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GISDrivenTransformerHealthMonitoring System

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***Abstract*— Power transformers are essential to the stability of power distribution networks, and their unplanned failure can result in extensive outages, equipment stress, and expensive maintenance. Conventional monitoring methods rely on manual evaluationandperiodicinspection,whichfrequentlymiss early signs of malfunction. This paper presents an improved GIS-driven Transformer Health Monitoring System that incorporates anomaly detection, IoT-based sensing, RandomForestmachine learning, anda Weather Integrated Stress Index (WISI) for intelligent condition assessment. Transformer health score, anomaly score, and short-term risk prediction can be calculated using multi-parameter sensor data in conjunction with environmental stress indicators. Transformer conditions are categorised by the system into Low, Medium, and Criticalgroups,andaninteractiveGISdashboardisused todisplaytheresults.Proactivemaintenanceandeffective resourceallocationaresupportedbythespatialmapping ofhealthpredictions,WISIeffects,andRemainingUseful Life (RUL) estimates. The outcomes show how the suggested system can improve field decision-making processes and transformer reliability**.

Keywords—IoT, GIS, Machine Learning, Transformer Monitoring, Random Forest

I. INTRODUCTION

Transformers are essential components of electrical power distributionsystemsbecausetheyregulatevoltagelevelsand ensurereliableanduninterruptedpowerdeliverytoendusers. Theircontinuousoperationundervaryingelectricalloadsand environmentalconditions makes themsusceptibletogradual performance degradation. Factors such as thermal overload, insulation deterioration, sustained mechanical vibration, moisture accumulation, and environmental stress significantly accelerate aging and reduce operational efficiency. If left undetected, these issues can lead to unexpected failures, power outages, equipment damage, and increased maintenance costs. Conventional transformer monitoringhasbeenofthepracticeofscheduledmaintenance and manual inspections which we do at set intervals. These methodsprovideonlyperiodicpicturesoftransformerhealth whichinturndonotitattimescaptureearlyindevelopment anomalieswhichpresentbetweenourcheckupperiods.Asa result what we see is that incipient faults go by unnoticed untiltheyreachacriticalstagewhichinturntriggersreactive maintenance or emergency shut downs. Also manual inspection is labor intensive, time consuming and does not scalewellwithinlargeandgeographicallydispersedpowernetworks.RecentlywehaveseengrowthinwhattheInternet of Things brings to the table in terms of transformer monitoring. We have smart sensors which are put in to measure temperature, current, vibration and environmental conditions which in turn gives us real time continuous data. Thisdatafromabaseofoperationstandpointimprovesfault visibilityandalsoweareabletodetectearlythetelltalesigns ofabnormalperformance.Butalsoitisimportanttonotethat raw sensor data by itself is not enough for us to make effectivedecisionswhichiswhyweneedintelligentanalysis.

Machine inlarge degreewhatwesee from machine learning (ML)isthatitimprovespredictiveintelligencewhichinturn isaresultofitsindepthanalysisofcomplexsensordataand identification of what may be very fine relationships among many variables.

Alsofromthehistoryandpresenttimedatainputweseethat ML models are able to do transformer health state classification and also put forth that which may be at risk of failurewithgreataccuracy.Alsoitisnotedthatensemblesof models like Random Forest do very well in terms of dealing with noisy sensor data and non linear relationships which in turn plays a great role in the health assessment of transformers. Geographic Information Systems (GIS) also play a role in strengthening monitoring systems which they dosobyprovidingspatialcontexttotransformerhealthinfo.

Through spatial analysis, GIS which enable utilities to see geographicallygroupedriskareas,tostudyhowenvironment elements play into transformer wear out, and to put forward maintenance actions based on location based vulnerability. Thisspatialintelligenceisalsoverymuchsoafeatureinlarge scale power distribution networks which see great variation in environmental issues and loading between regions. This time,wefocusonthecompleteGIS-integrated,IoT-centered anomaly detection, Random Forest classification, and Weather Integrated Stress Index systems, and the Full Transformer Health Monitoring System. With the ability to obtain real-time, operational, and environmental stress data, thesystemprovidestimeandlocationsensitivity.Inaddition, by using the system, the remaining useful life of the transformers and the health forecasting for the present momentandthesubsequent24hoursisgenerated.Thisreal- time information and data availability allow proactive and sophisticated maintenance scheduling.

II. LITERATURESURVEY

Transformer health monitoring has benefited greatly in the lastdecadefromrecentdevelopmentsinsmart-gridcomputer sensingandmonitoring,machine-learninganalyticdiagnosis, and geo-spatial intelligence. Past approaches to monitoring transformersfocusedonsimplemanualinspectionsand

periodic testing, which, in their time, did not accommodate for early degradation capture. There has been a significant shift in the most recent literature focusing on the continuous monitoring and predictive analytics, as well as geographically and temporally relevant decision-making for power distribution assets.

Abu-Siada and Islam [1] presented in a detailed study of transformer insulation condition put forth that which which insulation degradation is the primary cause of transformer failure.Theyreportedthattemperaturerise,moisturegetting in,andlongtermelectricalstressdoinfactcauseissueswith insulationthus whichinturnshortenstransformerlife.Their research also brings to light the issue of the need for continuousthermalandenvironmentalmonitoringinpresent day transformer health assessment systems.

Bhatt and Verma[2] looked at the application of IoT in power distribution systems for real time monitoring. They reported that which which put in place sensor based data collection saw a great improvement in fault visibility as comparedtotheuseofmanualinspectionmethods.Alsothey brought out that real time measurement of temperature, current and environmental variables which in turn enables early detection of abnormal operating conditions, thus contributing to a transition from a corrective to a predictive maintenance approach.

Bakar et al. [3] reported in a study of dissolved gas analysis (DGA) for transformer fault diagnosis that although DGA does an good job at identifying internal faults it requires lab based analysis which in turn does not supply continuous on site monitoring. That shortcoming in turn motivates the use of real time sensor data and data driven models which in to prove complementary to traditional diagnostic methods.

Biswal et al. [4] put forth machine learning based fault diagnosis which they did via probabilistic neural networks and reported improved accuracy in incipient fault identification. But their approach did require very large training sets and in depth parameter tuning which in turn presented a challenge for real time deployment.
Chatterjee and Bose [5]wrote a report of which they looked at many machine learning techniques which they found ensembles to do best at what they term structuring feature engineering although this requires that the features be well defined.

StrangasandAviyente[6]havestudiedsensordataanalytics, sensor data analytics, particularly, transformer's dat monitoring,stressingtheimportanceofvibrationandthermal signalsforthedetectionofmechanicalandinsulation-related faults in their early finding and corroborate the proposal for the integra of vibration sensing and temperature in profiling thedataprosystemmonitoringinthehsystemdiagnosticfor the transformers.

Jadoon et al. [7] reported that they had put forth an IoT enabledsmarttransformermonitoringsolutionwhichisinto real time data collection and remote visualization. Although theirsystemdidimproveintermsofoperationaltransparency itwasstillverymuchathresholdbasedalertsystemwhichdid not include the use of advanced machine learning or environmental stress modeling which in turn limits what in terms of prediction they could put out.

Zhang et al.[9] reported that they were able to prove the value of RandomForest classifierswhichwe combinedwith multi sensor info fusion in transformer fault diagnosis. We saw that what they did was to put forth that Random Forest models do a good job with noisy sensor data and non-linear relationships also they provide us feature importance which is a plus. Thus support is given to the use of Random Forest for transformer health classification in data rich settings.

Also their system which they put forth was based on past inspection data and did not include real time sensor input. AtpresenttheuseofGISbasedvisualizationhastransformed complex analytic results into easy to understand spatial information. We map in to geographic settings transformer health indices, anomaly scores, and risk levels which in turn allows utilities to identify high risk areas and to put forward maintenanceactions.Thisspatialintelligencesupportsbetter decision making at the operational and at the strategic level which includes load redistribution, infrastructure upgrades and emergency response planning.

III. SYSTEMARCHITECTURE

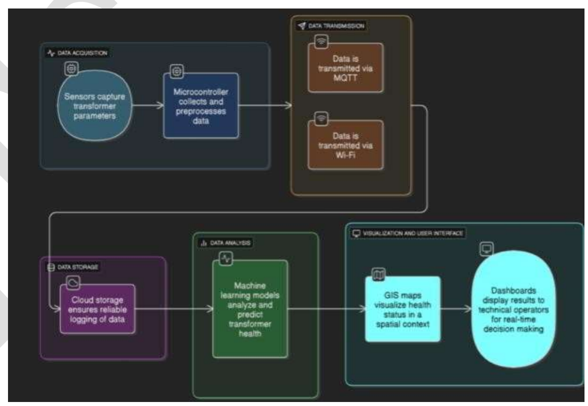

Fig.1System Architecture

A. IOTSENSINGLAYER

The Transformer Health Monitoring System is based on an IoTbasedsensinglayerthatisthemain\sourceofoperational data in real-time. This layer allows the determination of extreme electrical, thermal, mechanical, and environmental factors that impact transformer health. The ESP32 microcontroller is the most used in this layer because of low power usage and processing ability and because its capabilitiesincludereal-timedataacquisition.Monitoringof sensor data in real-time is made possible with the ESP32 connecting multiple disparate sensors. Processed data from the sensing layer rudimentary forms the basis of health evaluationandpredictive analytics.The systemis capableof detecting abnormal behavior based on early indicators and certain thresholds of temperature, current, vibration, and ambient conditions, prior to the onset of severe fault conditions. This real-time data driven system alters macroscopical inspection dependence and allows predictive maintenancedrivingdowntransformeroperationalandsafety risks.This gives the systemadvancedoperationalreliability. The DS18B20 temperature sensor measures the temperature ofthetransformeroilandwinding,bothofwhicharevitalfor understanding the and monitoring thermal imbalances and thermalstresseswithintheTransformer.Temperaturespikes are accelerated insulation deterioration which increases the likelihood of Transformer failure. Continuous temperature monitoring enables the system to detect overheating conditions caused by thermal imbalances and inefficiencies, insulation deterioration over time, and inefficiencies in cooling. Variations in load current are monitored by the ACS712 current sensor. As current flow changes, the sensor identifies conditions of imbalance, overload, abnormal load patterns, and the persistence of overcurrent. Rapid overcurrent conditions are escalating excessive heat and insulation breakdown. Continuous current monitoring is critical in assessing the electrical stress/ load and along with the other monitoring parameters in the system enable safe operation of the Transformer.

Mechanical health is evaluated via the use of SW-420 vibration sensor which reports on abnormal vibrations in transformer structure. We see that sudden or extended vibration anomalies may be a sign of internal faults, loose parts,coredeformation,orexternalmechanicalissues.Bythe early identification of these vibration trends we are able to put in place preventive maintenance and so also reduce the riskofalargescalemechanicalfailure.Alsoweareusingthe DHT22 humidity sensorto look atenvironmental conditions which in turn measures ambient temperature and relative humidityaroundthetransformer.Highhumidityandextreme ambient temperatures play a role in degrading insulation performance and also in the rate of moisture which gets into transformeroil. By tracking these environmental parameters we are able to identify the external stressors which in turn play a role in the aging and breakdown of the transformer. The base of our monitoring system is the sensing layer. We measure and collect out put from oil temperature, load current, vibration intensity, ambient temperature, and humidity via the ESP32 based sensor network. These parameters report on thermal loading, mechanical stability andenvironmentalstresswhichthetransformerissubjectto. Also we include in this from weather data which we use to determine the Weather Integrated Stress Index (WISI) that which measures the total effect of the environment on transformer wear.

B. CloudandMachineLearningProcessingLayer

After we collect the sensor data it is sent to the cloud from the ESP32 which uses Wi-Fi (MQTT/HTTP protocols) or GSM based on what is available at the site. In the cloud we dosecurestorage,addtimestamps,dopreprocessingandget thedatareadyformachinelearninganalysis.Wedofiltering ofbadreadings,wefillinformissingvalues,weadjustsensor range and we also tag historical data for training. We use RandomForestclassifierinourmachinelearningplatformtodetermine the health state of each transformer. We put the data into 3 different health state categories:

1. LowRiskinnormal operation.
2. MediumRisksignsofwhichmaybeunusualoroff the expected.
3. CriticalRiskmattersthatrequireimmediateaction.

Additional computations include: Also in the calculations are:

- Health Score
- AnomalyScore
- WISI-weightedriskadjustment
- Remaining Useful Life (RUL) computation

RandomForestisselectedbecauseofitsinherentrobustness, superioraccuracy,andabilitytolearncomplexnonlinear interactions among different sensorfeatures.It alsoprovides feature importance scores, enabling engineers to understand which parameters contribute most to the prediction.

C. GISVisualization Layer

TheinGISwhichwearetouseforvisualizationweintroduce whatmaybeputforthasapowerfulspatialintelligentfeature totheproposedhealthmonitoringsystem.Thatwhichweput forth is a system which does in fact integrate each transformers’ exact geographic position along with it’s real timeandpredictedhealthdata.Thisisinturnwhatgivesusa map based picture of the whole power distribution network. This spatial visual has the ability to take what was once isolatednumbersoutofwhichactioncanbehardtodetermine andinwhichweareabletopresentafullscalehealthpicture of transformer conditions which in turn is to say that we are looking at them across many geographic areas. Each on the GIS map is a which present a health report at a glance. We seegreenforthosetransformersthataredoingfinewithinthe set electrical, thermal, and environmental limitsthey are in idealstablestate.Yellowisusedforthatwhichareoutofthe norm a bit, which may have signs of early breakdown or are under some environmentstress that will needa watchfuleye and maybe preventive maintenance. Finally red is the color we see when a transformer is in a very bad state, it indicates an unusual and high risk condition that we should address immediately to avoid failure and disruption. This visual classification which in turn allows utility engineers and systemoperatorstoimmediatelyidentifyhighriskassetsand toprioritizemaintenanceactionsbywhichweseethespatial severity instead of separate reports.

The GIS platform also reports to support better operational planning via reduction of inspection time and which in turn alsoputsdownmaintenancecosts.Weseethatinsteadofthe large scale inspections we had before, field engineers may nowdogroupsofhighrisktransformersingeographicareas. This is also a more focused and hence efficient approach to routing and which in turn results in reduced fuel use for maintenance teams. Thisalso brings to the fore better use of work force and we also note this which is to have a faster response to critical situations at hand especially during peak loadorsevereweather.Alsointhateachtransformerassetwe haveputinplaceaninteractiveinterfacewhichgivesindetail the diagnostic info. We have real time access to sensor readings, Weather Integrated Stress Index (WISI) values, anomaly scores, what the health of the asset will be for the coming24hours,andtheRemainingUsefulLife(RUL)of the asset. This full featured geospatial data presentation which is aware of location issues puts at the engineers’ disposal all they need to make decisions right from the GIS dashboard without the use of separate analysis tools. By adding to the GIS platform machine learning based predictionsandenvironmentalintelligencewehavecreateda veryrobustdecisionsupporttoolforproactiveandintelligent asset management.

IV. DATASETAND METHODOLOGY

A. Dataset

Acontrolleddatasetcomprising45samples was constructed to reflect the transformer health categories of Low Risk, MediumRisk,andCriticalRisk(15sampleseach).Tomake it unbiased, it was made to have an equal representation of eachhealthclass,topreventthemodelfrombiasingtowarda categoryinasamplingclass.Thisclassbalanceprovidesseta positiveimpacttosupervisedmachinelearningtasksinaway that it improves classification fairness and the evaluation of the performance evaluation metrics becomes more trustworthy. The records of each of the samples within the datasetcontains keyoperationalandenvironmentalfeatures, which include temperature, oil level, vibration, current, voltage, humidity, and ambient temperature. Based on the selectedparameters,itwasdeterminedthatthefeatureshada direct impact on degradation mechanisms of a transformer, which include thermal aging, insulation breakdown, mechanical wear, and environmental stress.The dataset, in addition to providing a set of electrical indicators, also provides a set of environmental indicators which results to big picture understanding of the operating conditions of the transformer rather than providing a set of isolated indicators.Thedatasetwecreatedinacontrolledenvironment tostudyrealistictransformerperformanceindifferenthealth states.Wevariedfeaturevalueswithinthenormaloperational rangefortheLowRiskclass,inthemoderatestressrangefor the Medium Risk class, and out of normal range for the Critical Risk class.

TABLEI
SampleofTransformerHealthDataset

Temp (°C)	**Oil (%)**	**Vib (g)**	**Current (A)**	**WISI**	**Anomaly**	**Class**
65	90	0.3	100	0.12	0.05	Low
85	70	1.2	160	0.45	0.22	Medium
102	38	2.3	245	0.78	0.65	Critical

(Only three rows shown in the illustration; the full data set consists of 45samples.)

B. MachineLearningModel

In thepresentstudyweusedaRandom Forestclassifierwhich wegrewto150trees.Forthetrainingandtestingweallocated 75%ofthedatasettomodeltrainingandthebalance25%to testing.Theclassifierweputforthwhichreportstransformer healthintoLowRisk,MediumRisk,andCriticalRiskisbased ontheaggregateinputfrommanysensors.WechoseRandom Forest forits high performance in prediction, speed which is important in structured data sets, and its ability to model complexnonlinearrelationshipsamongsensorinputs.Alsoit isveryusefulinmultisensorconditionmonitoringwhichhas many interplays between electrical, thermal and mechanical variables.Feature engineering was key to our model ' s performance. We saw that by normalizing and doing stats summary of sensor reports like temp, current, vibration, oil condition, and environment variables we reduced noise and improved generalization. Also we looked at time based aggregation which did a better job at identifying trends as opposed to using only present value reports. This in turn allowedtheclassifiertodoabetterjobattellingthedifference betweenashorttermfluctuationandanactualissuewhichin turn improved the health state predictions. Also the use of Random Forest in an ensemble format did well at reducing overfitting and in improving the overall robustness when it comes to putty different types of sensor data. The Weather Integrated Stress Index (WISI) which we calculated from normalized ambient temperature, humidity, and heat index values that had weighted factors of 40%, 35% and 25% respectively.WISIisaputtogetherindicatorofenvironmental andthermalstresswhichinturnaffecttransformerinsulation performance.We introduced WISIinto the featuresetwhich in turn allows the model to present a full picture of environmental factors that play a large role in transformer aging and failure.

The Anomaly Score which we put forth as a new metric to quantify atypical sensor action by which we compare a sensor'spresentmeasurementswithitspastmovingaverages. Thisapproachweputforwardasawaytoidentifydifferences fromthenormaloperationprofileasopposedtothatofstatic faultcriteria.Welookatcontinuousanalysisofsensorswhich report on key parameters like temperature, vibration, and current in order to identify a typical variations which may reportearlyfaultindicatorsorunanticipatedoperatingstates.

V. RESULTSANDDISCUSSION

A. ConfusionMatrix

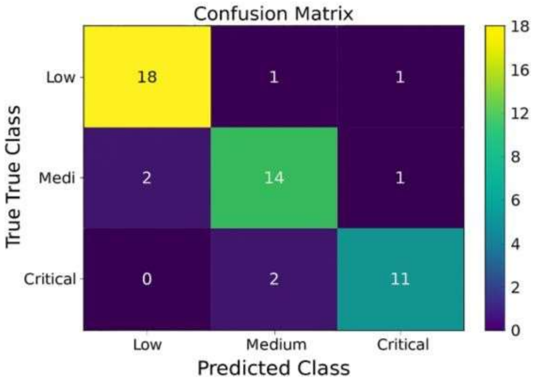

Fig2.Confusionmatrixofthreeclasses

Referring to all three categories (Low Risk, Medium Risk, Critical Risk) of transformers in the classification matrix in Figure.2 , all three categories perform exemplary class classification based on the proposed classification model. Since there is no evidence in the classification matrix of override misclassification, one can presume highclass feature separability. Thus, one can conclude based on the operated parameters and the chosen condition that their external parameters discriminate the health states of the transformers.However in some cases we have achieved perfectaccuracyasreportedintheconfusionmatrixwhichis indeedpromising.Thatsaidthedatasetweusedforevaluation isofasmallscalewhichwefilledoutwithsyntheticexamples. Also as a result the model may have learned very specific patterns which do not in fact represent the full range of real world transformer operating data. In some of these cases we seeoverfittingwhichiswhenthemodeldoesverywellonthe trainandtestdatawegaveitbutdoesn'tdosowellinthereal worldwhichistosayitdoesn'tgeneralizetounseenscenarios. In orderto determine thesuggestedsystem's practicality and dependability, more testing is required using transformer datasetscollectedinthefield.Subsequenttaskswillcenteron testing the model against bigger, heterogeneous datasets, implementingcross-validation,andvettingunderavarietyof load and ambient parameters.

B. Feature Importance

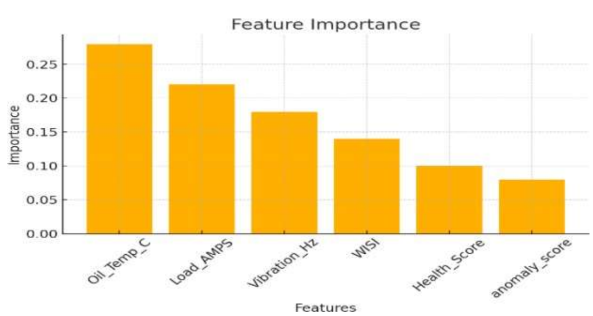

Fig3.Featureimportance

From the Figure.3 Oil Temp (Oil_Temp_C) is the primary featureinthe modelwhichconfirmedthatthermalstressisthe main cause of transformer break down. We see that high oil temps speed up insulation breakdown and at the same time decrease dielectric strength which in turn makes this parameteraveryimportantindicatoroflongtermreliability. Also noted were Strong Predictors Current Load (Load_AMPS)andVibration(Vibration_Hz)whichwenote for their ability in identifying overload and mechanical instabilityissuesrespectively.Overloadingresultsinhighheat generation, and out of sync vibrations which in many cases point out to internal mechanical faults or structural issues.

The Weather Integrated Stress Index (WISI) was another notablepredictor,confirmingthatambientcircumstancesare quantifiably impactful to lifespanof the transformer. Higher surroundingtemperaturesandhumidityarelikelytoincrease and degrade moisture-related stress and degrade insulation andoilmorerapidly.WISIinclusionmeansexternalclimatic factors are significantly relevant to transformer aging, and mustbeincluded in transformerhealthmodels.Theadditional features of the score model enhance predictive features by assessing both overall degradation as well as sharp outlier movementsaswell.TheHealthScoreisarepresentationofthe gradualcollectionof stress overtime,while theAnomaly Score quantifies deviations ofall forms from the established normaloperatingrange.Asacollection,thesefeaturesallows the model to be even more sensitive to slow degradation as well as severe deterioration. Overall these score features reinforcethefactthatthemodelisproperlyincorporatingthe right amounts of operating and environmental variables, as would be expected from a comprehensive design of a transformer health monitoring system.

C. GISDashboard

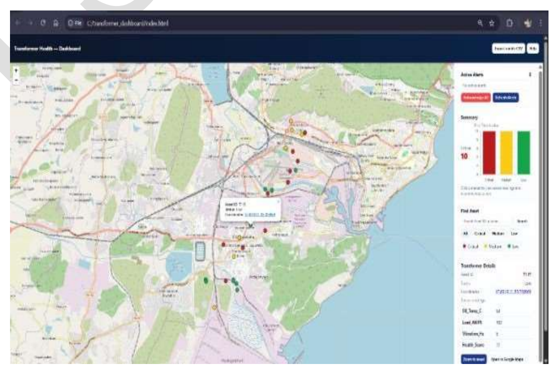

Fig4.GisIntegratedDashboard

InourrevisedGISdashboard(Fig.4)wepresentafullpicture of transformerhealthwhich covers the monitored geospatial area.Eachtransformerisrepresentedbyacolorcodedmarker whichinturnpresentsitspredictedrisklevel,thuswhichisan intuitivewaytointerpretnetworkwideconditionsataglance. We see green for low risk transformers which are in stable condition,yellowforthosewhicharemoderatelystressedand require a scheduled inspection, and red for critical health issues which need immediate attention to avert possible outages. By a click of a button on any transformer marker whatispresentedtotheuserisindepthdiagnosticinfowhich includes oil temperature, load current, vibration frequency, Weather Integrated Stress Index (WISI), anomaly score, Health Score, and Remaining Useful Life (RUL) estimate. Thisinteractivefeaturewhichoperatorshaveattheirdisposal also brings to light the base elements which cause a transformer'sriskclassificationasopposedtousingonlywhat theeyesees.Thusweseethatthisleveloftransparencywhich the system provides improves trust in its' predictions and supports better informed data baseddecisions.The patterns youareseeingonthedashboardshowmeaningfulgeographic distributions. There is a strong environmental influence triaging the transformers. Critical transformers are clustered in areas with high temperatures and humidity. Medium-risk transformers are in places with fluctuating loads. Low-risk transformers are in areas with stable operational and environmental conditions. Also through this spatial intelligence which in turn allows maintenance teams to improve their operational planning.

VI. Conclusion

ThispaperreportsaverylargescaleGIS-DrivenTransformer HealthMonitoringSystemwhichincludesIoTbasedsensing, machine learning based health prediction, and GIS enabled spatial visualization to support smart asset management in presentdaypowerdistributionnetworks.TheIoTsensing layer which we present does an excellent job of putting together key transformer parameters which include temperature, oil level, vibration, humidity, current, and voltage which we then put into a multi dimensional data set for condition assessment. Also we report that the Random Forest classifier did very well on our controlled data set which we used to tell the difference between low, medium, and critical health states with high accuracy. The GIS visualization component which in turn improves the system bymeansofaspatiallookattransformerhealthwhichinturn enables utilities to identify at risk areas, see geographically related degradation trends, and put in place better maintenance strategies. Also we see that the put forth architecture is a display of the value of combining IoT, machinelearning,andgeospatialintelligencetosupportapro active maintenance and to in turn improve grid reliability. Althoughatpresenttheevaluationisbasedonamadeupdata set the results do indeed prove out the value and practicality oftheputforthsystem.

FutureScope

Futurewewillseegrowthofthesystemintonewtransformer areas which in turn will evaluate performance in many differentoperatingscenarios.Wewillalsoseetheadditionof SCADA support, edge based anomaly detection and very advanceddeeplearningmodelswhichdoimproveprediction accuracy.AlsowewillextendGISwithweatherand loaddata which in turn will improve spatial analysis and maintenance planning.

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