported,
- the set of travel timetables C,
- the set of vehicle operators (drivers) K, assigned to vehicles when they transport goods between the nodes,
- the set of maintenance teams (mechanics) M that are required to service the vehicles after a break down.

2.1. Transportation assignments

The assignments are connected with specific needs for cargo transportation. The amount of goods in an assignment is expressed as a discrete number of standard containers. The assignments specify the source node from which the cargo is collected and the destination node it is carried to. The assignments are always either from the central node or to the central node. Assignments between other nodes are not allowed.

There is a fixed time in which each assignment must be completed. Depending on the nature of the DTS system, this time is fixed by local regulations or is part of the service agreement between the assignees and the transport service provider.

2.2. Nodes

There is a single central node and a number of local ones. The central node generates cargo destined to all the local nodes. It represents the connecting gateway to the other regional distribution centres. The assignments are generated independently in each node, using random distributions. Each local node has an attribute which determines its characteristic rate of assignments generation. The central node is described by an array of rates, one for assignments to each local node.

2.3. Vehicles

It is assumed that the vehicles are described with similar functional and reliability related parameters: capacity (expressed as the number of cargo containers it can carry), average cruising speed (determining the route latency), failure rate, renewal time. All the vehicles are based in the central node and travel from it to realize the assignments.

At any moment in time, each vehicle may be in one of the following states: it might be en route between nodes (a specific distance from the starting node, carrying specified amount of goods), it might be out of gear due to a failure, it might be waiting for cargo to be loaded, it might be stopped due to unavailability of a driver or due to regulatory rest period of its driver.

A vehicle may be realizing multiple assignments at the same time. It will be fully loaded if the pending assignments allow it. If there are insufficient assignments for nodes towards which the vehicle is destined, then it may be partially loaded or even travelling empty. It will collect goods en route if there are pending assignments in the visited nodes.

The vehicles are assumed to break down occasionally, in accordance to their reliability parameters (failure rates). They stop operation and wait for a maintenance team. On being repaired (after a random repair time), the vehicles continue the task they were realizing before breakdown. No transloading of the cargo is considered.

2.4. Vehicle operators

The number of operators is limited. Whenever a vehicle is assigned to a task (due to a timetable) an operator must also be associated with it. Any unallocated driver can be associated with any vehicle. Only one driver at a time is associated with a vehicle (since we do not consider long distance routes with standby drivers).

The work of vehicle operators is regulated by local and EU legislature. The daily working hours are limited (to 8 hours); there are also compulsory rest breaks while driving. Thus, at any time the driver can be in one of the following states:

- resting (not at work),
- unavailable (due to illness, vacation, etc.),
- available (at work – ready to start driving),
- pausing (having a break while driving),
- driving.

It is assumed that the vehicle operators work in 8 hour shifts. Thus, the state of each one changes to "resting" whenever his daily working time limit is exceeded and he arrives in the central node. He stays in this state until the beginning of his shift next day. Then, his state changes to available. If there is a pending driving schedule (timetable) and an available vehicle, then his state changes to "driving".

While driving, the driver has to heed the limits on the maximum length of time that he can work without a break. Normally, the timetables assure that the required breaks are fulfilled while the vehicle is loaded in the visited nodes. If a route is unnaturally long or there are travel delays on the way, then the driver is required to take a break en route. The parameters determining the daily working hours limit, maximum uninterrupted driving period, minimum break duration are associated with the vehicle operators' model.

Drivers are liable to sickness and other events that can make them temporarily unavailable. After a prescribed leave of absence they again become available at work. Driver illness is modelled as a stochastic process. The process is fairly complicated to reflect the typical periods of illness. Details of such a model are discussed in [8].

The allocation of drivers to the jobs (described by the timetables in the model) is governed by some simple rules:

- vehicles cannot carry goods between nodes if there is no operator available,
- the driver is chosen from among those, whose daily working time limit allows them to complete the job with at most 10% overtime (i.e. estimated journey time is less than 110% of the left work time limit).

2.5. Routes

Routes represent the direct connections between nodes of the system. They are characterized by the distance that the vehicles must travel. Taking into account the average travelling speed of vehicles, this determines the latency connected with moving from one node to another. This latency is further distorted by the travel delays, which represent the natural variation of latency, e.g. caused by the traffic congestion. These delays are modelled using a random distribution.

2.6. Timetables

Vehicles are travelling in accordance to fixed timetables (travel schedules). Each timetable determines the time to leave the central node and a sequence of nodes that must be visited by the vehicle as well as the times of these visits. It describes the daily work of the vehicle associated with the timetable, independent of the actual needs as determined by the assignments.

The set of timetables does not change in the analysed time horizon. It can be changed (reconfigured) at predetermined times such as different seasons of the year, holiday times, weekends. The schedule starts at the central node, on reaching each consecutive node in the timetable, the goods destined to it are unloaded and the goods waiting there are loaded in their place. The time used for unloading and loading is randomly chosen. If there are other vehicles in the node, then they are queued and the period of loading/unloading is extended commensurately. The timetable does not specify the time to leave a node (except the timetable start time).

When the vehicle returns to the central node (at the end of a schedule) it is completely unloaded. It can then be associated with another timetable or it may be placed in the pool of available vehicles, waiting to be associated with a job.

The timetables are not directly associated with vehicles or drivers. Instead, any available vehicle and operator is allocated to each schedule. If there are no vehicles or drivers available, then the timetable cannot be realized. The system model does not openly include an intelligent (human) decision centre or dispatcher. This is hidden in the implementation of the travel timetables.

2.7. Maintenance teams

The model does not distinguish any specific parameters of the maintenance teams, just their number. If a vehicle breaks down, it will be repaired by one of the maintenance teams. The distribution of the repair time is associated with the vehicle, not with the team. Each maintenance team repairs only one vehicle at a time. If all the maintenance teams are currently occupied, then the vehicle repair is delayed until one of the teams becomes available.

3. Critical State of Operation

The transport system is designed to cope with the normal load of work, under usual conditions of operation. In fact, it incorporates an economically justifiable level of redundancy that ensures uninterrupted operation in case of the expected incidents (driver absentees, vehicle break-downs, traffic delays) or normal fluctuations in the workload. The proposed model can be used to determine this level of redundancy, as discussed in [8, 9].

Critical state of operation occurs when the system is faced with an unpredictable coincidence of incidents that it is not designed to cope with. As such, critical state of operation is very unlikely and it is not economically viable to safeguard against it by having redundant resources. To investigate this state in more detail, it is necessary to introduce some measure of the "normality" of system operation. It is proposed to use for this purpose the ratio of on-time deliveries.

3.1. Ratio of on-time deliveries

The quality of service realized by the transport system is characterized by its ability to deliver all the cargo assignments on time. Each assignment has a guaranteed time of delivery T_g. The real time of delivery T is a random variable, which depends on the current volume of cargo, travel latency, faults of the vehicles, driver's sickness, etc. There are two possible relations between the delivery deadline T_g and the actual assignment realization T:

- If the assignment is completed before the deadline, i.e. $T \leq T_g$, there is no penalized delay. There is no reward for the early delivery, though.
- If the assignment is completed after its deadline, $T > T_g$, then there is a late delivery penalty incurred.

The short term measure of the quality of service is obtained by counting the assignments that are delivered on time (before the deadline). If the system is operational, it should realize all the assignments on time. On the other hand, a completely failed system does not realize assignments at all, causing them all to be delivered late. Thus, in a traditional system with up/down states only, the average ratio of on-time deliveries is equivalent to the system availability. In the considered analysis, the measure is not so easy to interpret, since the system hardly ever fails completely. Instead, if an incident occurs, some of the assignments are realized late.

The ratio of on-time deliveries A_r is defined as the proportion of assignments that are delivered on time to the total number of assignments in the system during a fixed time period. Of course, this measure is a random variable that reflects the nondeterministic properties of the whole system. We consider a 24 hour time period for determining the average ratio of on-time deliveries.

The sequence of time instances (t_0, t_1, … , t_n) fixes the boundaries of the consecutive days, for which the ratio is considered. $N_d(t_i, t_{i+1})$ denotes the number of assignments completed in (t_i, t_{i+1}). $N_{pd}(t_i, t_{i+1})$ denotes the number of those assignments, which are completed on time. There are also assignments, which enter the system in one period and are completed in the next. $N_{in}(t_i)$ denotes all assignments en route at time t_i. Correspondingly, $N_{pin}(t_i)$ denotes a part of these assignments, which are not yet late in delivery at time t_i (though they may become late during the next period). Average ratio of on-time deliveries is defined as:

$$A_r(t_i) = E\left(\frac{N_{pd}(t_{i-1}, t_i) + N_{pin}(t_i)}{N_d(t_{i-1}, t_i) + N_{in}(t_i)}\right), \tag{1}$$

where E denotes the mean value of the measure.

The ratio is used to characterize the reliability of the regional distribution centres (RDC). One has to set an acceptable level of the coefficient (e.g. 80%, 90% or 99%). By providing a sufficient level of redundancy (in the number of vehicles and drivers), the system can be designed to fulfil the requirements (ensure fault tolerance) in normal circumstances.

It is assumed that each RDC is characterised by its specific ratio of late deliveries. There is no global measure applied to the system as a whole. Each regional centre is independently assessed. The quality of system performance is a vector of the coefficients of late deliveries of the various centres.

Global measure can be defined on this vector, but this is not desirable as the penalties are local.

3.2. Condition for critical state of operation

The system is considered to operate in the critical state if the ratio of on time deliveries is significantly below an acceptable level for a number of consecutive days k_{crit}. This corresponds to the condition that the ratio is smaller than a set level A_{crit} in this period, i.e.

$$A_r(t_i) < A_{crit} \text{ for } \quad j = i, i+1, \ldots, i + k_{crit} \,. \tag{2}$$

A very important criterion of the system operation in critical state is its ability to regain normal operation. This is measured by the duration of the critical state of operation T_{crit}.

3.3. Operational risks leading to the critical state

The critical state of operation should never be attained in normal circumstances. Its probability is negligibly small in a properly designed system. This does not mean that it is impossible. There are a number of situations that may lead to this state of operation, all unrelated to the presented model. While they are improbable, there has to be a contingency planning to deal with them (in case they do occur). Some of these circumstances are discussed hereafter to support the need of such planning.

Periodic rapid increase of the service demand

This situation occurs naturally due to the seasonal changes in service demand. It manifests itself by much higher rates of assignments arriving in all the nodes. This is handled by the routine design of the transport system (periodic changes in the amount of available resources). More to the point, this risk may be connected with failures of other, competitive transport systems operating in the same region. In effect there is a sudden influx in service demand, swamping the system with assignments that it cannot handle. In consequence, the RDC cannot handle all the cargo and there is an accumulated backlog of assignments keeping the system in critical state.

Unforeseeable unavailability of a significant proportion of drivers

This can be caused by a strike of a part of the drivers. Else, it can be a consequence of an epidemic illness, such as flu or other virus infection. As a result, a significant proportion of the drivers may be simultaneously absent from work. Some of the travel schedules cannot be realized, building a backlog of unsettled or late assignments.

Unforeseeable reduction in the number of available vehicles

This is usually connected with disrupted supply chains, resulting in shortage of fuel or vehicle replacement parts. As a result, a significant part of the vehicles cannot be kept operational (as if they all failed simultaneously). The risk analysis is very similar to the previous situation.

4. Prediction of the System State Using Simulation

The normal state of operation of a regional distribution centre (RDC) is described by the model discussed in Section 2. The model can be analysed by a number of approaches, such as state-transition or fault tree analysis. Due to its complexity and large number of non-homogenous components, the most practical approach is based on Monte Carlo simulation [3]. In this approach, it is not necessary to enumerate all the system states (functional and reliability related), which significantly simplifies computations.

The analysis is performed using a simulator, custom designed for this purpose at Wroclaw University of Technology. It is based on the publicly available SSF simulation engine that provides all the required simulation primitives and frameworks, as well as a convenient modelling language DML [7] for inputting all the system model parameters. DML is a dedicated language used by the SSF simulation framework that supports a hierarchically structured representation of simulation model parameters. It is simple to use and more convenient than the GUI based interfaces of commercial simulators.

By repeating the simulator runs multiple times using the same model parameters, we obtain several independent realizations of the same process (the results differ, since the model is not deterministic). These are used to build the probabilistic distribution of the results, especially the average measures. For the purpose of the presented considerations, the simulator can be used to predict the ratio of on time deliveries.

This approach is obviously insufficient to analyse the critical states of operation. The simulator cannot reach such a state during normal simulation runs (due to its very low probability of occurrence). Thus, the simulator was modified to enable this analysis. The occurrence of risks mentioned in Section 3.3 can be predetermined manually in the simulator. Then, the simulator can be used to predict their effects on the rate of on-time deliveries. The system is analysed against its ability to resume normal operation after a disruption of service. This is measured by the period of time that the system remains in the critical state of operation. The time can be significantly longer than the actual duration of disruption. Moreover, the duration of the critical operation can be limited by some management decisions, as discussed in Section 5. The effect of these decisions can also be predicted by the modified simulator analysis.

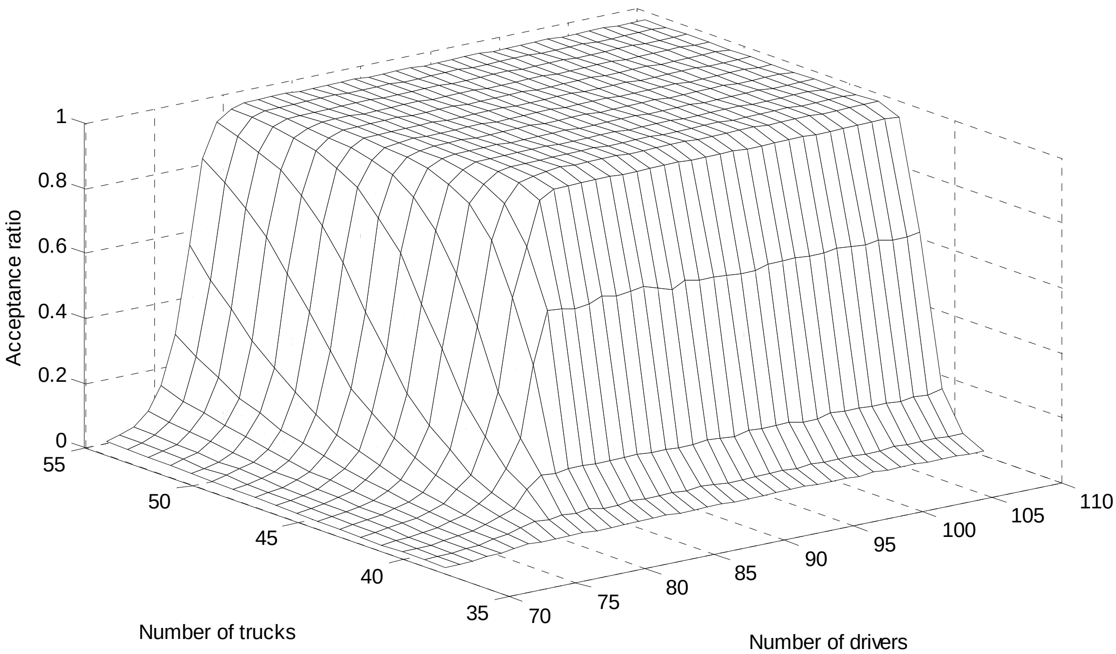

Figure 1. The average ratio of on-time deliveries for various numbers of vehicles and drivers

4.1. Case study

All the simulation results are based on the observation of the organization of the Polish postal service, specifically its Lower Silesian regional mail distribution centre. It consists of the central node located in Wroclaw and 22 local nodes located in main towns of the region. The distances between nodes, used in the simulation runs, were determined from a road map of Poland. The stream of assignments (generation of cargo) is assumed the same for all the destinations. It is modelled as a Poisson stream with the rate set to 4.16 per hour in each direction. On average this corresponds to 4400 containers to be transported every day.

The system is serviced by a number of vehicles, designed to fulfil the transportation demand with some redundancy. All the vehicles can each carry 10 containers at a time. The velocity of vehicles is modelled by the Gaussian distribution with the mean value of 50 km/h and standard deviation of 5 km/h. The average loading time is equal to 5 minutes. The mean time to failure of each vehicle is assumed as 20,000 hours. The average repair time is 5 hours (Gaussian distribution).

The vehicles are operated by drivers working in 2 shifts (morning: 6 a.m. till 2 p.m., afternoon: from 1 p.m. until 9 p.m.). The number of drivers is designed to fulfil the transportation requirements. The rates of drivers' disabilities are observed to be as follows:

- short sickness: 0.003,
- typical illness: 0.001,
- longer disability: 0.00025.

The system works with fixed timetables. These are organized so that the vehicles and drivers have a grace time of 20 minutes after completing one journey, before starting on the next one.

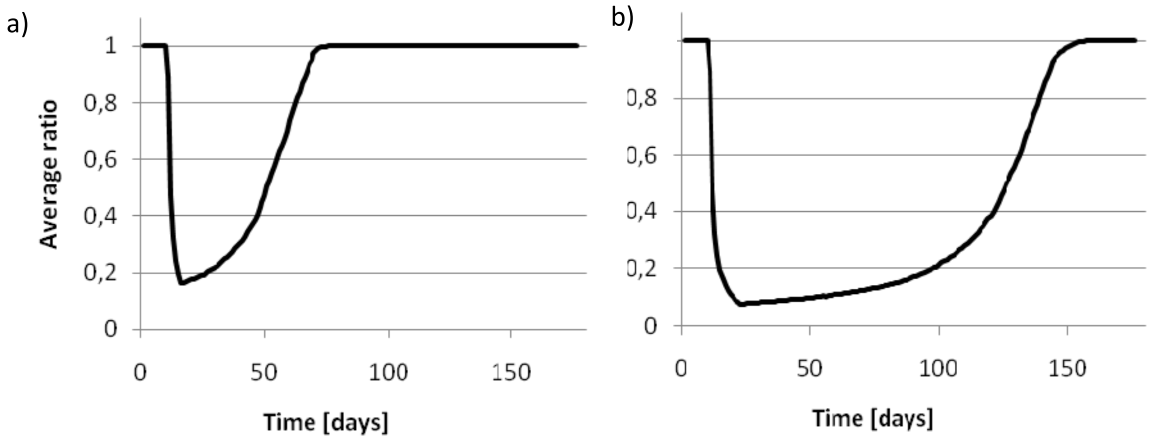

Figure 2. Daily average ratio of on-time deliveries: (a) with stoppage from day 10 until 15; (b) with stoppage from day 10 until 22

The numbers of vehicles and drivers are established on the basis of simulation in the normal state of operation. Figure 1 presents the results of this analysis – how the ratio of on-time deliveries varies depending on the number of vehicles and drivers provided in the system. The steep drop in the ratio corresponds to situations when the resources are too scarce to provide the required service. In this case, these numbers were fixed as 45 vehicles and 90 drivers. This assures that the total volume of cargo, that can be transported daily, exceeds the average demand by 15% (overall). This is accepted as a reasonable level of redundancy in the discussed system.

4.2. System analysis in critical state of operation

The system is analysed against the risks of periodic stoppage of service and of unforeseeable unavailability of a significant proportion of drivers. In each case the system is forced to a state of inoperability or reduced operability for a fixed period of time. This is illustrated on Figure 2, which presents the changes of the daily average ratio of on-time deliveries during the disruption and after resuming operation. On Figure 2a the system is being stopped for 5 days (on the 10th day). It should be noted that the measure does not drop to 0, even though the system is completely stopped. This is a consequence of counting undelivered goods that are not yet outdated at the end of each day as being on time (see Equation 1).

The critical state of operation is eliminated when the daily ratio of on-time deliveries reaches the predefined level A_{crit}. If this level is set at 0.99, then the duration of critical operation is assessed as 70

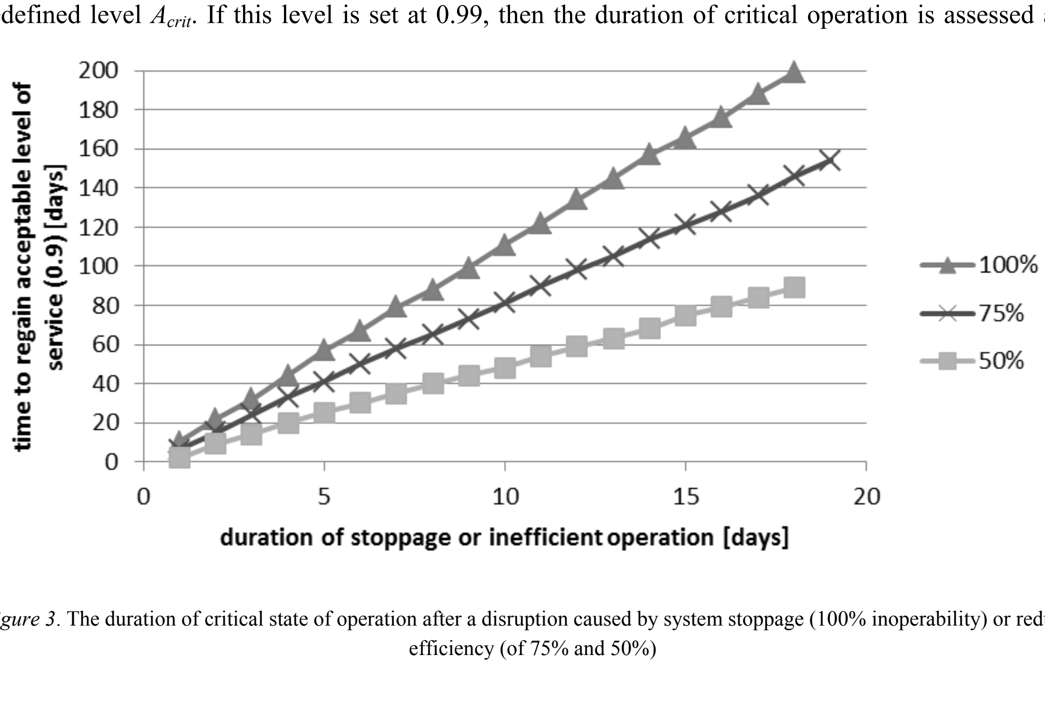

Figure 3. The duration of critical state of operation after a disruption caused by system stoppage (100% inoperability) or reduced efficiency (of 75% and 50%)

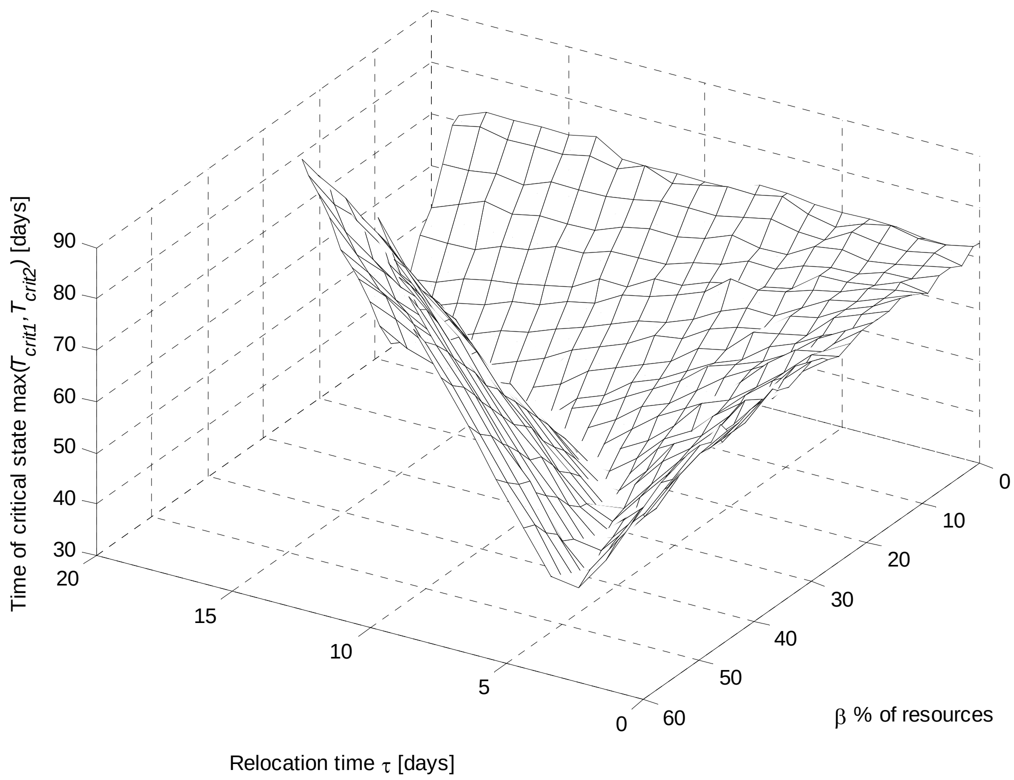

Figure 4. Time of critical state of operation max(T_{crit1}, T_{crit2}) of the two RDC's after temporary relocation of β % of resources between them (following 5 days of stoppage in one RDC)

days. Figure 2b presents a very similar analysis, but the period of system stoppage is 12 days. Then, the time required to regain normal operation is over 150 days.

Figure 3 presents the summarized results of multiple simulation runs, determining the duration of critical state of operation, assuming varied times of system disruption and the proportion of crew that is affected (100% corresponds to system stoppage). It should be noted that in the considered (reasonable) range of values the relation is almost linear, which can facilitate simplified analysis.

5. Assessment of Management Decisions

The situations identified in Section 4 require contingency planning, i.e. the system management should have some procedures for dealing with them if they occur. It is unacceptable to wait for the system to resume normal operation on its own – it simply takes too long! There has to be a procedure to acquire temporarily additional resources (drivers and vehicles) to speed up system recovery. In case of the considered hierarchically organized system, this can be achieved by displacement of some resources from one regional distribution centre to another. This is the type of management decisions that are being assessed in the paper. All the presented considerations assume that there are only two subsystems, i.e. the resource relocation affects only one subsystem that was exposed to the critical conditions and another, from which some resources may be relocated. This is done only for the sake of simplicity. The results can easily be generalized to include a number of sound subsystems that can donate resources to the affected one.

5.1. Management decisions and their consequences

The management decision, when reducing the consequences of critical operation, concerns the choice of:

- the time when the additional resources should be relocated from one regional centre to another; it is assumed that this intervention start immediately after normal operation is resumed after a stoppage or unavailability of the drivers; and it continues for τ days;

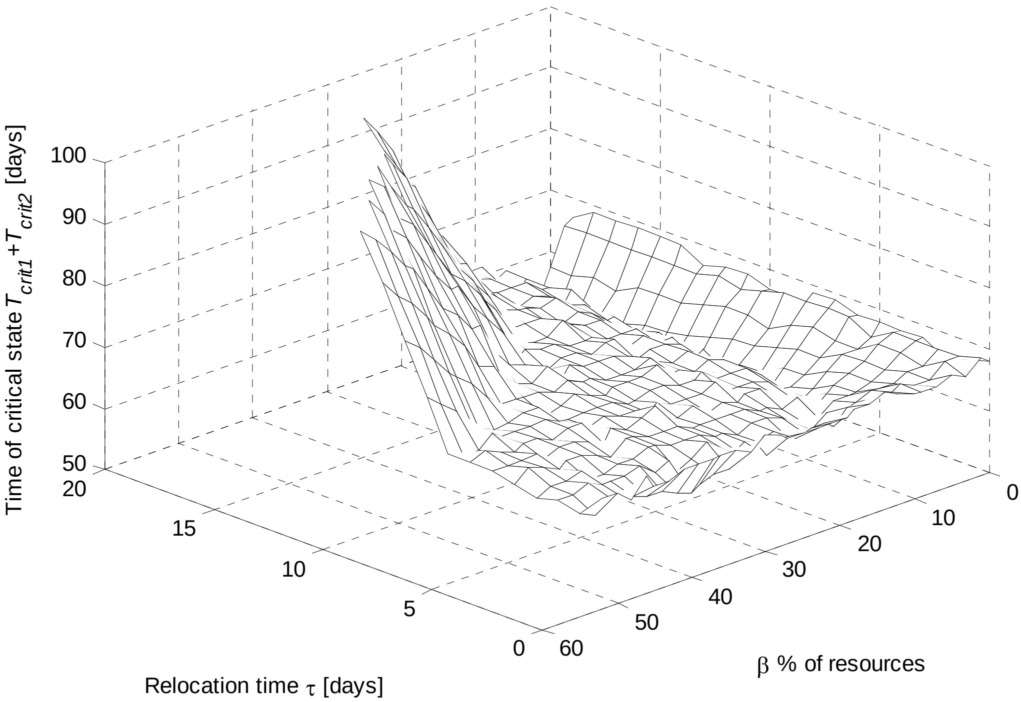

Figure 5. Time of critical state of operation $T_{crit1} + T_{crit2}$ of the two RDC's after temporary relocation of β % of resources between them (following 5 days of stoppage in one RDC)

- the number of drivers and vehicles that are relocated; this is expressed as a percentage β of the total number of drivers and vehicles allocated to a regional distribution centre.

Clearly, the greater and longer the intervention, the shorter is the critical state of operation. But, just as obviously the disruption in the other centres, from which the resources were relocated, is greater.

5.2. Assessment results

The various management strategies are characterized by the values of (β, τ). The system is analysed, by the proposed simulation technique, to obtain the corresponding duration times of the critical state of operation in the affected RDC's. As already mentioned, for the case study analysis, we have assumed that the resources are moved just between two similar regional centres, i.e. that only two centres are affected by the strategy and that the two centres are identical in terms of their models and initially allocated resources. The two affected RDCs both operate in the critical state for some times, denoted as T_{crit1} and T_{crit2}. In this case, instead of analysing independently these times, it is more meaningful to consider their sum $T_{crit1} + T_{crit2}$ and maximum value max(T_{crit1}, T_{crit2}).

Figure 4 presents the simulation results for the various strategies (β, τ) after a 5 day stoppage of the system. It should be noted that the fastest resumption of normal operation is achieved for the shortest maximum times. The ridge of local minima represents the alternate optimal management contingency plans for dealing with this stoppage, if one neglects the expenses of the relocation of resources.

The analysis performed for $T_{crit1} + T_{crit2}$ shows (Fig. 5) that near these values the sum of critical operation times is practically not affected by the choice of the management strategy.

6. Conclusions

The proposed method of analysing critical situations fills the gap that is not addressed by the traditional reliability approach. Normally, the transportation systems are designed with some redundancy to ensure continuity of service when foreseeable incidents occur, the key being their probability of occurrence. In the proposed method we deal with very improbable situations that are neglected in the reliability analysis due to their very low probability of occurrence. It is never economically justifiable to design the system to prevent them. Yet, low probability does not mean that these critical situations cannot occur. We propose a viable method of dealing with these situations and of assessing the various contingency plans.

It should be noted that the contingency plans' analysis is performed using a simulation tool that has been validated in normal operation conditions. This ensures the best chance of obtaining accurate predictions, since it is hardly possible to validate the tools against practical data collected from the critical state of operation (such data simply does not exist).

The analysis can easily be extended by taking into account the economic aspects of relocating resources between the RDCs. These relocation costs can significantly influence the choice of contingency plans. The impact of the choice of the cost factors can outweigh the analysed operational aspects.

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