B&H Electrical Engineering, Volume 20, Issue 1, 2026
ISSN:2566-3143, eISSN:2566-3151, DOI: 10.2478/bhee-2026-0014

Original scientific paper

Submitted: March 31, 2025

Accepted: October 20, 2025

SURVIVAL CURVES, RISKS AND ASSET MANAGEMENT: CONCEPT VALIDATION AND KEY TAKEAWAYS

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Abstract: Digitalisation in the energy sector has opened up a wide range of different methodologies to analytically support the asset management process. Compared to previous periods, technology is better and more sophisticated, so there is better opportunity to actually know the condition of assets in the grid nowadays. All this is not feasible without a well-organised database with sufficient data about devices operation. While some assets in the transmission network have a whole group of sensors and measurement equipment which, with appropriate processing, can determine the condition or Asset Health Index of the assets quite accurately, on the other hand there are several devices with very low number or even without sensors whose condition we still want to know. Here numerous methodologies which use available historical data can be used. These can estimate the condition of devices over a given period and associated probability of their failure. This paper gives a practical example of implementation of methodology for analysing probability of failure, the survival curves of individual assets and the difficulties of integration with economic indicators in order to obtain risks. Derived methodology relies a large historical data set to provide results. The majority of data originates from the TSO technical and operational databases, so the resulting survival curves are based on real data, not the general approximations. Identified challenges related to database structures and the availability of appropriate data will also be outlined to enhance the data collection process.

Keywords: asset management, survival curves, risk, failure probability, EAM, asset condition

INTRODUCTION

The primary goal of the regular maintenance of power system equipment, and also any other equipment, is to preserve the proper condition of equipment, ensuring its reliable operation with minimal failures and outages. However, the lifespan of each device is inherently limited. The consequences of failures and operational disruptions depend on many factors and vary from negligible to sometimes severe. Especially in the latter cases the utilities usually adopt scheduled equipment refurbishment and even its replacements at fixed time intervals—known as time-based maintenance. While this approach indeed reduces the likelihood of equipment failure, it also has downsides. For instance, prematurely retiring devices imposes a significant financial burden on companies and, ultimately, on the environment and secondly, numerous equipment outages due to preventive maintenance reduces its availability, representing a lost opportunity and extending the amortization period.

To reduce the number of un-needed preventive maintenance outages, a condition-based maintenance paradigm is being extensively introduced in utilities. Here, equipment refurbishment or even replacement is based on the emergence of signs of failure. Complete databases, containing accurate, validated and relevant data are a prerequisite to fully utilise advanced data analytics techniques. To achieve these an appropriate data chain must be established throughout all parts of the company, that are subjected to the generation, acquisition, and storage of various types of data. Here several dedicated analytics divisions are being established by utilities to overlook such process and support the existing procedures with advanced analytics, one of the first being the Diagnostics and Analytics centre (DAC) [1] in Eles [2], the Slovene TSO.

Finally, the maintenance strategy should evolve to a next level, being Risk Centred Maintenance (RCM), a goal of which is reduction of risk in the maintenance process. It is a natural evolvement of condition-based maintenance, as it combines the basic equipment operation data with extensive financial data (cost of equipment, maintenance, various types of outages) taking into account modern statistics methods. Its final outcome is quantified risk, considered as a combination of the probability of device failure and the consequences of such failures. As such, the methodology can be also applied to some types of power system assets [3].

This paper was submitted to the Conference of the South-East European Regional Council of CIGRE (SEERC 2025), held in Sarajevo, Bosnia and Herzegovina, on June 4–5, 2025.

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In transmission networks, while some assets are well-monitored with sensors and diagnostic tools, many others lack real-time monitoring. Therefore, data analysis techniques, including statistical methods and degradation modelling, play a crucial role in predicting asset failure probabilities and supporting maintenance decisions. As a trial, different approaches were tackled in evaluating the failure risks of assets in Eles, with one being further developed and successfully applied [4], [5]. Following paper gives an outlook to performed tasks and emphasises some challenges faced and to some extent overcome along the way.

1. ASSET CONDITION

In order to evaluate the asset condition and compare the condition of different assets, appropriate metrics must be introduced into the asset state evaluation system. This allows for state comparison among different assets and asset types and represent a corner stone in the transition from TBM through CBM and to final RBM.

In literature, the asset state is usually described by an Asset Health index (AHI). AHI is seen as a deterministic index, based on a number of asset related variables that are appropriately weighted and combined in the process. Definition of variables together with their weights is a burdensome process highly determined by practical knowledge of experts. As such, deterministic index is suitable for a quick comparison and prioritisation of similar types of assets. Due to complex trimming process and necessity of different diagnostic data, it is suitable for state assessment of important assets, that usually come in relatively small numbers, but consist of many sub-systems (e.g. transformers, overhead lines…)[6], [7]. The end result indeed quantifies each asset, but due to some shortcomings in the method, different measurements available in different assets and possible errors in weight trimming, its interpretation must be seriously reviewed.

On the other hand, power system consists also of assets, that comes in bulk numbers. This goes for the primary equipment in bays for example measuring transformers, circuit breakers and disconnectors. As these usually come as separate assets for each phase and at least or two per bay. Their population is big. Perhaps too big to relevantly assess their state through development of dedicated deterministic index. On the other hand, their number in operation, together with information of their previous operation and replacements, available in the database, allows for quantification of their condition through introduction of methods, long known in the field of statistics. Obviously, the results, obtained in a probabilistic manner, must be latter appropriately interpreted as these are usually true for the whole fleet of similar assets, rather than each asset of the fleet.

2. DATA

As the utilities have gathered vast amount of various data over the past decades, the initial goal of data analytics is to extract as much knowledge from this already available data as possible. In order to achieve this, the expert has to be on one had well aware of what data is available and on the other hand, of various methodologies that can utilise different data in a manner, to produce relevant end results[8].

The quality and accuracy of data are critical for reliable analysis. Therefore, data preprocessing steps involve identifying and addressing inconsistencies, missing entries, and erroneous records. Techniques such as data cleansing and normalization are employed to enhance data integrity, and additional data sources are consulted to fill gaps where feasible. Historical data on failures and maintenance activities are particularly valuable, as they offer insights into long-term trends and patterns.

2.1. Asset Types Suitable for Analysis

Only assets with adequate data coverage and consistency are suitable for advanced statistical analysis. Primary equipment, being instrument transformers (voltage, current, and combined types), circuit breakers, and disconnectors, were identified as asset types suitable for this study.

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2.2. Failure vs. Scheduled Replacement

In maintenance analytics, one must be aware of the data background, as was emphasized also through our analysis. To be concrete, distinguishing between asset failure and regular (scheduled or planned) replacement is critical. This distinction directly influences survival analysis results and the interpretation of degradation or failure probability curves. However, the ability to differentiate between these events depends heavily on the structure and quality of data in the asset management database.

If the reason for asset removal is not explicitly recorded—such as whether it was due to end-of-life failure, performance degradation, obsolescence, or network restructuring—the resulting survival or failure curves may represent general removal trends rather than actual failure rates. As observed in the our analysis, this limitation affects the accuracy of derived probability curves and constrains the ability to isolate failure-driven removals [5].

Moreover, the prevailing maintenance or better say operation strategy significantly affects how data reflects asset life cycles. Under a “run-to-failure” regime, assets are typically only replaced upon failure, resulting in survival data that closely reflects real degradation behavior. Conversely, with preventive or condition-based strategies, assets may be replaced earlier, based on different criteria with the goal to maintain the reliable system as a whole. This introduces right-censoring in the data and potentially skews failure probability estimates if not properly accounted for using methods like Kaplan-Meier survival analysis [4], [8].

Thus, improving database completeness—particularly by consistently recording removal reasons—and aligning maintenance documentation practices across departments are essential for accurate statistical modelling. Doing so enables more nuanced and accurate maintenance planning, distinguishing between true reliability issues and policy-driven replacements.

2.3. The Data

The Slovenian transmission network operated by Eles [2] comprises of over 3000 km of overhead transmission lines (OHL), with about 30 km of cable conduits. It also includes about 70 substations, containing, over 2700 instrument transformers, over 2000 switching, and circuit breaking devices.

Based on their population and the state of the data from the initial data analysis these bay devices were chosen for application of developed probabilistic survival analysis.

The primary data used in our analysis consists of historical records related to the operation and failure of transmission network devices. The data includes attributes like asset ID, installation and removal years, manufacturer information, voltage levels, operational status, and maintenance logs. Different types of assets, including instrument transformers, circuit breakers, and disconnectors, are considered, with varying levels of data completeness. The data is extracted from operational databases, maintenance logs, and historical records stored within the TSO’s database system.

Based on the described findings in the chapter, Eles is modifying its database structure in order to incorporate also the reasons for removal and allow for better analysis in the future. However, current analysis was subjected to lack of this information. Therefore, the results of the analysis are relevant to “asset removals” due to current maintenance and replacement strategy in Eles, rather than “asset failures” and should be interpreted as such.

3. METHODOLOGY

The analytical approach involves generating degradation curves using Weibull distributions, particularly for assets with limited data availability. For datasets with sufficient data, Kaplan-Meier survival analysis is applied to estimate the probability of failure and survival over time.

In both cases, a thorough analysis of the initial data must be performed to assess the data quality on one hand and to allow for proper interpretation of the end results.

To integrate economic considerations, cost functions are established to evaluate the financial impact of failures versus planned replacements. Costs of various scenarios must be evaluated in order to develop the risk from initial survival curves.

The main aspects of methodological segment tackled through our investigation are discussed in the following subchapters.

3.1. Replacement due to Asset Condition vs. Substation Refurbishment and other inconsistencies

An important distinction in asset management relates to whether an individual device is replaced due to its own condition (e.g., wear-out, diagnostics, or expected failure) or as part of a broader substation refurbishment project. In the first case, the decision is typically data-driven, based on metrics such as bad diagnostics result, asset health indices, failure probability, or risk assessments. In contrast, during substation refurbishments, assets are often replaced regardless of their condition, simply because they are part of a larger system being modernized or reconfigured.

This distinction is crucial when interpreting historical removal data. The database often lacks clear categorization of removal reasons, making it difficult to separate failure or condition-based replacements from project-driven ones [8]. Consequently, survival curves and degradation analyses may be affected by inclusion of early removals unrelated to asset reliability. When analysing the removals over the age of assets, the project-driven replacements are shown as peaks that highly deviate from the general distribution as can be seen in Figure 1. Such peaks affect the model and should be neutralised. In our case, we managed to corelate critical peaks with substation refurbishments and related observations were neglected from the analysis.

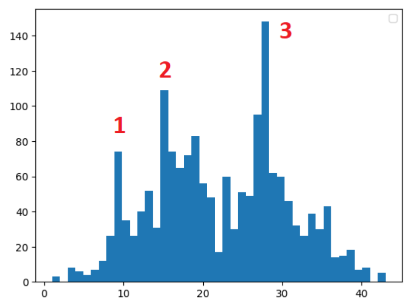


Figure 1: Example of peaks in initial database

To enhance accuracy, it is essential to include metadata in asset databases that clearly indicate the context of removal—whether due to failure, aging, obsolescence, or systemic renovation. Doing so supports more reliable planning, budgeting, and predictive modelling, and helps avoid overestimating failure rates in assets with otherwise acceptable performance.

Additionally, there are also inconsistencies due to changes in asset management databases, changes of procedures and migration of data among different tools over the past. These, call them database flaws were expected in the very beginning of the task since we are talking about relatively long time span of data. Similar as with peaks, also here a set of assets, that was supposedly removed prior or in the very beginning of incorporation of asset management database was neglected.

3.2. Degradation Modeling with common statistical Distribution

Degradation curves provide insights into the expected lifespan and failure probability of assets. The Weibull distribution is commonly used due to its flexibility in modeling various failure patterns, including early-life failures and wear-out failures [9]. Parameters such as shape and scale are estimated using historical removal and failure data. These curves enable maintenance planners to estimate optimal replacement intervals, reducing unexpected failures and maintenance costs.

Based on our initial analysis, we found out, that relying solely on the Weibull distribution is not appropriate as other distributions might better fit our historical data. Therefore, SciPy [10] library was used to find out the distribution, that best describes the data. In general, it was Double Weibul distribution, except for the switching equipment, where Double Laplace distribution fits the data best.

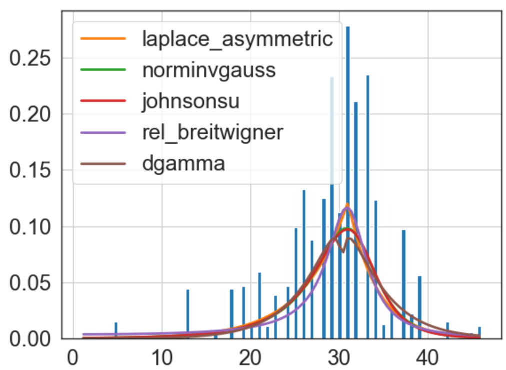


Figure 2: Fitting data to distribution example

3.3. Kaplan-Meier Survival Analysis

One of the initial goals of the work was to develop survival curves from the TSO's own historical data of assets. This is possible in cases where the historical, empirical database is large enough and it could be solely used for the definition of the asset specific degradation function. When it is not the case, the method from 4.2 must be used until sufficient data is gathered in empirical database.

For development of the asset-specific survival curves the Kaplan-Meier method is employed. It is a non-parametric method widely used in reliability engineering and statistics to estimate the probability of survival over time. In the context of power system maintenance, it can serve as an effective tool to estimate the Remaining Useful Life (RUL) of assets and predict the likelihood of failure within a specific period. The Kaplan-Meier estimator works by analysing the time-to-failure data of individual assets, allowing for the construction of empirical survival curves.

One of the key advantages of the Kaplan-Meier method is its ability to handle censored data, which is essential in maintenance analytics, as not all assets have failed at the time of analysis. Censoring occurs when an asset is still operational or when the failure time is not precisely known. The method accounts for this by adjusting the survival probability calculation at each time interval, thereby providing an unbiased estimate even with incomplete data.

In practical applications, Kaplan-Meier survival analysis is particularly useful when historical data availability varies across asset types. For instance, in transmission networks, some assets have long operational histories with few recorded failures, while others may have more frequent replacements. The Kaplan-Meier method accommodates such variations, enabling planners to derive meaningful insights from heterogeneous datasets. Moreover, combining Kaplan-Meier survival curves with risk assessment models can significantly enhance the maintenance decision-making process, guiding asset management strategies and optimizing replacement schedules.

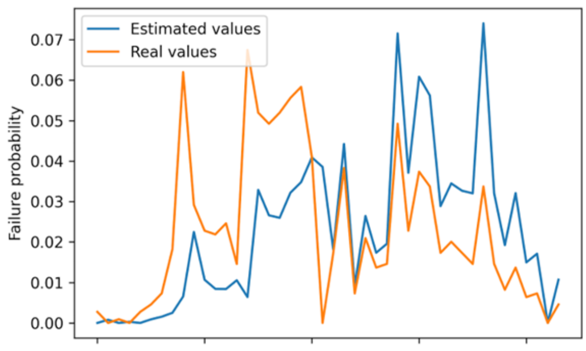


Figure 3: PDF of asset failure over its age,
real values (orange) vs. KM estimates with censoring (blue)

3.4. Risk and Probability Assessment

Risk analysis in the context of power system maintenance integrates statistical failure predictions with economic impact evaluation. The objective is to assess the expected

ISSN:2566-3143, eISSN:2566-3151, DOI: 10.2478/bhee-2026-0014

cost of asset failures and compare it with the cost of preventive measures, thus enabling optimized maintenance planning. The foundation of this approach lies in estimating the probability of asset failure within a defined period and evaluating the potential consequences of such failures. Probabilistic models are constructed to estimate the likelihood of failure over specific periods and to quantify the associated financial risks. These models provide a framework for comparing different maintenance strategies and prioritizing interventions.

To quantify risk, the Probability of Failure (PoF) is typically derived from statistical methods such as forementioned model distribution or Kaplan-Meier survival analysis. This probability is then multiplied by the associated Consequence of Failure (CoF), resulting in a risk metric that can be used for ranking assets and prioritizing maintenance actions. The consequence of failure may include direct repair or replacement costs, indirect system performance degradation, service interruptions, and potential regulatory penalties.

Cost analysis in risk-based maintenance planning involves determining the total life cycle cost of various maintenance strategies. This includes:

- Preventive maintenance cost, which covers scheduled inspections, condition assessments, and part replacements.
- Corrective maintenance cost, incurred when assets fail unexpectedly.
- Opportunity costs, resulting from system downtime or deferred capacity.
- Risk mitigation investment, where expenditures are allocated to reduce high-risk scenarios.

Due to lack of data in current Eles databases authors concluded, that it is currently next to impossible to appropriately quantify the CoF for various devices. As a result, the risk themselves were further analysed theoretically, based on generic cost data, that were applied to practical PoF's (or better say PoR-replacement-'s) for the purpose of Economic Impact evaluation and establishment of the whole concept. When the actual data is available, it could be then easily feed into the methodology.

3.5. Economic Impact Evaluation

The economic impact evaluation focuses on the cost-effectiveness of different maintenance and replacement strategies through comparison of the expected costs of corrective maintenance after failure with those associated with preventive maintenance or timely replacements. A central element of this approach is the formulation of one or more objective functions that guide the optimization process.

These objective functions—or cost criteria—can be constructed in various ways depending on how value is assigned to equipment performance, failure risk, and maintenance efficiency. Some formulations may minimize the total expected lifecycle cost, while others might prioritize minimizing risk-adjusted costs or maximizing asset availability. The selected criterion must align with the utility's strategic goals, operational constraints, and available data and can significantly influence the maintenance scheduling outcome.

Economic evaluations demonstrate potential cost savings through predictive maintenance strategies compared to traditional time-based approaches. Due to explained current state of the historical data, it was investigated on a conceptual level, further explained in [4].

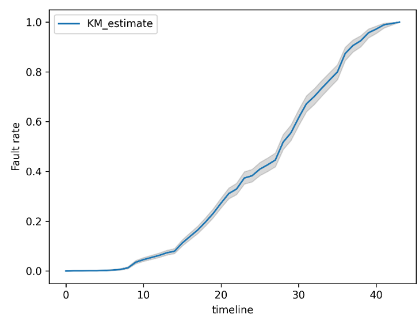
4. RESULTS

The displayed results highlight the survival probability curves for each asset type, showing the likelihood of operational continuity over time. Additionally, comparisons between failure probability and scheduled replacement probability are made to optimize maintenance planning. The derived survival curves demonstrate the effectiveness of the chosen statistical models and the validity of the data.

The results, that are already practically applicable and emerge from the probability of failure modelling are given bellow. The resulting curves are based on the Kaplan-Meier survival analysis of the pre-processed TSO's database of active and already decommissioned assets. Due to the level of information, curently available in the databases and the maintenance strategy, which favours the reliability of the network the results tell the probability of asset removal, rather than its failure. The results thus express the proprietary asset maintenance strategy of the Eles for the analysed set of assets. As such, it could be used for asset replacement planning in terms of forecasting required amount of different assets for regular replacement.

4.1. Probability of Removal

Utilising the preprocesed historical database of asset states of the already removed and operating assets in a Kaplan-Meier analysis, the cumulative distribution function (CDF) of asset removal can be derived as shown in Figure 4.



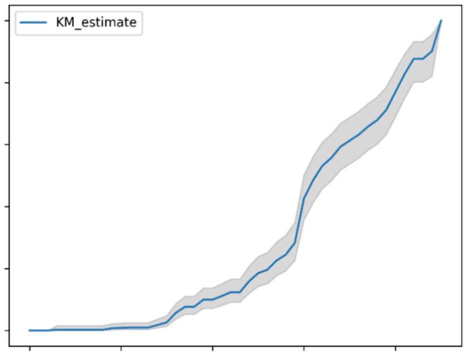


Figure 4: Cumulative probability of removal over the asset age with 95%confidence interval for instrument transformers (left) and circuit brakes (right)

The function gives the probability that the asset was removed prior certain age. One can notice that functions are not the same, explaining different behaviour of both assets in terms of their replacement. Hence, also their lifelong maintenance strategies differ.

4.2. Hazard rate

With some mathematics, the hazard rate function can be derived from the CDF. For abovementioned assets it is given in Figure 5. It allows for calculation of probability, that particular active asset will be removed in particular year, considering its age.

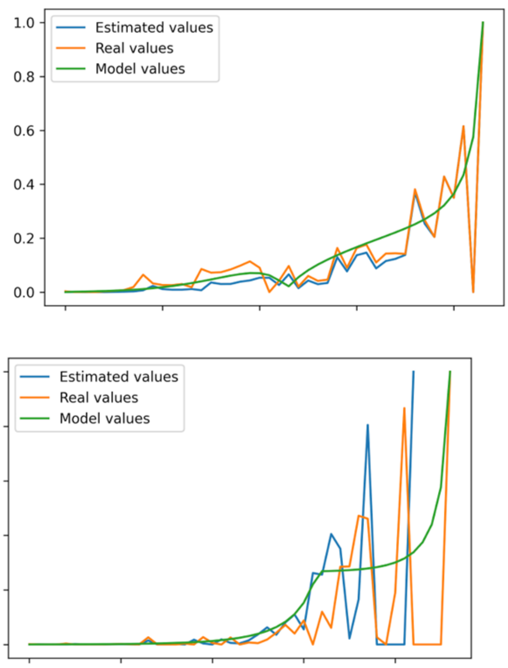


Figure 5: Hazard rate over the age for instrument transformers (left) and circuit brakers (right)

When extrapolated over the whole fleet, it also allows for estimation of a number of replacements, that will take place in particular year. Through which it enables a better resource planning. As the results are true only until the maintenance strategy remains the same, it also allows for detection or validation of maintenance strategy changes. As the functions emerge from the real life, one must know the fundamentals of the existing maintenance strategies in order to appropriately interpret results. Otherwise, it would be hard to explain why, in case of the instrument transformers, their probability of failure drops to zero somewhere around the middle of their lifetime. Knowing the field situation the phenomenon is easily explainable. Current maintenance strategy requires detailed inspection of the instrument transformers around that age through which critical assets are discovered and further removed. Therefore, if the asset managed to pass the inspection, it is highly unlikely for it to be removed in next few years.

4.3. Comparison of ageing among the subgroups

In case of sufficient data for the dataset to be statistically representative, assets can be grouped to subgroups based on the grouping parameters (e.g. type, manufacturer, voltage level…) and given groups can be compared. Figure 6 gives such comparison for two groups of instrument transformers.

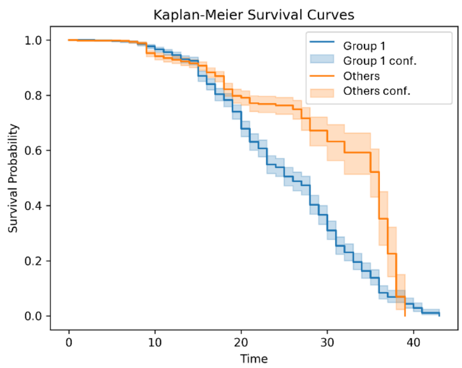


Figure 6: Probability of survival for two sub- groups of assets

One can notice, that in first part of lifetime, assets belonging to the ''Group 1" have slightly better survival probability than other assets, meanning the ''Group 1" assets get replaced slightly latter in this life phase. To be sinceere, the difference in this part is within the confidence interval of both groups and is not siginificant. On the otherhand, during the second third of life span, ''Group 1" assets are being replaced earlier, than other assets. It levels out again in the very last period.

The results on the one hand imply that ''Group 1" assets perform poorly, compared to the rest of the initial dataset. But this is not necessarily the truth, as the first are in average older than others, have more data about removals available and, as they are older, the maintenance strategy might have changed in between, so the profiles are not necessarily directly comparable. Based on further analysis and internal discussions, all of the stated arguments are to some extent true in this case.

5. CONCLUSION

While the presented methodology provides a robust framework for failure probability estimation, certain limitations remain. Data quality and completeness issues impact the accuracy of survival analysis. Moreover, statistical models may not fully capture the stochastic nature of real-world asset behaviour, highlighting the need for continuous data collection and model updating. Integrating these results into decision-making processes involving risks also requires further consideration of economic and operational priorities.

The estimated numbers are correct until the replacement strategy remains the same. Consequently, the method could support (prove) the transition in maintenance strategy as the offset between the modelled forecast and the number actual replacements indicates the change of the maintenance strategy. This should eventually happen, due to the ongoing transition in maintenance strategy, which gives greater weight to the asset condition over of its age.

Utilisation of risk-based methodologies require a comprehensive and clean data foundation. Historical inconsistencies such as missing removal reasons, asset misidentifications, or duplicated entries, as seen in used legacy databases, complicate the generation of reliable profiles. Addressing these issues necessitates dedicated data quality assurance teams and the implementation of automatic validation algorithms. Additionally, assessment of the required wholesome costs of failures is difficult. Many of the costs, particularly indirect or societal ones, are difficult to quantify in real life. Moreover, inconsistencies in failure reporting, lack of standardized cost categories, and incomplete data records can significantly affect the accuracy of cost analysis. For example, in the survival curve analysis of instrument transformers, it was often not possible to distinguish whether a unit was replaced due to failure, obsolescence, or system upgrades, which directly impacts the estimated CoF.

Despite some challenges, which were to some extent overcome throughout the project, methods based on the statistical methods are suitable for strategic decision-making as shown in the results. When effectively implemented, these enable asset managers to plane and allocate resources more efficiently and reduce unplanned outages. Further development of the CoF's would also allow for risk optimisation and maintenance budget quantification with quantifiable metrics.

Ongoing efforts in database enhancement and cross-departmental data harmonization, as undertaken by ELES's Diagnostics and Analytics Centre, are key enablers for the broader adoption of these advanced maintenance optimization techniques.

REFERENCES

[1] 'Diagnostično analitski center ELES', DAC. Accessed: Jan. 04, 2023. [Online]. Available: https://dac.eles.si/
[2] 'ELES, Ltd., Electricity Transmission System Operator | Eles d.o.o.' Accessed: Jan. 04, 2023. [Online]. Available: https://www.eles.si/en
[3] R. Ross, Reliability Analysis for Asset Management of Electric Power Grids, 1st ed. Wiley, 2019. doi: 10.1002/9781119125204.
[4] D. Bokal et al., 'Primerjava optimiziranih politik vzdrževanja skupin številnih naprav prenosnega elektroenergetskega sistema', in Zbornik 6. SLOVENSKE KONFERENCE O VZDRŽEVANJU V ELEKTROENERGETIKI, Maribor: CIGRE-CIRED, 2024.
[5] Mitja Antoncic, Yury Tsimberg, Viktor Lovrencic, Ana Lovrencic, and Uros Kerin, 'ASSET SURVIVAL CURVES AND THE ASSET MANAGEMENT PROCESS', presented at the 16. KONFERENCA SLOVENSKIH ELEKTROENERGETIKOV, Bled: CIGRE-CIRED, 2023.
[6] A. Gubina, L. Nagode, A. Polajner, D. Bokal, B. Zupanc, 'Uvajanje indeksa stanja naprave (AHI) za energetske transformatorje v Elesu; Elektronski vir :: COBISS+'. Accessed: Jan. 03, 2023. [Online]. Available: https://plus.cobiss.net/cobiss/si/sl/bib/11710292
[7] J. Zupančič, T. Medved, A. F. Gubina, M. Antončič, M. Bečan, and U. Kerin, 'Cross-functional Integration of Grid Operation with Predictive Asset Management', in 2022 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Oct. 2022, pp. 1–5. doi: 10.1109/ISGT-Europe54678.2022.9960362.
[8] Mitja Antoncic, Denis Kozjek, Uros Kerin, Jernej Zupancic, Andrej Gubina, and Tomi Medved, 'Big Data based maintenance planning – data mining and utilisation', in Cigre International Symposium Muscat, Mar. 2023.
[9] Conseil international des grands réseaux électriques, Ed., Guidelines for the use of statistics and statistical tools on life data: [CIGRÉ], Working group D1.39. Paris: Cigré, 2017.
[10] P. Virtanen et al., 'SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python', Nature Methods, vol. 17, pp. 261–272, 2020, doi: 10.1038/s41592-019-0686-2.

BIOGRAPHY

Mitja Antončič received his PhD in 2021 from the Faculty of Electrical Engineering, University of Ljubljana, where he was employed as a young researcher in the Laboratory for Electricity Networks and Devices. In 2021, he joined ELES, where he works in the Diagnostic and Analytics Center, operating within the Asset and

Project Management Division. His daily tasks focus on the data analysis, manipulation and interpretation, the development of dedicated algorithms, and the establishment of procedures enabling advanced analytics based on available technical and operational data within asset management processes.

Jošt Osolin completed his master's degree at the Faculty of Electrical Engineering, University of Ljubljana, in 2024. He joined ELES in 2023, initially as a scholarship recipient and is now a full-time employee in the Diagnostic and Analytics Center, where he also carried out his master's thesis on the analysis of circuit breaker condition, supported by protection relay data. His responsibilities include providing data support, performing analyses, assisting with projects, and implementing advanced technologies for the management and maintenance of high-voltage equipment.

Miha Bečan graduated from the Faculty of Electrical Engineering, University of Ljubljana, in 2007. He began his professional career as a researcher at the Elektroinštitut Milan Vidmar, focusing on high-voltage technology, insulation coordination, and testing of power equipment, while also serving as an assistant lecturer at the university. In 2019, he joined ELES, the Slovenian combined transmission and distribution system operator, where he works within the Diagnostic and Analytics Center (DAC). His current activities are centered on data analytics and value creation from available data to support asset management and maintenance optimization of high-voltage equipment. He is leading the implementation of Building Information Modelling) within ELES and actively explores emerging digital technologies for assessing equipment condition and supporting lifecycle management. Miha is also strongly engaged in standardization and professional associations. He serves as the Chair of the Slovenian Technical Committee for Insulators (SIST TC Insulators), is an active member of the Slovenian CIGRE-CIRED National Committee, and represents Slovenia in the CIGRE Study Committee B2 (Overhead Lines).

Uroš Kerin earned his PhD from the Faculty of Electrical Engineering at the University of Ljubljana, Slovenia. From 2010 to 2017, he worked at Siemens Power Technologies International in Erlangen, Germany, as a Senior Key Expert, leading or contributing to major international infrastructure projects in power transmission, distribution, and the oil and gas industries. He joined ELES in 2017 as a senior power systems expert and technical lead. Since 2019, he has served as Assistant Director for Asset and Project Management, driving the organizational and professional development of the division. Currently, he leads the Diagnostics and Analytics Center at the Beričevo Technology Hub and serves as an Executive Advisor to the CEO of ELES.