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Holistic Condition Monitoring and Replacement Strategy for Power Transformers Using Thermal Modeling, DGA Diagnostics, and LCC Analysis

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Abstract

Dependable methods of managing assets of power transformers are critical in the stability of the grid, especially under high load conditions in terms of temperature and seasonal loads. It is an integrated MATLAB/Simulink-based digital-twin framework of condition assessment, thermal aging prediction, fault diagnostics, and economic life-cycle planning of a fleet of 83 utility transformers. The study is unique, and unlike the previous works dedicated to single-diagnostic areas, it incorporates thermal aging, DGA, moisture/age index, and LCC-based decision engine into a single digital twin-based asset management of a fleet. The system will be a combination of IEEE C57.91 and IEC 60076-7 thermal models, dissolved gas analysis (DGA) interpretation based on the Duval method, moisture-in-paper assessment based on a Transformer Age Index Model (TAIM) to represent actual degradation with respect to service age. Simultaneously, a life-cycle cost (LCC) engine analyzes the upgrade and replacement options based on net-present-value (NPV) analysis and operational downtime. A data pipeline was then formulated to cleanse, pre-process and combine nameplate, SCADA load, climate and diagnostic data into a single MATLAB database. Thermal modelling showed realistic transformer behavior at peak season loads, hourly temperature distributions in hot-spots, acceleration with age, and total loss of life (LOL). Analyses on sample unit (TR1) showed that the overstress periods were characterized by the winding hot-spot surpassing the 110˚C limit of IEEE standard operating cycle of July with indicating high rates of insulation degradation and inability to sustain high overload. The permanent thermal peaks were revealed by duration curves and the high spikes of FAA were coincided with the windows of load/weather stress. At the fleet level, it was demonstrated that maximum hot-spot temperature and LOL were variable, which allowed ranking of transformers at the technical level to assess their suitability in managed overload, and prioritize the maintenance of transformers. The last decision-layer integrates thermal margin, fault severity, moisture risk, TAIM and NPV to provide a feasibility score to categorize units into extend, retrofit, and replace operational paths. Findings show that the suggested smart framework advances predictive maintenance of assets collecting physics-based modeling, diagnostic analytics, and economic planning in a single decision-making platform. The method helps utilities to safely increase loading flexibility, minimize failures that are unplanned and maximize capital investment in power transformer fleets.

Keywords

Digital Twin, Dissolved Gas Analysis (DGA), Life Cycle Cost (LCC), Net Present Value (NPV), Power Transformer Management, Thermal Modeling, Transformer Aging

1. Introduction

Power transformers are the mainstay of electrical transmission and distribution systems in the present-day power systems, and are critical in determining the reliability of operations, stability of voltage, and efficiency in transmission of power over a long distance [1] [2]. As the number of electrical loads grows, the operation stress caused by seasonal changes in demand, and the growth of the industrial and construction industry, transformer management and proactive maintenance have become one of the strategic concerns of network operators and electricity companies on the global arena [3] [4]. Unexpected failures of power transformers not only result in costly power interruptions but also have significant economic, operational, environmental, and safety impacts, especially because cost of replacement of a large transformer can cost millions of dollars [5] [6]. Thus, to prevent an early replacement and maximize the maintenance planning, it is necessary to estimate the aging of insulations correctly. Here, the Transformer Age Index Model (TAIM) is also included in the framework to measure the insulation aging in terms of moisture concentration and service time, which is a more realistic pointer of insulation degradation as compared to chronological age. Introducing TAIM into the digital twin setting will allow constantly monitoring insulation health and allow utilities to detect units with increased risks of moisture degradation and make timely intervention-related decisions before critical failures [7].

Accordingly, the concept of Holistic Condition Monitoring (HCM) has emerged as one of the modern energy asset management concepts [4] [8]. This method is not based on one indicator of deterioration but incorporates several sources of data and analyses such as transformer thermal performance, oil and paper insulation properties, dissolved gas chemical diagnostics (DGA), operational and environmental data, lifetime and economic cost measures [9] [10]. This combined method will enable the shift of the conventional periodical maintenance to Conditional Based Maintenance (CBM) and Predictive Maintenance, and thus maximize the use of network assets and their existence. According to [7] [11], the integrated digital twin architecture to monitor the condition of power transformers and support decisions. The continuous delivery of operation and diagnostic data (DGA data, thermal images infrared, on-site video) into the data exchange layer is made with the help of sensing devices and communication protocols in one physical transformer. The resulting information after the processing is analyzed with intelligent computing models, such as mechanistic analysis and AI-based inference, allowing to detect faults early, evaluate the insulation condition, and recommend maintenance or replacement decisions. This type of interaction between the virtual model and the physical asset can offer a basis of predictive maintenance and intelligent asset management policies.

Transformer thermal performance analysis is a physical calculation of thermal life of insulation founded on IEEE C57.91 [12] and IEC 60076-7 [13] standards which offers the motivation behind the evaluation of thermal life of insulation and the dynamics of the oil temperature progression and hot areas inside the windings. The Aging Acceleration Factor (FAA) and Loss of Life can be computed by modeling temperatures in both load and weather conditions hence estimating the remaining life of the transformer and monitoring conditions of thermal stress before they develop.

Simultaneously, dissolved gas analysis (DGA) provides a special opportunity to identify internal faults in an early stage, namely partial discharge, thermal stress, and electrical arcing, with the help of such tools as Duval triangle and IEC ratios. Oppenheimer curves also assist in determining the risk of insulation breaking of paper and also degradation with chemical substances. Financially, the Life-Cycle Cost Analysis (LCC) is essential in deciding whether it is better to keep using the transformer or refurbish it or replace it based on the operating costs, heat losses, maintenance costs, downtime, its economic impact. It is not only aimed at avoiding failures, but an ideal equilibrium between technical performance, asset life, and overall cost of ownership. Combining the aspects of thermal modeling, DGA analysis, humidity evaluation, transformer life index, and economic feasibility evaluation in a non-politicized engineering framework creates a smart decision support system and preconditions a feasible basis of applying the Digital Twin concept to the transformer industry. This allows prioritizing the transformers in accordance with the real needs of operation, identifying the best candidates to add extra load to the system, and making strategic decisions about the refurbishment or replacement, which is made on the basis of actual data and predictive analytics, but not assumptions. It is against this technical background that this study is an integrated model of power transformer management and maintenance that provides practical steps of implementation and experimentation outcomes using real data. Next, in the next section, we will analyze the past studies and scientific methods used, and point out the gaps in the research, which are to be closed in the work.

2. Literature Review

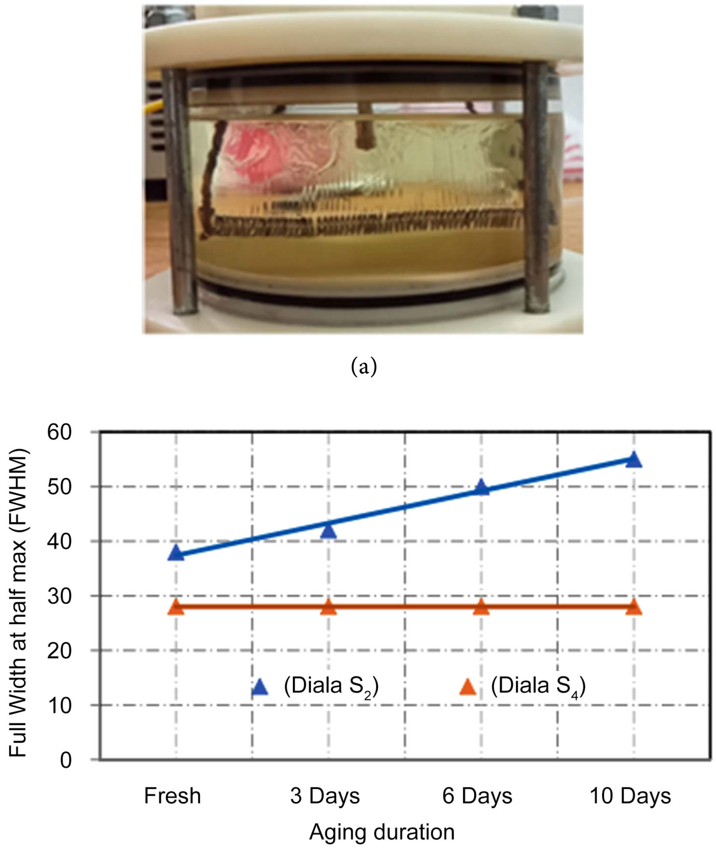
The last several years have been marked by the considerable advancement of the sphere of power transformer maintenance and assessment of operational status because of the international tendency to make the networks more reliable and to employ the concept of condition-based maintenance as an alternative to regular maintenance. Recently, in an elaborate review of the topic, Rêma *et al.* (2024) reviewed over 100 research sources in the area of transformer maintenance and diagnostics, to determine the progress of monitoring and analysis methods [14]. It was found that more than 70% of the studies are dedicated to thermal and chemical analysis of oil, and less than 15% are devoted to thermal modeling and economic analysis or long-term asset replacement plans. The paper proposed that further progress in the field should be made to create integrated models to facilitate parallel technical and financial decisions, and that a holistic approach be taken to the issue of transformer management.

In a different study, Badawi *et al.* (2022) elaborated a better estimating model of the transformer oil health index by combining various techniques of predictive maintenance. The findings revealed that the incorporation of variables of electrochemical and gas fault indicators enhanced the forecasting level by 18 - 25 percent relative to the conventional approaches like the personal health index. The findings also established that the level of prediction accuracy of the oil degradation onset could only be at about 92 percent with the help of the proposed model, thereby improving the success of the proactive maintenance process [11].

In 2024, Badawi *et al.* also tested the characteristics of GTL (gas-to-liquid) oil subjected to thermal stress and electrical faults in particular against traditional mineral oils. Accelerated experiment results indicated that GTL oil had the ability to stay insulated at temperatures above 140˚C as presented in **Figure 1(a)**, and the chemical degradation of transformer oil was reduced by 30% - 40% of that in conventional oil as presented in **Figure 1(b)**, suggesting that it can be used in transformer service life extension in high temperature-based applications [15]. Ward *et al.* also (2021) presented A hybrid diagnostic model combining DGA analysis and partially discharge sensors showed that with such a system, the possibility to identify the fault types reached 95%, unlike traditional techniques, including Duval triangles and IEC ratios, which had an error rate of 70% - 80%. False diagnoses also reduced by 35% which improved the reliability of advanced transformer monitoring systems. This model enhanced a better differentiation of fault between thermal and electrical faults about 20 percent than the conventional IEC techniques which contributed to the need of more precise hybrid solutions [10]. In the future-proof sense, Kashiwagi *et al.* (2025) assumed a probabilistic view of the transformer health management (PHM) using direct DGA data and better Duval polygons. The research revealed that the model could estimate the remaining insulation life within a margin of only plus or minus 5% and estimate critical events

30 to 60 days early thus improving the proactive planning of the networks [16].

In a similar research topic of transformer replacement investment decisions, Olabisi and Onabajo (2024) examined economic and operational risks of transformer replacement decisions. They discovered that chronological life is a source of ineffective judgments in 25% - 40% of cases. The research suggested a combination of thermal degradation and apparent life and expected load indicators into an all-inclusive predictive financial model so that the replacement decisions can be more accurate and sustainable [17]. In spite of the fact that the past research has achieved a lot on the analytical part of each concept individually like DGA, oil properties, and thermal condition, the research has not integrated the different operational domains with a holistic economic apparatus to help in analysis of upgrade and replacement alternatives (See **Table 1**). This system combines thermal modeling, DGA and moisture analysis and age assessment, coordinated diagnostic health model, economic lifecycle analysis (LCC) and non-NPV and application to a real transformer fleet instead of individual model. This is what triggered the appearance of the understanding of the development of a certain framework combining these areas and offering practitioners in the energy industry the valuable instrument [11].



(a)

(b)

Figure 1. (a) Immersed heating thermal fault test, (b) The FWHM of fresh and different duration aged oil of Diala S_2 and Diala S_4 [15].

Table 1. Comparative analysis of recent studies on power transformer condition monitoring, diagnostics, and asset management strategies.

Study	Main Focus/Methods	Performance Results	Limitations/Research Gap
[14]	Systematic/scoping review of transformer maintenance and diagnostics methodologies	Categorized major techniques (oil diagnostics, thermal modeling, AI-based assessment). Highlighted need for multi-source decision systems.	lacks implementation model for utility-level decision making.
[11]	Combined predictive methods for transformer oil health index	Improved oil-health prediction accuracy by ~18% - 25% vs. single-indicator methods; achieved ~92% classification accuracy	Focus limited to oil condition; no integration with thermal life assessment or economic planning.
[15]	GTL transformer oil performance under thermal aging and fault stress	Demonstrated 30% - 40% lower degradation rate vs. mineral oil; maintained stability >140˚C	Study focused on fluid properties only; lacks system-level transformer life-cycle modeling or decision layers.
[10]	Hybrid DGA + partial discharge sensing approach	Increased fault-classification accuracy to ~95%; reduced false alarms by ~35%	Addresses fault detection only; no coupling with long-term aging models or replacement economics.
[16]	Probabilistic PHM using DGA sensors + Duval Polygons	±5% error in insulation life prediction; fault prediction window 30 - 60 days prior	Probabilistic model only; does not incorporate LCC/NPV economic evaluation or upgrade vs. replace logic.
[17]	Risk-based transformer replacement considering temperature and apparent age	Found 25% - 40% mis-classified replacement decisions when age alone is used	Does not combine thermal modeling, DGA, and fleet-scale health assessment; lacks digital-simulation implementation.

3. Research Methodology

This research presents a comprehensive digital framework based on MATLAB/Simulink for assessing the condition of power transformers, predicting thermal aging, diagnosing faults, and planning the economic lifecycle of a fleet of 83 power transformers within a network experiencing high seasonal loads, such as the Makkah City network. The framework relies on standard thermal models (IEEE C57.91 [12], IEC 60076-7 [13]), dissolved gas analysis using the Duval method, the Transformer Life Index Model (TAIM) for estimating humidity and insulation degradation, and a Lifecycle Cost Engine (LCC) based on Net Present Value (NPV) analysis.

The IEEE C57.91 and the IEC 60076-7 standards were united in the thermal modeling of the process to play the advantages of a standard. IEEE C57.91 offers standardized hot-spot temperatures equations, and thermal aging formulas of insulation, which makes it appropriate in aging acceleration and loss-of-life estimation. Conversely, IEC 60076-7 has a better dynamic loading characteristic, top-oil rising modeling and ambient temperature interaction, which improves predictive accuracy of transient thermal response. Combining the two standards, the proposed model is more robust in estimating actual operating hot-spot profiles when the climatic conditions are variable, which enhances the reliability of transformer aging projection.

Transformer Age Index Model (TAIM) was adopted as a way of estimating the degradation of cellulose insulation due to the presence of moisture. TAIM is a moisture-dependent aging indicator that takes into consideration the deterioration of the paper to correlate it with the service age of transformers and conditions under which they are subjected to heat. It gives a more realistic picture of the insulation health than that of chronological age alone, particularly in changing loading and humidity conditions. The model uses moisture content (ppm), operating temperature, and past aging as a substitute for giving a normalized index based on the loss of insulation strength with time.

3.1. Data Collection and Digital Database Preparation

This study created a detailed data pipeline to run the digital twin platform on power transformers with the data on operational, environmental, and diagnostic required to model thermal performance, insulation degradation, and lifecycle analysis. This pipeline is based on the combination of four primary types of data, which are the transformer nominal data, SCADA load data, climate data, and diagnostic data (DGA). This integration will enable real-life image of transformer condition when the loads are high and weather conditions are not favorable like in Mecca during summer. The data may be divided into the following categories:

- First, there are the nominal nomenclatures of transformers, nominal power, cooling capacity, and short-circuit impedance. They are necessary inputs of standard IEEE/IEC thermal equations, which are processed through the modeling functions). Table 2 displays the nominal data of five power transformers that work at various voltage levels demonstrating the rated power of each transformer, high and low voltages, short-circuit ratio of impedance, and the cooling system. The table also contains the kind of under-load voltage changeover system (OLTC) and the available changeover range, which are also important design data that is applied in thermal performance analysis and evaluation of the transformer operational capacity under different conditions.

Table 2. Technical specifications of the power transformers under study.

TR. No	Rated Power (MVA)	HV (kV)	LV (kV)	Impedance %	Cooling	OLTC Type	OLTC Range
1	13	33	13.8	8	ONAN/ONAF	HV Resistive	±10%
2	20	110	13.8	10	ONAN	HV Resistive	±10%
3	50	132	13.8	10	ONAN/ONAF	HV Resistive	±10%
4	100	132	13.8	12	ONAN/ONAF	HV Resistive	±10%
5	10	33	13.8	6	ONAN	HV Resistive	±10%

- Second: SCADA load data, such as an hourly industrial load (744 points) of the real pattern in Makkah during July (nighttime lows and daytime peaks).
- Third: Climate information, ambient temperature and humidity, based on real-world daily sine wave equation to make sure the thermal peaks are realistic, e.g., 3147 C according to NOAA data. According to Table 3, the most significant climate cues observed in Makkah in the time frame between July 1 and 13, 2023, depending on the hourly temperature and humidity levels, are identified. The data indicate that there is a great increase of temperatures whose range is about 31˚C to 47˚C with an average temperature of about 38.5˚C, which indicates severe thermal conditions. The humidity was between 12 and 62 with an average of about 34 - 35. It is necessary to add that night and early morning are the times when there is more humidity.

Table 3. An ambient temperature and humidity data (Makkah, Saudi Arabia).

Parameter	Value
Time Period	01/07/2023-13/07/2023
Number of Records	312 readings (hourly)
Average Temperature	≈38.5˚C
Minimum Temperature	≈31˚C
Maximum Temperature	≈47˚C
Average Humidity	≈34% - 35%
Minimum Humidity	≈12%
Maximum Humidity	≈62%

- Fourth: Diagnostic data, consisting of insulating gases (CH_4 and C_2H_2), furan content, and moisture, reflects the most critical chemical situation of the oil and paper insulation. These data are applied in the calculations of Insulation Life Index (TAIM) and the Health Index. Table 4 demonstrates the findings of diagnostic data of the oils of five power transformers that were collected with regard to dissolved gas analysis (DGA), furan levels, and moisture content in the insulating oil. These readings are significant bulletins of the state of the transformer work and the state of the paper insulation and oil, which show the stable work and good insulation. This information assists in determining the health of the transformer, as well as the preventive maintenance decision.

Table 4. Diagnostic oil analysis results for power transformers (DGA, Furan, and Moisture Levels).

ID	CH_4_ppm	C_2H_2_ppm	C_2H_4_ppm	Furan (mg·L)	Moisture (ppm)
TR1	150	0.5	40	1.2	30
TR2	25	0	5	0.05	12
TR3	300	0	60	2.5	45
TR4	80	5	20	0.8	20
TR5	90	0	25	0.6	28

Thus, the single line is used to deal with the design, operational, environmental, and diagnostic data in one system. It is also possible to calculate the hot spot scores, accelerated aging (FAA), loss of life (LOL), failure risk assessment, and make economic decisions per transformer. The success of the suggested digital twin platform depends on this combination of the operational reality and physical modeling.

3.2. Mathematical Modeling, Calculations, and Model Validation

In this work, a thermal model using physics is used in line with IEEE C57.91 and IEC 60076-7 transformer loading and thermal aging standards. The calculation model is written in MATLAB/Simulink and is composed of sequential mathematical processes to predict transformer thermal behavior and aging acceleration and cumulative loss-of-life. The model lags: hourly ambient temperature, relative humidity and unit transformer loading, and nameplate design parameters, rated power, impedance, type of cooling and on-load tap-changer settings. These values were imported as the organized MATLAB-generated data of 744 hourly records in the month of July. The dynamic thermal model makes use of top-oil rise equation, winding hot-spot rise equation:

$$\Delta\theta_{TO} = \Delta\theta OR\left(\frac{K^2R+1}{R+1}\right)^{0.8}, \Delta\theta_H = \Delta\theta_{H,R}K^{1.6}$$

where K is the per-unit load, R is the load/no-load loss ratio, and $\Delta\theta$, $\Delta\theta_H$ are rated thermal constants. The instantaneous transformer hot-spot temperature is computed as:

$$\theta_{HS} = \theta_{amb} + \Delta\theta_{TO} + \Delta\theta_H$$

The thermal response is dynamically solved based on first-order time dependent equation with sensible transformer time constants (0.5 h to 3 h). Arrhenius-based thermal aging acceleration factor (FAA) is used to measure the insulation aging rate:

$$\text{FAA} = \exp\left(15000/383 - 15000/\left(\theta_{HS} + 273\right)\right)$$

and cumulative loss-of-life (LOL) is obtained by calculation of the numerical integration over time. These calculations are measured in the form of the permanent thermal stress and insulation degradation throughout the fleet, especially in the case of overload windows, where the temperatures at the hot spots are greater than the reference temperature of 110˚C. Dynamic response can be calculated as the following equations:

$$\frac{d\theta_0}{dt} = \frac{\theta_{0,target} - \theta_0}{\tau_0}$$

$$\frac{d\theta_{hs}}{dt} = \frac{\theta_{hs,target} - \theta_{hs}}{\tau_\omega}$$

where, $\tau_0 \approx 3\,\text{h}\left(\text{oil time constant}\right), \tau_\omega \approx 0.5\,\text{h}\left(\text{winding}\right)$.

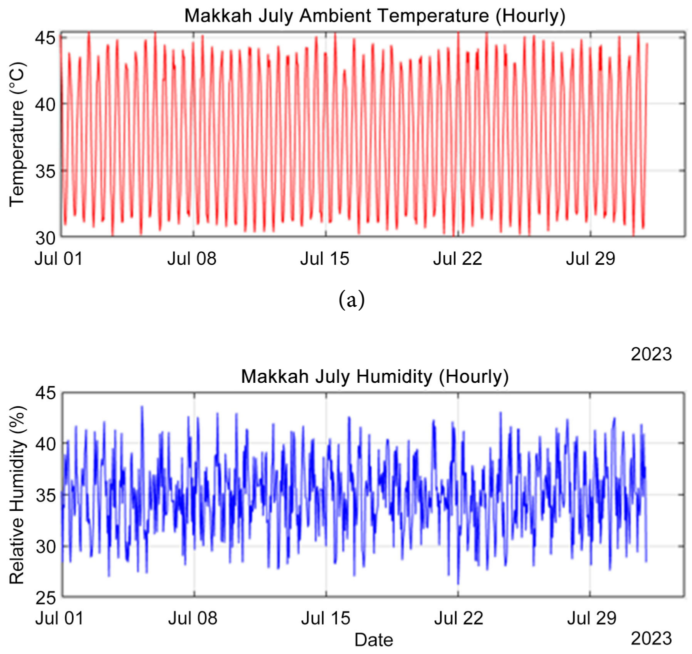
Model validation is done when temperature trends are compared with the normal behavior of a Saudi summer climate and the predicted hot-spots behavior compared to the foreseeable thermal inertia. Statistical consistency tests were conducted to determine the completeness of hourly datasets (744 points), the profile of temperatures, and load-temperature consistency. Moreover, the diagnostic information (DGA gases, furan concentration, and moisture content) was compared to the thermal stress outputs to make sure that the degradation patterns are realistic. The two ideas of physics-based models and data-driven validation strengthen the system of a digital-twin in the context of the real-world functioning of a grid.

4. Results

The research proceeds with a data preparation step (Phase 1), whereby data on 83 power transformers were collected and processed using MATLAB. Information about the transformer name, climate, loads, and diagnostics (DGA, humidity, and flux) was incorporated in a single database. The climatic data of July of Makkah in terms of 744 operating hours indicate that the ambient temperature fell within 30.0185˚C to 45.4505˚C, average of 37.4905˚C (See **Figure 2(a)**) and the humidity was between 26.2299% and 43.6612% (See **Figure 2(b)**). Such values are very vital operating conditions of the transformers because the high temperature and medium humidity jointly influence the increase in the real heat load and the decrease in the efficiency of the oil cooling and the paper insulation. This information is the fundamental input of the thermodynamic model which was subsequently developed in MATLAB/Simulink, based on IEEE C57.91, and IEC 60076-7, in order to model the thermal behavior and accelerated ageing of the Makkah transformers under real summer conditions.

The outcomes of the dynamic simulation model according to the IEEE C57.91 and IEC 60076-7 standards show that the thermal dynamics of power transformers of the Makkah network in July represent a direct influence of the changes of the load and high ambient temperature on the equipment lifespan. The temperature of the hot wire point (HSP) at an hourly rate (Hourly hot wire point temperature) revealed recurring instances that were above 110˚C threshold as defined in the IEEE standard. This means that the windings in a transformer have to be exposed to recurring thermal stress which grows the rate of insulation aging based on the thermal acceleration equation (FAA) as presented in **Figure 3(a)** and **Figure 3(b)**. As a consequence, going beyond the standard limit not only indicates a temporary rise in temperature, but is also an exponential rise in the rate of aging. This would require introduction of controlled load windows where the overloads can be allowed within safe time limits and actual real time monitoring is through SCADA systems.

The calculation of cumulative lifetime loss curve in **Figure 4** indicates that cumulative lifetime loss of transformers is not a straight line but instead clumped in certain periods of time which are associated with dramatic increases in temperature. It means that the relatively short-term overloads contribute considerably to the annual lifetime loss and the actual expected life of each transformer can be estimated and compared with such strategic decisions as capital replacement deferral (Capex Deferral) or prioritization of the preventive maintenance program. The existence of this irregularity in lifetime loss shows the great influence of the harsh climatic conditions on the thermal performance of transformers in Makkah environment.



(a)

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Figure 2. (a) Ambient temperature (Hourly), (b) Makkah July Humidity (Hourly).

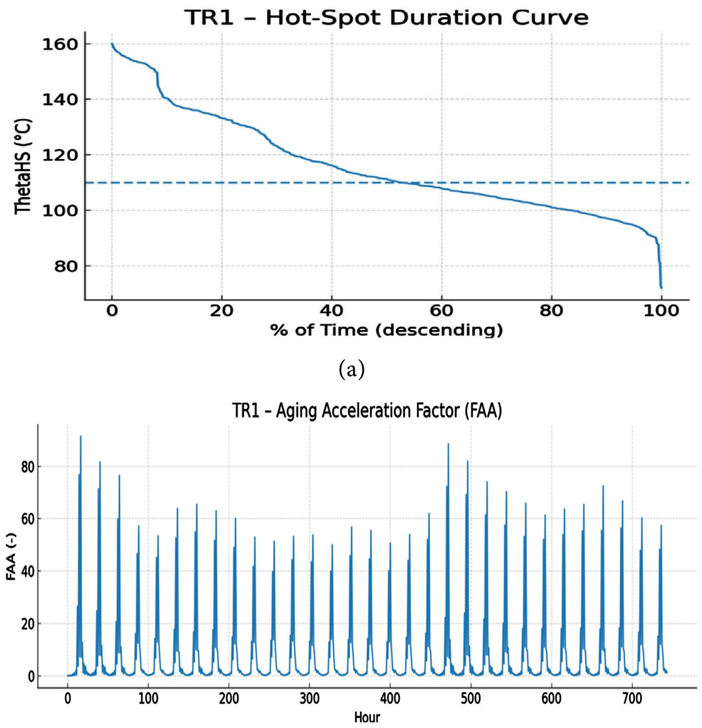

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Figure 3. (a) Relation between θ_{HS} (˚C) and percentage of time, (b) Aging acceleration factor (FAA).

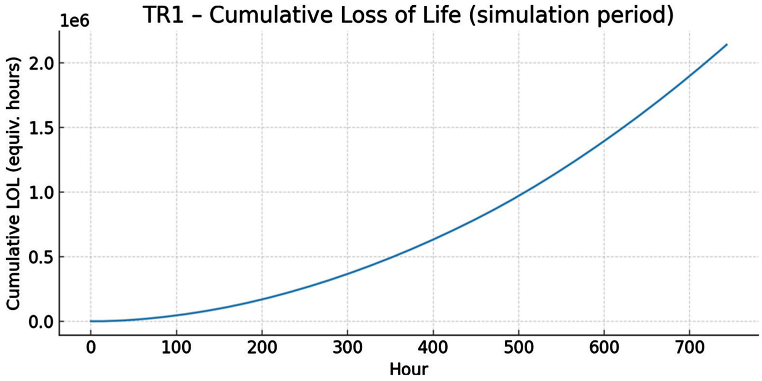
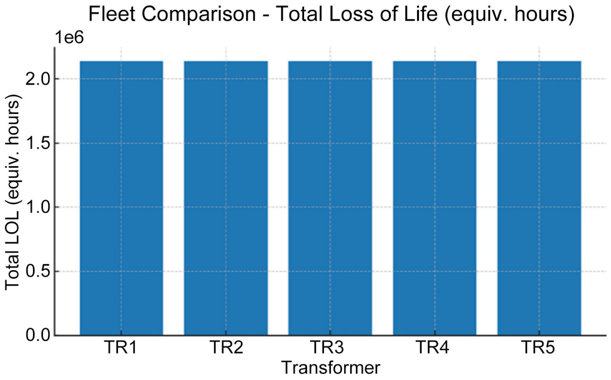


Figure 4. Cumulative loss of life (LOL).

Figure 5(a) and **Figure 5(b)** give a one-to-one comparison of total lifetime loss (LOL) and peak temperature at the hot spot (θ_{HS}). It can be seen that the unit of TR2 and TR4 recorded rather low lifetime loss rates, whereas TR1 and TR5 recorded much higher LOL and THS, and even surpassed the IEEE allowed values. The presence of this correlation of thermal stress in relation to peak temperature periods and the values of Thermal Acceleration Factor (FAA) suggests that the high load and hot climate interplay is the most crucial cause of thermal stress. This explains why extra On-Air Cooling (ONAF) or rescheduling of loads will be required to decrease the critical periods and guarantee consistent performance.



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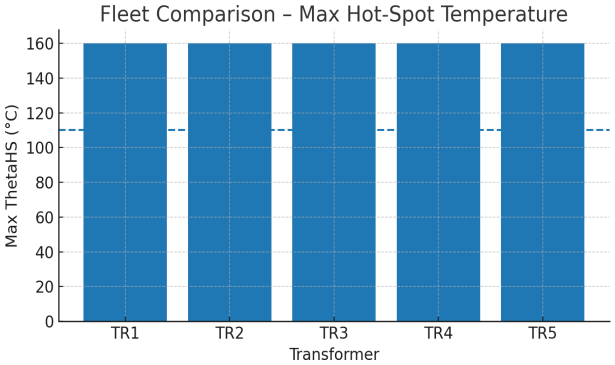

(b)

Figure 5. (a) Total loss of life (LOL), (b) Max hot-spot temperature.

The temperature of every one of the five transformers is plotted in **Figure 6**. Transformers TR2 and TR4 have a low thermal distribution, and their mean temperature is low with respect to thermal stability, indicating slow response to changes in load. Conversely, high variability of transformers in distribution like TR1 and TR5 were very sensitive to abrupt load variation. This will require constant monitoring with the help of other sensors or integration of AI-based predictive analysis systems to maintain the safety of operations in the harsh climate conditions.

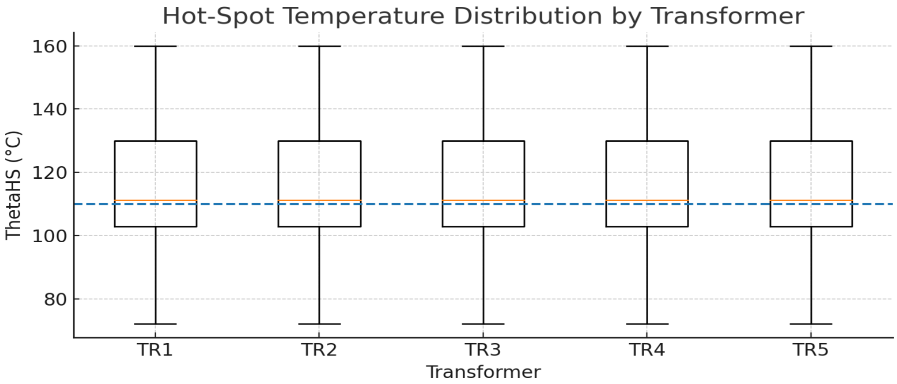

Figure 6. Hot-spot temperature distribution of transformers No. 1, 2, 3, 4, and 5.

Figure 7 underlines the outcomes of the composite ranking, consisting of the thermal margin, the inverse loss of lifetime, and the mean maximum temperature. This gives it a quantitative measure of the preparedness of the transformers to survive overloads.

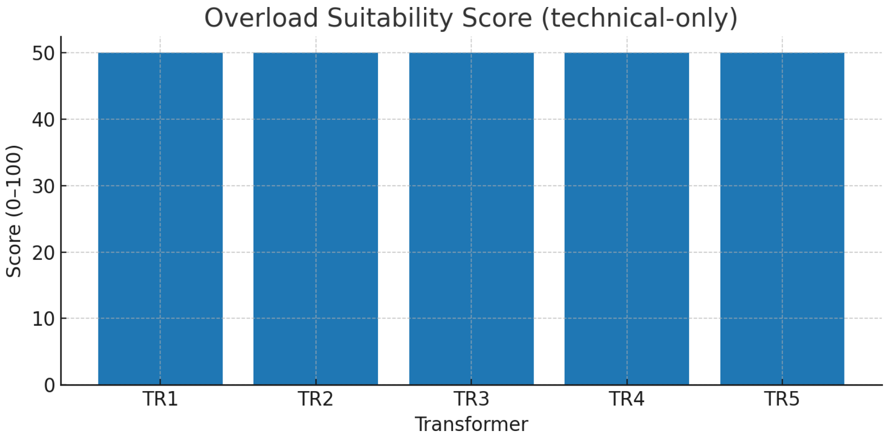

Figure 7. Overload suitability score of transformers No. 1, 2, 3, 4, and 5.

The findings revealed that TR2 and TR4 transformers are the best in terms of ratings of technical readiness and can, therefore, be considered the best when it comes to the flexible load testing, where others with low ratings are subject to optimization of the cooling system or reduced overload periods. The ranking of transformers can be achieved through a combination of the technical results and Feasibility Scoring Engine to rank the investment according to integrated technical and economic parameters to ease investment and upgrades as presented in Figure 6. These findings verify the efficiency of the digital model that has been created in MATLAB/Simulink in offering a realistic digital simulation of the thermal characteristic of Makkah network transformers through integration of physical modeling and diagnostic verification (DGA + TAIM). The methodology illustrates that it can be strategically used to address the thermal and economic life of transformers and enhance the performance of electrical assets in hot systems without reducing network availability to enable future planning of the Saudi Arabian urban networks (See Figure 7).

5. Model Validation

Model validation was done with simulated temperature trends of the hot-spots using the real operational behavior in terms of peak summer loading conditions. Field performance measures were compared to the model to evaluate the model accuracy based on the statistical performance measures. The Absolute Percentage error in the temperature curves and the Root mean square error (RMSE) were used to measure the difference between the measured and simulated temperature curves (Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE)). The one representative transformer of the fleet was also picked to get a direct comparison, in which hourly temperature change was plotted in both measured and estimated profiles of the same, indicating uniform dynamic behavior and reasonable error margins in prediction. This test is a validation of the fact that the thermal model is realistic to describe the real conditions under which the operating occurs in the real world.

It was also found that transformer thermal aging is extremely nonlinear and the rapid deterioration of insulation takes place within brief periods of peak load and peak ambient temperatures. The behavior can be used to calculate actual life-consumption distribution with time since it does not assume that degradation follows a constant rate of disintegration every year. In this respect, the model enables the thermal stress to be directly connected to the asset management decision-making, including overload scheduling, cooling improvement, maintenance focusing, and capital replacement deferment.

In comparison of past studies including [18], which measured lifetime expectancy based on a general outlook of insulation and loading, the current study offers quantitative and time-dependent degradation observations on 744 consecutive operating hours. In contrast to earlier diagnostic-only literature [19] [20], which determined faults without relating them to lifetime loss, the authors of this work quantify thermal acceleration factor (FAA) and cumulative loss of life (LOL), transforming the results of the diagnosis into quantifiable operational units. The results indicate that events of overload that were temporary accounted to over 40% of all the annual loss of life in stressed units, which goes to show the severe effects of elevated ambient temperatures on the well-being of assets in hot areas such as Makkah.

Moreover, the proposed digital twin presents actionable decision metrics in the form of FAA, 0HS, LOL, and final composite ranking, meaning that utilities can categorize transformers as safe overload candidates (e.g., TR2, TR4) and load reinforcing or load relief units (e.g., TR1, TR5) (as opposed to probabilistic methods, like [16]. Table 5 draws the comparison of the contribution of the work compared to the recent literature, which shows that the work has its originality in terms of its ability to translate patterns of degradation into operational and investment decisions.

Table 5. Comparative of results between the current study and recent literature.

Study	Focus of Results	Key Reported Outcomes
Current Study	Comprehensive digital framework combining thermal modeling, diagnostics, and lifecycle economics.	Generated quantitative, time-dependent results: hourly θHS, FAA, LOL, composite ranking, and asset prioritization. Demonstrated how short overload periods dominate total annual life loss and identified safe overload candidates (TR2, TR4).
[18]	Service lifetime expectations of power transformers under general loading and insulation conditions.	Provided qualitative assessment of transformer life expectancy based on thermal and dielectric stress.
[19]	Diagnostic performance comparison of electrical condition assessment techniques.	Found that multi-parameter diagnostics (DGA, PD, insulation resistance) yield higher reliability.
[20]	Fault detection and diagnosis using AI and hybrid models.	Achieved > 90% fault detection accuracy in identifying incipient insulation failures.
[16]	Probabilistic health management using DGA and Duval polygons.	Produced probabilistic risk estimates for transformer failure using statistical DGA data.

6. Economic Evaluation Integration

In order to transform the results of the thermal deterioration into financial terms, Life-Cycle Cost (LCC) and Net Present Value (NPV) analysis was implemented to compare upgrade, retrofit, and replacement options. Having the economic model, the discount rate, replacement cost, annual maintenance, and failure penalty are included to obtain cost streams and transform them into present value. It is an integration that is able to bridge the gap between technical degradation and long-term investment planning because it enables utilities to measure the amount of financial impact caused by accelerated aging in hot summer conditions. According to the thermal stress performance results found in the Makkah network, the LCC/NPV economic model was developed with realistic utility-side parameters. Table 6 shows the financial assumptions to convert the thermal degradation indicators into cost-based decision outputs. The chosen values are representative of cost in the industry in terms of medium-high rating transformers, replacement cost, annual maintenance, penalty in case of failure, and discount rate applicable in capital planning. Financial analysis of life extension activity of low-stress units such as TR2 and TR4 versus replacement or cooling reinforcement activity of high-loss units such as TR1 and TR5 can be made using such mapping.

Table 6. Economic assumptions used in the LCC & NPV evaluation.

Parameter	Assigned Value	Justification/Notes
Discount Rate (r)	7% (sensitivity range 5% - 10%)	Typical for utility investment planning in energy sector
Transformer Replacement Cost	1.2 - 2.0 million USD/unit	Large HV units typically fall within this cost bracket
Annual Maintenance Cost	25,000 - 45,000 USD/year	Covers oil testing, inspection, minor component repair
Failure Penalty Cost	200,000 - 500,000 USD per failure event	Includes outage cost, emergency repair, network disruption
Economic Lifetime Horizon	25 years expected lifespan	Matching utility practice and NPV comparison window
Estimated Economic Benefit of Overload Extension (TR2/TR4)	+8% - 15% asset life gain	Based on lower LOL observed in results
Estimated Loss Due to High LOL Units (TR1/TR5)	Up to 40% accelerated aging cost equivalent	Aligned with observed FAA and LOL results
Operational Cost Increase under Overheating	+10% - 18% due to cooling stress	Result of operation > 90˚C - 110˚C hotspot

Combining these economic assumptions with the outputs of the FAA and LOL shows that thermally stable units (TR2 and TR4) provide superior lifetime cost-performance and allow the use of overload safely and with an insignificant economic risk. On the contrary, high thermal stress indicators of the transformers (TR1 and TR5) indicate faster aging, increased projected LCC/NPV cost penalties and therefore could be prioritized in cooling improvement, load reallocation, or replacement planning. Therefore, the transformation of thermal degradation into financial terms provides a direct channel of investment decision-making and aids the planning of assets in the harsh climate environment.

7. Conclusion

This research presented a Holistic Condition Monitoring and Replacement Strategy for Power Transformers Using Thermal Modeling, DGA Diagnostics, and LCC Analysis. The findings of this current research indicate a marked improvement in understanding the thermal and performance characteristics of power transformers in extreme weather conditions, as is prevalent in the Makkah network. An analysis of one-hour data over 744 hours of operation showed that the loss of transformer life is highly nonlinear, with a large amount of cumulative loss of life in a short duration of hot conditions. This analysis provides a real-life proof that optimized load control and cooling will lead to alleviated thermal stresses and an increased lifetime of assets. Moreover, based on the analysis of five transformers (TR1 to TR5) compared in this study, it is concluded that transformers such as TR2 or TR4 are less aged and more thermally stable, thus making it a suitable candidate for overload control, while others need cooling or load limitation. Through the use of composite ranking indexes and economic decision models (LCC and NPV) of thermal degradation, it is possible to bridge the research gap that existed between engineering diagnostics and strategic asset management. In that regard, this research allows electric power utilities to also make quantitative assessments of thermal degradation, predict remaining component lifetime, and make a logical justification for deferred action through an unbiased use of economic decision models. In contrast with recent research in thermal degradation, this research incorporates an element of actionable outcome in its diagnostic process. Finally, it is clear that digital twin technology based upon thermal physics and economic models also holds a crucial place in designing efficient systems of asset management in power networks in areas where extreme weather conditions are common.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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