Journal of Engineering Sciences

Vol 11, Issue 7,July/2020

ISSN NO:0377-9254

PREDICTION OF POWER TRANSFORMER LIFETIME THROUGH MACHINE LEARNING

Pooja G[1], Preethi M[2] , Jeevabavatharani B[3], Hemanandhini I G[4]

[1]*Department of Computer Science and Engineering, Sri Ramakrishna Engineering College, India*

[2]*Department of Computer Science and Engineering, Sri Ramakrishna Engineering College, India*

[3]*Department of Computer Science and Engineering, Sri Ramakrishna Engineering College, India*

[4]*Department of Computer Science and Engineering, Sri Ramakrishna Engineering College, India*

***Abstract*— Prediction of the remaining life of high-voltage power transformers is an important issue for energy companies because of the need for planning maintenance and capital expenditures. Lifetime data for such transformers are complicated because transformer's lifetime can extend over many decades because of transformer's specific designs and manufacturing processes involved in them. In this system we develop statistically based predictions for the lifetimes of an energy company's fleet of high-voltage transmission and distribution transformers. The company's data records begin in 1950, providing information on installation and failure dates of transformers. Although the dataset contains many units that were installed before 1950, there is no information about units that were installed and failed before 1950.We use a parametric lifetime model to describe the lifetime distribution of individual transformers. We develop a statistical procedure, based on machine learning models, for computing a prediction interval for remaining lifetime of individual transformers now in service. Then extend these ideas to provide predictions and prediction intervals for the cumulative number of failures, over a range of time, for the overall fleet of transformers. Using machine learning algorithms, we effectively got the power transformer loss values that is the predicted year loss of the transformer then it was sent through mail to the end-user.**

Keywords*— *Capital, Transformer

1. INTRODUCTION

Machine Learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. It focuses on the development of computer programs that can access data and use it to learn for themselves. The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide.

Benefits of Machine Learning:

Some of the benefits of Machine Learning are

- Accurate Lifetime value prediction
- Automation
- Continuous Improvement
- Handling Multi-dimensional data
- Solve spam detection Problems

Types of Machine Learning:

There are three different types of machine learning. They are

a. Supervised machine learning

Supervised Learning is the one, where you can consider the learning is guided by a teacher. We have a dataset that acts as a teacher and its role is to train the model or the machine. Once the model gets trained it can start making a prediction or decision when new data is given to it.

b. Unsupervised machine learning

The model learns through observation and finds structures in the data. Once the model is given a dataset, it automatically finds patterns and relationships in the dataset by creating clusters in it. What it cannot do is add labels to the cluster, like it cannot say this a group of apples or mangoes, but it will separate all the apples from mangoes. Suppose we presented images of apples, bananas, and mangoes to the model, so what it does, based on some patterns and relationships it creates clusters and divides the dataset into those clusters. Now if a new data is fed to the model, it adds it to one of the created clusters.

c. Reinforcement Learning

It is the ability of an agent to interact with the environment and find out what is the best outcome. It follows the concept of the hit and trial method. The agent is rewarded or penalized with a point for a correct or a wrong answer, and on the basis of the positive reward points gained the model trains itself. And again once trained it gets ready to predict the new data.

2. LITERATURE SURVEY

Ashkan Teymouri, Behrooz Vahidi their performance and remaining useful lifetime depend on the state of the oil-impregnated paper. Changing the oil over the lifetime of a transformer is possible, but it is not possible to change the insulation paper. Thus, the end of the paper lifetime will also be the end of the transformer lifetime.

Y. Cui, H. Ma, T. Saha, C. Ekanayake, D. Martin in their research a moisture dependent thermal model (MDTM) for estimating transformer hot spot temperature is proposed. In this model, nonlinear thermal resistance is formulated by considering both oil and cellulose (paper and pressboard) of the transformer.

Evangelos Pournaras, Jose Espejo-Uribe their research introduces analytical results from which two optimization strategies for self-repairable Smart Grids are derived. The model proposed for self-repairable Smart Grids is extensible as other optimization strategies can be further tested as well.

Chiodo, D. Lauria, F. Mottola, and C. Pisani their research they closed- form relationship was derived between the transformer's lifetime and the distributional properties of the stochastic load. The usefulness of the closed-form expression is discussed for sake of design, even if a few of the considerations also are performed with respect to operating

Razavi-Far, R. Farajzadeh-Zanjani, M. Saif their research provides reasonable diagnostic performances confirm the ability of the proposed novel class-imbalanced learning technique in diagnosing bearing defects, independently from the imbalance ratios.

3. EXISTING SYSTEM

The remaining useful life (RUL) of transformer insulation paper is largely determined by the winding hotspot temperature (HST). Frequently the HST is not directly monitored and it is inferred from other measurements. However, measurement errors affect prediction models and if uncertain variables are not taken into account this can lead to incorrect maintenance decisions. Additionally, existing analytic models for HST calculation are not always accurate because they cannot generalize the properties of transformers operating in different contexts. In this context, this paper presents a novel transformer condition assessment approach integrating uncertainty modeling, data driven forecasting models and model-based experimental models to increase the prediction accuracy and handle uncertainty. The proposed approach quantifies the effect of measurement errors on transformer RUL predictions and confirms that temperature and load measurement errors affect the RUL estimation. Forecasting results show that the extreme gradient boosting (XGB) algorithm best captures the non-linearity of the thermal model and improves the prediction accuracy amongst a number of forecasting approaches. Accordingly, the XGB model is integrated with experimental models in a Particle Filtering framework to improve thermal modeling and RUL prediction tasks. Models are tested and validated using a real dataset from a power transformer operating in a nuclear power plant.

4. PROPOSED SYSTEM

Machine learning method used for the proposed system. It's very effective for prediction and analysis. We use a parametric lifetime model to describe the lifetime distribution of individual transformers. We develop a statistical procedure, based on machine learning models, for computing a prediction interval for remaining life for individual transformers now in service. We then extend these ideas to provide predictions and prediction intervals for the cumulative number of failures, over a range of time, for the overall fleet of transformers. Using machine learning algorithms are working very effectively, finally, we got the power transformer loss values then it was sent through the mail to the server. Using machine learning models like support vector machine, random forest, decision tree, naive Bayes, multi-layer perceptron. In this, each model performance

was analyzed after choose the best one of this and predict the lifetime of power transformer using the web application and send through the mail.

Advantages:

- Evaluate the models
- Got more accuracy and perfect output
- Flask server make a local server

5. FLOW CHART

Initially the dataset is first split into testing data and training data. Then they are given as input for the model selection. Once when the model with highest accuracy is identified it is given as input to the flask server along with the user input then the flask server acts as a local server and displays the output.

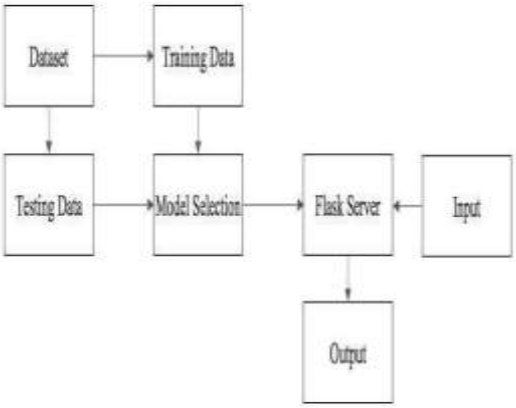

Fig.1 Flow Chart

6. IMPLEMENTATION

6.1 Dataset splitting into train and test:

As we work with datasets, a Machine Algorithm works in two stages. We usually split the data around 15%-85% between testing and training stages. Trained data is collected using various parameters such as production year, oil type, load, watts, transformer type, loss, testing, year_ loss.

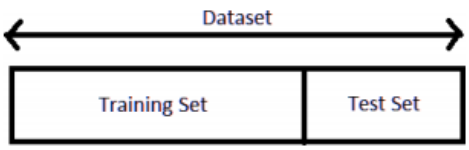

Fig.2 Dataset Splitting

Prerequisites for Train and Test Data

We can install these with pip- pip install pandas

pip install sklearn

We use pandas to import the dataset and sklearn to perform the splitting.

You can import these packages as-

```
>>> import pandas as pd
>>>from sklearn.model_selection import train_test_split
>>>from sklearn.datasets import load_iris
```

6.2 Model Selection:

Naive Bayes (NB): The samples are classified based on the outcome of the maximum posterior probability computed amongst all the different classes. This type of classifier is easily modeled and is typically suitable for large datasets.

Accuracy level-18.54%

K-Nearest Neighbor (KNN): It classifies objects based on the closest training examples in the feature space. The idea behind KNN is to find a predefined number of training samples closest in distance to a given query instance and predict the label of the query instance from them. KNN is finds a path around the graph.

Accuracy level-52.98%

Random Forests (RF): Random forests is a supervised learning algorithm. It can be used both for classification and regression. It is also the most flexible and easy to use algorithm. A forest is comprised of trees. It is said that the more trees it has, the more robust a forest is. Random forests create decision trees on randomly selected data samples, gets prediction from each tree and selects the best solution by means of voting. It also provides a pretty good indicator of the feature importance.

Accuracy level-94.31%

Artificial Neural Networks (ANNs): ANNs are typically structured in layers made up of a number of interconnected nodes. The hidden layers then link to an output layer where the answer (health index level in our case) is the output.

Accuracy level-88.54%

From the above machine learning algorithms for prediction, random forests algorithm gave the maximum accuracy (94.31%) and hence in our project to predict the transformer year loss we have used random forest algorithm.

6.3 Flask Framework Creation:

Python has a number of web frameworks like Flask, Django, Pyramid etc. that can be used to create web applications and APIs. We have used Flask framework because it is light weight and easy to setup. By using Flask framework, we are creating the home page in our project where user can give the value for the input parameters which are specified. Once we have a small Flask application running, we'll iterate on this site, turning it into a functioning API. Using this local host the predicted year loss is sent through mail to the end-user.

Flask framework installation command

– >> pip install flask from flask import * app = Flask(name) @app.route("/")

Fig.3 Home Page

6.4 Output Prediction:

Using the training data, the various machine learning models such as Naive Bayes, K Nearest Neighbor, Artificial Neural Networks and Random forests where tested. Among all the above used machine learning algorithms for prediction, Random forests algorithm gave the maximum accuracy of 94.31%. And hence in our project to predict the remaining lifetime of the transformer random forests algorithm is used.

X-Axis-Name of the algorithms

Y-Axis-Accuracy Levels

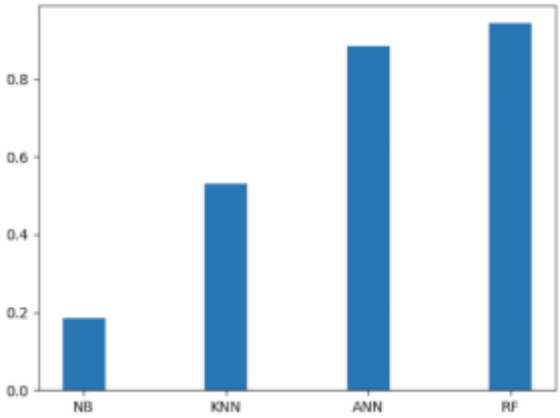

Fig.4 Model Prediction Graph

6.5 Sending mail to an end-user:

Output which is the predicted year loss of the transformer is sent to end user through mail. To send mail python library file SMPTLIB is imported. This is more efficient way to send information to end user.

Code to send mail :

import smtplib

s=smtplib.SMTP('smtp.gmail.com',587)s.starttls()s.login("sendermailid",message=str(y_pre)s.sendmail("sender","reciver", message) s.quit() return str(y_pre)

Fig.5 Mail to the end-user

7. SYSTEM SPECIFICATION

1. Hardware Specification:
   1) System: Windows 7,8,10 (64 bits)
   2) 4GBRAM

2. Software Specification:
   1) Pythonv2.7.15
   2) Anaconda 5.3.

8.CONCLUSION

Machine Learning models have been used for the effective prediction and analysis of the transformer and to predict the remaining lifetime of the transformer. It has been demonstrated that the integration of machine learning (ML) models with experimental models improves transformer lifetime estimations. Parametric lifetime model was used to predict the lifetime distribution of the individual transformers. The statistical procedure was developed for computing the remaining life of individual transformers which are now currently in use. By using the machine learning algorithms, the power transformer loss values were calculated and intimated through an email to the end users before the transformer has been completely destructed. By intimating in prior to the end users about the lifetime of the transformers we can easily reduce the cost of failure of the transformers. We can also alert the end users about the remaining lifetime of the transformer and avoid the failure of the transformer by providing the proper maintenance in advance.

ACKNOWLEDGMENTS

We express our deepest gratitude to Project Guide and Coordinator of our Computer Science and Engineering department who gave constant support and encouragement throughout this work.

REFERENCES

[1] Li Wang, Qingjie Wang, Weiqi Wang, Temperature Monitoring Of Distribution Transformer Windings Based On Fiber Bragg Grating Array,*2nd International Conference On Electrical Materials And Power Equipment,2019.*

[2] R.A.ABD El-Aal, K.Helal, A.M.M. Hassan, S.S.Dessouky, Prediction of Transformers Conditions and Lifetime Using Furan Compound Analysis, 2019.

[3] Yun-lei Cai, Duo Ji, Dong-feng Cai,A KNN Research Paper Classification Method Based On Shared Nearest Neighbor, *in Proceedings Of NTCIR-8 Workshop Meeting*,2010.

[4] Debo Cheng,Shichao Zhang,Zhenyun Deng.,KNN Algorithm With Data Driven K Value, *International Conference On Advanced Data Mining And Applications*,2014.

[5] M.Akhil Jabbar,B.L. Deekhatlu Priti Chandra, *International Conference On Computational I Intelligence:ModelingTechnique And Applications,(CIMTA),2013*..

[6] Christian Osorio,Nandan Sawant,Transformer Lifetime Prediction,Intelligent Energy Projects.

[7] Gongde Guo,Hui Wang,David Bel., KNN Model Based Approach In Classification, European Commission Projects ICONS.