Using Machine Learning to Predict and Avoid Malfunctions

A Revolutionary Concept for Condition-Based Asset Performance Management (APM)

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Abstract—**In the renewable energy industry, a single component malfunction can significantly impact the entire network's performance. Asset failures in solar and wind farms can bring down a whole network of infrastructure, affecting thousands of customers and decreasing network reliability, costing hundreds of thousands of dollars. Therefore, there is a strong imperative to predict and avoid malfunctions in such highly connected systems. Sophisticated reliability models using new Machine Leaning (ML) techniques are proving to be a game-changer for asset performance management. Data and artificial intelligence are being used to predict malfunctions at any future point in time and facilitate the shift to condition than time-based maintenance. Early detection and more precise information can indicate which components or equipment will need to be repaired or replaced and when. This is allowing asset managers to plan maintenance efficiently and avoid unplanned and expensive disruptions. In this paper, we outline how machine learning (ML), combined with industry expertise, can estimate the probability of failure for specific failure modes and components. The methodology illustrates a specific failure mode using a large wind farm case study, where a significant number of component failures occurred within a short space of time. The problem is solved using a two-step solution, firstly predicting the future probability distribution of a parameter given its current value, and secondly, determining the probability of the malfunction given the predicted parameter value. This allows a standardized and more accurate approach for prognosticating malfunctions of technical components, thus determining their remaining useful life (RUL). The estimated RUL of the component is robust as it is based on probabilities for the malfunction of the component at a number of future points in time. Machine learning algorithms are also used for temperature forecasting to closely and continuously monitor the gearbox health status. A Holt-Winters model has been used for the purpose of forecasting and it shows more accurate results compared with other models.**

Keywords*—*Asset Performance Management (APM), wind turbine, Machine Learning, Markov Chain, LSTM, RUL

I. MACHINE LEARNING TECHNIQUES

A variety of models of machine learning techniques, including K-Means algorithm, Gaussian Mixture Models, K-Nearest Neighbour (KNN) and Autoregressive Integrated Moving Average Models were used in [3-6] for prognosis modelling of various types of equipment. Even though these models can be applied for different component types, their limitation is that they can only predict a single future parameter value or component state. They cannot forecast random processes or events, such as malfunctions related to different parameters, and/or represent unprecedented states.

To improve the maintenance strategy and replacement of parts intervals, while reducing the likelihood of malfunction, it is possible to develop models for functional units like plants to ascertain the reliability as described in [2]. However, these models are very complicated and are unsuitable for predicting malfunctions before they occur or over an extended time into the future[1]. Additionally, different reliability models are designed for each specific machine. Therefore, the reliability system becomes more complicated as the models differ completely for static and dynamic equipment types, such as a gas turbine and a transformer, which both are used in a power plant. It will result in an overly complex reliability model that is computationally inefficient for large industrial plants with various components (machines). Moreover, a new reliability model must be designed for each type of component or device , which would be a costly and time-consuming process [2].

II. METHODOLOGY -FULL PROGNOSIS CYCLE

In the following sections, two Machine Learning (ML) techniques are introduced in detail and applied to show the forecasting of component malfunctions in a wind turbine and a power transformer to improve condition monitoring, diagnosis and prognostics.

A- Prognostics Stochastic Model

By determining a conditional probability distribution $P_{t0+\Delta t}(a|a(t_0)$ for a parameter of the component for a future point in time $t_0 + \Delta t$ given the current value $a(t_0)$ of the parameter; and by determining a conditional probability $P_{t0+\Delta t}\ (M|a(t_0))$ for a malfunction M at the future point in time $t_0\ + \Delta t$ given the current value $a(t_0)$ of the parameter based on the conditional probability distribution $P_{t0+\Delta t}\ (a|a(t_0)$ and on a conditional probability distribution $P(M|a)$ for the malfunction M given the parameter a; then

$P_{t0+\Delta t}\left(M\middle|a(t_0)\right) = f\left[P_{t0+\Delta t}\left(a\middle|a(t_0)\right), P(M|a)\right]$. The two-step approach of predicting firstly the future probability distribution of a parameter given its current value, and determining secondly the probability of the malfunction given the current value of the parameter based on its conditional probability given the parameter, allows a simple, general approach for determining the malfunctions of technical components. In the first step, well-known methods for predicting future parameter values can be used which are independent of both the functioning of the component and of the malfunction. The probability of the malfunction is calculated in the second step based on the conditional probability of the malfunction given the parameter.

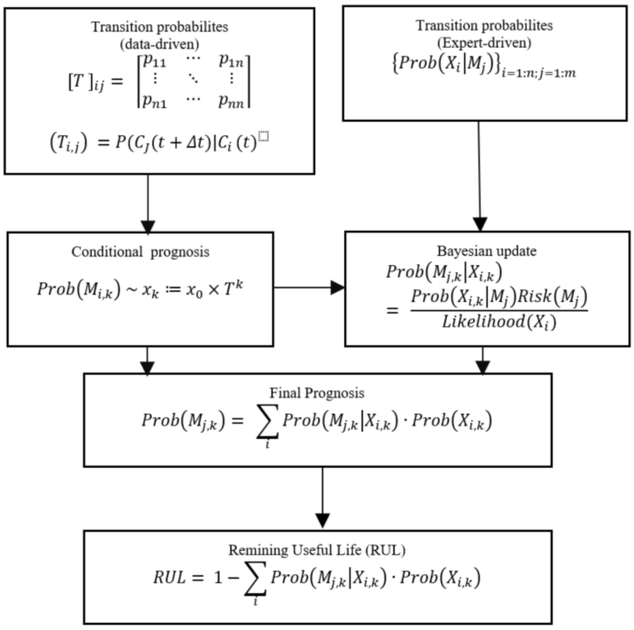


Fig 1. Probability of malfunction algorithms breakdown

A-1 Algorithm Breakdown

Fig Φιγ 1 shows the steps for calculating the probability of malfunction from the transition probabilities matrix to the final prognosis [2].

- In the first step the transition matrix T for the selected parameter has to be determined, with the entry in the i-th row and the j–th column representing the probability the parameter will have a transition from category i to category j in one time step.
- In the second step the conditional probability distribution $P(M_k|C_i)$ for the single malfunction M_k given the discrete value states C_i of said parameter for $i = 1, \ldots, N$ is provided. The probability $P(C_i|M_k)$ that the parameter is in a certain state C_i, when the malfunction M_k occurs, can be determined on the basis of expert assessments. The probability $P(M_k)$ of the single malfunction M_k can be retrieved in different ways. It is determined on the basis of malfunction statistics for the component or on the basis of malfunction statistics for identical or equivalent components[1][2].
- The state $C(t_0 + L \cdot \Delta t)$ of the parameter at a future point in time after L iterations is predicted. This is performed on the basis of a stochastic process model, such as a Markov chain, by multiplying the current state $C(t_0)$ with the transition matrix T.
- The probability of a single malfunction M_k at the future point in time $t_0 + L \cdot \Delta t$ is determined. The stochastic model combines Markov chains for predicting the discrete value state of the parameter at a future point in time with the conditional probability distribution $P(M_k|C_i)$ for the malfunction M_k given the discrete states C_i of said parameter. This yields the probability of the malfunction M_k at the future point in time $t_0 + L \cdot \Delta t$, given current discrete parameter value state $C(t_0)$. On the basis of the probability of a malfunction for at least one future point in time, or preferably several points in future points in time, a potential malfunction event or the remaining useful lifespan can be estimated.
- In the last step, the method estimates the remaining useful life of the component based on the calculation of malfunctions probability of the component for the given number of future points in time [2].

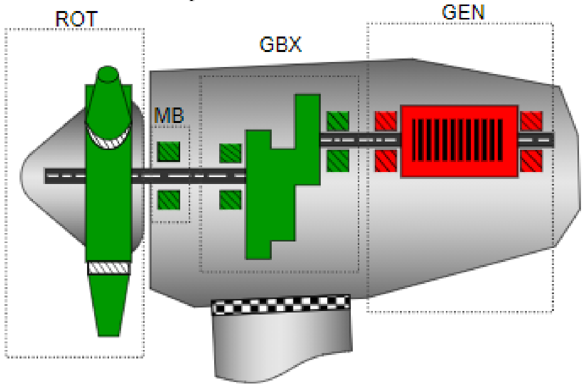


Fig 2. Wind turbine structure

III. RESULTS AND DISCUSSION

A-2 Implementation of the prognostics stochastic model

To verify the effectiveness of the prognostic stochastic model, this paper takes the fluid coupling temperature of a 2.1 MW turbine as the primary research parameter. For the prognosis model, the data was recorded by SCADA for the time interval of 10 - min from November 2018. The preliminary recorded data includes the time, active and reactive power, wind speed, generator rotor speed, ambient temperature, internal nacelle temperature, oil temperature from gearbox bearing and fluid coupling, vibration (axial and radial) and other parameters. Some abnormal data points related to the shutdown point or breakdown time have been removed. In addition, the operating status information from the unit, such as the generator over-temperature pitch system failure, including start-up and shut down condition, is saved through the SCADA system. When the generator rotor is rotating at high speed, a large amount of heat is generated. Moreover, the actual fluid coupling temperature is affected by the outdoor temperature, and it fluctuates along with the season. The fluid coupling oil viscosity is relatively high at lower temperatures, so the oil movement through the oil inlet hole becomes very small. Consequently, the high viscosity fluidity of the oil becomes poor. Then, the conduction/exchange of heat inside the fluid coupling becomes considerably inferior, resulting in higher and higher fluid coupling temperatures, which falls into a vicious circle. Eventually, the result of a temperature rise in fluid coupling will be damage to the entire transferring mechanical power from the gearbox to the generator's rotor[7]. Figure 4 shows historical data for the fluid coupling temperature from 2018.

Based on this history, we can see that the fluid coupling failed in mid-August 2019.

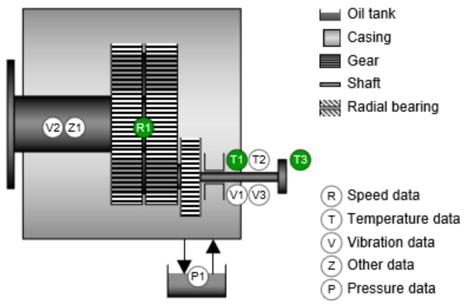


Figure 3 Gearbox / fluid coupling 2D model

As shown, the temperature increased gradually from April 2019 until the date the failure happened. In the first step to perform the prognostic stochastic implementation and validation model, the linear regression calculation was performed. In linear regression, it is assumed that a linear system defines the relationship between the dependent variable and one or more independent variables. The linear regression filters the outside temperature and temperature generated from the generator speed to achieve the coefficient. The calculated coefficient is 0.8. Filtering both the outside temperature and generator speed temperature from the fluid coupling temperature will reduce the fault alarm and enables the calculation of the probability of failure to be more precise.

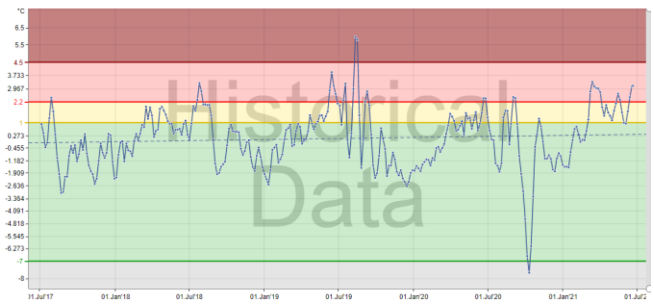


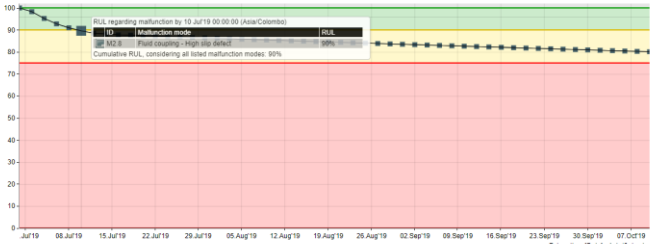
Figure 4 Historical data - fluid coupling temperature (moving average) filtered by outside temperature and generator speed temperature

Table 1 shows the validation of the model in predicting the increased probability of failure (POF) two months before the fluid coupling actually failed. As seen from the table, the risk of failure increased to 13%. However, the risk of failure for the malfunctions introduced for the turbine generator remains at zero. On the other hand, the generator bearing defect failure risk increases to 2%, but it is still at a low risk of failure.

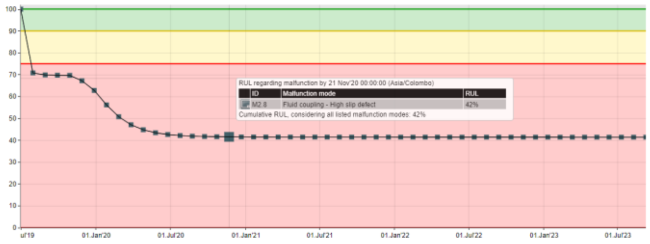
Table 1 Risk calculation two months before malfunction happened

Malfunction modes	Data sources	24.Jun	01.Jul	08.Jul	15.Jul	22.Jul	29.Jul	05.Aug	12.Aug	19.Aug	26.Aug	02.Sep	09.Sep
Cooling system defect - fan	T1 T2 E1	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Inverter defect matrix failure IG...	T1 T2 E1	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Inverter defect DC bus failure	T1 T2 E1	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Winding defect	T4 E1	0%	0%	0%	0%	0%	0%	0%	1%	1%	1%	2%	2%
Generator bearing defect	T1 T2 V1 V2	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Power leads defect	T1 T2 E1	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Fluid coupling - Low slip defect	T5 R1	10%	11%	11%	11%	12%	12%	12%	12%	12%	12%	12%	12%
Fluid coupling - High slip defect	T5 R1	25%	27%	27%	28%	29%	30%	30%	30%	30%	30%	30%	30%
Fluid coupling - Blast	T5 R1	7%	8%	8%	8%	9%	9%	9%	9%	9%	9%	9%	9%
		25%	27%	27%	28%	29%	30%	30%	30%	30%	30%	30%	30%

Figure 5 – (a) shows that the RUL calculation will decrease by 25% according to the data collected before the event happened. In addition, Figure 5 – (b) illustrates that the RUL will reduce by 35% and reach 40%, twelve months after the failure if the fluid coupling issue is not rectified.



(a)



(b)

Figure 5 – (a), (b)- Calculation RUL of fluid coupling curve for twelve days and five years after the failure respectively

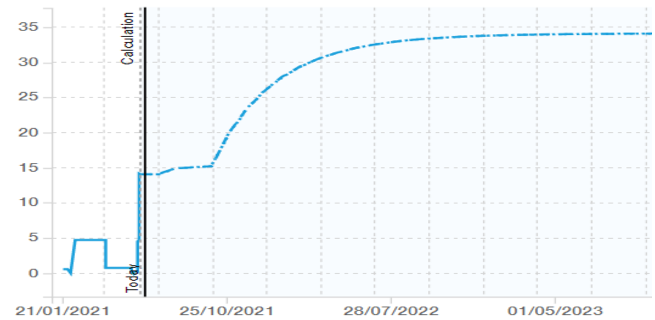


Figure 6 Future fluid coupling probability of failure (POF) calculation

Figure 6 shows the prediction of an increase in the probability of failure after the fluid coupling malfunction. The risk can be reduced to an acceptable level by performing an appropriate maintenance program to keep the wind turbine components in a healthy condition at low risk of failure.

A-1 -Wind Turbine Step up - Transformer Insulation Defect Prediction

Transformers are the weakest component in a wind turbine. They are imposed with many challenges during their operational life. Some of the challenges are voltage harmonics and DC offset due to the use of converters for providing the 50 HZ power to the collector system. These converters make various harmonic orders, creating eddy current and stray losses that would be the root of further temperature rises inside the transformer [14].In addition, variable loading cycles due to wind speed fluctuations are another challenge for wind turbine transformers. The main problem due to unsteady wind conditions is no-load losses, particularly when the wind speed is under the acceptable value and the generator does not produce power. This condition takes the transformer to an under-load situation, which causes the core losses to increase and resulting in dielectric insulation defects due to an increase in thermal issue cycling [14]. The consequence of these challenges is the eventual break down of insulation and an acceleration of the insulation ageing process. The main malfunction of the wind turbine transformer is insulation defect or ageing, and the parameters for predicting the malfunction are harmonics, winding and oil temperatures (top and bottom), moisture and gas concertation (CO_2/CO and starry gases). The transformer was diagnosed with an internal fault in mid-December 2020 - stray gasses were generated inside the transformer indicating a thermal fault. The transformer was suffering from continuous heat generated inside the transformer, accelerating the insulation degradation and speeding up the transformer ageing. The CO_2/CO ratio with the formation of a significant amount of combustible gases is a strong indication of paper involvement.

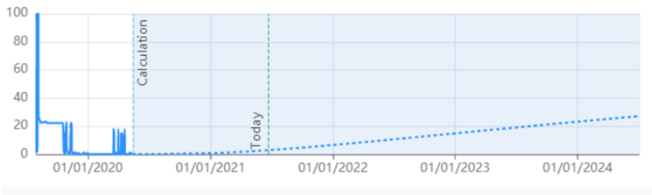


Figure 7- 5 year probability of failure (POF) calculation

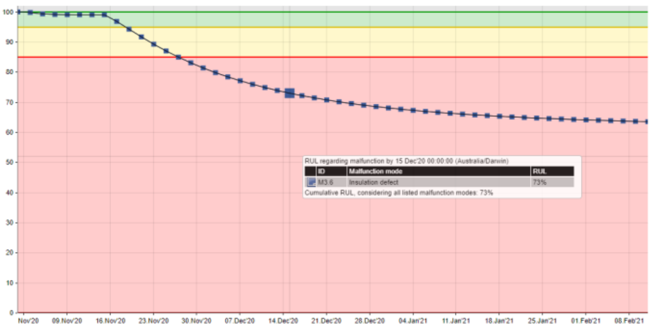


Figure 8- 12 weeks RUL calculation after the failure

Figure 8 shows that the RUL of the transformer insulation decreased by around 30 % after the transformer was diagnosed with a severe thermal fault in mid-December 2020. On the other hand, Figure 9 shows the forecasted RUL reduction by another 28% in mid-July 2021, which will dramatically decrease if the fault is not rectified by proper corrective maintenance.

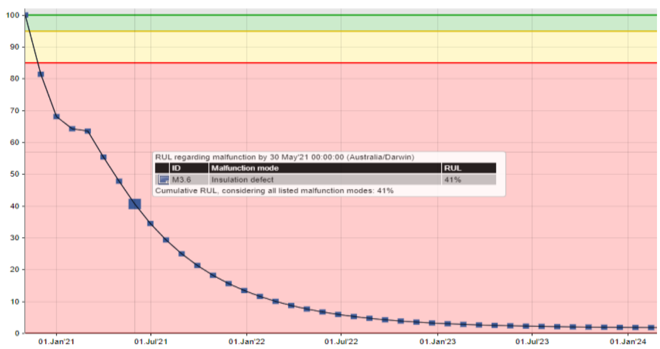


Figure 9 - 5 years RUL forecasting curve after fault

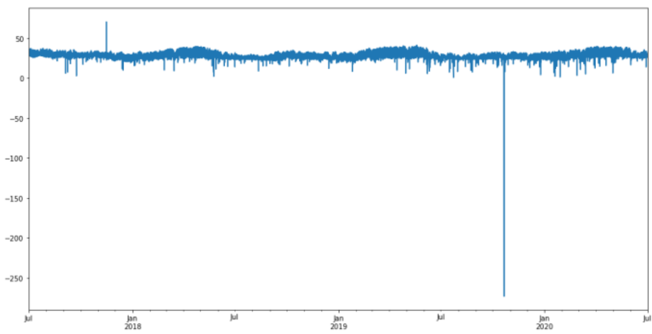
B. Methodology of Fluid Coupling Temperature Forecasting

Given that the status of the fluid coupling is closely related to the health condition of the gearbox, the fluid temperature is analysed in more detail and is forecasted to provide some early insights into the temperature fluctuation. Besides indicating potential abnormal operation of the gearbox based on the historical relationship between fluid temperature level and gearbox status, the forecasting of the fluid coupling temperature also potentially enables users to utilise the thermal reserves of the coupling more efficiently [7]. Instead of using the daily average data, hourly and 30-minute average interval data of the fluid coupling temperature are used to capture more dynamic information. It has been assumed that the fluid coupling temperature contains details of the ambient or outdoor temperature because the fluid coupling part is not insulated. Although a linear relationship has been identified using the daily average data of the outdoor and fluid temperatures, the relationship may not be the same when hourly or 30-minutesinterval data are used. To forecast the fluid coupling temperature values, the following steps are conducted in this paper:

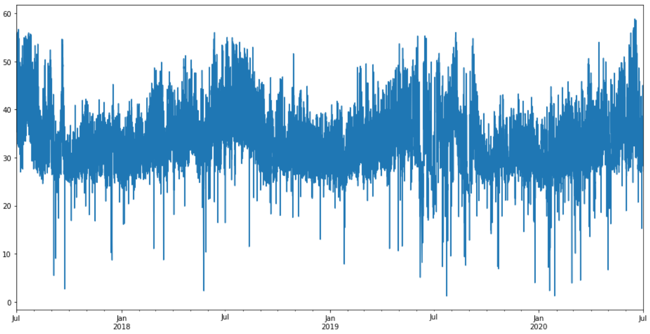
- Step-1: Producing larger size, e.g. hourly aggregated data for visualization
- Step-2: Cleaning data in terms of missing data, outlier data, etc.
- Step-3: Conducting correlation analysis
- Step-4: Determining the regression methodology and algorithms based on Step-3
- Step-5: Determining the forecasting strategy based on Step-4
- Step-6: Implementing forecasting algorithms and assessing the results.

B-1 Fluid Coupling Temperature Forecasting

In this section, a resampling of the outdoor temperature and the fluid coupling temperature is conducted on an hourly average basis. The timeline of the selected data is from '2017-07-01 00:10:00' to '2020-07-01 00:00:00', which results in 15,7824 data points. It has been identified that 3,857 data points contain empty values. Therefore, interpolation is conducted to fill out the missing data. Linear interpolation is used as it makes sense that temperature does not change dramatically within 10 minute- intervals. Both the outdoor temperature and the fluid coupling temperature are then plotted as shown in Figure 10 (a) and (b) respectively.



(a)



(b)

Figure 10- Hourly average temperature: (a) outdoor temperature and (b) fluid coupling temperature

It can be seen from Figure 10 (a) that there are at least outliers in the outdoor temperature, which do not reflect the temperature change correctly and will need to be removed before any further analysis. After further consultation with relevant industry representatives, it has been confirmed that the outdoor temperature sensor has not been 100% accurate, but the fluid coupling temperature data is correct. Therefore, the Elliptic Envelope algorithm in Python is used for the outlier detection in the outdoor temperature data only. There are 265 outlier data points detected as a result. The temperature plots after the outlier removal is shown in Figure 11. You can see that the obvious outliers have been removed by comparing this with Figure 10.

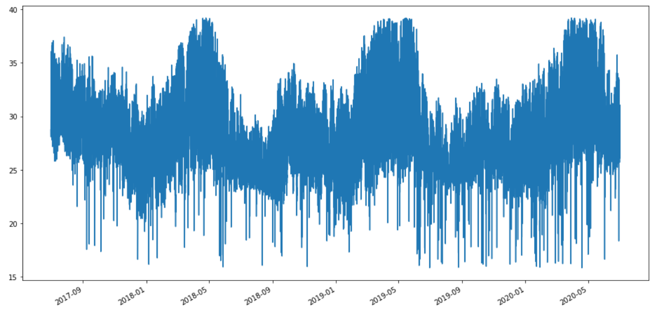
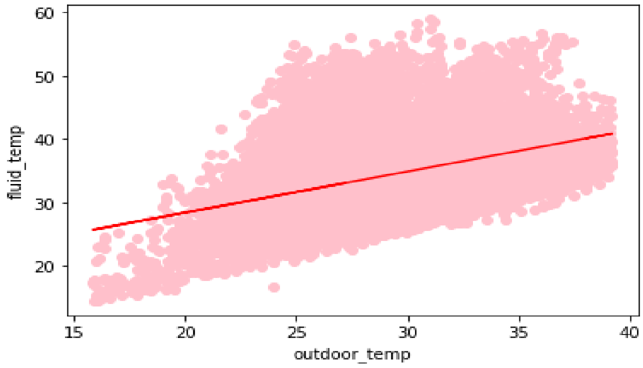


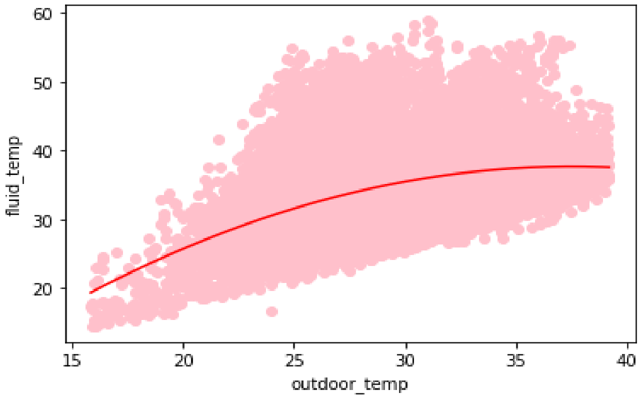
Figure 11- Hourly average outdoor temperature after data cleaning

Given that a linear relationship has been identified using daily average data, Person's correlation is calculated to see how strong the linear relationship is between the outdoor temperature and the fluid coupling temperature on an hourly basis. The resulting correlation coefficient is 0.411, which means there is no strong linear relationship between the two types of temperature. To further assess the correlation without linear assumption, Spearman's correlation is calculated to be 0.415, which also indicates a weak correlation between the outdoor temperature and the fluid coupling temperature when hourly data is used. Attempts to conduct a linear regression and a second degree polynomial regression result in Figure 12 (a) and (b) respectively.

Based on both the correlation analysis and the regression attempt, it is determined that univariate forecasting of the fluid coupling temperature, rather than taking into consideration the outdoor temperature, is a more suitable method. Given the data-drive nature of the forecasting problem, machine learning is employed in the paper. . Some of the popular machine learning algorithms for forecasting include the Holt-Winters method, the Autoregression Integration Moving Average method, and the deep learning models etc [8].



(a)

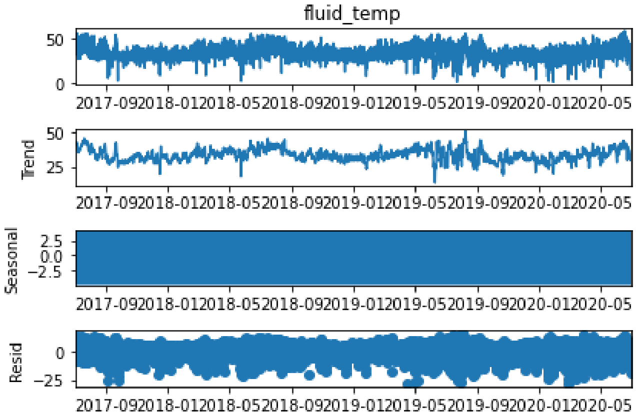


(b)

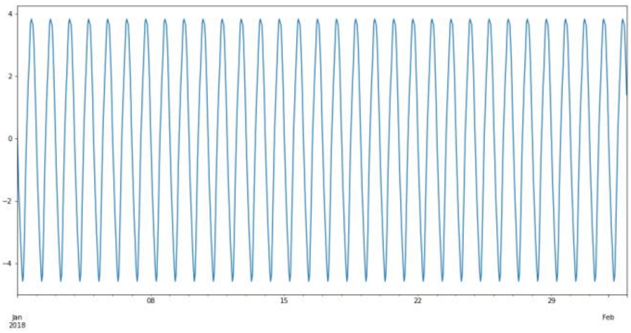
Figure 12 -Attempts of regression between the outdoor temperature and the fluid coupling temperature: (a) linear regression and (b) polynomial regression

For the fluid temperature forecasting in this paper, the Holt-Winters method and the Long-Short Term Memory (LSTM) deep learning model are used to obtain the forecasting models, considering the characteristic of the data and efficiency of the algorithms in being applied to the relatively large dataset. The Holt-Winters method [15] also known as the Triple Exponential Smoothing method, uses exponential smoothing factors to fit a model to the historical data, from which future data can be predicted. The smoothing factors take into account the level, trend and seasonality of the studied dataset, which makes Holt-Winters suitable for forecasting time series data that exhibits both trends and seasonal variations. LSTM, being a type of artificial neutral network model, is derived from RNN (Recurrent Neural Networks) [15]. In RNN, a recurrent layer is made up of particular neurons that present recurrent connections, so that an output value is correlated with the historical data of the inputs. LSTM networks provide an internal memory that captures both short-term and long-term memories, and are extremely suitable for sequence perdition such as time series forecasting problems.

To understand the fluid coupling temperature data further, an ETS (Error/Trend/Seasonality) decomposition is conducted on the hourly data for the period of '2017-07-01 00:10:00' to '2020-07-01 00:00:00'. The ETS decomposition results are shown in Fig. 13, where the 4 plots from top to bottom are the original fluid coupling temperature (same with Fig. 10 (b)), the trend, the seasonal and the residual components of the fluid temperature data. It can be seen from Fig. 13 that there is no obvious trend of the fluid coupling temperature. A zoomed-in period of the seasonal component plot in Figure 13 (b) shows a weak seasonality, which could be because of the wind power variation due to some wind speed patterns through day and night.



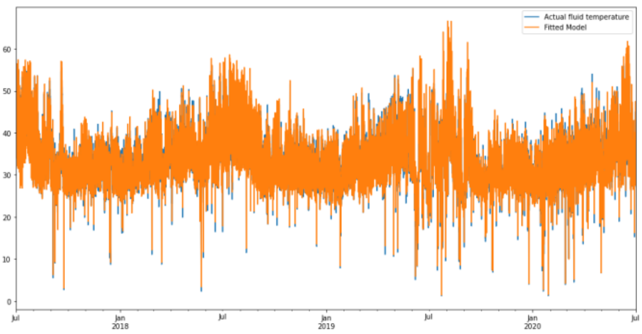
(a)



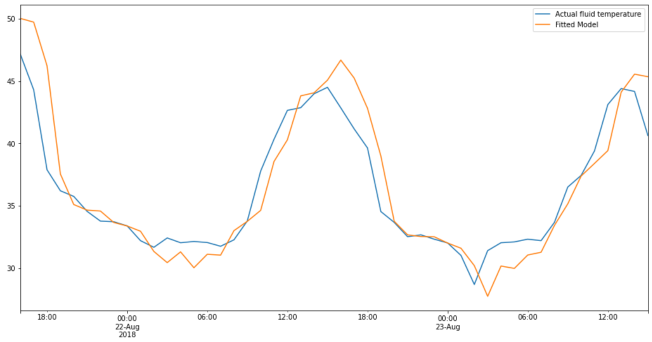
(b)

Figure 13- Fluid coupling temperature decomposition: (a) full ETS decomposition and (b) seasonal component.

Before splitting the hourly fluid data into training and test data, the entire period of data, i.e. between the time of ‘2017-07-01 00:10:00’ and ‘2020-07-01 00:00:00’, is used to build a fitted model using the Holt-Winters method. Figure 14 shows the actual fluid coupling temperature (in blue) against the Holt-Winters fitted model (in orange), where Figure 14 (a) is the fitting picture for the whole dataset and Figure 14 (b) is a zoomed-in period of the fitting for better visualisation. It can be observed that the underlying Holt-Winters model derived from the available data fits these data nicely. This means the Holt-Winters method is suitable for the forecasting purpose in this paper.



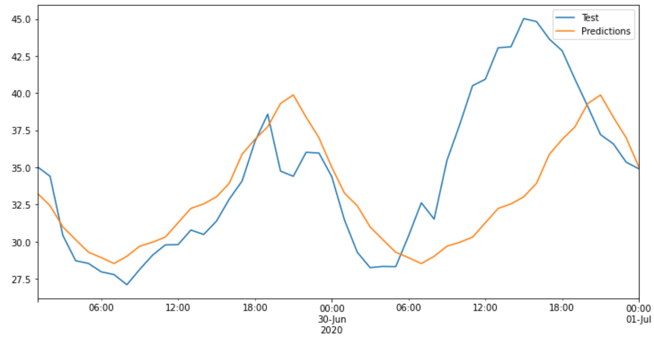
(a)



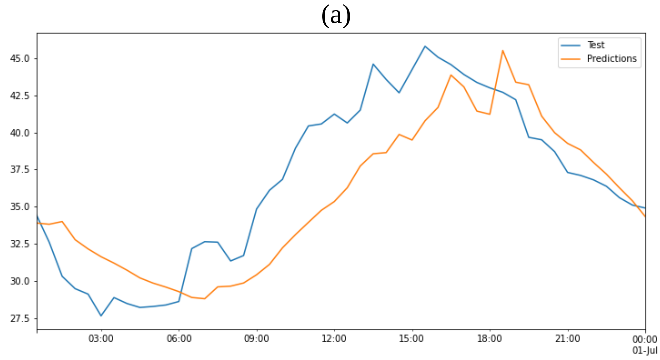
(b)

Figure 14- Fitted model using the Holt-Winters method comparing with the actual data: (a) full data fitting and (b) zoomed-in data fitting

The fluid coupling temperature data is split into a training data set and a test data set, which are the periods of ‘2017-07-01 00:00:00’ to ‘2020-06-29 00:00:00’ and ‘2020-06-29 01:00:00’ to ‘2020-07-01 00:00:00’ respectively. A forecasting model is trained using the training data by applying the Holt-Winters algorithm. The model is then tested on the test data for performance assessment. Figure 15 (a) shows the predicted fluid temperature data versus the test data. It can be seen that the predicted data matches the actual data fairly well, but there is some delay and fluctuation mismatch in predicting the temperature of the last 24 hours. Root mean squared error is used as the metric to numerically measure the accuracy of the model. The resulting error for the Holt-Winters model when hourly data is used is 4.67. In an attempt to improve the forecasting model, 30-minutes interval data is used under the Holt-winter algorithm and the test and prediction comparison is shown in Figure 15 (b). The resulting error for the Holt-Winters model when half-hourly data is used is 3.31, which indicates a better forecasting model than when half-hourly data is used.



(a)



(b)

Figure 15- Holt-Winters predictions: test data and predicted data comparison on (a) an hourly basis and (b) half-hourly basis.

Compared to Holt-Winters, a disadvantage of using LSTM is the relatively slow computation rate. To train an LSTM model with 2 hidden layers using hourly data, it took the computer more than 2 hours to complete, while Holt-Winters only needed a few minutes even with half-hourly data. For this reason, it would be ideal to have a supercomputer to implement LSTM efficiently. With the resources available, the authors did not proceed to train LSTM models further using half-hourly data or more frequent data points, as the computation time would be too long. Figure 16 shows the comparison between the testing data and the predicted data for the last 12 hours in the available dataset. It can be seen that compared to Holt-Winters, LSTM tends to under predict the fluctuation of the fluid temperature. Also, the root mean squared error of the trained LSTM model is 4.59, which is not as good as when half-hourly data is used for Holt-Winters. However, given that artificial neural networks provide better results with more data, LSTM is promising in terms of future investigation.

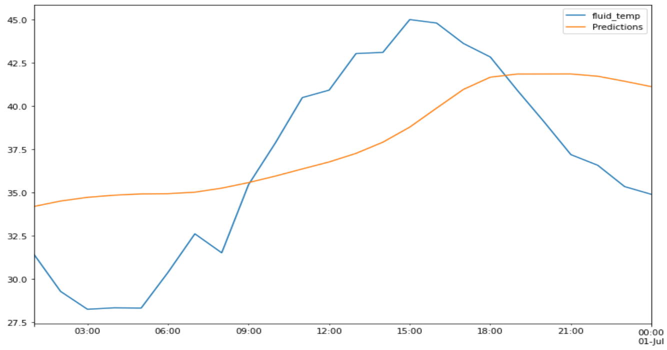


Figure 16- LSTM predictions: test data and predicted data comparison on an hourly basis

Given the above, the Holt-Winters model is used for the forecasting of the fluid temperature for 24 hours into the future using half-hourly data. A Holt-Winters model is retrained using the whole available dataset from '2017-07-01 00:00:00' to '2020-07-01 00:00:00'. The resulting forecasting of the fluid coupling temperature is shown in Figure 17. It is noted that not all data points are shown in Figure 17 as it would be impossible to see the forecasted results clearly.

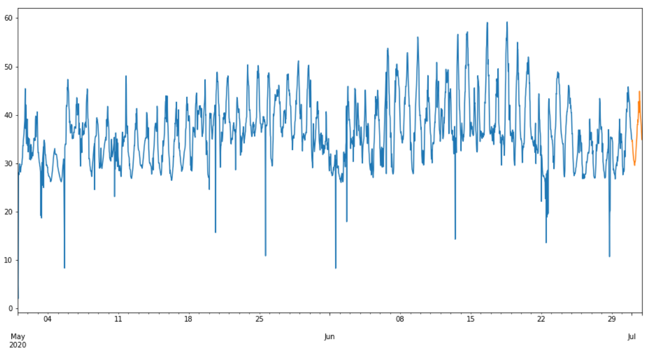


Figure 17 Holt-Winters forecasting results.

IV. Conclusion

ML approaches applied to condition monitoring may improve diagnostics (detect current failures) and prognostics (anticipate future failures) when appropriate architecture and techniques are selected. Once a problem or fault is detected, it can be determined, providing the appropriate directions for its correction. Additionally, by detecting the trend of the data, the algorithms can be used to determine the most probable period in which the turbine's components might start to present failures. This study shows that the application of Machine Learning algorithms for condition monitoring of wind turbines and power transformers has clear potential. Furthermore, to continuously monitor the gearbox operation, the fluid coupling temperature is forecasted 24 hours into the future by a Holt-Winters model that was trained in the paper. Future work for fluid temperature forecasting includes retraining a forecasting model with longer time periods to increase accuracy and improve the implementation efficiencies of machine learning algorithms. The present technique addresses the prediction of malfunctions of components, units, and fleets of technical entities. The invention is especially applicable to industrial asset management , but also to other fields.

The method comprises the step of estimating a remaining useful life of the component on the basis of probabilities for the malfunction of the component given the number of future points in time. TheRUL is shortened if the above described methods predict an earlier malfunction. It can be prolonged by removing the cause of the malfunction through maintenance, change of operational scenario, etc.

V. References

[1] F. Kirschnick, Configuration of malfunction prediction for components and units of technical entities, US 2017/0236064 A1, Aug. 17, 2017

[2] F. Kirschnick, Malfunction prediction for components and units of technical entities US2003220719

[3] Bradley, Paul S., Kristin P. Bennett, and Ayhan Demiriz. "Constrained k-means clustering." Microsoft Research, Redmond 20.0 (2000): 0.

[4] Kuang, Quansheng, and Lei Zhao. "A practical GPU based kNN algorithm." Proceedings. The 2009 International Symposium on Computer Science and Computational Technology (ISCSCI 2009). Academy Publisher, 2009.

[5] Bruneau, Marine, et al. "A clustering package for nucleotide sequences using Laplacian Eigenmaps and Gaussian Mixture Model." Computers in biology and medicine 93 (2018): 66-74.

[6] Supervised and Unsupervised Machine Learning Techniques Applied to SCADA and Vibration Data for Diagnostics and Prognostics of Two Wind Turbines' Drivetrains F. L. FREITAS, G. L. MOURAO, M. H. NISHIOKA AQTech Power Prognostics Brazil

[7] J. Chu , P Gue , Zhenyu Chen, ''Condition Monitoring of Wind Turbine Gearbox Bearing Based on Deep Learning Model'' IEEE Access, 2019

[8] SA Instrumentation & Control Magazine: Online: https://www.instrumentation.co.za/news.aspx?pklnewsid=30771

[9] K. Verma, and S. Paul, Eds. Singapore: Springer Singapore, 2020, pp. 189–198.

[10] G. Bonaccorso, Machine Learning Algorithms, Packt Publishing, 2017, pp. 289–319.

[11] Georgy Jose & Rani Chacko. ''A Review on Wind Turbine Transformers'' International Conference on Magnetics, Machines & Drives (AICERA-2014 iCMMD)

[12] K. Verma, and S. Paul, Eds. Singapore: Springer Singapore, 2020, pp. 189–198.

[13] G. Bonaccorso, Machine Learning Algorithms, Packt Publishing, 2017, pp. 289–319.

[14] Georgy Jose & Rani Chacko. ''A Review on Wind Turbine Transformers'' International Conference on Magnetics, Machines & Drives (AICERA-2014 iCMMD)

[15] Yuanyuan Fan, A. Evangelista, V Indumathi, ''Evaluation of Remote or Virtual Laboratories in E-Learning Engineering Courses'' IEEE Golobal Engineering (EDUCON), 2021

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