Composite Index for Managing Emergency Repair in Electrical Utilities under Heterogeneous Incident Data

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***Abstract* — The paper focuses on the management of emergency repair crews in distribution systems characterized by high emergency rates and heterogeneous incident data. The study examines the human-machine system, Human–Tools–Logistics, which necessitates a compact, interpretable, and data-resilient readiness indicator. The scientific novelty lies in the development of a non-compensatory composite operational readiness index for crews, based on the geometric aggregation of three sub-indices: Human, Tools, and Logistics.**

A two-stage methodology for constructing the composite operational readiness index is proposed. In the first stage, heterogeneous data and expert knowledge regarding personnel, equipment, logistics, and environmental conditions are integrated through a multi-agent data fusion framework. In the second stage, normalized sub-indices (*H*/*T*/*L*) are developed using fuzzy logic. Finally, the operational readiness index is aggregated as a normalized weighted geometric mean, ensuring its non-compensatory nature.

Simulation software was developed to model emergency scenarios in Moscow power grids. For a fixed point in time, the index values are calculated for multiple crews to match them with an incident and establish the most effective crew for that incident. The impact of temperature, traffic congestion, crew size, along with personnel experience and qualifications is analyzed. The analysis demonstrates diminishing returns on crew size and saturation of the experience curve, alongside the significant influence of adverse meteorological conditions and traffic congestion.

The proposed index is compared with existing simulation-based, probabilistic, and optimization-oriented models, as well as fuzzy-logic and decision support systems. The findings demonstrate that the proposed operational readiness index offers superior interpretability for dispatcher decision-making and can be seamlessly integrated into assignment and routing optimization tasks, facilitating bottleneck identification and dispatcher training.

***Index Terms* — Emergency repair; human-machine system; composite index; fuzzy logic; multi-agent system; heterogeneous data; decision support system.**

I. INTRODUCTION

Modern electric utilities operate under high incident rates, driven by increasing anthropogenic impact, growing grid loads, and significant infrastructure aging [1]. The emergency repair agility directly depends on the performance of decision support systems (DSS). In many cases, these systems do not meet operational requirements due to limited monitoring and diagnostic capabilities, as well as the complexity of tasks managed by dispatchers in control centers. Consequently, during emergencies, dispatchers assign repair crews by balancing multiple, often conflicting factors: personnel qualifications and fatigue, equipment serviceability, availability of spare parts and transport, and stringent regulatory time limits for power restoration.

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In practice, dispatchers deal with spatiotemporal data, characterized by semantic heterogeneity and incompleteness. For example, telemetry data are delayed, meteorological data are aggregated by day or month, and personnel records are structured according to diverse skill taxonomies.

These circumstances require investigating the repair as a human-machine system, in particular to form a highly skilled repair crew for a specific incident. The model of such a system must take into account the entire set of technical, logistical, and human factors, given high data uncertainty.

Existing approaches for managing emergency repair, such as integer or stochastic optimization, simulation, and probabilistic modeling, effectively capture logistics and resource constraints [2–9]. However, when modeling the readiness of repair crews, these approaches typically rely on assumptions that limit their real-world applicability. Specifically, crew readiness is often treated as static or uniform, disregarding accumulated personnel fatigue, differences in experience and qualifications, current crew composition, and the operational context. In a number of models, the human factor is either aggregated into fixed performance coefficients or completely excluded from the objective function, being addressed only through rigid constraints. Such assumptions are acceptable for logistics and resource allocation analysis, but under high incident rates and uncertainty, the formally optimal solution does not correspond to the actual ability of the crew to perform the work rapidly and safely.

Recently, fuzzy logic has been widely adopted to formalize expert knowledge and construct interpretable aggregates of crew readiness for emergency repair. The Mamdani-type inference and Maintenance Support Potential systems transform qualitative expert rules, based on linguistic variables, into stable numerical assessments [10, 11]. This approach represents a significant advancement over the isolated indicator analysis, as it facilitates the processing of fuzzy and subjective categories inherent to human judgment. To incorporate the human factor, sensory and ergonomic monitoring of personnel is applied: wearable devices and multisensory algorithms enable the detection of fatigue and cognitive risks [12]. One of the approaches to address decision-support challenges is to employ intelligent systems (deep learning [13, 14], reinforcement learning [15]), which are capable of formulating emergency repair strategies under uncertainty.

While such approaches enhance the planning adaptability, crew readiness remains fragmentary or outside the scope of the optimization objective, reducing process interpretability for management. Practical implementation requires a compact and explainable readiness criterion that can be included in the objective function or constraints, and used for retrospective analysis and training of dispatchers.

All of the aforementioned methods are multifactorial, as they consider various aspects (logistics, resources, crew size). However, direct and simultaneous processing of multiple factors results in a high computational load on the method, requiring labor-intensive tuning. Such circumstances lead to a multifactorial paradox: the more factors are explicitly included, the less manageable and reproducible the system becomes [16]. The dispatcher is faced with diverse sub-indices but cannot determine which of them to influence to reduce restoration time. The problem is exacerbated in the optimization of hierarchical distributed control systems, where an excessive number of parameters leads to increased computational complexity and a loss of transparency in decisions [17].

This problem can be addressed by utilizing composite (aggregated) indices. Such indices enable heterogeneous indicators to be combined into a single numerical criterion, thereby simplifying the ranking and comparison of objects [18–20]. Therefore, to overcome the multifactorial paradox and capture the necessary factors, a single, composite index is required to preserve interpretability and exhibit robustness against data omissions or noise.

II. Methodology

The objective of this study is to develop a composite operational readiness index (ORI) for crews, considering the interaction of human-machine systems. This indicator is designed to assess the degree of repair crew readiness to reduce restoration time under incomplete, noisy, desynchronized in time/space and semantically inconsistent data. The objects of the study are emergency repair crews and their readiness in three subsystems: Human (H), Tools (T), and Logistics (L), which are further defined as sub-indices. We will assume that the ORI is defined as an integral indicator of crew readiness to handle a specific class of incidents, normalized in [0;1] and its optimization enables rapid crew selection for emergency repair. The scientific novelty of the study lies in the development of non-compensatory ORI for crews, providing enhanced interpretability of its specific sub-indices, which reduces subjectivity of dispatch decisions.

Correct and reproducible calculation of the ORI is ensured through the use of the sequential data processing and aggregation methodology. The first stage involves pre-processing and aligning input heterogeneous data, including their multi-agent integration, cleansing, normalization and semantic harmonization using expert knowledge on the subject domain. This stage generates a unified dataset of input factors describing the state of human, technical, and logistical subsystems. In the second stage, fuzzy rules and membership functions are established for each set of factors, enabling the conversion of heterogeneous quantitative and qualitative characteristics into normalized sub-indices (*H/T/L*), which reflect the level of readiness of the respective subsystems. Next, the obtained sub-indices are aggregated into a composite (integral) ORI for crews using a non-compensatory geometric aggregation, which ensures managerial interpretability of the index and its robustness against data omissions and noise.

The ORI is defined as the weighted geometric mean of the normalized sub-indices of human, technical, and logistical factors, considering external penalty factors, and has the following form:

$$ORI = H^{\alpha} T^{\beta} L^{\gamma} R_{penalty} ,$$

where H, T, L are the sub-indices – Human, Tools, and Logistics, $\alpha + \beta + \gamma = 1$ includes the weights of each sub-index, respectively, $R_{penalty}$ is the rules (adjustments) for meteorological conditions, traffic conditions, and mismatch of work profiles.

The fundamental difference between the proposed index and additive composite indices is non-compensatory geometric aggregation: a low value of any sub-index reduces the entire ORI and cannot be offset by other sub-indices. The non-compensatory geometric aggregation is selected due to the fact that the target aggregation must be resilient to decreases in critical factors (additive aggregation does not meet this requirement).

Normalization is necessary as the criteria are divided into those that necessitate maximization and those that should be minimized. For maximized criteria, normalization is performed using the formula:

$$x_i = \frac{\ddot{x}_i - a_i}{b_i - a_i} ,$$

where x_i is the primary (non-normalized) value of the criterion, $[a_i, b_i]$ is the range of allowable values for the criterion.

For criteria to be minimized, normalization is performed using the formula:

$$x_i = \frac{b_i - \ddot{x}_i}{b_i - a_i} .$$

As a result, all criteria follow the trend: “the more, the better.”

The weights of sub-criteria are assigned using the pairwise comparison method [21, 22]. A pairwise comparison matrix is constructed to quantify the relative preference of one criterion over another. The principal eigenvector corresponding to the principal eigenvalue is calculated. The weights of the criteria are derived following the normalization of the eigenvector. A decision maker conducts pairwise comparisons based on experience and intuition. The pairwise comparison matrix is checked for consistency, and a consistency index is calculated, which enables the decision maker to identify potential

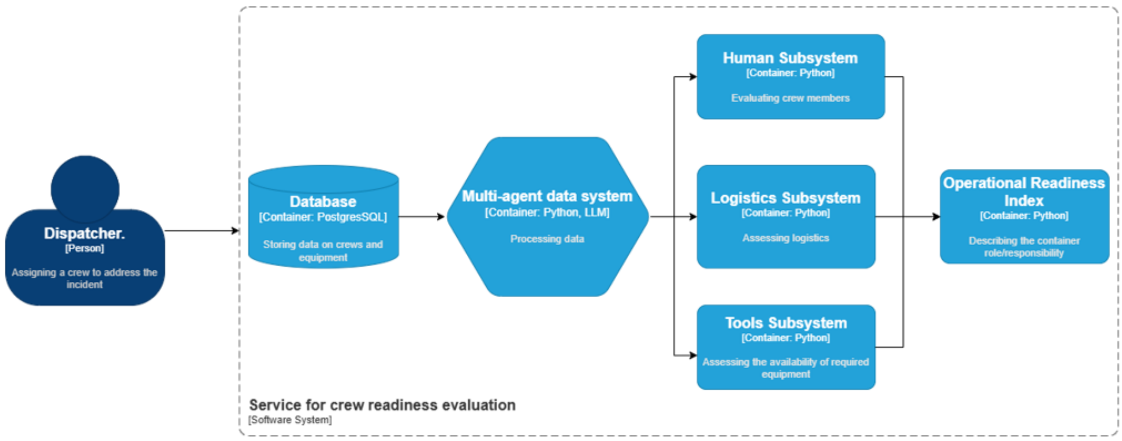

Fig. 1. C4 diagram of a comprehensive model for assessing crew readiness to perform emergency repair.

problems in their assessments. Further studies will aim to develop a methodology for automatic weight assignment, with partial or complete exclusion of human intervention from the process of determining criterion importance.

Figure 1 shows a C4 diagram of a comprehensive model for assessing crew readiness to perform emergency repair under conditions of data heterogeneity. The diagram illustrates the main subsystems, data sources and computing components, as well as the data flows between them.

The diagram shows external data sources, including information about incidents, traffic congestion, meteorological conditions, personnel data, and equipment serviceability. These data are fed into resource assessment modules and then into a multi-agent integration and data pre-processing module, where the source information is cleansed, normalized, and harmonized temporally and semantically. The processed data are then used in the composite index calculation module to generate normalized sub-indices for the subsystems of Human (*H*), Tools (*T*) and Logistics (*L*). At the final stage, the sub-indices are aggregated into the ORI for a crew, which serves as a target metric in the operator assignment and decision support tasks.

III. RESULTS

A computational experiment was conducted to assess the effectiveness of the ORI based on the proposed methodology. Emergency scenarios in the distribution system were modeled utilizing simulation software developed in Python. An open dataset of requests for emergency repair from the data.mos.ru portal was used as the input data [21]. It contains information about incidents, request arrival times, incident descriptions, and coordinates of damaged facilities. The repair crew deployment points (branches or service centers of the electric utility) are specified by a proxy list of coordinates for the districts of Moscow. Estimated times of arrival (ETA) were calculated using the OSRM routers, adjusted for meteorological conditions based on data from the Open-Meteo service [22]. Where necessary, the concurrent work density in the area covered by the electric utility branch (service center) was taken into account.

The data on the crews were generated using a specialized data generator, developed based on the Faker library [23]. A random number generator is initialized with a fixed seed for reproducible datasets during repeated runs (essential for algorithm verification). Two interrelated tables are generated: a list of crews assigned to specific substations and the composition of the crews. Each crew is described by an identifier, substation, operating company, type of repair, substation voltage levels, administrative affiliation, crew size, average experience, and skill set. Crew members are characterized by their role, qualifications, experience, and key skills. The generator has a built-in list of five representative substations in the Moscow Region, with recorded coordinates, administrative district, and electric utility for each substation.

N crews with *k* members are formed for each substation. The type of repair is selected from a list of typical scenarios for the electric utility (for example, a broken conductor on an overhead power line), which ensures a variety of functional loads. The average experience of an electrician, safety level, and equipment are randomly selected from predetermined normative ranges and data lists.

The constant settings established for the experiment are as follows:

– Time zone: UTC+3 (Moscow);
– Service center load radius (for active requests): 3.0 km;
– Radius for assessing the density of emergency repair near the incident: 1.0 km;
– Maximum mobilization time: 10 minutes;
– Maximum arrival time: 60 minutes.

The effectiveness of the calculation method is evaluated by simulating the fatigue and experience of the repair crew members for the following scenarios. In the fatigue-based heuristic scenario, a specialist readiness decreases linearly over a 12-hour shift as follows:

$$h_{fatigue}(t) = \begin{cases} 1, & t = 0, \\ -\frac{t}{12}, & 0 < t < 12, \\ 0, & t > 12. \end{cases}$$

The 12-hour threshold is set as the upper limit of a typical shift in the emergency repair scenarios under consideration. The function $h_{fatigue}(t)$ represents the linear degradation of readiness from the start of the shift to 12 hours with a cutoff, which is consistent with dispatch planning practices. After 12 hours, the probability of personnel errors increases, therefore, a condition where $h_{fatique} \le 0$ is not allowed, and employee replacement/rotation is initiated. Furthermore, varying the threshold in the range of 10–14 hours leads to a change in the final ORI within ± 3% of the median for the generated

TABLE 1. Results of the ORI Calculations by Incident

ID	Address	Service center	ETA (min.)	*H*	*T*	*L*	ORI
0	42 Bolshaya Polyanka Street, Building 1	VDNKh	8.9	0.62	0.85	0.94	0.79
0	42 Bolshaya Polyanka Street, Building 1	Cheremushki	28.0	0.62	0.80	0.83	0.74
0	42 Bolshaya Polyanka Street, Building 1	Nagatino	29.8	0.62	0.80	0.82	0.74
1	2nd Vrazhsky Lane, Building 5	VDNKh	15.8	0.62	0.85	0.90	0.78
1	2nd Vrazhsky Lane, Building 5	Cheremushki	15.6	0.62	0.80	0.90	0.76
1	2nd Vrazhsky Lane, Building 5	Nagatino	15.9	0.62	0.80	0.90	0.76

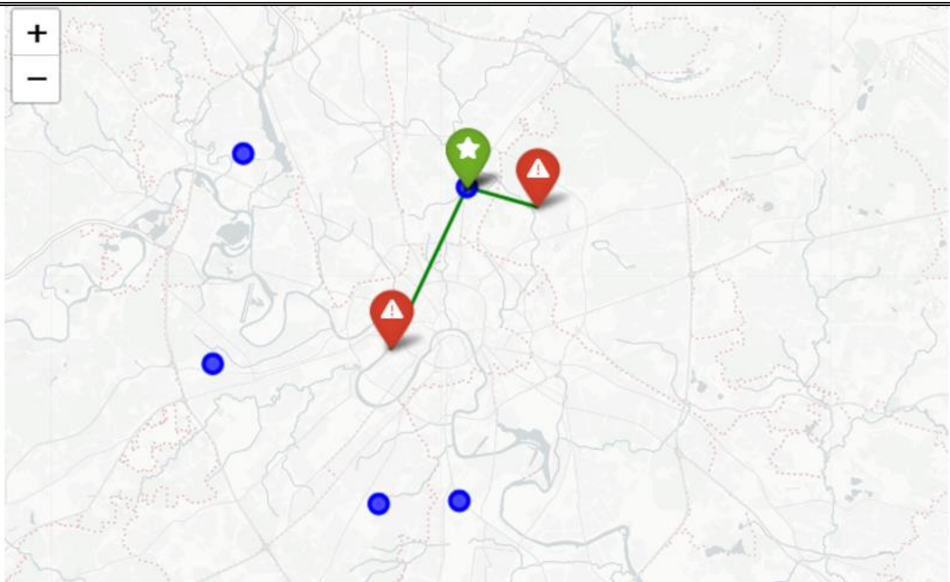

Fig. 2. Potential deployment points of the most effective repair crews for addressing a specific incident.

scenarios. The simulation of the influence of experience in performing similar tasks is based on the concept of diminishing marginal utility of training, widely used in human factor modelling. According to classical theories of the learning curve, the initial accumulation of experience leads to rapid growth in efficiency, while subsequent repetitions of similar tasks provide a significantly smaller increase in performance [24].

The experiment aims to determine which crew (service center) is most prepared to promptly respond to each incident in Moscow. The experiment was conducted on 2025-08-01 at 10:00:00. Table 1 shows the ORI values calculated for several incidents.

Figure 2 shows an example of a graphical user interface designed to identify the most effective crew based on a specified performance metric. Blue markers indicate the locations of the available crews, while red markers denote the incident sites. The location of the most effective crew is highlighted in green.

The study also involves an ORI sensitivity analysis regarding changes in temperature, crew size, and average crew experience. Figure 3 shows the relationship between the average ORI value and ambient temperature at fixed values of human (H) and logistics (L) sub-indices. Average ORI is defined as the mean value of the indicator calculated based on the total number of crews generated and incident scenarios under specified temperature conditions.

The sensitivity of the final index to meteorological conditions at fixed H and L sub-indices is demonstrated for a scenario where temperature drops below the “normal” range. In this case, the ORI decreases due to penalties in the T/L components (icing, tools, and execution speed). As shown, the ORI decreases as the temperature falls below the comfort zone. Notably, weather penalties are not offset by high H or L values, necessitating proactive support measures from the DSS regarding spare parts, equipment, and work conditions.

Figure 4 shows the relationship between the average value of the ORI and crew size for fixed values of T and L.

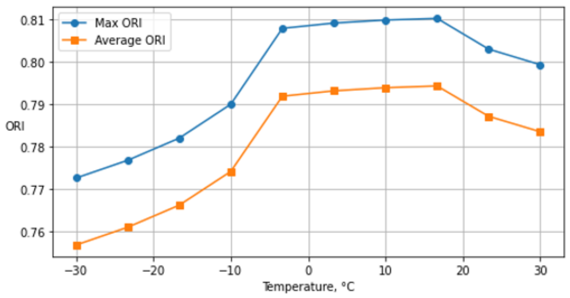

Fig. 3. ORI values at fixed H and L versus varied temperatures.

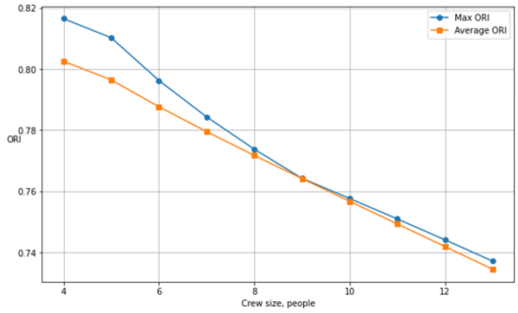

Fig. 4. ORI values at fixed T and L versus a varied crew size.

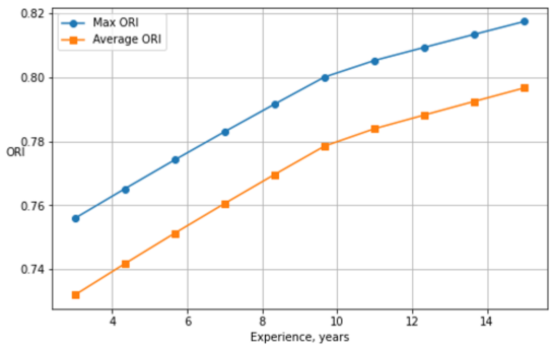

Fig. 5. ORI values at fixed of T and L versus varied average experience of the crew.

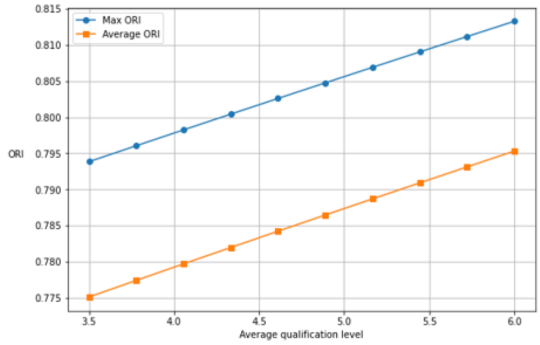

Fig. 6. ORI values at fixed T, L versus varied average qualification level of the crew.

The graph demonstrates the effect of diminishing returns on crew size. As the number of people increases, the ORI decreases monotonically, indicating reduced efficiency.

Figures 5 and 6 show the contribution of experience and qualifications to the sub-index *H* within the final index. Experience increases the ORI up to a saturation threshold. It holds true for certain incidents, if there is a sufficient level of experience and qualifications. Experience in similar types of repairs is a heuristic with a linear increase in utility of experience up to 10 repairs, followed by

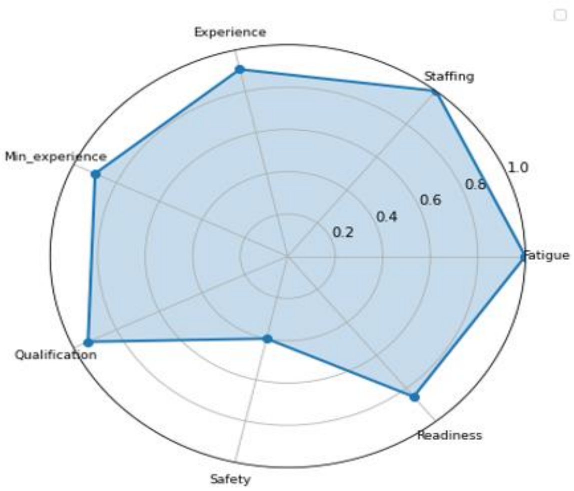

Fig. 7. Dependence within the H components for determining the most effective crew.

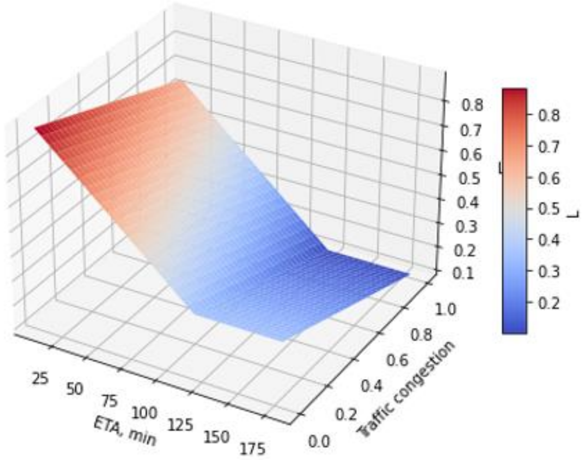

Fig. 8. 3D surface diagram for the sub-index L (ETA, traffic congestion).

saturation. The saturation threshold of 10 repairs sets the point of diminishing marginal utility:

$$e(n) = 1 - (1 - \beta)^n .$$

At $\beta \approx 0.15$, the index exceeds 0.8 at approximately $n = 10$. Beyond this point, the increase is less than 5% for every five additional repairs, which is consistent with the observed law of diminishing returns (Fig. 5). The graph shows that the experience acquisition saturates after approximately 10 similar repairs, negligibly affecting the final index relative to the T and L factors.

Figure 7 illustrates the relative values of the seven metrics constituting the sub-index H for the leading crew for a single incident (at the VDNKh service center). Vertices close to the outer radius indicate strengths. The petal diagram of the H components visualizes the parameters of the leading crew and serves as a recommendation for the DSS: which component to strengthen in order to increase the operational readiness of the crew (Fig. 7). Thus, the components of the index can serve as a system for identifying bottlenecks and developing recommendations for enhancing crew readiness. The recommendations may involve upgrading competence, conducting training, and changing the composition, which links the index to management measures.

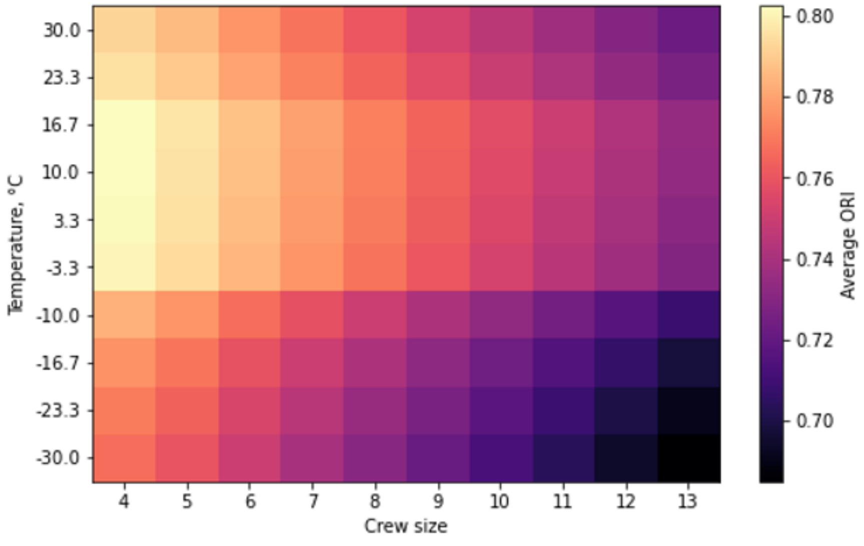

Fig. 9. Heat map for the average ORI, based on the sensitivity analysis of the "temperature – crew size" parameter pairs.

The 3D surface shows the dependence of the sub-index L on arrival time and traffic congestion levels under a fixed weather penalty (Fig. 8). A non-linear degradation of the sub-index is observed when the estimated time of arrival (ETA) exceeds approximately 90 minutes or the traffic congestion level is higher than 0.6. In this case, the sub-index drops to values between 0.3 and 0.4, even if the other factor is moderate. The high readiness zone is concentrated where the ETA is less than 60 minutes and traffic congestion is below 0.4, representing the target operational range to be achieved through optimized routing and traffic prioritization measures.

Based on the sensitivity analysis of the "temperature – crew size" parameter pairs, a heat map for the average ORI is constructed (Fig. 9). Each cell of the heat map corresponds to the average level of readiness for a given combination of temperature and crew size. Averaging across multiple scenarios mitigates the influence of random variations in crew composition and the spatial distribution of incidents, highlighting stable patterns of influence of the parameters under consideration on the final index.

There is a pronounced zone of the elevated ORI values at moderate temperatures (+10 to +20°C) and sufficient crew size (8–12 people). When the temperature drops below 0°C, there is a steady decline in the average ORI, associated with increased penalties in the technical and logistical components (deterioration of equipment operating conditions, slower operational pace, and increased time losses). In this range, increasing crew sizes only partially compensates for the decrease in readiness, as the return on additional personnel is significantly reduced. A similar effect of diminishing returns on crew size is observed even under favorable temperature conditions. Once the threshold staffing level is reached, a further expansion of the crew has a negligible impact on the ORI due to the human factor saturation and coordination constraints.

The results confirm the non-compensatory nature of the composite ORI: unfavorable external conditions (in particular, low temperatures) cannot be completely offset by enlarging the crew size. This circumstance underscores the necessity for comprehensive management decisions that include not only personnel expansion but also technical and logistical support measures. The heat map clearly demonstrates that the optimal strategy for managing emergency repair is to form crews of adequate size, taking into account meteorological conditions rather than mechanically increasing resources. Consequently, the ORI enables the identification of areas for most effective resource allocation and serves as a tool to support informed dispatch decisions.

Thus, the application of the composite ORI was studied to select the most effective service center/crew in Moscow at a fixed point in time (2025-08-01 10:00:00 Europe/Moscow), considering the ETA for the road network, meteorological conditions, local service center load, technical suitability for the type of repair, and the human factor. The visualization of "incident–optimal service center" enables the rapid ranking of crews (Fig. 2). The ORI serves as a compact and interpretable criterion that simultaneously supports assignment, staffing, and routing. Concurrently, decomposition into sub-indices (H/T/L) transforms findings into specific management decisions aimed at reducing restoration/repair duration.

IV. Discussion

The obtained results demonstrate both the practical and scientific significance of the proposed composite ORI. The ORI enables the characteristics of the human-machine system "Human – Tools – Logistics" to be combined in a single numerical scale and directly used in assigning and routing crews. Mapping the ORI values and matching the "incident – the most effective crew" pairs provide dispatchers with a convenient ranking tool, while decomposition by $H/T/L$ sub-indices enables the targeted identification of bottlenecks and the planning of recruitment, training, and resource reallocation.

The scientific novelty lies in the development of a non-compensatory composite ORI for crews, based on the geometric aggregation of three normalized sub-indices. Unlike additive criteria and fuzzy logic models, a low value of any sub-index ($H/T/L$) significantly reduces the final index, regardless of high values in the others. This fact ensures that critical bottlenecks remain transparent for management.

A comparison with simulation-based, probabilistic, and optimization-oriented models, as well as DSSs, shows that in most studies, the crew readiness is either set fragmentarily or in the form of strict constraints. The proposed approach formalizes the crew readiness as a compact composite criterion that is robust against data omissions and suitable for integration in the objective functions of repair, acting as a link between logistics and the actual state of the human-machine system.

Theoretically, the study develops a methodology of composite indices for human-machine systems. We propose the coordinated integration of heterogeneous data, normalization and non-compensatory geometric aggregation.

It is worth noting that a direct numerical comparison of the proposed ORI with alternative metrics within the framework of the experiment is complicated by the lack of indicators that are directly comparable in terms of their purpose and structure in open sources. Most current studies focus either on optimizing logistic indicators (arrival time, number of restored nodes, total damage) or on a partial assessment of individual factors of crew readiness, without integrating them into a single non-compensatory criterion. The verification of the proposed index will be a focus of further studies. A full numerical comparison of the ORI with other indices is applicable within the framework of a pilot implementation in the production systems of electrical utilities, which provide access to retrospective data on actual restoration time, performance, and dispatch decision errors.

V. Conclusion

The paper proposes an approach to formalizing the operational readiness of emergency repair crews for distribution system in the form of a non-compensatory composite ORI. The index captures the key components of human-machine systems and is based on normalized sub-indices (Human, Tools, Logistics), aggregated using a weighted geometric mean. The developed composite index prevents the masking of bottlenecks and ensures that managers can interpret the contribution of each factor.

The proposed solution relies on the multi-agent integration of heterogeneous data concerning personnel composition and experience, equipment serviceability, logistics specifics, and external conditions. Additionally, fuzzy logic is applied to normalize and generalize the input data. Using Moscow's power grids as an example, we demonstrated the effectiveness of the index with the simulation software developed within the study. The case study involved calculating ORI for a set of crews, establishing the "incidents – the most effective crews" pairs, and conducting a sensitivity analysis of the contribution of meteorological conditions, traffic congestion, crew size, experience, and qualifications.

The findings indicate that the proposed ORI can be used as an element of objective functions and constraints in assignment and routing tasks, as well as a tool for visual diagnostics and decision support for dispatchers. Methodologically, the study advances the approaches to the construction of composite indices for human-machine systems and multi-criteria management tasks. Further study will focus on calibrating the model parameters using retrospective data from electrical utilities, transferring the methodology to other regions and services (including emergency response and transportation services), and integrating the ORI into the dispatcher DSS.

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