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**MATHEMATICAL EVALUATION OF OPERATIONAL RELIABILITY INDICATORS
OF OVERHEAD BRIDGE CRANES BASED ON DEFECT SEVERITY,
INSPECTION DATA, AND REMAINING USEFUL LIFE**

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**МАТЕМАТИЧЕСКАЯ ОЦЕНКА ПОКАЗАТЕЛЕЙ ЭКСПЛУАТАЦИОННОЙ
НАДЕЖНОСТИ МОСТОВЫХ КРАНОВ НА ОСНОВЕ ТЯЖЕСТИ ДЕФЕКТОВ,
ДАННЫХ КОНТРОЛЯ И ОСТАТОЧНОГО РЕСУРСА**

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Abstract. Operational reliability assessment for overhead bridge cranes remains fragmented across structural reliability analysis, non-destructive inspection, condition monitoring, and remaining useful life prediction. Existing studies usually treat these directions separately: accident reliability is evaluated through fault-tree, Markov, and fuzzy Bayesian models; girder failure is assessed probabilistically under uncertain design parameters; structural integrity is examined through finite-element analysis and non-destructive testing; and fatigue or bearing degradation is predicted through damage accumulation and stochastic prognostic models. This paper proposes a unified mathematical framework for evaluating operational reliability indicators of overhead bridge cranes by combining three information streams: normalized defect severity, inspection evidence quality, and predicted remaining useful life. The framework defines component-level and system-level reliability indicators, introduces a confidence-adjusted defect severity index, applies Bayesian updating for new inspection cycles, and links degradation state to time-dependent hazard and reliability functions. The proposed indicators are designed to support maintenance prioritization, inspection scheduling, and continued-operation decisions for critical crane subsystems, such as girders, end carriages, hoisting mechanisms, wire ropes, brakes, wheels, and gearboxes. Although the study is methodological rather than experimental, it is structured for direct implementation using routine inspection sheets, non-destructive testing results, sensor-based monitoring data, and maintenance histories. The main contribution is an integrated decision-support formulation that preserves the mechanical meaning of defects while providing a probabilistic interpretation of operational reliability.

Аннотация. Оценка эксплуатационной надежности мостовых кранов до настоящего времени остается разобщенной между расчетами конструкционной надежности, неразрушающим контролем, мониторингом технического состояния и прогнозированием остаточного ресурса. В существующих исследованиях эти направления, как правило, рассматриваются отдельно: аварийные события анализируются с применением дерева отказов, марковских цепей и нечетких байесовских сетей; вероятность отказа главных балок оценивается с учетом неопределенности нагрузок и геометрических параметров; техническое состояние металлоконструкций исследуется с помощью конечно-элементного моделирования и методов неразрушающего контроля; а остаточный ресурс отдельных узлов прогнозируется на основе накопления повреждений и стохастических моделей деградации. В данной статье

предложена единая математическая основа для оценки показателей эксплуатационной надежности мостовых кранов путем объединения трех информационных потоков: нормированной тяжести дефектов, качества инспекционных данных и прогнозируемого остаточного ресурса. В работе определены показатели надежности на уровне компонента и системы, введен индекс тяжести дефекта с учетом достоверности контроля, использовано байесовское обновление при поступлении новых результатов обследования, а также установлена связь между состоянием деградации, функцией интенсивности отказов и функцией надежности. Предложенный подход предназначен для поддержки решений по приоритетности ремонта, планированию инспекций и допуску крана к дальнейшей эксплуатации. Методика может быть реализована на основе стандартных актов обследования, результатов неразрушающего контроля, данных мониторинга и истории технического обслуживания.

Keywords: overhead bridge crane, operational reliability, defect severity, inspection data, remaining useful life, Bayesian updating, structural health assessment, maintenance decision support.

Ключевые слова: мостовой кран, эксплуатационная надежность, тяжесть дефектов, данные контроля, остаточный ресурс, байесовское обновление, оценка технического состояния, поддержка принятия решений по техническому обслуживанию.

Safe operation of in-service bridge cranes depends on the ability to detect fatigue-critical zones, quantify defect growth, and estimate residual life before failure occurs[4].

Recent reliability work on overhead cranes has also shown that failure probability is not static; it evolves with time, state transitions, and interacting failure modes [1].

The gap is not a lack of methods, but a lack of integration. Structural reliability studies quantify failure probability under uncertainty, inspection-oriented studies localize critical damage zones using finite-element and non-destructive approaches, and prognostic studies estimate remaining useful life for specific crane subsystems, such as bridge members and hoist gearbox bearings [2-5].

In practice, maintenance engineers need one interpretable operational reliability indicator, not four disconnected models. This paper proposes such an indicator. The central idea is that crane reliability at time t should be evaluated as a function of observed defect severity, the evidential strength of inspection data, and the predicted remaining useful life of each critical subsystem. Overhead-crane reliability has been modeled with fault tree analysis integrated with fuzzy Bayesian networks and Markov chains; one reported case found system reliability decreasing by 67.9% after 60 months under the modeled scenario [1].

That result is important because it shows that reliability evaluation must be dynamic rather than purely deterministic. Probabilistic analysis of overhead-crane bridge girders has shown that uncertainty in wheel loads and geometric parameters can strongly change failure probability, and that in some cases a geometric scaling factor of 1.1 was needed to reduce the failure probability from roughly $10^{(-0.3)}$ to about $10^{(-4)}$ when variability was modest [2].

This supports using uncertainty-aware reliability indicators rather than point estimates. Inspection studies on crane metal structures have shown that combining finite-element modeling with magnetic coercive non-destructive control can identify high-risk zones, such as bearing-box regions and beam-connection areas, and can confirm crack-prone operating states associated with adverse stress-strain behavior [3].

This suggests that inspection data should not be treated as a simple pass-or-fail variable; instead, it should modify the confidence and local severity assigned to structural components. For prognostics,

the residual fatigue life of in-service bridge cranes has been estimated using stress-time histories, rainflow counting, Forman crack-growth relations, and Miner damage accumulation [4].

For rotating crane equipment, the remaining useful life of quay crane hoist gearbox bearings has been predicted under dynamic operating conditions using operating-mode classification, a Wiener degradation process, ARIMA load prediction, and condition-activated particle filtering [5].

These studies justify treating RUL as a measurable prognostic input to reliability rather than as a separate maintenance output.

Condition-index approaches also support integration. A data-driven asset health index for quay cranes has been built from IoT sensors, PLC data, information systems, and traditional maintenance records in order to compare conditions across assets and prioritize maintenance investment [6].

This is conceptually close to the indicator proposed here, but the present paper adds an explicit probabilistic reliability interpretation. Finally, inspection quality matters because some defects are hidden. Review work on crane steel wire ropes has shown that visual inspection alone can miss internal damage, while electromagnetic, acoustic emission, ultrasonic, optical, thermal, and related monitoring methods provide richer evidence for condition evaluation [7].

Specific rope-testing work has also reported that surface rupture may appear only after internal wire disintegration, which is exactly the kind of delayed observability that should reduce confidence in inspection-based condition estimates [8].

Problem formulation: Consider an overhead bridge crane decomposed into n critical subsystems:

$$C = 1, 2, \dots, n \quad (1)$$

Typical members of C include the main girder, end carriage, trolley frame, hoisting rope, drum, hook block, hoist gearbox, travel wheels, and brake-drive assembly.

For each component i at time t , we define three state variables: defect severity, $S_i(t)$; inspection evidence quality, $Q_i(t)$; remaining useful life, $L_i(t)$.

The objective is to construct a component reliability indicator, $R_i(t)$, and a system operational reliability indicator, $ORI(t)$, satisfying:

$$ORI(t) = \Psi(R_1(t), R_2(t), \dots, R_n(t)) \quad (2)$$

where $\Psi(\cdot)$ is a system aggregation operator consistent with the crane's structural and functional dependencies. Defect severity model. Let each component have m_i observable defect attributes, such as crack length, corrosion depth, permanent deflection, bearing vibration, rope broken-wire count, or thermal anomaly. We then define severity as a weighted composite:

$$S_i(t) = \sum_{j=1}^{m_i} w_{ij} d_{ij}(t), \quad \sum_{j=1}^{m_i} w_{ij} = 1 \quad (3)$$

The weights w_{ij} should reflect mechanical criticality. For example, crack growth near welded girder junctions should generally carry higher weight than superficial coating loss, because crane metal-structure studies identify localized high-stress connection zones as especially important for integrity assessment [3]. To account for defect class, severity can be stratified into four ordered levels:

$$\text{Level 0: } S_i < \theta_1, \quad \text{Level 1: } \theta_1 \leq S_i < \theta_2, \quad \text{Level 2: } \theta_2 \leq S_i < \theta_3, \quad \text{Level 3: } S_i \geq \theta_3$$

These thresholds are engineering policy parameters and may be calibrated based on failure history, standards, or expert elicitation. Inspection evidence model: Inspection observations do not have uniform credibility. Visual inspection, ultrasonic testing, magnetic flux leakage, acoustic

emission, and strain measurement do not provide the same detectability, especially for hidden rope or welded-joint damage [7, 8].

Define inspection confidence as follows:

$$Q_i(t) = 1 - \prod_{k=1}^{r_i(t)} (1 - q_{ik}) \quad (4)$$

where $q_{ik} \in [0,1]$ is the confidence contribution of inspection event k for component i , and $r_i(t)$ is the number of relevant inspections up to time t .

A single-event confidence value can be expressed as: A single-event confidence value can be expressed as:

$$q_{ik} = \alpha_{M_{ik}} \beta_{I_{ik}} \gamma_{A_{ik}} \quad (5)$$

where: $\alpha_{M_{ik}}$ is the method reliability coefficient, $\beta_{I_{ik}}$ is the inspector or system quality coefficient, $\gamma_{A_{ik}}$ is the accessibility or coverage coefficient. This formulation makes poor evidence visibly weak. A superficial visual inspection of an enclosed or rope-core-critical region should produce lower q_{ik} than calibrated electromagnetic or magnetic-coercive inspection of a known high-stress zone [3, 8].

The confidence-adjusted severity is then:

$$\tilde{S}_i(t) = Q_i(t)S_i(t) + (1 - Q_i(t))S_i^{prior}(t) \quad (6)$$

where $S_i^{prior}(t)$ is the prior severity estimate derived from historical behavior, design vulnerability, or previous inspection cycles. Remaining useful life model. Let $L_i(t)$ denote the predicted remaining useful life of component i in hours, cycles, or months. The source of $L_i(t)$ depends on subsystem type. For structural members subject to fatigue, $L_i(t)$ may be derived from stress-history simulation, rainflow counting, crack-growth laws, and cumulative damage rules, as already demonstrated for bridge cranes [4].

For rotating or rolling elements, $L_i(t)$ may be estimated with stochastic degradation models such as Wiener-process formulations combined with dynamic operating-condition prediction and particle filtering, as shown for crane hoist gearbox bearings [5].

To integrate heterogeneous units, define normalized remaining life:

$$\Lambda_i(t) = \frac{L_i(t)}{L_i^{ref}}, \quad 0 \leq \Lambda_i(t) \quad (7)$$

where L_i^{ref} is the nominal reference life for the component. To keep the indicator bounded, transform it to:

$$U_i(t) = \frac{\Lambda_i(t)}{1 + \Lambda_i(t)} \quad (8)$$

so that $U_i(t) \in [0,1)$ and larger values imply greater life reserve. Component reliability indicator. A practical component-level indicator should decrease when severity rises, increase when inspection confidence improves, and decrease when normalized remaining life falls. One convenient formulation is the exponential hazard form:

$$h_i(t) = h_{i0} \exp \left(\beta_i \tilde{S}_i(t) - \eta_i U_i(t) + \xi_i z_i(t) \right) \quad (9)$$

where: h_{i0} is baseline hazard, $\beta_i > 0$ controls severity effect, $\eta_i > 0$ controls life-reserve effect, $z_i(t)$ captures operational stressors such as overload rate, duty class, shock events, or environmental exposure. The component reliability over decision horizon Δ is:

$$R_i(t, \Delta) = \exp\left(-\int_t^{t+\Delta} h_i(\tau) d\tau\right) \quad (10)$$

For routine implementation with discrete inspection periods:

$$R_i^{(k)} = \exp(-h_i^{(k)} \Delta_k) \quad (11)$$

This gives a direct reliability interpretation, unlike a purely ordinal health score. If a simpler algebraic indicator is preferred, define:

$$CRI_i(t) = \omega_1 (1 - \tilde{S}_i(t)) + \omega_2 Q_i(t) + \omega_3 U_i(t), \quad \omega_1 + \omega_2 + \omega_3 = 1 \quad (12)$$

where $CRI_i(t) \in [0,1]$. This index is easier to deploy, but it is less rigorous than the hazard-based reliability model.

System operational reliability indicator. An overhead bridge crane is not a pure series system, but many safety-critical subsystems behave approximately as one during operation. If failure of any critical component causes mission loss, a conservative system model is:

$$ORI(t, \Delta) = \prod_{i=1}^n R_i(t, \Delta)^{c_i} \quad (13)$$

where $c_i \in [0,1]$ is the functional criticality coefficient.

Taking logarithms gives:

$$\ln ORI(t, \Delta) = \sum_{i=1}^n c_i \ln R_i(t, \Delta) \quad (14)$$

which is useful for parameter estimation and sensitivity analysis.

For managerial interpretation, define a score on a 0 to 100 scale:

$$Score(t, \Delta) = 100 \times ORI(t, \Delta) \quad (15)$$

and classify: Grade A: $Score \geq 90$; Grade B: $75 \leq Score < 90$; Grade C: $60 \leq Score < 75$; Grade D: $Score < 60$; These are policy thresholds, not physical laws. Bayesian update with new inspection cycles. After a new inspection at time t_{k+1} , the component severity state may be updated recursively:

$$p(S_i | \mathcal{D}_{k+1}) \propto p(\mathcal{D}_{k+1} | S_i) p(S_i | \mathcal{D}_k) \quad (16)$$

where $\mathcal{D}_{k+1}$ is the new inspection dataset.

If the severity state is discretized into levels 0,1,2,3, then the posterior expected severity is:

$$\mathbb{E}[S_i | \mathcal{D}_{k+1}] = \sum_{s=0}^3 s p(S_i = s | \mathcal{D}_{k+1}) \quad (17)$$

This fits naturally with the dynamic reliability logic used in overhead crane fault-tree, Bayesian, and Markov models [1]. Decision rules for maintenance and inspection: the proposed framework supports three linked decisions. First, maintenance priority can be based on marginal reliability loss.

$$MPI_i(t) = -\frac{\partial ORI}{\partial R_i} \quad (18)$$

A component with large $MPI_i(t)$ and low $R_i(t)$ should be prioritized. Second, inspection scheduling can be driven by low confidence and high consequence:

$$ISI_i(t) = \kappa_1 \tilde{S}_i(t) + \kappa_2 (1 - Q_i(t)) + \kappa_3 (1 - U_i(t)) \quad (19)$$

Higher $ISI_i(t)$ implies earlier reinspection. Third, continued-operation acceptance may be based on:

$$ORI(t, \Delta) \geq ORI_{min} \quad (20)$$

If this inequality is violated, the crane should be derated, repaired, or removed from service, depending on the consequence class. The main contribution of this paper is unification. Existing crane studies already provide the ingredients: dynamic reliability reasoning for overhead crane events, probabilistic treatment of uncertain girder resistance and load effects, defect localization through coupled numerical and non-destructive evaluation, and subsystem RUL estimation for both structural and rotating elements [1-5].

What has been missing is a single operational indicator that preserves engineering meaning. The second contribution is the explicit treatment of inspection quality. This matters because hidden rope or joint defects may be poorly represented by visual inspections alone, while multi-source health indexing becomes more robust when sensor, PLC, and maintenance records are fused rather than treated separately [6, 8].

The limitation is equally clear. The present paper proposes a mathematically consistent framework, but it does not calibrate coefficients such as β_i , η_i , and c_i using a real fleet dataset. Those parameters should be learned from failure history, expert judgment, accelerated testing, or digital-twin simulation.

Conclusion

A practical operational reliability indicator for overhead bridge cranes should not be based on defects alone, nor on inspection records alone, nor on remaining useful life alone; it should fuse all three. This paper proposes a mathematical framework in which normalized defect severity, inspection confidence, and remaining useful life are integrated into component hazards, component reliability functions, and a system-level operational reliability indicator. The framework is consistent with current crane literature on probabilistic reliability, structural integrity assessment, fatigue-life prediction, subsystem prognostics, and data-driven crane health indexing. Its main value is decision support: it can rank components for maintenance, trigger targeted inspections, and provide an interpretable threshold for safe continued operation. A natural next step is empirical validation on a fleet of overhead bridge cranes using historical inspection reports, sensor streams, non-destructive testing results, and maintenance outcomes.

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