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Impact of terrain characteristics on the availability of transport systems using continuous-time Markov chain

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ABSTRACT

Ensuring technical availability is crucial for military transport systems to perform their tasks under complex conditions, especially during armed conflict. In this paper, the authors propose a seven-state continuous-time Markov chain (CTMC) model for the frontline operations area that describes transitions among the task-execution state, five repair levels, and the irreparable-damage state. The model accounts for the phase of operations, the operational zone, the direction of effort, terrain conditions, and the baseline loss rate as factors influencing system degradation. The analysis was conducted across 120 scenarios, and the model's performance was evaluated by the time to reach a critical availability level below 0.50. The average availability time decreased from 17.27 days on flat terrain to 12.21 days in complex terrain (a reduction of 29.9%). A sensitivity analysis using the repeated-measures FANOVA method showed that terrain significantly affects the system's operational capabilities. The results indicate that, in addition to the intensity of defensive operations, difficult terrain is the primary factor reducing the availability of transport systems.

Keywords: availability, combat multipliers, CTMC, transport systems, sensitivity analysis.

INTRODUCTION

The availability of a transport system is the ability to perform its intended tasks within a specified timeframe and under specific conditions while maintaining the required reliability and availability parameters [1]. From a systemic perspective, availability encompasses both technical aspects (the serviceability of transport vehicles) and organizational aspects (the availability of infrastructure and the efficiency of logistics processes) [2]. Reliability assessment is an important tool for improving the efficiency of technical equipment maintenance, as it enables the identification of critical states and the rationalization of maintenance and repair activities [3]. The availability of transport systems is a key factor in ensuring the effectiveness of military operations. These systems are responsible for troop movement, the delivery of supplies and equipment, and logistical support. Their reliable functioning enables operations at both the tactical and operational levels [4,5]. Modern conflicts and crises are characterized by the dynamic, complex nature of the environment; therefore, maintaining a high level of technical availability of transport systems is crucial to the effectiveness of operations [6,7].

In wartime conditions, the assessment of the technical availability of transport assets is closely linked to the level of combat losses, which significantly determine their current serviceability, availability, and ability to perform tasks [8,9]. Increased intensity of use and combat damage place a greater load on the technical maintenance subsystem, while limited maintenance and repair resources may require postponing the most labor-intensive repairs and concentrating activities on maintaining minimum mission capability. In the analysis of transport systems operating within the military, combat losses are variable and dependent on a range of situational, operational, and environmental factors. This means their predictions should consider not only the baseline level of losses, but also the battlefield factors and conditions that may either increase or decrease this level. The literature on forecasting military equipment losses highlights, among other things, the stage of combat, the position of troops within a combat formation, the direction of attack and terrain type, with their impact accounted for using correction factors [10,11]. In turn, predictive and simulation analyses also take into account troop strength, climatic conditions, the tactical situation, the degree of surprise, and the level of training [12]. Consequently, combat losses should be regarded as the result of the interaction of many variables, rather than as a constant (or relatively constant) parameter. From the perspective of availability modelling, this approach corresponds to multifactor mathematical models in which the probability of failure is described as a function of the combined effects of operational loads and environmental impacts [13].

In the literature, the impact of terrain on the availability and reliability of facilities and technical systems is addressed primarily indirectly, through its effects on mobility [14], the risk of immobilization [15], operational loads [16], and the rate of damage accumulation [17,18]. The authors emphasize that terrain is a fundamental factor determining military mobility during mission execution [19,20]. Passability is determined not only by general terrain features, such as slope gradient, elevation changes, or surface composition, but also by micro-topographic elements that can create natural obstacles limiting vehicle movement [21,22]. The properties of the ground and the terrain cover are also of significant importance. Soil characteristics, such as bearing capacity, moisture content, and susceptibility to deformation, affect wheel sinking, slippage, developed traction force, and travel speed, and consequently the actual mobility of the vehicle [23]. Similarly, the density and structure of vegetation, as well as the quality of remote sensing data used for its description, influence trafficability assessment [24]. The assessment of a vehicle's ability to perform tasks in diverse terrain conditions is analyzed in terms of mission mobility reliability. This approach extends the deterministic assessment of passability because it accounts for the variability and spatial dependence of terrain environment parameters, such as ground properties and slope, which can lead to a loss of mobility along the entire route despite seemingly favorable local conditions [14,25].

From the perspective of facility and technical system availability and reliability, terrain is a significant operational factor because it affects the mobility of transport vehicles, the intensity of loads, the rate of damage accumulation, and the need for maintenance and repairs. Including terrain in the model is justified because environmental conditions can significantly alter the course of a facility's degradation, thereby affecting the system's availability and reliability parameters [13]. Consequently, terrain impacts the technical availability and operational readiness of transport systems and should be included in simulation models for readiness assessment [26], particularly for military facilities [5,27].

The aim of this article is to identify and quantitatively assess the impact of terrain on the technical availability of transport systems operating in combat conditions. In particular, the study analyzed how terrain affects variability in results and differences in the availability function A across specific operational configurations. For this purpose, a proprietary seven-state Continuous-Time Markov Chain (CTMC) model was developed to describe transitions among the task-execution state, successive repair levels, and the state of irrecoverable losses. The model accounts for the phase of operations, the operational zone, the direction of effort, and terrain conditions, enabling analysis of changes in the technical availability function over time and the determination of when a critical level, defined $A(\mathrm{t}) < 0.50$, is reached. The main contributions of the paper are as follows:

- development of an original seven-state CTMC model to describe the operational process of transport means under combat conditions;
- formalization of the influence of tactical and operational factors, including terrain conditions, on the technical availability of a transport system;
- assessment of the impact of four terrain classes on the time required to maintain technical availability across a set of 120 analytical scenarios;
- determination of the significance and magnitude of the terrain factor effect using FANOVA and measures of differences between trajectories of availability functions.

The paper is divided into five sections. The first section presents the research problem and a literature review covering transport system availability, combat losses, and the influence of terrain conditions on the mobility and reliability of technical objects and systems. The second section describes the research methodology, including the definition of tactical and operational input variables, the method for assigning correction coefficients to the operational phase, operational zone, direction of effort, and terrain class, and the incorporation of these into the transition intensities of the CTMC model. The third section presents the results of the numerical analysis for the adopted analytical scenarios, with particular emphasis on the behavior of the technical availability function, the time required to reach the critical availability level, and the sensitivity analysis assessing the influence of terrain conditions on the transport system's operation. The fourth section discusses the limitations of the proposed modelling approach, its validation perspectives, and its practical applicability. The fifth section draws conclusions from the research, highlighting the significance of terrain conditions in shaping the technical availability of transport systems under combat conditions.

METHODOLOGY

Tactical and operational input variables

Modeling losses in land operations requires defining selected tactical and operational input variables that organize combat activities in time and space, thereby explicitly linking the tactical situation to the parameters of the CTMC model. This study employs a set of descriptive categories comprising: the area of operations, the phase of operations, the direction of effort (main and minor), and terrain conditions. The selection of these categories stems from their widespread use in land operations doctrines for organizing and controlling operations, as well as from the need to limit the number of variables to those that are critical for estimating the intensity of losses and the readiness of the transport system in the analyzed model [10].

The forward edge of the battle area (FEBA) is a key reference line that organizes the operational space. It separates friendly main forces from the enemy and delineates the area of direct combat engagements [28]. In this study, FEBA serves as the primary spatial reference for planning maneuver activities, coordinating fire support, and dividing the operational area into analytical zones. In the battlefield diagram shown in Figure 1, the FEBA is treated as a spatial reference line from which the further division of the operational space into zones is derived and relative to which phase lines and axes of effort are interpreted. This line enables the coordination of troop maneuvers, the synchronization of artillery fire, and the control of reserve movements.

After designating the FEBA, the operational space is divided into functional areas that enable the analysis of simultaneous operations across different parts of the formation (close area, deep area, and support area) [10]. For this model, three analytical zones designated as ZONE A–C have been adopted. These zones reflect the depth of the defense system (successive defensive positions) and are consistent with the functional division of the operational area [10]:

- Zone A (close area) – the first defensive position in direct contact with the enemy. In a typical configuration, its forward boundary coincides with the FEBA. Frontline units operate in this zone, and fire and maneuver activity is at its highest intensity.
- Zone B (deep area) – the second defensive position deep within the formation. It encompasses the operations of second-wave units and tactical reserves, as well as those that penetrate deep into the enemy's formation.
- Zone C (support area) – the formation's rear area (command posts, reserves, logistical elements), enabling stabilization of the defense and preparation for recovery and counterattack operations.

In the model, it is assumed that the highest intensity of losses occurs in Zone A, decreases in Zone B, and Zone C serves as an area for stabilizing the defense and preparing a counterattack, as reflected in the operational-zone structure presented in Figure 1.

The second component is the temporal division of activities into phases. In planning practice, operational phases are defined using Phase Lines (PL), which serve as means of controlling the operational space and facilitate the coordination of activities among multiple elements of a formation [11]

Three phases (Phase I–III) have been adopted, separated by the PL GREEN, PL WHITE, and PL YELLOW lines (Figure 2). In this context, phase

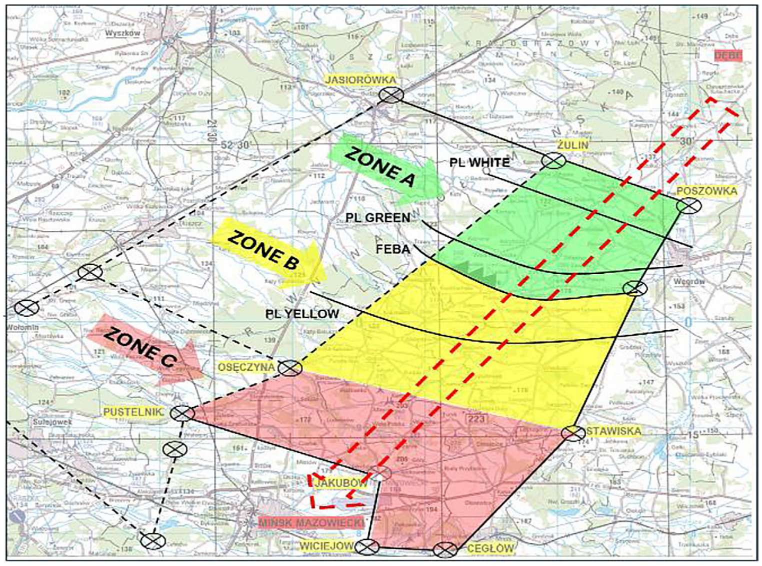

Figure 1. Main course of operation and analytical operational zones

lines serve as indicators of the progress of operations over time and are used to link the dynamics of the tactical situation with casualty parameters across successive stages of combat.

Another key element of operational planning is the designation of the main and minor (supporting) directions of attack. This reflects the principle of concentration of effort, whereby the majority of forces and resources are concentrated along the main direction, while the minor direction provides flexibility in response to changes in the tactical situation. As illustrated in Figure 1, the main line of attack passes through successive phase lines and key terrain features, whereas the

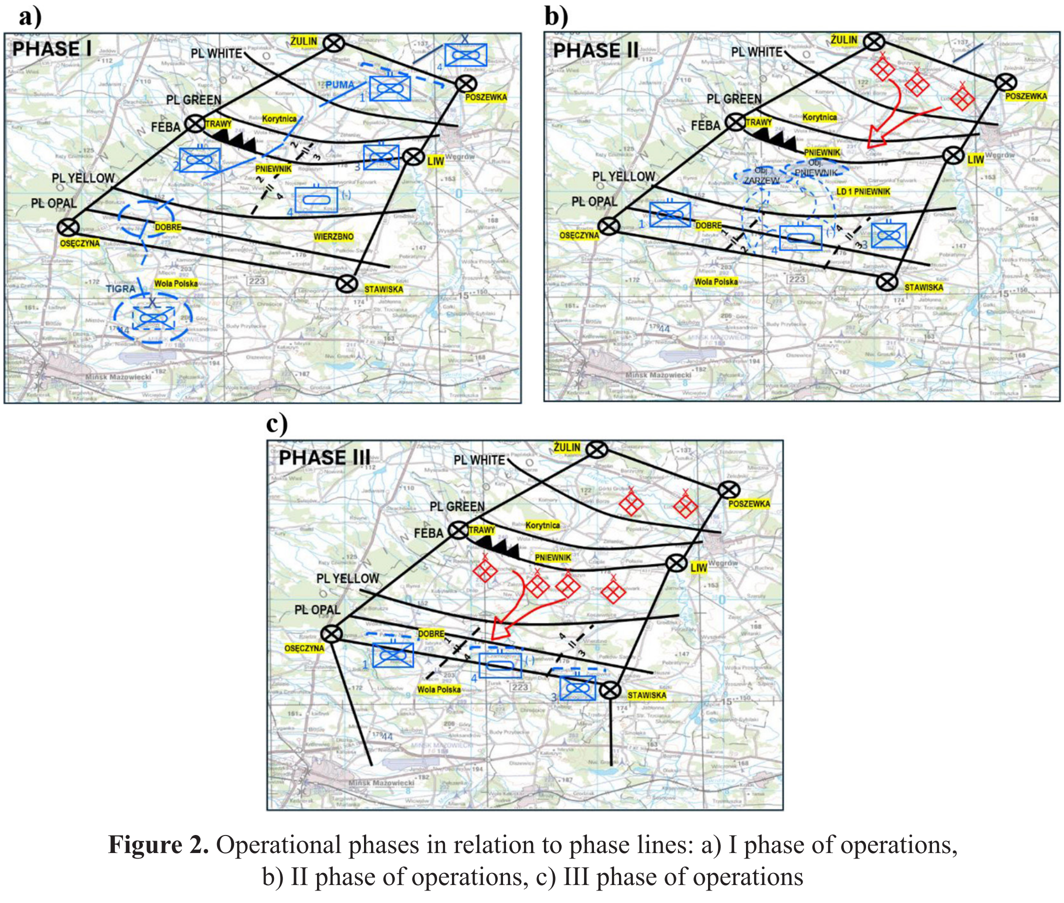

Figure 2. Operational phases in relation to phase lines: a) I phase of operations, b) II phase of operations, c) III phase of operations

alternate direction may be used to maintain the momentum of the operation if the situation develops unfavorably along the primary axis.

For the purposes of modeling losses, an assumption was made that, as the phases of the operation progress, the focus of operations shifts deeper into the defense system. During the stage when the enemy approaches the defensive perimeter, combat contact and engagement are concentrated in the FEBA area and the first defensive position (Zone A). During the breakthrough phase, operations cover Zone A and move into Zone B, while during the deep-seated combat phase, the focus of operations shifts to Zones B–C. A summary of the adopted model combinations is presented in Table 1. It should be emphasized that this limitation is of an analytical nature (reduction of unlikely combinations in the adopted scenario structure) and is not treated as a rule applicable in every variant of a tactical situation.

The introduced variables (zone, phase, and direction of attack) do not fully exhaust the factors that determine the intensity of losses. In operational practice, terrain is a significant modifier of both the course of combat and the effectiveness of maneuver and fire, affecting observation, concealment, the channeling of movement, the pace of operations, and the availability of approach routes. For this reason, terrain has been included as a separate variable in the model, distinguishing the conditions for conducting operations from the transport system's readiness parameters. For the purposes of this study, four terrain types were identified (Figure 3), which serve as input variables in the model [29,30]:

Open flat terrain (terrain 1) – provides wide fields of view and facilitates direct fire, but limits cover and increases exposure to enemy fire. From a mobility perspective, it enables high speeds and high column throughput on firm ground, while increasing tactical risk during movement.

Hilly wooded terrain (terrain 2) – increases cover and camouflage, reduces visibility, and more often channels movement onto specific roads or access routes. For transport, this typically means lower average speeds and greater variability in travel time (due to slopes, curves, and narrow sections), which affects schedule stability and the ability to maintain the pace of operations.

Mountainous/wet terrain (terrain 3) strongly channels movement along valleys and mountain passes, increases the significance of terrain obstacles, and limits the number of possible routes. In terms of mobility, the risk of losing passability increases (with "slow go"/"no go" areas), and maintaining continuous movement more often requires engineering support and consideration of ground bearing capacity.

Major Obstacle Terrain (terrain 4) – a type of terrain where the course of operations is determined by barriers (e.g., rivers, floodplains, infrastructure, narrowings) and the associated crossing points and bypass routes. Tactically, it favors defense by narrowing the attack's direction. In terms of transportation, the critical factors are the capacity and load-bearing parameters of

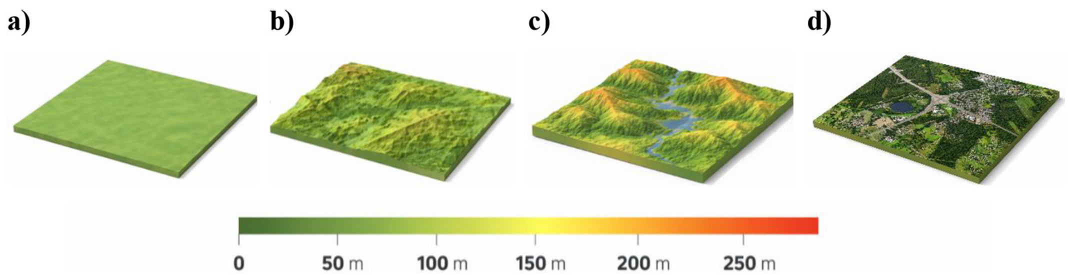

Figure 3. Examples of four types of terrain: a) open flat terrain, b) hilly wooded terrain, c) mountainous/wet terrain, d) major obstacles terrain

Table 1. Adopted (model) phase–zone combinations

Phase	Zone		
	A – close area	B – deep area	C – support area
Phase I – Approach to defensive line	✓	-	-
Phase II – Breakthrough in defense	✓	✓	-
Phase III – Combat in-depth defense	-	✓	✓

engineering structures, as well as the risk of congestion in bottlenecks.

The proposed model treats the terrain as a multiplier, whose variability is analyzed in terms of its impact on the time required for the transport system's combat availability to fall below the critical threshold ($A(t) < 0.50$). This approach is consistent with the methodology in which factors that enhance or limit operational effectiveness are modeled as force multipliers influencing the course of combat and the dynamics of casualties [31].

Mathematical model of loss intensity

To enable quantitative modeling of losses and the analysis of transport system availability, the tactical-operational variables defined in the preceding subsection (phase of operation, operational zone, direction of effort, and terrain conditions) were formalized as a set of tactical-operational multipliers, whose values are presented in Table 2.

These coefficients reflect the relative impact of battlefield conditions on the intensity of losses and, consequently, on the dynamics of the transport system's readiness. The adopted approach is multiplicative. The operational context is first aggregated by Equation 1, and this multiplier is then combined with the baseline loss intensity in Equation 2 to obtain the loss intensity used in the CTMC model [33,34].

The aggregated combat dynamics multiplier (ACDM), defined as [32]:

$$ACDM = PM \cdot ZM \cdot DM \cdot TM \tag{1}$$

where: PM – phase multiplier, ZM – Zone Multiplier, DM – direction multiplier, TM – terrain multiplier.

The ACDM value obtained from Equation 1 is then used to scale the baseline loss intensity. The resulting Loss Intensity (LI) is calculated using Equation 2 [32]:

$$LI = BLI \cdot ACDM \tag{2}$$

where: BLI – baseline loss intensity.

The values of the adopted coefficients are presented in Table 2. They are based on empirical research in operations research [29] and serve as standardized multipliers to account for the impact of tactical factors on the course of combat operations.

There were 10 valid combinations of phase and operational zone, which, when paired with two variants of effort direction (main and minor), formed a set of baseline scenarios. Each baseline scenario was then defined for three levels of BLI, corresponding to the variants: low (min), medium (avg), and high (max). A detailed list of baseline scenarios, including the assigned phase of operations, operational zone, direction of effort, and baseline loss intensity level, is presented in Appendix A. As a result, 30 baseline scenarios were obtained, differing in both tactical-operational configuration and loss intensity level. In the next step, each scenario was expanded to include four terrain-condition variants, corresponding to four terrain classes with increasing operational difficulty, resulting in a total of 120 analytical scenarios. Each factor was assigned numerical values as multiplicative coefficients, reflecting its impact on loss intensity and on the dynamics of changes in system readiness. These coefficients were treated as constants within a given category (Table 2) and served to scale the baseline level of damage process intensity. For each scenario, the curve of the system availability function A(t) was determined over the time interval from 0 to 365 days, evaluated on a discrete time grid with a step size of 0.1 days (2.4 hours). Such high temporal resolution enables an accurate representation of the system's technical availability decline and the identification of critical moments. The structure of the obtained output data enables a direct comparison of the time-dependent availability function A(t) curves for different terrain variants within the same base scenario, which forms the basis of the analysis.

Continuous-time Markov chain model

The process is described as a continuous-time Markov chain [35,36]. At the initial time $t = 0$, the system is in a state of full technical serviceability, as given by Equation 3:

$$p_1(0) = 1, p_i(0) = 0 \text{ for } i \neq 1 \tag{3}$$

The model illustrates transitions between states of use, failure, and multi-level technical renewal. It also accounts for an absorption state corresponding to the permanent loss of system functionality [5].

The developed model identifies the following operational states (presented in Figure 4):

- S_1 – task execution. This status involves the direct use of a functional technical asset for transport tasks, standby duty, and the support of combat operations.

Table 2. Tactical-operational multipliers used in model [32]

Factor	Symbol	Category / level	Value
Phase of operation	PM	Phase I – Approach to defensive line	1.15
		Phase II – Breakthrough of defense	1.25
		Phase III – Combat in depth	1.05
Operational zone	ZM	Zone A – Close area	1.20
		Zone B – Deep area	1.10
		Zone C – Support area	1.00
Direction of effort	DM	Main direction	1.30
		Minor (supporting) direction	1.10
Terrain conditions	TM	Open flat terrain	1.00
		Hilly wooded terrain	1.10
		Mountainous/wet terrain	1.20
		Terrain with major obstacles	1.30
Baseline Loss Intensity	BLI	Minimum	0.06
		Average	0.08
		Maximum	0.10
Failure Mode Proportion	FMP	R1	0.18
		R2	0.12
		R3	0.10
		R4	0.27
		R5	0.18
		Irrecoverable loss (IL)	0.15

- S_2 – level 1 service (R_1). This level covers basic maintenance tasks and small repairs requiring up to 40 man-hours (mh), performed directly by the user or by the lowest level of technical support within 12 hours. The goal of these activities is to quickly renewal technical serviceability without significantly taking the equipment out of service.
- S_3 – level 2 service (R_2). This level includes repairs with a labor intensity of up to 60 mh, performed in field conditions by tactical-level repair units. The equipment is temporarily taken out of service, and the time required to restore its operational readiness ranges from 12 to 24 hours.
- S_4 – level 3 service (R_3). This category includes more complex repairs with labor intensity up to 120 mh, requiring the deployment of appropriate field infrastructure. The restoration process is carried out within the area of operations within 24–72 hours.
- S_5 – level 4 service (R_4). This category includes repairs with a labor intensity of up to 300 mh, requiring the use of stationary technical workshops and specialized diagnostic and repair facilities. These are carried out outside the combat zone within 72–144 hours.
- S_6 – 5th-level service (R_5). This category includes repairs with a labor intensity of up to 4,000 mh, performed in industrial facilities or specialized repair units and lasting more than 144 hours. It involves comprehensive restoration of technical service life, often corresponding to a major overhaul or modernization.
- S_7 – irretrievable losses (absorption state). This state applies to technical assets whose renewal is impossible or impractical for technical, economic, or tactical reasons. It is the system's final status, in which the asset is permanently taken out of service.

The adopted process description is consistent with the damage response procedure, which includes damage assessment, a decision to postpone repairs, emergency repairs, evacuation to technical support facilities, or removal of the facility from further use [37,38].

Figure 4 shows the state and transition diagram of a seven-state CTMC model describing the stochastic operation of a technical system under combat conditions. Operation is understood as the transition of an object within the system from one state to another.

Based on the directed operation graph (Figure 5), according to Equation 4 a transition intensity matrix was constructed Λ [36,39]. Its elements describe the intensities of state transitions λ_{ij} or μ_{ij}.

Equation 4 below differentiates between transition intensities associated with failure (λ_{ij}) and those associated with the technical renewal process (μ_{ij}), which facilitates the physical interpretation of the model parameters. Off-diagonal elements $\lambda_{ij}(i \neq j)$ denote transition intensities from state S_i to state S_j, and in particular:

- λ_{1j} for j = 2, ..., 7 represent the intensity of failures leading to a transition from the operational state to states of technical renewals or irrecoverable losses,
- μ_{i1} for i = 2, ... , 6 describe the intensity of renewal of technical functionality as a result of the completion of the repair process.

Using the matrix Λ, defined in Equation 4, the time-dependent state probability vector is obtained from Equation 5. The instantaneous probability of the object being in state S_j at time t is defined as the j-th component of the vector, given by the relation [36, 39]:

$$p(t) = p(0)e^{Qt},\ j = 1, ..., \tag{5}$$

where: $p(t) = p(t)\ [p_1(t), p_2(t), ..., p_7(t)]$ is the state probability vector.

The calculations were performed for a discrete time vector $t \in [0.365]$ with a step size of 0.1 day, which allows for high-resolution time histories.

The transition intensities associated with failures were estimated based on the expected values of the time to failure, as shown in Equation 6 [5,36]:

$$\lambda_{1j} = \frac{1}{E(T_{1j})} \tag{6}$$

where: $E(T1j)$ is the expected value calculated based on a discrete failure time distribution.

Initially, the following parameter was defined for each type of failure:

$$w_j = LI \cdot FMP_j \tag{7}$$

$$\Lambda = \begin{bmatrix} -(\lambda_{12}+\lambda_{13}+\lambda_{14}+\lambda_{15}+\lambda_{16}+\lambda_{17}) & \lambda_{12} & \lambda_{13} & \lambda_{14} & \lambda_{15} & \lambda_{16} & \lambda_{17} \\ \mu_{21} & -\mu_{21} & 0 & 0 & 0 & 0 & 0 \\ \mu_{31} & 0 & -\mu_{31} & 0 & 0 & 0 & 0 \\ \mu_{41} & 0 & 0 & -\mu_{41} & 0 & 0 & 0 \\ \mu_{51} & 0 & 0 & 0 & -\mu_{51} & 0 & 0 \\ \mu_{61} & 0 & 0 & 0 & 0 & -\mu_{61} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{4}$$

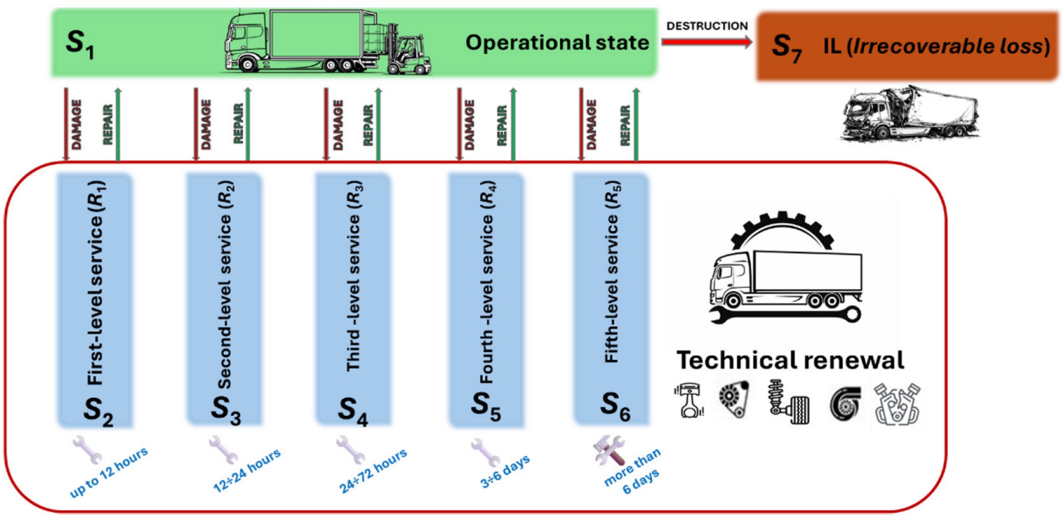

Figure 4. A concept diagram of process states in an operational transport system

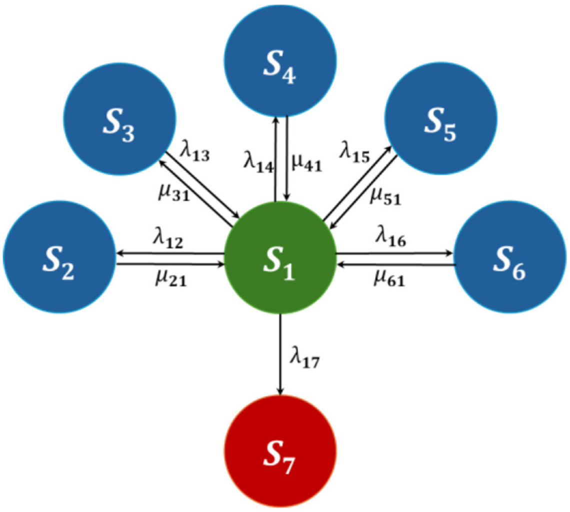

Figure 5. Graph of allowed transitions for a 7-state Markov model

where: FMP_j is the proportion of failures of type in the total failure structure (R_1–R_5, IL).

The distribution of contributions FMP_j forms the basis for decomposing the aggregated damage parameter. In accordance with Equation 1, the ACDM value was calculated as the product of coefficients for the phase of operations, the operational zone, the direction of operations, the terrain, and the BLI level. Based on this, the time-to-failure distribution $F_j(t_k)$ was constructed:

$$F_j(t_k) = P(T_j \le t_k) =$$

$$= F_j(t_{k-1}) + (1 - F_j(t_{k-1}))w_j \tag{8}$$

where: $F_j(t_k)$ is the probability of damage of type j occurring no later than at time t_k.

Using this, the probability function was then defined as:

$$f_j(t_k) = F_j(t_k) - F_j(t_{k-1}) \tag{9}$$

Equation 9 defines the discrete distribution of the time-to-failure j. The expected value of this distribution is then calculated using Equation 10:

$$E(T_{1j}) = \sum_k t_k \cdot f_j(t_k) \tag{10}$$

The transition intensities associated with technical renewal were determined based on the expected repair time for a given repair type $j(T_{repair}, j)$ and the number of available repair crews (n_j), according to Equation 11 [38,40]:

$$\mu_{j1} = \frac{n_j}{T_{repair,j}} \tag{11}$$

where: n_j – number of available maintenance and repair resources, $T_{repair,j}$ – expected completion time of repair type j.

The intensity of transitions in technical renewal processes models the system's regenerative capacity and depends on both the labor intensity of repairs and the available maintenance and repair resources. Finally, the technical availability function is defined in Equation 12 [5,36]:

$$A(t) = p_1(t) \tag{12}$$

that is, the probability that the object is in state S_1.

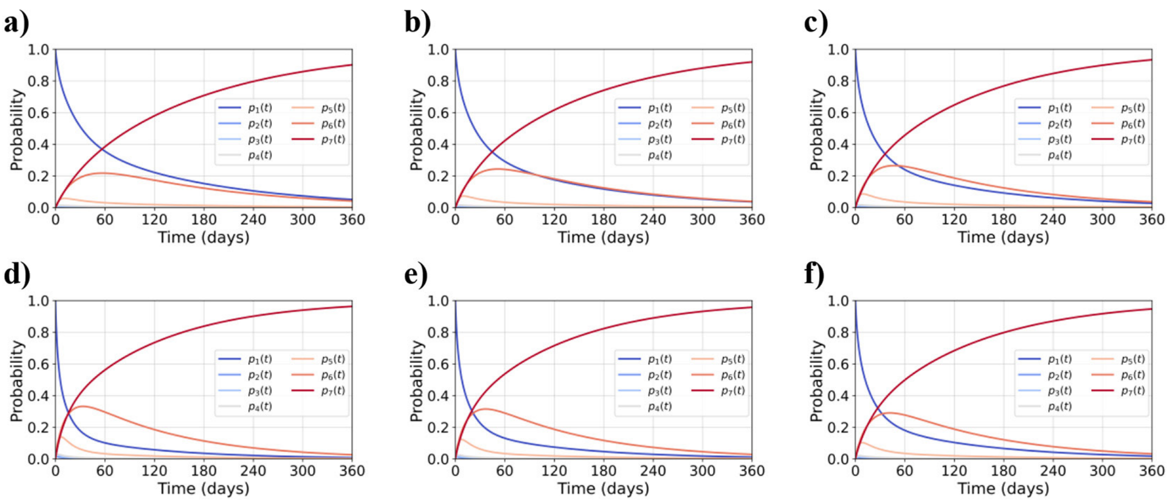

Figure 6. Comparison of selected operational combat scenarios: a) SC_10_1_Terrain_1, b) SC_10_2_Terrain_1, c) SC_10_3_Terrain_1, d) SC_03_3_Terrain_4, e) SC_03_2_Terrain_4, f) SC_03_1_Terrain_4

RESULTS AND DISCUSSION

The results of numerical analyses of the CTMC model show the evolution of the probability distribution of system states $p_i(t)$, $i = 1, \ldots, 7$ over time, enabling a quantitative analysis of the degradation and technical renewal process under combat conditions. The analysis was performed for a set of 120 analytical scenarios, differing in BLI and ACDM parameters. Based on the obtained trajectories obtained from Equation 5 and the availability definition in Equation 12, the critical time t_{crit}, defined as the moment when the technical readiness function falls below the threshold $A(t) = 0.50$, as given in Equation 13:

$$t_{crit} = \inf\{t \geq 0 : A(t) < 0.50\} \tag{13}$$

The probability distributions shown in Figure 6 indicate the evolution of the system.

Over time, a monotonic decrease $p_1(t)$ is observed, corresponding to the operational state S_1. The probabilities of intermediate states S_2-S_6, described by the functions $p_i(t)$, exhibit a transient nature and reach local maxima, reflecting the flow of objects through successive levels of technical renewal. As the value of BLI increases, these maxima shift toward smaller values of t, indicating an increase in the intensity of the flow of objects directed toward technical renewal processes and an increase in the load on the system's maintenance and renewal capacity. At the same time, a monotonic increase is observed in the probability of state S_7. This absorbing-state behavior is formalized in Equation 14:

$$\lim_{t \to \infty} p_7(t) = 1 \tag{14}$$

This illustrates the irreversible nature of the process leading to the loss of operational capability.

The scenario with the most favorable configuration of operational factors, analyzed for terrain 1 (SC_10_1_Terrain_1), exhibits the highest operational durability, with values starting at 31.5 days. By contrast, the scenario with the most unfavorable configuration of operational factors, analyzed for terrain 4 (SC_03_3_Terrain_4), yields the lowest operational durability, reaching a minimum of 5.7 days. Compared with the most favorable variant, the time required to maintain technical readiness was reduced by 25.8 days, i.e., by 81.90%, thereby quantifying the combined effect of loss intensity, operational configuration, and terrain conditions on system degradation. In SC_03_3_Terrain_4, the accelerated decline in $A(t)$ was accompanied by a marked accumulation of probability in the absorbing state S_7, reflecting irreversible loss of operational capability.

The obtained trajectories provide the basis for determining the critical time t_{crit}, which is analyzed in detail in the next subsection.

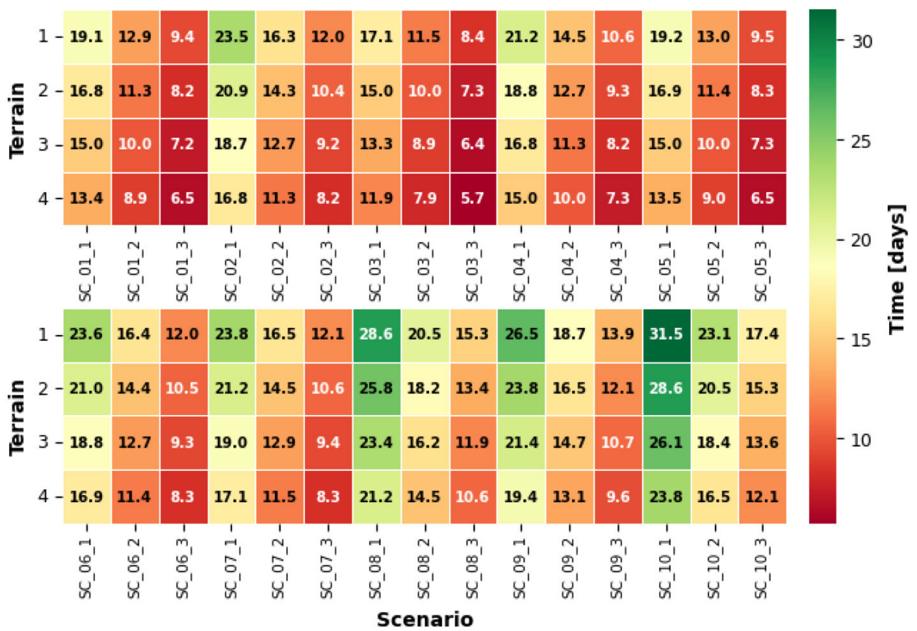

Figure 7. Heat map of t_{crit} values in the scenario-area framework

Analysis of critical time to achieve the required availability

The time at which the system loses its ability to remain operationally ready above the 0.50 threshold is particularly important for the system's operational availability. The results confirm that the operational process under combat conditions is multifactorial and highly nonlinear, and that its dynamics are determined by the cumulative effect of operational parameters. A complete summary of t_{crit} values for all analyzed scenarios and terrain classes is presented in Appendix B.

The heatmap of t_{crit} values for all 120 scenarios, shown in Figure 7, provides a synthetic overview of the results. The full set of values ranges from 5.7 to 31.5 days, with a mean of 14.59 days and a median of 13.45 days. Across all 30 analyzed base scenarios, a uniform monotonic trend is observed, with the transition from terrain 1 to terrain 4 is always accompanied by a decrease in the value. This indicates that deteriorating terrain conditions shorten the time to reach the critical state, regardless of the configuration of the other scenario parameters. The highest values are concentrated in scenarios with the lowest loss intensity and the most favorable configuration of operational multipliers, particularly in the SC_10 and SC_08 scenario groups. The lowest values were recorded in scenarios SC_03, SC_04, and SC_05 for terrain 4, where the cumulative impact of adverse conditions leads to the system reaching a critical state the fastest, defined as the technical readiness level falling below the adopted critical threshold.

For terrain 1, the average time for availability to fall below 50% is 17.27 days, with a median of 16.45 days and a range of 8.4–31.5 days. For terrain 2, the average decreases to 15.27 days; for terrain 3, to 13.62 days; and for terrain 4, to 12.21 days. This means that the transition from the most favorable to the most restrictive terrain class, on average, reduces readiness duration by 5.06 days (29.9%). From an operational perspective, this result indicates that as terrain conditions deteriorate, the process of losing transport system availability accelerates systematically, regardless of the phase of operations, operational zone, direction of effort, and BLI level. The impact of the baseline loss intensity also remains significant. Taking all terrain classes into account, the average t_{crit} is 19.99 days for the minimum BLI level, 13.73 days for the average level, and 10.06 days for the maximum level. Increasing the BLI from the minimum to the maximum level therefore reduces the average availability time by 9.93 days, i.e., by 49.70%.

Figure 8 complements the analysis of absolute values by showing relative differences between pairs of terrain classes. The sensitivity of the results to changes in terrain conditions was assessed for each scenario group, distinguishing among minimum, average, and maximum levels of defense intensity. The highest relative differences occurred in the Terrain 1 vs. Terrain 4 comparison, with a range of 24.44-32.14% and an average of 29.88%.

For the Terrain 1 vs. Terrain 3 pair, the average difference is 21.65%, with a range of

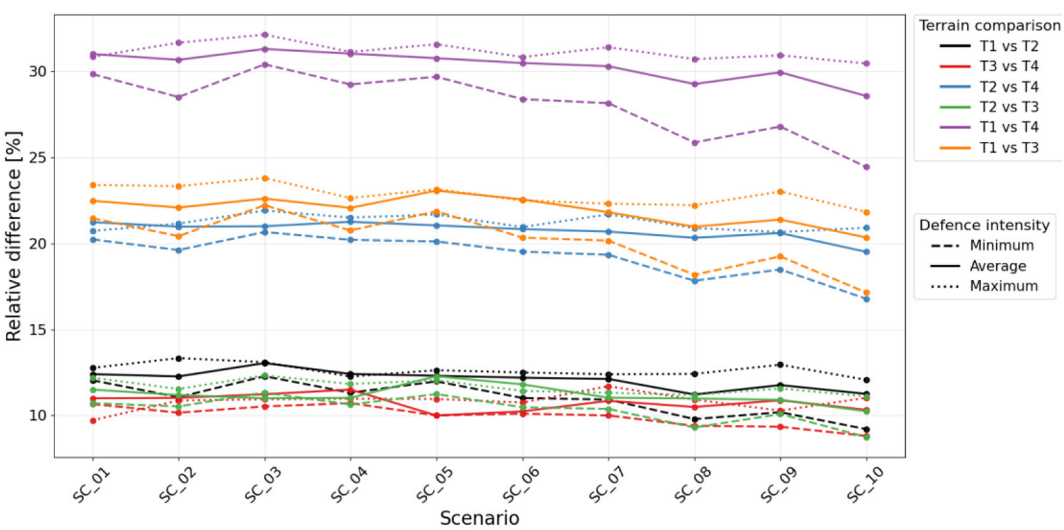

Figure 8. Relative differences in critical availability loss time (t_{crit}) between pairs of terrain classes in the analyzed scenarios

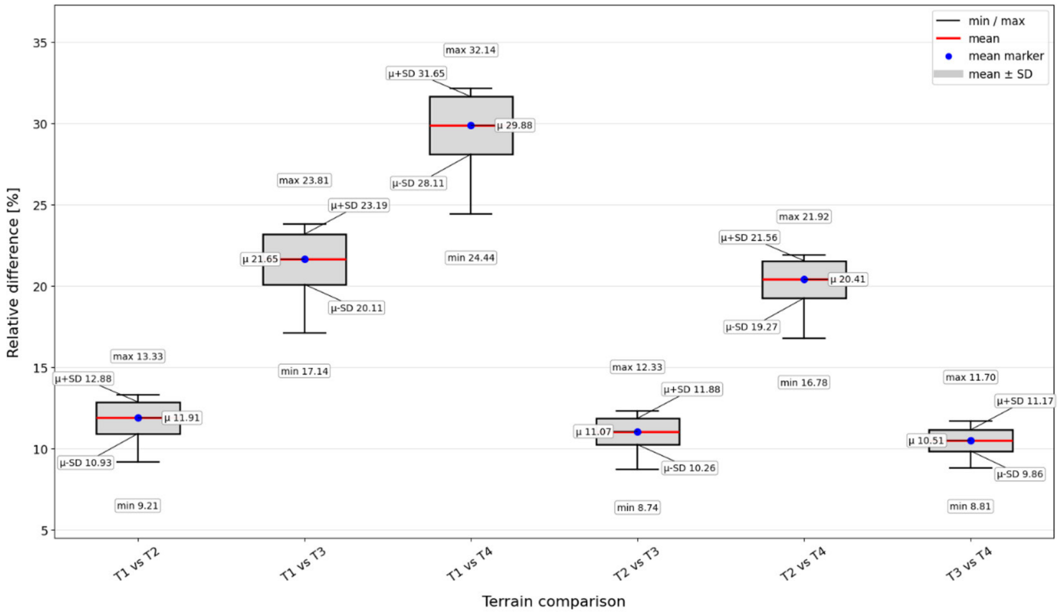

Figure 9. Distribution of relative differences t_{crit} for pairwise comparisons of terrain

17.14–23.81%. For the terrain 2 vs. terrain 4 pair, the values are 20.41% and 16.78–21.92%, respectively. The lowest values were observed for comparisons of adjacent terrain classes: terrain 1 vs. terrain 2–11.91%; terrain 2 vs. terrain 3–11.07%, and terrain 3 vs. terrain 4–10.51%. This relationship indicates that terrain influence increases as the difference between the compared classes increases.

The box plot (Figure 9) shows that relative differences among the analyzed terrain classes vary little across the full range of scenarios, as evidenced by the narrow interquartile ranges. This indicates that terrain conditions influence the model's response in a systematic, repeatable way. The highest median relative difference occurs in the terrain 1 vs. terrain 4 comparison (Me = 30.47%; Q1 – Q3 = 29.25 – 30.99%; MIN – MAX = 24.44 – 32.14%), indicating that the contrast between the extreme terrain classes is the strongest, while variability across scenarios remains limited. Similar differences are observed for the terrain 1 vs. terrain 3 and terrain 2 vs. terrain 4 pairs, though their medians are lower (Me = 22.08%; Q1 – Q3 = 20.81 – 22.60%) and (Me = 20.71%; Q1 – Q3 = 20.14 – 21.04%). The smallest contrasts occur in the terrain 1 vs. terrain 2, terrain 2 vs. terrain 3, and terrain 3 vs. terrain 4 pairs, with medians of 12.23%, 11.15%, and 10.69%, respectively, and relatively narrow interquartile ranges. These results indicate that even a transition between adjacent terrain classes produces a consistent change in the model's response.

Sensitivity analyses

Due to the functional nature of the model's response and the observational dependency resulting from the block structure of the baseline scenarios, the influence of terrain conditions on the course of the technical readiness function was assessed using a repeated-measures functional analysis of variance (FANOVA) [41,42]. In the adopted design, each baseline scenario was treated as a block, while the four terrain classes were treated as levels of the within-block factor. The model response was the trajectory of the availability function observed on a discrete-time grid ranging from 0 to 365 days, with a step size of 0.1 days (2.4 hours).

Two complementary analytical approaches were used in the study. The first (repeated-measures FANOVA) was used to verify whether variation in the terrain parameter leads to statistically significant changes in the course of the readiness function over the entire analyzed time horizon. The second involved a quantitative description of the magnitude of differences between readiness trajectories for the four terrain classes. The influence of the terrain factor was assessed separately in each of the 30 base scenarios. To this end, all other scenario parameters are held constant, and then the four curves $p_1(t)$ corresponding to the four terrain variants are compared. The methodology for conducting the FANOVA test is presented in Appendix C.

The results summarized in Table 3 indicate that in all 30 base scenarios, the terrain factor had a statistically significant effect on the course of the availability function. The values obtained in each case ($p < 0.05$) confirm that variations in terrain conditions led to significant changes in the availability trajectory over time. The statistical values $F_{terrain}$ ranged from 3499.49 (SC_10_1) to 9165.62 (SC_01_3), and η_p^2 ranged from 0.9210 to 0.9683. This shows that, after accounting for the time effect, the influence of terrain was very strong and clearly exceeded the residual variability. The highest sensitivity to changes in terrain class was observed in scenarios SC_01_3, SC_05_3, and SC_03_3, for which $F_{terrain}$ were 9165.62, 9157.05, and 9137.84, respectively, with equal η_p^2 to 0.9683, 0.9683, and 0.9682. In this group of scenarios, the average deviation of terrain trajectories $\Delta\bar{p}_1$ ranged from 0.0686 to 0.0697, while the maximum instantaneous difference $\Delta p_{1,max}$ ranged from 0.0801 to 0.0803. This result indicates that the terrain's influence was most pronounced in scenarios with the highest rate of loss of technical readiness. The lowest values of the test parameters were obtained for scenarios SC_10_1, SC_08_1, and SC_09_1.

In this group, the values $F_{terrain}$ ranged from 3499.49 to 3972.78, and η_p^2 from 0.9210 to 0.9298. At the same time, $\Delta\bar{p}_1$ took values ranging from 0.0506 to 0.0584, and $\Delta p_{1,max}$ from 0.0635 to 0.0706. This means that even in scenarios with lower sensitivity, the terrain effect remained pronounced, although the scale of variation in the readiness trajectory was smaller than in variants with faster system degradation. Across the entire set of scenarios, the values $\Delta\bar{p}_1$ ranged from 0.0506 to 0.0707, and $\Delta p_{1,max}$ from 0.0635 to 0.0803. These results indicate that a change in terrain class led to a persistent and repeatable variation in the course. The values presented in Table 3 confirm that the impact of the terrain factor remains significant in all analyzed configurations and that it increases markedly in scenarios characterized by a more rapid decline in availability.

The temporal dimension of the results is illustrated by the heatmap of the spread between availability trajectories for the individual terrain variants (Appendix D). At the initial time, the spread was zero in all scenarios, which follows directly from the initial condition A(0) = 1. In the following days, a rapid increase in the terrain effect was observed. The average difference between the four terrain variants, calculated for the entire set of scenarios, reached 0.0603 after 5 days, 0.0720 after 10 days, and 0.0749 after 15 days. The maximum average effect occurred around day 17, amounting to 0.0751. Subsequently, a gradual

Table 3. Sensitivity of the baseline scenarios to the terrain multiplicator, according to the results of the FANOVA analysis

Scenario ID.	$F_{terrain}$	η_p^2	$\Delta\bar{p}_1$	$\Delta p_{1,max}$	Scenario ID.	$F_{terrain}$	η_p^2	$\Delta\bar{p}_1$	$\Delta p_{1,max}$
SC_01_1	5303.32	0.9465	0.0673	0.0771	SC_06_1	4376.31	0.9358	0.0624	0.0737
SC_01_2	7661.86	0.9623	0.0707	0.0794	SC_06_2	6156.67	0.9535	0.0694	0.0784
SC_01_3	**9165.62**	**0.9683**	**0.0696**	**0.0801**	SC_06_3	8129.43	0.9644	0.0707	0.0796
SC_02_1	4392.49	0.9361	0.0625	0.0738	SC_07_1	4344.20	0.9354	0.0621	0.0735
SC_02_2	6186.01	0.9537	0.0695	0.0784	SC_07_2	6098.17	0.9531	0.0693	0.0783
SC_02_3	8160.61	0.9645	0.0707	0.0796	SC_07_3	8066.14	0.9641	0.0707	0.0796
SC_03_1	5892.87	0.9516	0.0689	0.0781	**SC_08_1**	**3745.13**	**0.9258**	**0.0552**	**0.0679**
SC_03_2	8387.49	0.9655	0.0707	0.0797	SC_08_2	4951.73	0.9429	0.0659	0.0762
SC_03_3	**9137.84**	**0.9682**	**0.0686**	**0.0803**	SC_08_3	6563.87	0.9563	0.0700	0.0788
SC_04_1	4804.53	0.9412	0.0652	0.0757	**SC_09_1**	**3972.78**	**0.9298**	**0.0584**	**0.0706**
SC_04_2	6899.78	0.9583	0.0703	0.0790	SC_09_2	5398.36	0.9474	0.0676	0.0773
SC_04_3	8794.40	0.9670	0.0704	0.0798	SC_09_3	7202.97	0.9600	0.0706	0.0792
SC_05_1	5279.78	0.9462	0.0672	0.0771	**SC_10_1**	**3499.49**	**0.9210**	**0.0506**	**0.0635**
SC_05_2	7628.75	0.9622	0.0707	0.0794	SC_10_2	4458.00	0.9369	0.0630	0.0742
SC_05_3	**9157.05**	**0.9683**	**0.0697**	**0.0801**	SC_10_3	5795.52	0.9508	0.0687	0.0780

but systematic weakening of the terrain effect was observed. The average spread decreased to 0.0704 on day 30, 0.0529 on day 60, 0.0410 on day 90, 0.0335 on day 120, and 0.0236 on day 180. Further along the time horizon, the effect remained present, though clearly weaker, reaching 0.0199 after 210 days, 0.0168 after 240 days, 0.0119 after 300 days, and 0.0082 on day 365. The average spread decreased to 0.0704 on day 30, 0.0529 on day 60, 0.0410 on day 90, 0.0335 on day 120, and 0.0236 on day 180. Further along the time horizon, the effect remained present, though clearly weaker, reaching 0.0199 after 210 days, 0.0168 after 240 days, 0.0119 after 300 days, and 0.0082 on day 365. This trend indicates that the influence of terrain conditions was most pronounced in the initial and intermediate phases of the process, i.e., in the period preceding and partially overlapping with the trajectories reaching the critical availability level $A(t)<0.50$.

In the later stages, as the system degraded and an increasing number of trajectories moved into the low-availability range, the differences between terrain variants gradually decreased, but did not disappear completely even by the end of the analyzed period. The highest instantaneous sensitivity was recorded for scenario SC_09, where the spread between terrain trajectories reached 0.0803 at t=8 days. The group of scenarios with the highest sensitivity also included SC_03, SC_15, SC_12, and SC_08 (the same cases that were characterized by the highest values in the FANOVA analysis. The lowest maximum deviation values, however, were found for scenarios SC_28, SC_22, and SC_25. The resulting Figure D1 in Appendix D shows that the terrain's influence was not temporary but persisted throughout the analyzed time interval and systematically varied the course of the availability function.

PRACTICAL APPLICABILITY AND LIMITATIONS

From a practical perspective, the proposed CTMC model can be used as a decision-support tool for preliminary assessment of the operational sustainability of military transport systems in frontline operations areas. The model allows decision-makers to compare alternative tactical-operational scenarios, estimate the expected time to reach a critical availability level, and identify configurations in which terrain conditions, the phase of operations, the operational zone, and the direction of effort accelerate the loss of transport-system availability. Therefore, the model may support the planning of maintenance resources, the prioritization of repair capabilities, and the assessment of the minimum time window during which the transport system can maintain the required operational capability.

The proposed approach can also be compared with other reliability and availability modelling methods reported in the literature. Classical statistical reliability models, including reliability-function estimation and censored failure-data analysis, are useful for describing time-to-failure characteristics of vehicles, but they do not explicitly represent transitions between several operational and repair states [1,33,43]. Markov and semi-Markov models are widely used to assess technical readiness and availability of transport and machinery systems [5,35,36,39,44,45]. Compared with semi-Markov models, the CTMC approach adopted in this study is less flexible because it assumes exponentially distributed sojourn times, but it is simpler to parameterize and enables transparent scenario-based analysis of availability trajectories. In contrast, simulation-based mission mobility reliability models provide detailed assessment of route passability and terrain-related mobility uncertainty, but they usually focus on mission completion or route reliability rather than on the combined process of combat losses, multi-level technical renewal, and irrecoverable damage [15,25,46]. The contribution of the present model is therefore its ability to integrate tactical-operational multipliers with a multi-state availability model of a transport system operating under combat conditions. Potential validation of the model should primarily be based on operational data containing the number of available vehicles over time, the occurrence and type of damage, the assigned repair level, repair duration, irrecoverable losses, the number of available maintenance resources, and the tactical-operational context in which the vehicles operated. Such data would make it possible to calibrate the transition intensities and multipliers used in the model and then compare the simulated availability function with observed availability trajectories. Validation could include comparison of observed and predicted state probabilities, the time required to reach the critical availability threshold, and the distribution of vehicles among repair levels. Due to the limited availability and sensitivity of real combat data, an intermediate validation stage may be performed using field-exercise records, expert assessment, or high-fidelity simulation outputs [43].

A limitation of the adopted model is the use of fixed tactical and operational coefficients and the discrete classification of terrain conditions into four classes, both of which oversimplify the actual variability of the operational environment. These limitations also point to directions for further research. In particular, it is reasonable to empirically refine the model parameters and verify their consistency with operational data. Further work should also include a more detailed description of terrain conditions and a departure from some assumptions regarding the constancy (or relative constancy) of parameters by accounting for their variability over time. Another important direction for development is extending the analysis to larger transport structures, where operational readiness depends not only on the history of damage and repairs to a single facility, but also on shared maintenance and repair resources and on the organization of technical support.

CONCLUSIONS

Research has shown that field conditions significantly influence the operational availability of a transport system in combat. The seven-state CTMC model enabled a formal mapping of transitions among the task- execution state, successive levels of technical renewal, and the state of irrecoverable losses, providing a basis for a quantitative assessment of how tactical and operational factors affect the dynamics of system degradation.

In the analyzed set of 120 scenarios, the time to reach the critical availability level, defined as $A(t) < 50\%$, ranged from 5.7 to 31.5 days. Across all 30 baseline scenarios, the transition from terrain 1 to terrain 4 reduced the duration of technical availability, confirming the impact of deteriorating field conditions. The average decreased from 17.27 days for terrain 1 to 12.21 days for terrain 4, a reduction of 5.06 days (29.90%). Simultaneously, increasing the baseline loss intensity from the minimum to the maximum level reduced the average time to maintain readiness by 9.93 days, i.e., by 49.70%. This indicates that terrain is not a dominant factor relative to the other model parameters, but remains an independent and operationally significant source of variability in the model's response.

The results of the sensitivity analysis confirmed that terrain is a persistent and strong determinant of the availability trajectory. Across all baseline scenarios, a significant impact on the availability trajectory was observed, with statistics ranging from 3,499.49 to 9,165.62 and partial coefficients ranging from 0.9210 to 0.9683. Differences between trajectories corresponding to individual terrain classes persisted throughout the entire analyzed time horizon, with the greatest intensity observed in the initial and intermediate phases of the degradation process. This means that terrain conditions should be treated as a separate analytical factor that significantly influences the operational sustainability of the transportation system.

It should be emphasized that the proposed stochastic model is a robust analytical tool for planning and decision- making, enabling the optimization of resource allocation and enhancing operational resilience across diverse and challenging geographical conditions.

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