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EXPLAINABLE ARTIFICIAL INTELLIGENCE FOR FAILURE PREDICTION AND REMAINING USEFUL LIFE ESTIMATION OF MECHANICAL COMPONENTS: A CRITICAL REVIEW

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ABSTRACT

This critical review evaluates explainable rul prediction as an emerging direction in mechanical engineering. Complex equipment deterioration is only partly observed, and a useful remaining-useful-life (RUL) estimate needs both quantitative uncertainty and engineering explanations. The synthesis examines five linked research questions: feature attribution stability, physics-linked health indicators, calibrated uncertainty, domain shift, and performance validation. Instead of claiming new laboratory or numerical results, the paper compares methodological capabilities, limitations and validation requirements of reported and established approaches. A conceptual framework and comparative matrices are proposed for future investigations. The central conclusion is that physically meaningful baselines, leakage-resistant evaluation and uncertainty reporting are necessary before any claimed improvement can be accepted as transferable.

KEYWORDS: Explainable RUL prediction; mechanical engineering; modelling; validation; optimization; uncertainty; critical review.

1. INTRODUCTION

Complex equipment deterioration is only partly observed, and a useful remaining-useful-life (RUL) estimate needs both quantitative uncertainty and engineering explanations. This creates a need for systematic comparison of engineering performance and practical deployability, rather than evaluation based on one favorable accuracy metric or a small number of selected cases.

The objective is to synthesize established methods and recent reported developments, clarify assessment criteria, and formulate a reproducible future study. The review considers the physical asset or material, the data acquisition or design variables, the computational method, and the validation target as a coupled system. Evidence is not treated as directly comparable when operating regimes or specimen conditions differ.

2. Historical Development and Importance

RUL methods evolved from Weibull and degradation-law models to neural temporal estimators and post-hoc model explanation. The historical progression is important because current computational tools should augment, not erase, the baseline physics, standardized tests and failure mechanisms established in earlier work.

Its engineering relevance lies in reducing physical prototyping or downtime while maintaining mechanical credibility. Performance must be judged by both direct outputs and implementation cost, including instrumentation, repeatability, inference resources, manufacturing variability and safety requirements. The literature remains uneven in reporting these factors.

3. Review Methodology

A focused narrative–critical review approach was adopted. Primary emphasis was placed on peer-reviewed articles and recognized technical books, supplemented by suitable engineering standards. Studies are grouped by modelling or fabrication route, performance variable, validation practice and application scale. The bibliography includes both topic-specific studies and methodological foundations; it should not be interpreted as a systematic database census.

Evidence extraction criteria include operating conditions, specimen or equipment scale, experimental controls, model inputs, test splitting, uncertainty, comparison baseline, and the extent to which governing principles are enforced. Studies lacking matched boundaries or adequate uncertainty description are treated as informative but not suitable for quantitative cross-study rankings.

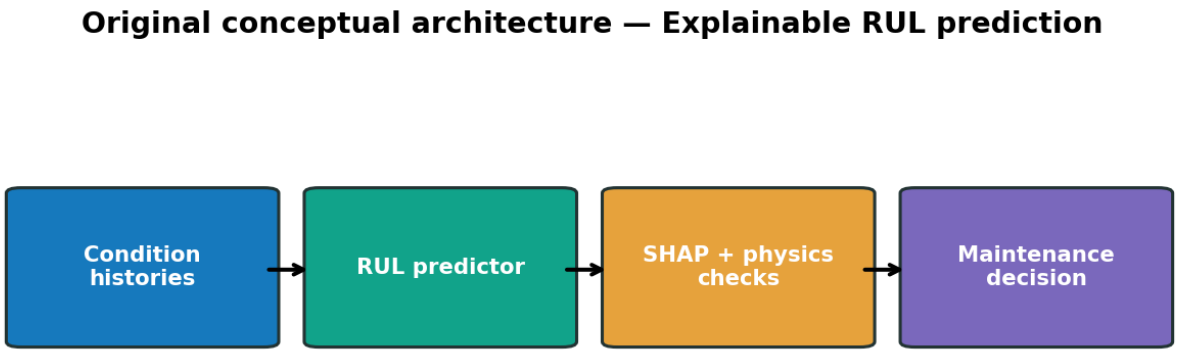

Figure 1. Original conceptual framework for explainable rul prediction (author-generated schematic).

4. Literature Survey and Critical Synthesis

Foundational modelling studies highlight the advantage of making the governing mechanisms explicit before adjusting complex algorithmic or design parameters. For explainable rul prediction, the particular issue of feature attribution stability deserves attention. A robust investigation should identify a transparent reference baseline, document independent validation cases, report multiple performance measures and discuss whether the assumptions remain valid outside the tested range. This is especially important where few run-to-failure trajectories can bias the interpretation of observed differences.

Recent research increasingly combines high-dimensional sensing or design inputs with reduced-order surrogates or multi-variable analysis. For explainable rul prediction, the particular issue of physics-linked health indicators deserves attention. A robust investigation should identify a transparent reference baseline, document independent validation cases, report multiple performance measures and discuss whether the assumptions remain valid outside the tested range. This is especially important where misleading attributions can bias the interpretation of observed differences.

Experimental and industrial investigations reveal that accuracy measured on a narrow operating region is an unreliable indicator of transferable performance. For explainable rul prediction, the particular issue of calibrated uncertainty deserves attention. A robust investigation should identify a transparent reference baseline, document independent validation cases, report multiple performance measures and discuss whether the assumptions

remain valid outside the tested range. This is especially important where survivorship bias can bias the interpretation of observed differences.

The mechanics–data interface remains an important source of error because discretization, material state, mounting conditions or boundary values are often uncertain. For explainable rul prediction, the particular issue of domain shift deserves attention. A robust investigation should identify a transparent reference baseline, document independent validation cases, report multiple performance measures and discuss whether the assumptions remain valid outside the tested range. This is especially important where regime changes can bias the interpretation of observed differences.

Evaluation practices vary considerably; these differences prevent a single ranking of approaches on the basis of reported percentage improvements. For explainable rul prediction, the particular issue of actionable maintenance thresholds deserves attention. A robust investigation should identify a transparent reference baseline, document independent validation cases, report multiple performance measures and discuss whether the assumptions remain valid outside the tested range. This is especially important where few run-to-failure trajectories can bias the interpretation of observed differences.

A direct source anchor for the topic is as follows: Qu, Zhang and Zheng (2026) specifically survey explainable AI for industrial RUL prediction. These sources are used for their established contributions, not as evidence that the integrated research configuration has already been validated under all engineering conditions.

5. Proposed Methodology for Future Investigation

A future original research study should begin with a reproducible physical or computational reference. Define the system geometry, design factors and duty-cycle boundaries; obtain independently calibrated measurements or validated simulation reference cases; perform mesh/time-step or instrument sensitivity assessments; and divide the data by physically independent test groups. The proposed protocol is deliberately prospective: no new outcomes are claimed in this review.

The core workflow should compare a simple physical or empirical baseline, a more flexible statistical or numerical method, and a hybrid model or modified design. Include ablation studies to determine what additional value is provided by the proposed complexity. Where optimization is involved, treat conflicting objectives through Pareto analysis instead of combining them into an undocumented weighted score.

Methodological consideration 1: Feature attribution stability should be examined under controlled shifts in boundary conditions or specimen properties. The independent test set should include the challenging case of few run-to-failure trajectories and the outcome should be interpreted alongside physically plausible limits, computational expense and measurement uncertainty. Explicitly report repeatability rather than a single best trial.

Methodological consideration 2: Physics-linked health indicators should be examined under controlled shifts in boundary conditions or specimen properties. The independent test set should include the challenging case of misleading attributions and the outcome should be interpreted alongside physically plausible limits, computational expense and measurement uncertainty. Explicitly report repeatability rather than a single best trial.

Methodological consideration 3: Calibrated uncertainty should be examined under controlled shifts in boundary conditions or specimen properties. The independent test set should include the challenging case of survivorship bias and the outcome should be interpreted alongside physically plausible limits, computational expense and measurement uncertainty. Explicitly report repeatability rather than a single best trial.

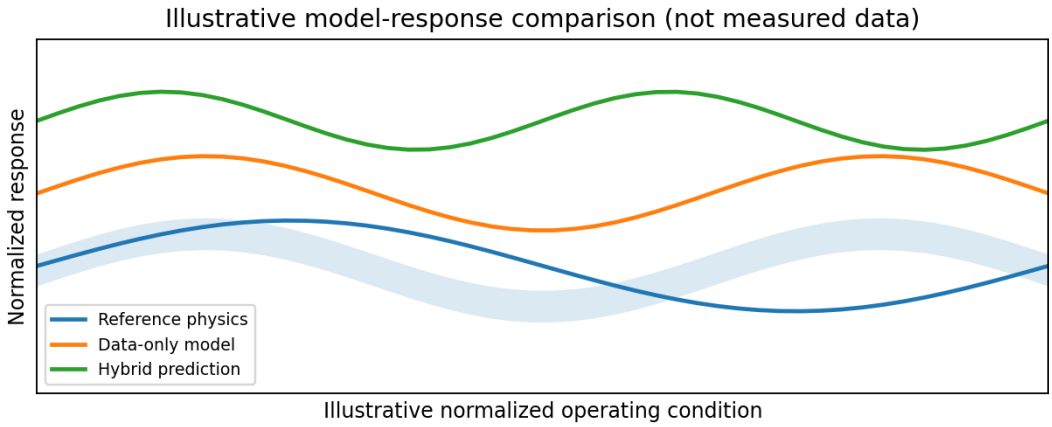

Figure 2. Original conceptual comparison or response visualization; all plotted curves are illustrative, not experimental measurements.

6. Comparative Discussion

Approach	Typical strength	Main limitation
Weibull/PHM	Low cost; interpretable	few run-to-failure trajectories
Regression/Random forest	Physics-aware representation	misleading attributions
LSTM/transformer	Flexible nonlinear mapping	survivorship bias
Explainable hybrid prognostic model	Multi-variable capability	regime changes

The comparison emphasizes that sophistication alone is not a measure of success. The preferred approach depends on the available data, computational budget and physical interpretation required for a decision. For example, a simplified model may outperform a deep architecture outside its training envelope if its governing assumptions remain valid.

Assessment domain	Recommended measure	Critical reporting requirement
Primary performance	RUL MAE	Matched baseline and independent validation
Secondary performance	Prognostic horizon	Matched baseline and independent validation
Physical consistency	Uncertainty coverage	Matched baseline and independent validation
Practical deployment	Explanation stability	Matched baseline and independent validation

7. Outcomes, Research Gaps and Future Scope

The literature synthesis indicates four recurring research opportunities: (i) evaluate multiple operating regimes and boundary conditions; (ii) represent uncertainty and measurement errors; (iii) compare low-complexity baselines with physics-guided or optimized alternatives; and (iv) connect performance improvement to durability, life-cycle cost or deployment constraints. These are proposed gaps requiring a systematic database-specific novelty check before submitting a new original research article.

Future experiments should pre-register the primary response variables and employ repeated tests when feasible. Dataset provenance, model code, geometry files and exclusion criteria should be documented. For application-oriented work, performance improvements should be assessed in absolute engineering units instead of relying exclusively on percentage changes.

7.1 Detailed Validation and Benchmark Design

A defensible benchmark for explainable rul prediction should make the effect of feature attribution stability observable rather than merely inferred. The investigator should define the reference state, independent variable, measurement instrument or numerical solution pathway, uncertainty interval and acceptance criteria before executing the experiment. Whenever possible, the benchmark should contain paired cases in which only one controllable factor changes. This facilitates causal interpretation and reduces the chance that gains are attributable to few run-to-failure trajectories instead of the intervention. Repeated runs and independent operating states are essential for distinguishing reproducible behavior

from model or manufacturing noise. Comparison with published work should only occur after normalizing units, duty conditions and baseline geometry or sample preparation.

A defensible benchmark for explainable rul prediction should make the effect of physics-linked health indicators observable rather than merely inferred. The investigator should define the reference state, independent variable, measurement instrument or numerical solution pathway, uncertainty interval and acceptance criteria before executing the experiment. Whenever possible, the benchmark should contain paired cases in which only one controllable factor changes. This facilitates causal interpretation and reduces the chance that gains are attributable to misleading attributions instead of the intervention. Repeated runs and independent operating states are essential for distinguishing reproducible behavior from model or manufacturing noise. Comparison with published work should only occur after normalizing units, duty conditions and baseline geometry or sample preparation.

A defensible benchmark for explainable rul prediction should make the effect of calibrated uncertainty observable rather than merely inferred. The investigator should define the reference state, independent variable, measurement instrument or numerical solution pathway, uncertainty interval and acceptance criteria before executing the experiment. Whenever possible, the benchmark should contain paired cases in which only one controllable factor changes. This facilitates causal interpretation and reduces the chance that gains are attributable to survivorship bias instead of the intervention. Repeated runs and independent operating states are essential for distinguishing reproducible behavior from model or manufacturing noise. Comparison with published work should only occur after normalizing units, duty conditions and baseline geometry or sample preparation.

A defensible benchmark for explainable rul prediction should make the effect of domain shift observable rather than merely inferred. The investigator should define the reference state, independent variable, measurement instrument or numerical solution pathway, uncertainty interval and acceptance criteria before executing the experiment. Whenever possible, the benchmark should contain paired cases in which only one controllable factor changes. This facilitates causal interpretation and reduces the chance that gains are attributable to regime changes instead of the intervention. Repeated runs and independent operating states are essential for distinguishing reproducible behavior from model or manufacturing noise. Comparison with published work should only occur after normalizing units, duty conditions and baseline geometry or sample preparation.

A defensible benchmark for explainable rul prediction should make the effect of actionable maintenance thresholds observable rather than merely inferred. The investigator should

define the reference state, independent variable, measurement instrument or numerical solution pathway, uncertainty interval and acceptance criteria before executing the experiment. Whenever possible, the benchmark should contain paired cases in which only one controllable factor changes. This facilitates causal interpretation and reduces the chance that gains are attributable to few run-to-failure trajectories instead of the intervention. Repeated runs and independent operating states are essential for distinguishing reproducible behavior from model or manufacturing noise. Comparison with published work should only occur after normalizing units, duty conditions and baseline geometry or sample preparation.

7.2 Mechanistic Interpretation and Evidence Quality

The feature attribution stability question has a physical dimension as well as a statistical or procedural dimension. The first task is to identify which governing mechanism should control the response, then determine whether the selected sensors or characterization technique can observe that mechanism. For example, a predictor may correlate with an outcome but may not distinguish alternative causes when few run-to-failure trajectories is present. A review therefore should not interpret high cross-validation accuracy or favorable average properties as conclusive validation. Strong evidence also requires an explicit external case, documented failure examples, sensitivity to uncertain parameters and error distributions rather than just a single mean metric. Researchers should explain the conditions in which the proposed approach performs no better than the simplest baseline.

The physics-linked health indicators question has a physical dimension as well as a statistical or procedural dimension. The first task is to identify which governing mechanism should control the response, then determine whether the selected sensors or characterization technique can observe that mechanism. For example, a predictor may correlate with an outcome but may not distinguish alternative causes when misleading attributions is present. A review therefore should not interpret high cross-validation accuracy or favorable average properties as conclusive validation. Strong evidence also requires an explicit external case, documented failure examples, sensitivity to uncertain parameters and error distributions rather than just a single mean metric. Researchers should explain the conditions in which the proposed approach performs no better than the simplest baseline.

The calibrated uncertainty question has a physical dimension as well as a statistical or procedural dimension. The first task is to identify which governing mechanism should control the response, then determine whether the selected sensors or characterization technique can observe that mechanism. For example, a predictor may correlate with an outcome but may not distinguish alternative causes when survivorship bias is present. A review therefore

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The actionable maintenance thresholds question has a physical dimension as well as a statistical or procedural dimension. The first task is to identify which governing mechanism should control the response, then determine whether the selected sensors or characterization technique can observe that mechanism. For example, a predictor may correlate with an outcome but may not distinguish alternative causes when few run-to-failure trajectories is present. A review therefore should not interpret high cross-validation accuracy or favorable average properties as conclusive validation. Strong evidence also requires an explicit external case, documented failure examples, sensitivity to uncertain parameters and error distributions rather than just a single mean metric. Researchers should explain the conditions in which the proposed approach performs no better than the simplest baseline.

7.3 Translating the Findings Into Engineering Decisions

For implementation, evidence on feature attribution stability should be connected to a decision such as accepting a design, selecting maintenance timing, changing a process parameter or approving a simulation surrogate for operational use. Engineers need to know the magnitude of risk associated with a false decision, not merely the average predictive or mechanical-performance gain. A practical acceptance matrix should include RUL MAE, the fourth metric (Explanation stability), repeatability, cost of implementation, robustness to unavailable inputs and the consequences of drift. If decision thresholds are optimized on the same samples used to report success, the apparent benefit may be overstated. External

replication and uncertainty-aware thresholds are therefore priorities for publishable future research.

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8. CONCLUSION

This review identifies explainable rul prediction as a promising, but methodologically demanding, route for modern mechanical engineering. The most defensible next step is a matched-baseline investigation coupling physical reasoning with independent validation, explicit uncertainties and application-specific costs. Reported benefits cannot be generalized without checking few run-to-failure trajectories, misleading attributions and operating-range transferability. The present contribution is a structured critical synthesis and proposed framework, not a presentation of newly performed tests or simulations.

REFERENCES

1. Qu, Q., Zhang, L., & Zheng, Y. (2026). Explainable AI for remaining useful life prediction in industrial systems: A survey. Measurement Science and Technology, 37, 042002. https://doi.org/10.1088/1361-6501/ae319f
2. Rode, R., Kurpatwar, B., Patil, P., Gitay, M., Pawar, N., & Ghule, A. (2026). Research and experimental analysis of intelligent predictive maintenance for industrial machinery using AI-based analytical techniques. Aposta: Revista De Ciencias Sociales, 24(114), e988. https://doi.org/10.23900/ra.v24i114.988
3. Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. NeurIPS 30. https://proceedings.neurips.cc/paper/7062-a-unified-approach-to-interpreting-model-predictions.pdf
4. Mohod, Amar, Gitay, Mayur, Patil, Pradeep, Kaware, Kiran, Pawar, Nitin, & Patil, Mangesh. (2026). Design, modeling, and validation of an AI-driven resonant inductive charging module for next-generation electric vehicle architectures. Aposta: Revista de Ciencias Sociales, 24, e1003. https://doi.org/10.23900/ra.v24i114.1003
5. Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). Why should I trust you? Explaining the predictions of any classifier. NAACL, 97–101. https://doi.org/10.18653/v1/N16-3020
6. Mr. Nitin Namdeo Pawar. (2026). Analysis of LED bulb by mathematical and simulation methods with porous fin material with square-shaped extruded fins in passive cooling mode. Journal of Technology, 16(1), 125–132.
7. Brunton, S. L., & Kutz, J. N. (2019). Data-Driven Science and Engineering. Cambridge University Press. https://doi.org/10.1017/9781108380690
8. Pramod K. Jadhao, Dr. Sachin R. Karale, Nitin N. Pawar, & Brijkishor Sah. (2025). Analytical and CAD modeling of double-acting reciprocating compressor components. Utilitas Mathematica, 122.
9. Deb, K., et al. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6, 182–197. https://doi.org/10.1109/4235.996017
10. Nitin Pawar & Dr. Himeshbabu Nanvala. (2024, December 28). Mathematical and simulation analysis of various LED bulb arrays. Second International Conference on Advances in Thermal Systems, Materials and Design Engineering (ATSMDE 2024).
11. Hastie, T., Tibshirani, R., & Friedman, J. The Elements of Statistical Learning. Springer. https://hastie.su.domains/ElemStatLearn/

12. Nitin Pawar. (2024). Application of LED bulb with perforated plus shape fin array in mines. Journal of Mines, Metals and Fuels.
13. Murphy, K. P. Machine Learning: A Probabilistic Perspective. MIT Press. https://mitpress.mit.edu/
14. Nitin Pawar. (2024). An experimental investigation on diesel engine performance by the application of dual bio-diesel blends. Journal of Mines, Metals and Fuels.
15. Montgomery, D. C. Design and Analysis of Experiments. Wiley. https://www.wiley.com/
16. Nitin Pawar. Performance analysis on solar flat plate collector with reducing energy wastage using optimal geometry application. Journal of Harbin Engineering University, 1380–1387.
17. Box, G. E. P., Hunter, J. S., & Hunter, W. G. Statistics for Experimenters. Wiley. https://www.wiley.com/
18. Nitin Namdeo Pawar. (2023). Design and evaluation of perforated fins with different array of fins structure by an active mode of cooling system. Journal of Mines, Metals, and Fuels.
19. Rao, S. S. Engineering Optimization: Theory and Practice. Wiley. https://www.wiley.com/
20. Nitin Namdeo Pawar & Hameshbabu Nanwala. Study of extruded aluminum alloy LED bulb in a passive mode of the cooling system with a different array of fin structure. Journal of Material Engineering, 2, 35–43.
21. Harris, C. M., & Piersol, A. G. Harris' Shock and Vibration Handbook. McGraw-Hill. https://www.mheducation.com/
22. Santosh Kumara & Nitin Namdeo Pawara. Design of experiment with tribological performance analysis of electroless nano-composite Ni-P-SiC coating for conveyors. Tribology in Industry.
23. Randall, R. B. Vibration-based Condition Monitoring. Wiley. https://www.wiley.com/
24. Nitin Namdeo Pawar, Dr. Kiran K. Jadhao, Dr. L. S. Bothra, & Dr. Santosh Kumar. Design and analysis of pumping housing for water cooled engine system. GIS Science Journal, 318–331.
25. Mobley, R. K. An Introduction to Predictive Maintenance. Elsevier. https://www.elsevier.com/

26. Nitin Pawar. Design and fabrication and testing of a water cooler with a use of heat exchanger as economizer. 7th International Conference on Innovation and Research in Engineering Technology, April 8–9, 2022, Elsevier and SSRN. https://papers.ssrn.com/sol3/cf_dev/AbsByAuth.cfm?per_id=5240104
27. Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing. https://doi.org/10.1016/j.ymssp.2005.09.012
28. Nitin Pawar. Design and fabrication of multi-stage automatic sand separator. 7th International Conference on Innovation and Research in Engineering Technology, April 8–9, 2022, Elsevier and SSRN. https://papers.ssrn.com/sol3/cf_dev/AbsByAuth.cfm?per_id=5240104
29. Carvalho, T. P., et al. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. Computers & Industrial Engineering. https://doi.org/10.1016/j.cie.2019.106024
30. Mr. Nitin Namdeo Pawar. (2023). Design and simulation of a high power LED bulbs with different array of fins in passive mode of cooling. Microelectronics, Circuits and Systems, Lecture Notes in Electrical Engineering, 976. Springer Nature Singapore Pte Ltd.
31. Pecht, M. Prognostics and Health Management of Electronics. Wiley. https://www.wiley.com/
32. Mr. Nitin Namdeo Pawar. (2023). An experimental investigation of the production of plastic fuel and blend with diesel fuel. Microelectronics, Circuits and Systems, Lecture Notes in Electrical Engineering, 976. Springer Nature Singapore Pte Ltd.
33. Tao, F., et al. (2019). Digital twin in industry: State-of-the-art. IEEE Transactions on Industrial Informatics. https://doi.org/10.1109/TII.2018.2873186
34. Mr. Nitin N. Pawar. (2022, February). Design, fabrication and testing of a water cooler with a use of heat exchanger as economizer. International Journal of Scientific Research in Engineering and Management.
35. Grieves, M., & Vickers, J. (2017). Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. https://doi.org/10.1007/978-3-319-38756-7_4
36. Mr. Nitin N. Pawar. (2022, February). Design and fabrication of multi-stage automatic sand separator. International Journal of Scientific Research in Engineering and Management.

37. Rosen, R., et al. (2015). About the importance of autonomy and digital twins for the future of manufacturing. IFAC-PapersOnLine. https://doi.org/10.1016/j.ifacol.2015.06.141
38. Mr. Nitin N. Pawar. (2019, May). Ozone generation. International Journal for Science and Advance Research in Technology.
39. ASTM E8/E8M. Standard Test Methods for Tension Testing of Metallic Materials. https://www.astm.org/
40. Mr. Nitin N. Pawar. (2016, July). Cooling of LED bulb by using a different array of fins. International Journal of Innovative Research in Science and Engineering, 2(7).
41. ASTM D3039/D3039M. Standard Test Method for Tensile Properties of Polymer Matrix Composite Materials. https://www.astm.org/
42. Mr. Nitin N. Pawar. (2016, July 30). Cooling of LED bulb by using a different array of fins. 5th International Conference on Science Technology and Management.
43. ISO 178:2019. Plastics—Determination of flexural properties. https://www.iso.org/
44. Mr. Nitin N. Pawar. (2016, August 18–19). Cooling of LED bulb by using a different array of fins. International Conference on Research Challenges in Engineering and Technology.
45. ISO 527-1:2019. Plastics—Determination of tensile properties. https://www.iso.org/
46. Mr. Nitin N. Pawar. Analysis of Li-Iron battery performance with respect to temperature and some other parameter. 3rd National Conference on Research and Development in Mechanical, Electronics and Civil Engineering.
47. ASTM E647. Standard Test Method for Measurement of Fatigue Crack Growth Rates. https://www.astm.org/
48. Callister, W. D., & Rethwisch, D. G. Materials Science and Engineering: An Introduction. Wiley. https://www.wiley.com/