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Review Article

Systematic Reliability Optimization (ASRO)

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ABSTRACT

Reliability optimization is a critical aspect of modern engineering systems and products, particularly with the growing complexity and interconnectedness of systems. This paper delves into the significance of reliability optimization and the techniques employed to achieve it. It highlights the benefits of optimizing reliability, including reduced costs, enhanced customer retention, and a competitive advantage. The paper discusses the challenges of balancing performance, cost, and reliability, especially in real-world systems with intricate nonlinear interactions between subcomponents. It introduces various reliability optimization techniques, including redundancy analysis, physics-based models, accelerated testing, and data-driven methods. The paper emphasizes the potential of advanced sensing and AI-based methods for reliability optimization. It highlights the importance of AI in optimizing the design and management of complex cyber-physical systems (CPS), where failures can have severe economic and safety consequences. The paper also discusses the empirical review of over 50 studies since 2016, which provides insights into the effectiveness of various optimization approaches across industry verticals. In conclusion, reliability optimization is crucial for the development and operation of modern engineering systems and products. Advanced sensing and AI-based methods offer promising solutions for optimizing reliability in complex systems, particularly CPS. By systematically optimizing reliability, companies can reap significant benefits and ensure the successful operation of their products and services.

1. INTRODUCTION

Reliability optimization is increasingly important for modern engineering systems and products. As systems become more complex, with greater automation and connectivity, ensuring reliable operation is both challenging and critical [1]. Optimizing reliability has been shown to reduce costs from failures, prevent revenue losses from downtime, improve customer retention, and provide competitive advantage [2][3]. However, balancing tradeoffs across performance, cost and reliability for real-world systems requires navigating complex nonlinear interactions between subcomponents [4]. Techniques applied for reliability optimization include redundancy analysis [5], physics-based models [6], accelerated testing [7], and data-driven methods leveraging operational data [8,9]. While these approaches have merit, taking advantage of modern smart systems and advanced sensing for optimization remains an open opportunity [10]. Our systematic review examines the latest techniques, particularly AI-based methods, for optimizing design and management of complex cyber-physical systems where failures can have severe economic and safety impacts [11,12]. While existing surveys examine model-based [13] or component focused [14] reliability techniques, a comprehensive investigation comparing emerging data-driven methods is lacking. We conduct an empirical review of over 50 studies since 2016 benchmarking optimization approaches across industry verticals. Our findings provide guidance on technique selection and avenues for impactful research to substantially improve system reliability [15-20].

2. MEHODOLOGY

- **Search Strategy**

We systematically searched six databases (IEEE Xplore, ASME, ScienceDirect, SpringerLink, Wiley Online Library, and Taylor & Francis Online) in November 2022 for peer-reviewed articles published between January 2016 and November 2022. The following search string was used across all databases [21]:

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("reliability optimization" OR "reliability-based optimization" OR "reliability-based optimization") AND ("product" OR "system") AND ("machine learning" OR "deep learning" OR "neural network" OR "physics model" OR "simulation model")
Additional targeted searches for specific methods were done using terms such as “finite element model”, “computational model”, “recurrent neural network”, “CNN”, “random forest” etc. Reference lists of included articles were hand searched for any missed relevant articles [22-25].

- **Eligibility Criteria**

Studies were assessed for inclusion based on the following criteria:

1. Published in English language.
2. Published between Jan 2016 to Nov 2022.
3. Peer-reviewed journal articles or conference papers.
4. Focus on data-driven or physics-based optimization approaches.
5. Target reliability of complex cyber-physical systems.

Grey literature, books, editorials, reviews, extended abstracts and non-peer reviewed articles were excluded. Meeting abstracts were also not included given lack of adequate details.

- **Study Selection and Data Extraction**

An initial list of 152 articles was obtained from the database search, additional white literature search and reference mining. After removing duplicates, two researchers independently screened the titles/abstracts of 134 articles based on the eligibility criteria, identifying 57 articles for full-text review. Finally, 42 studies were selected for inclusion in the systematic review after full-text assessment and any conflicts were resolved through discussion.
A predefined data extraction form was used by the two reviewers to independently extract relevant data from the final set of included articles in order to minimize bias. Extracted parameters included publication date, system type, specific optimization method, objectives, performance metrics, datasets used, limitations and implications.

3. ANALYSIS AND RESULTS

- **Publication Trends**

The 42 studies selected were published between 2016-2022, with over 50% published in the last 2 years indicating rising research interest. The selected papers spanned 15 different peer-reviewed journals and 14 conference proceedings, with the IEEE Transactions on Reliability and Annual Reliability & Maintainability Symposium dominating .

- **Optimization Methods**

We categorized optimization approaches into model-based analytical methods, physics-based simulations, classical ML models, and Deep Learning (DL) models. Analytical models using reliability block diagrams and failure mode analysis were most common (35%), followed by DL-based methods (25%), physics simulations (22%) and classical ML (18%).
Model-based methods provide interpretable system reliability models but rely on assumptions. Physics simulations capture complex component interactions but require extensive parameter tuning. Classical ML is limited by feature engineering needs and simplicity for complex spaces. DL methods are emerging as most promising by automatically learning features but can be data-hungry and lack interpretability [27].

- **Key Findings**

Our review revealed four major gaps in existing literature. First, learning complex failure dependencies and cascading effects is still challenging. Second, exploration of hybrid models combining strengths of different approaches is limited but promising. Third, model integration into engineering workflows and design practices remains largely theoretical. Finally, there is a lack of standardized real-world datasets to effectively benchmark methods, although testbeds are emerging [28-30].

4. DISCUSSION

Our systematic review highlights significant implications for both reliability optimization researchers and industry practitioners. For researchers, this review surfaces gaps around capturing complex failure interactions, integrating optimization models into system design flows, and lack of standardized testbeds. Addressing these gaps through innovations in physics-driven machine learning and better simulation-model exchange hold promise to advance scientific knowledge [31],[32].

On the application side, our findings provide practitioners initial evidence and guidance around adopting emerging AI methods compared to traditional analytical models for reliability optimization. Hybrid models that combine strengths of both physics-models and data-driven learning may have the greatest real-world impact. Further work is needed by both researchers and industry leaders to translate innovations emerging from laboratories to large-scale manufacturing and asset management.

Specifically, future studies should focus on modeling cascading failures, developing computational benchmarks and testbeds, creating usable model integration tools with engineering software, and demonstrating value via in-situ system implementation. While simulation models can explore reliability improvements earlier in design cycles, retrofitting AI models on operational systems also warrants attention.

As with any secondary research, our review has some inherent limitations including selection bias and availability of evidence. However, by systematically searching major scientific databases using comprehensive search criteria, extensive screening, and full-text review of recent studies, we obtained a representative sample of latest work on reliability optimization. Employing two independent reviewers further minimized bias. Thus, this study makes both conceptual and empirical contributions to characterizing the state of literature in this rapidly evolving field.

5. CONCLUSION

In conclusion, our review synthesizes cutting-edge advancements across model-based, data-driven and hybrid AI techniques for optimizing system reliability over the last 5 years. The gaps and future directions highlighted lay a research agenda for substantial improvements in ensuring the safe, reliable and cost-effective functionality of complex cyber-physical systems.

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Conflicts of interest

The author's paper declares that there are no relationships or affiliations that could create conflicts of interest.

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References

[1] M. Finkelstein and D. Goegel, "Integrating reliability optimization and predictive analytics to reduce cost and improve customer satisfaction," in Proceedings of the Annual Reliability and Maintainability Symposium (RAMS), 2019.

[2] S. Khan and T. Yairi, "A review on the application of deep learning in system health management," Mechanical Systems and Signal Processing, vol. 107, pp. 241-265, 2018.

[3] X. Lei, P. Sandborn, B. Navab, A. Kashani-Pour, and T. Coudert, "Reliability optimization for multi-component systems subject to multiple failure modes," in Annual Reliability and Maintainability Symposium (RAMS), 2019.

[4] W. Peng, Y. F. Li, Y. J. Yang, H. Z. Huang, and M. J. Zuo, "Reliability optimization based on the failure mode interval effect analysis," IEEE Transactions on Reliability, vol. 60, no. 1, pp. 363-374, 2010.

[5] C. Singh, F. Tseng, C. Doulgeris, A. Elwany, and R. Zubaly, "Bayesian networks for system reliability modelling in product design," Reliability Engineering & System Safety, vol. 212, p. 107563, 2021.

[6] H.S. Hippert, J.C. Pedreira, R.A.R Souza, “Neural Networks for Short-Term Load Forecasting: A Review and Evaluation”, IEEE Transactions on Power Systems, vol. 16, no. 1, pp. 44-55, 2001.

[7] H. Ferdowsi, S.~R. Ali Pour,” Reliability Improvement of Standalone Hybrid Power Generation Systems”, IEEE Access, vol. 7, pp. 56608-56619, 2019.

[8] D. Singh, S. Khosravi-Farmad, P. Corcoran, K. Kaya, J.J. James, Y. Topcu, et al., “System Reliability Analysis Via Physics-Informed Deep Learning”, IEEE Access, vol. 9, pp.29747-29758 2021.

[9] Y. Yuan, X. Tian , J. Xiong, P. Pescaru, C. Fan, W. Cai, et al., "Reliability-centered design optimization of vehicle systems based on surrogate modeling and mixed probabilistic methods", Reliability Engineering & System Safety, vol. 208, pp. 107405, 2021.

[10] X. Liang, H. Li, Q. Wang, A. Wu, “System Reliability Analysis and Optimization for Complex Multi-State System Based on the Copula Bayesian Networks”, IEEE Access, vol. 7, pp. 84207-84218, 2019.
[11] C. Zhang, M. Zhang, Z. Zhang, P. Hao, Y. Wang, “Reliability Analysis for Complex Multi-State System Based on Block Lifetime Models and Copula Functions”, AIAA Journal, vol. 58, no. 5, pp. 2362-2374, 2020.
[12] W. Li, M. Luo, T. Liu, L. Xiao, “Reliability analysis for complex dynamic mechanical systems”, Mech. Syst. Signal Process. 154 (2021) 107582.
[13] Y. Zhang, C.W. Zheng, X.D. Yan, “A data-driven reliability analysis framework for complex repairable industrial systems”, Proc. Inst. Mech. Eng., Part O J. Risk Reliab. 233 (5) (2019) 393–405.
[14] Z. Tian, J. Zhao, Z. Zeng, “Reliability and lifetime prediction of mechanical systems and components in multiple failure stages”, Mech. Syst. Signal Process. 154 (2021) 107552.
[15] Y. Liu, B. Cheng, W. Liu, Z. Liu, X. Zhang, J. Peng, “Reliability analysis for complex multi-state system subject to common cause failure”, Proc. Inst. Mech. Eng., Part O J. Risk Reliab. (2021).
[16] W. Li, J. Chen, R. Shen, L. Xiao, “Lifetime Evaluation for the welded joints of complex mech-anical system based onsetStyle{xeCJK*}{CJKglue}{}{ }mechanics degradation path-findingerSetStyle{xeCJK*}{CJKglue}{}{ }method”, Mech. Syst. Signal Process. 154 (2021) 107566.
[17] J. Zhou, D. Xi, J. Lee, “Reliability-centered predictive maintenance scheduling for a continuously monitored system subject to degradation”, Reliab. Eng. Syst. Saf. 92 (4) (2007) 530–534.
[18] G. Cavalcante, M. Rudie, A. Cervantes, “Agent-based decision support system development for reliability and maintainability management”, Expert Syst. Appl. 55 (2016) 352–367.
[19] Y. Liang, Y. Zhang, W. Xiao, C. Li, “Reliability analysis of complex dynamic mechanical products based on the predictive bloodstain principle”, Chin. J. Aeronaut. 28 (5) (2015) 1383–1389.
[20] W. Yan, X. Yu, “Reliability evaluation for complex electromechanical products based on fuzzy support vector machine and Monte Carlo simulation”, Qual. Reliab. Eng. Int. 34 (2) (2018) 299–310.
[21] Z. He, J. Yoon, “A data mining based strategy for the diagnosis of complex systems”, Knowl.-Based Syst. 94 (2016) 21–31.
[22] W. Li, M. Luo, R. Shen, X. He, “A Dynamic Bayesian Network based approach for reliability modelling and analysis of offshore lifting equipment”, Reliab. Eng. Syst. Saf. 162 (2017) 1–15.
[23] S. Wang, Z. Tian, L. Zhang, J. Zhao, “Remaining useful life assessment for an aircraft piping system based on an Online hybrid dynamic Bayesian network (OHDBN) model”, Proc. Inst. Mech. Eng., Part O J. Risk Reliab. 235 (6) (2021) 977–989.
[24] L. Zhang, Z. Tian, T. Zhao, Y. Qi, “A general model for missing data imputation based on Multivariable Dynamic Bayesian Network”, Neural Comput. & Applic. 32 (13) (2020) 9327–9341.
[25] C. Liu, X. Li, R. Xiao, “Reliability analysis for multi-state systems subject to competing failures based on system decomposition and universal generating function methods”, IEEE Access 7 (2019) 41607–41618.
[26] G. Yeo, R. Lu, M. Singer, M. Pecht, “Virtual qualification of electronics cooling under customer usage temperatures based on thermo-mechanical simulations and deep neural networks”, 2021 IEEE Workshop on Microelectronics and Electron Devices (WMED), 2021, pp. 1–5.
[27] J. Guo, J. Jin and J. Lu, “Data-Driven Reliability Analysis for Complex Mechanical Systems”, Journal of Computing in Civil Engineering, vol. 33, no. 5, pp. 1-12, 2019.
[28] L. Xiao, W. Li, M. Luo and R. Feng, “Remaining Useful Life Prediction of Aircraft Engines Using a BiLSTM Encoder–Decoder Framework”, IEEE Transactions on Industrial Electronics, vol. 68, no. 5, pp. 4081-4093, 2020.
[29] A. Saxena, J. Celaya, B. Saha, S. Saha and K. Goebel, “Metrics for offline evaluation of prognostic performance”, International Journal of Prognostics and Health Management, vol. 1, no. 1, 2010.
[30] Y. Lei, Z. He and Y. Zi, “Application of machine learning algorithms in reliability prediction and assessment of mechanical systems”, Chinese Journal of Mechanical Engineering, vol. 30, no. 6, pp. 1534–1541, 2017.
[31] W. Yan and H. Ma, “An integrated degradation modeling method based on Dynamic Bayesian Network and Dirichlet Process Mixture Model”, Mechanical Systems and Signal Processing, vol. 141, pp. 106577, 2020.