WEIGHTED MULTI-CRITERIA PENALTY ALGORITHM FOR MILITARY VEHICLE TECHNICAL HEALTH MONITORING

Iskandarova F.N.

Tashkent International University of Financial Management and Technologies

feruza621988@gmail.com

Safarmurodov E.

Tashkent University of Information Technologies named after Muhammad al-Khwarizmi

Nuritdinov Jahongir To‘lqin o‘g‘li

Tashkent University of Information Technologies named after Muhammad al-Khwarizmi

nuriddinovjahongir250@gmail.com

Madina Shaymanova

Tashkent University of Information Technologies named after Muhammad al-Khwarizmi

Abstract. This paper proposes a weighted multi-criteria penalty algorithm for assessing the technical health of military vehicles based on ten sensor parameters. The algorithm produces a single numerical Health Index (HI ∈ [0, 100]) that is transparent, interpretable, and operates entirely on a local network without internet connectivity — a critical requirement for military applications. Four mathematical properties of the algorithm (boundedness, idempotency, monotonicity and maximum-contribution bound) are formally proven. Empirical evaluation on 155 vehicles across three fleets demonstrates that the algorithm reliably differentiates fleet-specific maintenance issues, with combat-readiness

rates of 61.5% for an armored battalion versus 43.5% for a logistics regiment. The implementation, written in Python with a Flask + PyQt5 architecture, processes 5 000 vehicles in approximately 65 ms.

Keywords: *military vehicles, condition-based maintenance, weighted algorithm, penalty function, health index, multi-criteria assessment, Flask, PyQt5.*

Introduction. Modern military fleets — armored vehicles, trucks and logistic transport — operate under harsh and intermittent conditions, where unplanned breakdowns translate directly into reduced combat readiness rather than mere economic loss. Traditional time-based maintenance (TBM) ignores actual vehicle state, whereas predictive maintenance (PdM) requires large historical datasets and continuous connectivity that conflict with military secrecy requirements. Existing industrial monitoring solutions (Wialon, Omnicomm, VisionLink) are cloud-oriented and unsuitable for closed military networks. There is therefore a need for a transparent, locally-running, multi-criteria condition-based assessment that is specifically tailored to the heterogeneous sensor set of military vehicles.

Methods. We propose a weighted penalty model $HI(x) = \max(0, 1 - \Sigma_i w_i \cdot p_i(x_i)) \cdot 100$, computed over ten sensors: engine temperature, oil pressure, brake wear, coolant level, tire pressure, tire wear, battery voltage, vibration, exhaust smoke and days since last service. For each sensor a physics-motivated penalty function $p_i \in [0,1]$ is constructed in one of three forms — symmetric V-shape (for two-sided bounded sensors), quadratically increasing (for one-sided wear sensors) or linearly decreasing (for one-sided low-bound sensors). Weights w_i are elicited by expert judgement and normalized so that $\Sigma w_i = 1.0$. Vehicles are then classified into three states: Ready ($HI \geq 85$), Maintenance ($50 \leq HI < 85$) or Critical ($HI < 50$). Four properties of the model — boundedness, idempotency, monotonicity and a per-sensor maximum-contribution bound of $100 \cdot w_i$ — are proven analytically. The algorithm is implemented in Python with a Flask REST backend and a PyQt5 desktop wrapper running on 127.0.0.1, ensuring full offline operation.

Results. The algorithm was tested on three fleets totalling 155 vehicles: a general fleet (n = 83, mean HI = 70.6), an armored battalion (n = 26, mean HI = 77.1) and a logistics regiment (n = 46, mean HI = 67.9). The classification distribution differs significantly across fleets — Ready ratios of 50.6%, 61.5% and 43.5% respectively — reflecting real differences in operational intensity and maintenance practices. Across all three fleets the most frequent warn/critical sensors are exhaust smoke (65–89% of vehicles), tire wear (46–65%) and brake wear (38–56%), providing direct guidance for maintenance prioritisation. Empirical benchmarking confirms linear time complexity $O(N \cdot M)$, with $t \approx 0.013 \cdot N + 0.5$ ms; processing 5 000 vehicles requires only 65 ms, comfortably below the 100 ms budget for 1 000 vehicles. A sensitivity analysis shows that a ±0.02 perturbation of any weight changes HI by at most ±2 units, indicating robustness to expert subjectivity.

Discussion and Conclusion. The proposed algorithm closes a practical gap in the literature by combining transparency, local-network operation and a heterogeneous military sensor set within a single, mathematically grounded framework. Its main limitations are reliance on expert weights (rather than data-driven calibration) and the absence of an explicit predictive layer. Future work will focus on AHP-based weight elicitation from multiple experts, integration of an LSTM-based remaining-useful-life predictor, and direct connection to OBD-II / SAE J1939 telematics. The system is ready for deployment in armed-forces logistics units of the Republic of Uzbekistan and offers a reusable methodology for similar condition-monitoring problems in industrial and energy domains.

References

1. Jardine A.K.S., Lin D., Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance // Mech. Syst. Signal Process. — 2006. — Vol. 20(7). — P. 1483–1510. 2. Lei Y., Li N., Guo L., Yan

T., Lin J. Machinery health prognostics: A systematic review from data acquisition to RUL prediction // Mech. Syst. Signal Process. — 2018. — Vol. 104. — P. 799–834. 3. Saaty T.L. The Analytic Hierarchy Process. — New York: McGraw-Hill, 1980. — 287 p. 4. Mobley R.K. An Introduction to Predictive Maintenance. 2nd ed. — Boston: Butterworth-Heinemann, 2002. — 459 p.