INNOVATIVE ANALYTICS TO ESTIMATE THE PROBABILITY OF FAILURE AND REMAINING USEFUL LIFE OF MEDIUM VOLTAGE BREAKERS

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ABSTRACT

This paper illustrates an innovative analytics, also known as performance model, to estimate the probability of failure and remaining useful life of Medium Voltage (MV) breakers. The new proposed approach provides relevant information for a successful condition-based and predictive maintenance strategy.

The performance model presented in this paper is based on analysis of the failure modes, causes and mechanisms. It is modular and scalable in order to take into account different scenarios of data availability (from static product nameplate data to dynamic condition monitoring and test data), applicable to a MV breaker of any manufacturer. The scope of the performance model is to provide the current health condition and estimate the probability of failure within a period of time, residual useful life, risk of failure and a level of accuracy based on the coverage of the failure modes under the condition monitoring. In addition, the performance model calculates the accuracy of the equipment health condition based on data availability and equipment knowledge.

This paper presents the successful application of the proposed performance model on significant circuit breaker (CB) real cases both in industries and in utilities, explaining the benefits of the scalable approach. A first case shows the application of the analytics based on statistical information and environmental condition. Another case describes, instead, how to take advantage of advanced condition monitoring sensors in order to increase the accuracy of the performance model outcomes.

INTRODUCTION

Aging assets, an aging workforce, the introduction of networked smart grids, a proliferation of intelligent devices on the power grid as well as Internet of Things (IoT) are challenging utilities and industries to find more effective and efficient ways to maintain and monitor their critical assets.

The traditional objective is to maintain high availability and reliability of the installed base. Nowadays many asset owners are looking at smart asset management, which is taking in account also the predictability because they have realized that avoiding unexpected outages, managing asset risks and maintaining assets before failure strikes are critical goals to improve the bottom line.

According to [2] the asset manager needs condition assessment to calculate the risk associated with failure, and therefore better plan maintenance, retrofit and replacement budgets. In addition, the ISO 55000 [3] clearly defines the benefits of asset management highlighting the crucial role of risk. Briefly, risk is defined as a combination of the probability of failure and the consequences of the occurrence of the failure. The consequences of failure occurrence can be also defined as criticality or importance level of the asset.

Smart asset management based on data analytics can dramatically improve the following benefits: extend the asset life times, increase predictability of performance and health, which ultimately helps the asset managers planning, and prioritizing risk mitigation actions.

This methodology requires the availability of data, therefore asset condition assessment and condition monitoring are the pillars of any advanced maintenance strategy. An overview [4] describes the status and open research topics related to the condition assessment of Medium Voltage (MV) breakers and switchgears.

Data analytics is generically a set of algorithms processing the gathered data to predict the future asset performances. Typically, prediction analytics-based is a process of using statistical and data mining techniques to analyze historic and current data sets, to create rules and predictive models and to predict future events. This is also called asset performance analytics, which is broadly aimed at optimizing the value of production assets by analyzing asset data to predict future failures and prevent downtime.

This paper describes an innovative analytics approach for MV circuit breakers based on performance, failure mode and asset design analysis, and how it is applied in real applications.

ANALYTICS FOR SMART ASSET MANAGEMENT

Different data analytics methods can be used to detect varieties of failure modes, like for instance statistical data analysis, critical range and limits check, pattern and trend recognition. Most of these tools require a relevant quantity of data in terms of time-series data. However, most of MV switchgears performs few operations per year and the biggest part of the installed base embeds no or a limited number of sensors. Therefore, the accuracy of standard data analytics will not be enough and the new big data analytics solutions cannot be used due to limited amount of data. The innovative proposed approach, here called performance model, is based on failure mode analysis as

well as asset sub-components behaviour analysis, exploiting the existing available data sources.
According to [1] performance model is defined here as a mathematical model assessing the current health condition and predicting the future health condition of a device or a system over time. In addition, the performance model provides information on the nature and causes of a potential impending failure. The performance model is, in other words, a mathematical model for condition monitoring, diagnostics and prognostics [9].
Since the performance model described in this paper provides an assessment of the probability of failure, remaining useful life, risk, root causes of an impending failure, etc., for a device or system, it represents the foundation of any preventive, predictive and proactive maintenance solution.

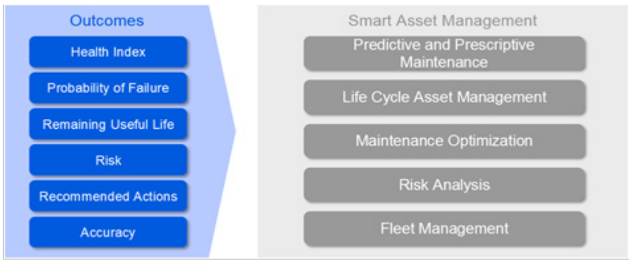

Figure 1: performance model outcomes for smart asset management

Aim of the performance model is to compute the performance of an asset, expressed as a set of values for a few predefined Key Performance Indicators (KPIs), together with an estimation of their accuracy. It also provides hints to the customer and/or service personnel, in the form of messages that could be:

- Indications of possible imminent problems (predictions) with the asset, e.g. the reliability of a specific part of the asset decreased below a critical level.
- Notifications of mitigation actions (prescriptions), like the need to perform one or more maintenance tasks.

MODEL : SCALABLE AND FLEXIBLE

MV installed base scenario in utilities and industries vary a lot, mostly due to the long assets lifetime (even 40-60 years). For instance considering MV breakers, it is quite common to have different types of equipment in just one plant: by model, by rating and by age. Moreover, in a plant there can be substation with or without Intelligent Electronic Devices (IED) able to provide data.
Therefore, the design of the asset performance model needs to be scalable and flexible in order to consider the variable environment in terms of equipment type, data source availability and asset knowledge.
The performance model applies to an asset. An asset is a specific instance of an asset type (or equipment type). In the context of MV, the asset type could be, e.g., a specific type (or variant) of Circuit Breaker (CB).
Each asset can be decomposed in subsystems, which in turn can be furtherly decomposed down to components, obtaining a tree-like structure as depicted below:

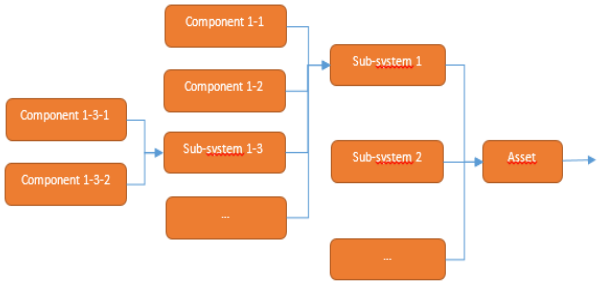

Figure 2: asset modeling by decomposition

For each asset type, the model considers a collection of possible failure modes of the asset: the value of a KPI for the whole asset is computed aggregating the values of that KPI for each failure mode
For the sake of asset performance modelling, the decomposition will stop at the level of Least Replaceable Unit (LRU), i.e. components available as spare parts that can be replaced by service personnel.

MV CIRCUIT BREAKER DECOMPOSITION

The modular approach of the performance model is based on the decomposition by failure modes and asset sub-components. The approach fits perfectly for MV circuit breakers, which exist in different interruption technology, operating mechanism, ratings, and therefore presenting different type of failure modes.
The performance model can consider condition monitoring or assessed data to evaluate the condition of each sub-component. When the available data cannot cover the sub-component evaluation, then the model runs a statistical function, which is based on the quality information collected by the manufacturer Quality Management Team, failure reports and service activities.
Table 1 collects an example of the frequency and Cumulative Distribution Functions (CDF) of the time-to-failure [8] by asset components and failure modes [7]. It is possible to have more failures per component. The CDF is calculated using a Kaplan-Meier [5] estimator for every component.

Failure	**Component**	**Frequency**	**CDF**
Open Trip Coil short circuit	Mechanical Chain	f_1 [%]	X_{MECH}
Lubrication loss			
…			
…	Charging Motor	f_2 [%]	X_{CHGM}

Damper Oil leakage	Actuator	f_3 [%]	X_{ACT}
…			
…	…	…	
FM_k	C_k	F_k [%]	X_{Ck}

Table 1: Decomposition of a CB

In case the MV switchgear has IEDs or any other data source (e.g. specific sensors), the available condition data can be assigned to the proper monitored components and failure modes. This would increase the accuracy of the performance model results, compared to the statistical functions.
For this reason, the model calculates the so-called Index of Coverage (IC), which is the sum of the frequencies of the monitored components. Higher IC means higher level of model outputs confidence.

MODEL OUTPUT AGGREGATION

As described before the performance model shall estimate several outputs. The most important are: the Probability of Failure (POF) and Remaining Useful Life (RUL).
POF [6] is the asset probability of failure at a specific time, given a certain asset age (days from commissioning or number of operations), expressed as *POF (t | age)* where *t* is the time from *age* to end of life.
Moreover, from POF is possible to derive a so-called Health Index (HI), which is a measure of the current health condition of the asset.
RUL is an estimation of the time-to-maintenance or time-to-failure of the asset given a certain asset age, expressed as *RUL (· | age)*.

If it is also available the consequence of failure or asset criticality as input, the model can combine it to the calculated POF, in order to estimate the Risk of failure.
For each asset type, the model considers a different set of failure modes. Moreover, for each calculated output a specific algorithm can be used for the <KPI, failure mode> couple.
The model computes POF and RUL for each applicable failure mode and then aggregates them to obtain the overall asset KPIs.
The asset POF is

$$POF = 1 - \prod_i (1 - POF_{comp_i})$$

where $POF_{comp\text{-}i}$ is the POF computed for the i-th applicable component/failure mode.
The asset RUL is

$$RUL = \min_i \{RUL_{comp_i}\}$$

where $RUL_{comp\text{-}i}$ is the RUL computed for the i-th applicable component/failure mode.

The decomposition to single failure modes/components and the above-defined aggregation functions let the performance model being modular and scalable.
When a new algorithm for a specific component (with its own specific inputs and parameters) is available, it can easily be added to the performance model as shown in the figure below where a new ALGOXV1 is added to the model.

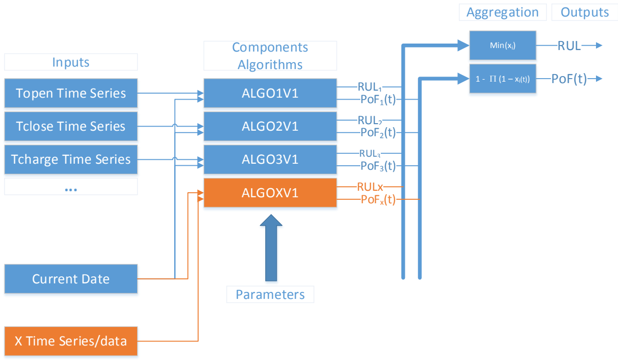

Figure 3: scalability of PM

Each algorithm receives specific inputs and parameters, in order to calculate: RUL (· | age), POF (t | age) and messages (prescriptions).

Every algorithm block is independent and can be implemented with any function like neural network, fuzzy logic, Monte Carlo simulation [10]. The unique constraint is about the generated outputs, as shown in Figure 4, to let the model runs the aggregation.

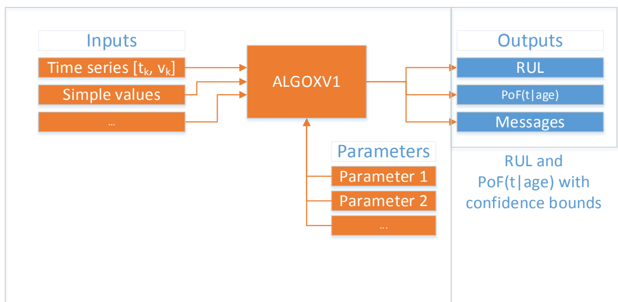

Figure 4: component model

APPLICATION CASES

The first case has input data composed of historical data, asset inspections and observations reports, operator interviews and performance tests. Instead, the second case, considers also online condition monitoring data collected by a dedicated MV breaker monitoring IED. These two different cases highlight the flexibility and scalability of the model.

Performance model based on statistical data

This first case considers a model based statistical data calculation. The minimum required equipment information are the commissioning date (to determine the age), the last maintenance activity, and the last circuit breaker operation occurrence.

The explanation of the case focuses on the spring charging motor component and its failure modes.

In this case, the algorithm receives as input the CDF of the time-to-failure of the selected component type, mainly calculated on endurance tests quality reports, using Kaplan-Meier, as shown in Figure 5.

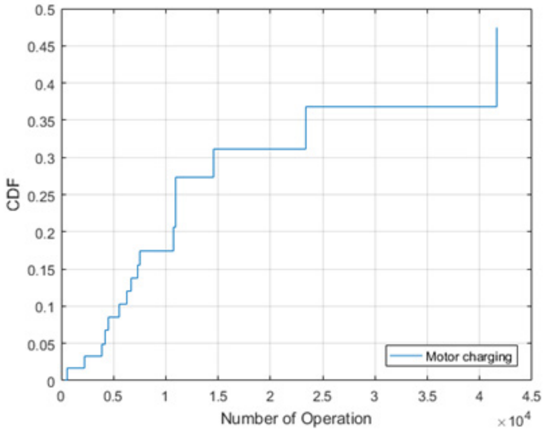

Figure 5: CDF of the time-to-failure of a type of spring charging motor

The algorithm of the selected component calculates the POF during its life, applying the above CDF. In this case, equipment life is expressed in number of operations, and POF is calculated considering a prediction window of 1000 future operations.

In this application, considering the consequence of failure (criticality and costs) of this equipment within the plant, a component POF alert threshold is calculated.

Figure 6 shows that at around 9000 operations, the component POF exceeds the given threshold; and the model generates an alert. After the repair activity (substitution of the motor), the calculated component POF goes back to a value close to its "as-new" level.

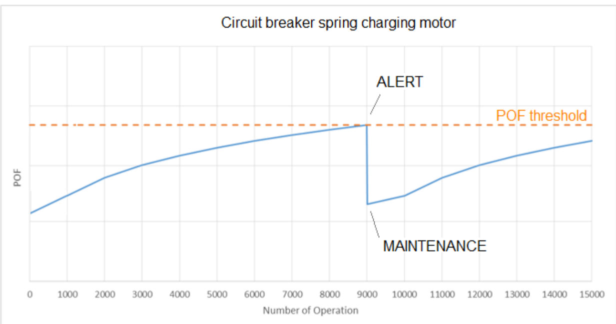

Figure 6: statistic model KPI

Performance model based on continuous condition monitoring

To explain the use of online monitored data, the case focus onto the CB spring charging motor failure mode, and the charging time series.

In this case, the algorithm uses Monte Carlo simulations with two main parameters: operation timings and time span between operations. The simulation are used to estimate the POF and the RUL.

Figure 7 shows on the top the spring charging time series, and on the bottom the POF in 24 months timeframe. During normal operations (initial part), where the spring charging time is in a normal range, the calculated POF is low (below 5%). Several operations before the motor failure POF increased up to 50%, due to an abnormal trend in the time-series. The higher POF indicates a possible failure and also the required mitigation actions, for instance, inspection and substitution of the motor, before the failure and a potential unscheduled down-time.

The chart shows also the POF value after the motor repair activity, again below an acceptable threshold of 5% (threshold specific for this case).

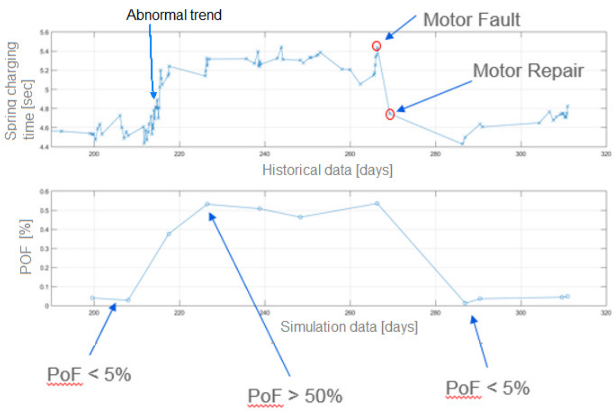

Figure 7: spring charging motor POF(t)

Report

The model outputs, represented graphically in Figure 8, shows an example. A spider chart reports the POF as health indexes for each subsystems/components within coloured areas (red, yellow, green), which represents serious degradation, signs of degradation and normal aging and therefore indicating the required mitigation actions urgency.

Then the report expresses the RUL as the number of CB residual switching operations.

At the end, the report collects the automatically generated mitigation actions, in order to drive and focus the service activity.

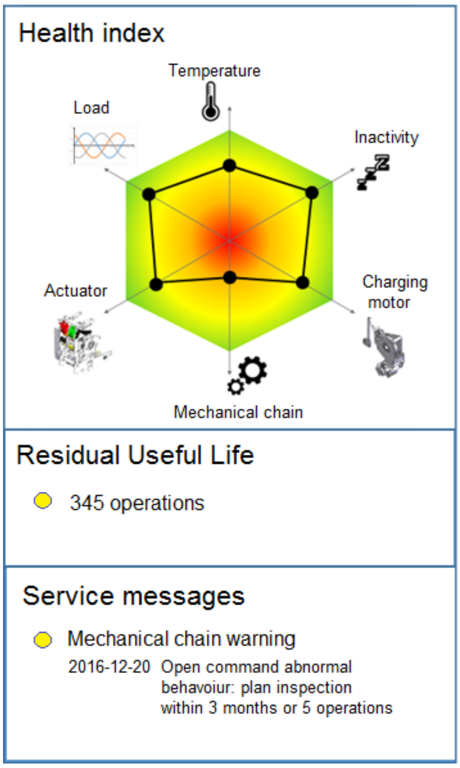

Figure 8: Circuit Breaker Reporting Example

CONCLUSION

This paper illustrates an innovative method to estimate the probability of failure and the residual useful life of MV Circuit Breaker, based on a performance model. This solution allows the Circuit Breaker health prediction (prognostic), which is the base for condition-, predictive- and prescriptive-based maintenance strategies.

The decomposition in subsystems/components let the model be applicable to different input scenarios based on the available data and required accuracy. The modular framework based on independent components KPIs aggregation function allow upgrading the algorithms when new data sources or additional asset knowledge is available.

The paper describes two cases demonstrating the scalability of the model in terms of different data sources. The first case shows the model results based on statistical data, while the second uses real-time condition monitoring data.

The performance model reports outputs in a graphical way, with service prescriptions, easy to understand and apply.

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