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IoT-Enabled Real-Time Monitoring and Loss-of-Life Estimation of Distribution Transformers

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ABSTRACT

A distribution transformer is required in power distribution networks to step down the voltage relevant and usable for consumers. Its failure not only disrupts electricity supply but also incurs high replacement costs, with broader economic implications. Ensuring reliable operation, therefore, requires accurate and continuous monitoring of its performance. This paper presents IoT-Enabled Real-Time Monitoring and Loss-of-Life Estimation of Distribution Transformers developed and tested on a 10 kVA, 0.415 kV prototype distribution transformer, connected to three residential loads. A dedicated data acquisition system was developed, which monitors key parameters: load current, phase voltage, transformer oil level, ambient temperature, and oil temperature in real time over 14 days. An algorithm was implemented to analyze daily load profiles and hotspot temperature data, which were then used to estimate transformer loss of life. The results show that transformer ageing is highly sensitive to load variation. During weekdays, the cumulative equivalent ageing reached 2.22 hours per day, corresponding to a daily loss of life of 0.00296%. On weekends, higher residential loads increased cumulative ageing to 4.79 hours, with a corresponding life loss of 0.0063%. A simulated one-hour peak load of 1.43 pu resulted in 25.75 hours of ageing, translating to a life loss of 0.034%, demonstrating the severe impact of overloads. These findings emphasize that peak load periods dominate insulation ageing and can substantially reduce service life if unchecked.

Keywords: IoT, real-time monitoring, loss of life, distribution transformer.

1. INTRODUCTION

Distribution transformers are critical components of power system networks which performs voltage transformation for end-user consumption. Their ratings dictate the distribution of load across the network, and the ratings are not to be exceeded for proper functioning of the transformers. Under normal operating conditions, distribution transformers typically have a longlife span of 30–50 years[1], [2]. They are built to withstand a certain degree of overloading for some time without serious consequences. However, the overloading of the transformer should be avoided so as not to accelerate its ageing which is affected by heat generated from the overload [3]. Preventing such degradation requires accurate and continuous monitoring of transformer health.

Traditionally, monitoring has relied on manual inspections of temperature, oil, and load conditions, which are usually performed after a fault. This process is slow, labor-intensive, and disruptive, often resulting in power outages during maintenance. Consequently, identifying transformer faults at incipient stages is essential for reliable power supply and economic stability.

Transformer faults are strongly associated with increased load, winding temperature rise, and insulation degradation [4]. Various methods have been proposed to monitor transformer health conditions.

The study by [5] focused on predictive maintenance of transformers, where a cloud-based monitoring model that integrates GSM and IoT technologies was proposed. The study presented a real-time data logging through wireless modules, and the results showed improved responsiveness in fault detection and reduction in maintenance time. Similarly, [6] addressed the problem of distribution transformer condition tracking by designing a GSM-enabled monitoring system that measured load current, oil level, and voltage. The system successfully demonstrated the ability to transmit real-time alerts, thereby increasing monitoring accuracy. [7] integrated GSM and IoT with machine learning techniques to identify critical anomalies in transformer performance using energy usage patterns and ambient sensor data The result shows that the hybrid model effectively identified critical anomalies before failure occurred. Expanding on these approaches, [8] proposed a dual Wi-Fi and GSM monitoring system capable of issuing SMS alerts when abnormal conditions were detected. The study highlighted improved communication resilience in remote environments. Similarly, [9] worked on IoT-driven transformer health monitoring using an ESP32-based microcontroller platform, which provided predictive maintenance insights through low-cost, real-time sensor integration. These approaches highlight how integrating GSM and IoT-based infrastructures improves fault detection reliability, particularly in remote grids where manual supervision is limited.

Beyond communication technologies, researchers have investigated thermal and insulation life modeling. [5] proposed a scalable IoT framework with embedded memory that autonomously recorded transformer faults. The study highlighted the value of local memory for reducing dependency on constant connectivity. [10] presented an enhanced insulation life assessment model that incorporated moisture content and oil-cooling circulation modes to enhance prediction accuracy under real-world conditions. The approached refined the standard life estimation framework in traditional IEC method, and result indicated better accuracy in predicting insulation aging under diverse operational environments. [11] compared traditional IEC thermal models with advanced machine learning methods such as artificial neural networks, temporal convolutional networks, and time-series dense encoders. The ML-based approaches provided more accurate predictions of top-oil and hot-spot temperatures, significantly improving insulation life estimation.

Another strand of research has focused on fiber-optic sensing technologies. Advanced Energy [12] introduced a Luxtron® M-1100 fiber-optic monitoring setup, which offered sub-0.5 °C accuracy across a wide temperature range. This high precision enabled improved detection of overload conditions and early warning of hotspot development. [13] conducted a comprehensive review of Fiber Bragg Grating (FBG) sensors for transformer monitoring. The study highlighted the immunity to electromagnetic interference and ability to simultaneously measure multiple

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parameters. Based on these findings, the authors concluded that FBG sensors provide a reliable and practical solution for condition monitoring in harsh electrical environments**.** Complementing this, [14] carried out experimental validation by embedding FBG sensors directly into transformer windings. the sensors effectively tracked dynamic hotspot variations under fluctuating load conditions, confirming practicality for real-time monitoring.

In hotspot temperature prediction, both physics-based and data-driven approaches are increasingly applied. [15] combined finite element modeling (FEM) and computational fluid dynamics (CFD) to simulate winding temperature behavior under varying loads, demonstrating accuracy improvements over IEC standards. [16] validated hotspot locations through a multiphysics framework integrating thermographic imaging and electromagnetic simulation, offering practical verification of predicted thermal regions. Building on these approaches, [17] introduced an extended dynamic mode decomposition (EDMD) method that accelerates thermal–fluid simulations while maintaining fidelity to full CFD models, making real-time predictive monitoring feasible.

It can be observed that distribution transformer health monitoring has evolved from manual inspection to intelligent, data-driven systems. Studies addressing IoT and GSM-based monitoring, fiber-optic sensors, and advanced thermal simulations consistently highlight improvements in accuracy, reliability, and cost-effectiveness. Nevertheless, many existing methods still rely on human interpretation of field data, which introduces error therefore, this study propose a cloud-based monitoring device which focuses on accurate transformer loss-of-life estimation to further improve reliability and extend operational life.

2. METHODOLOGY

The proposed system's overall structure is illustrated in Figure 1, comprising the prototype transformer, data acquisition system, data logger units, and the load. Figure 2 provides a visual representation of the prototype transformer, a three-phase 10kVA, 415V/220V oil natural air natural (ONAN) transformer. This prototype shares key characteristics with a conventional distribution transformer, making it suitable for data collection purposes. However, the conventional transformer is bigger in size and ratings which determines the load capacities as compared to the prototype transformer employed in this study. The data acquisition system connected to the prototype is subdivided into the transducer, microcontroller and Wi-Fi module.

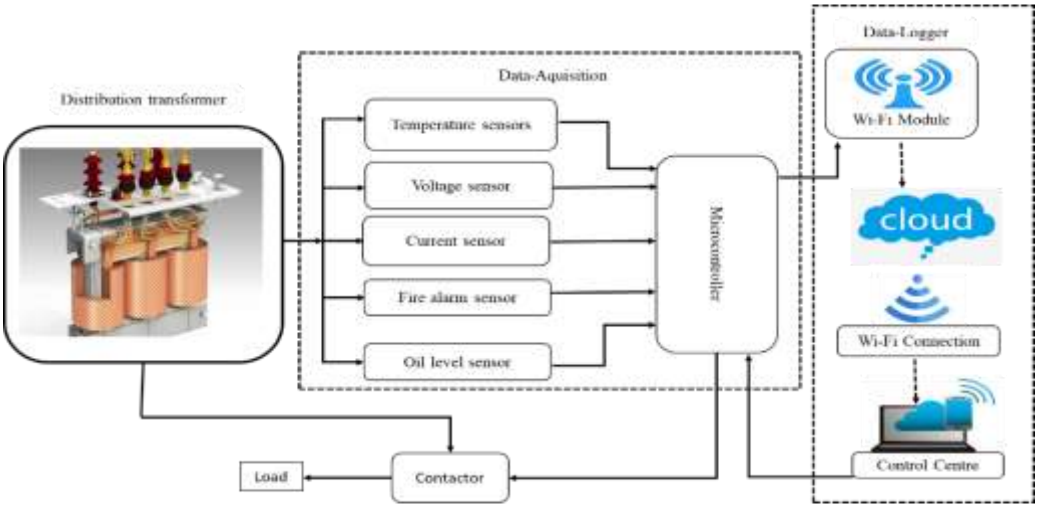

FIGURE 1. Cloud-based condition monitoring of distribution

The transducers detect essential parameters from the prototype distribution transformer. The sensed signals undergo conditioning before being transmitted to the microcontroller, which performs computations based on predefined instructions. Subsequently, the microcontroller executes instructions to log real-time data onto a cloud server through a data logger at specified intervals. The logged data is then presented and stored for subsequent analysis.

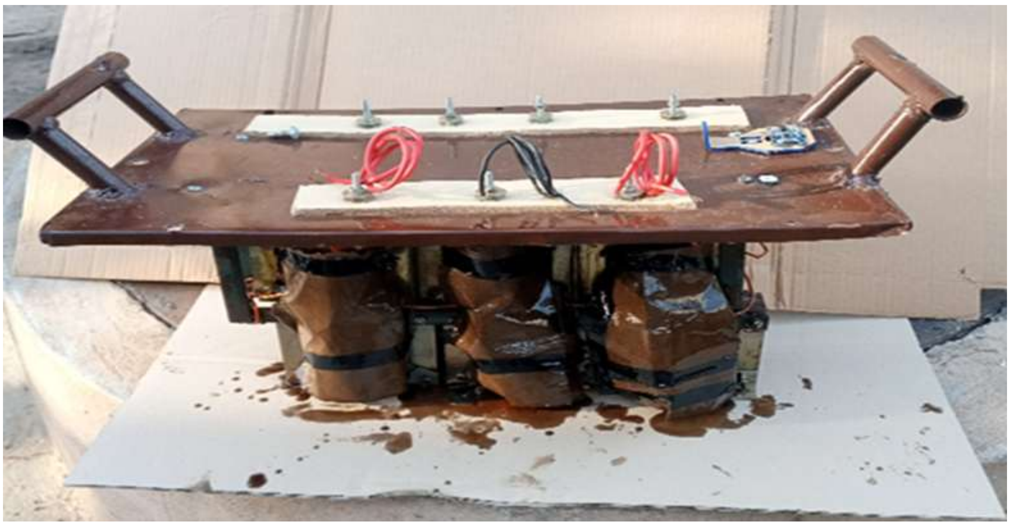

FIGURE 2. Three Phase distribution transformer

2.1 DATA ACQUISITION SYSTEM PROCEDURE

The process of collecting data entailed assessing the number of appliances in each household along with their respective power ratings. The combined power demand for the residences totaled 7.826kW. To prevent overloading of the prototype distribution transformer, a 10kVA three-phase prototype transformer was chosen, and its specifications is shown in Table 1. Additionally, for improved accuracy, appropriate sensors were meticulously selected and calibrated to align with digital multimeter readings. the details on the data acquisition procedure and algorithm developed can be found in [18]

TABLE 1
Distribution transformer Specifications

S/n	Basic Transformer Information	Ratings
1	Power	10 kVA
2	No. of phases	3 Phase
3	Frequency	50 Hz (± 5%)
4	Type of cooling	ONAN (Oil natural / Air natural)
5	No. of windings	Two winding Transformers
6	Method of connection	Delta/ Star
7	Rated top oil rise over ambient temperature	40^0C
8	Rated hot spot rise over top oil temperature	45^0C
9	Winding exponent "m"	0.9
10	Output voltage	(415V ± 10%)
11	Current (primary/secondary)	45A / 14.11A

2.2 DAILY LOAD CURVE

Accurate estimation of a distribution transformer's life parameters necessitates a comprehensive understanding of its daily load pattern. This involves monitoring of the consumer load demand at regular intervals throughout the day. In our study, real-time daily load profiles were collected from three residences in Airport Road, Gbagba area, Ilorin, Kwara State, Nigeria, with coordinates (N 8º26'24.6867" E 4º 30'51.1308") over a two-week period. The data, recorded at approximately 5-minute intervals, were stored in the cloud via the developed devices, resulting in 288 data points representing the daily load curve. These data were further retrieved from the cloud to analyze the transformer loss of life.

To determine the actual operational age of the distribution transformer, it is crucial to assess the daily load demand it encounters. The prototype transformer was monitored for an average of 14 days, considering variations attributed to intermittent power supply. To accommodate these fluctuations, a daily load curve was computed by averaging the data collected over the two weeks for each 24-hour period. Additionally, for consistency, the demand values were converted from kilowatts (kW) to per-unit values, ensuring a uniform representation. As a result, all measured values were transformed into per-unit values for further analysis. Figure 3 shows the load curve of the buildings on the transformer.

3. MATHEMATICAL MODEL FOR TRANSFORMER LOSS OF LIFE

3.1 TRANSFORMER AGEING EQUATIONS

The knowledge of the hot spot temperature is crucial to the monitoring of transformer status. The winding temperature indicator does not directly measure the winding hot spot or any winding temperature. Therefore, the winding hot spot temperature can be evaluated using equation 1 [4]

$$\theta_{HS} = \theta_{AMB} + \theta_{OIL} + \Delta\theta_{HR}(K)^{2m} \tag{1}$$

Where, θ_{HS} = Hot-spot temperature, $\theta_{AMB} = Ambient\ temperature,$ θ_{OIL}= Top-oil temperature, $\Delta\theta_{HR}$= Rated hotspot temperature rise above top oil, m = Winding exponent and K is the ratio of the specified load to rated load,

$$K = \frac{I_{actual}}{I_{rated}} \tag{2}$$

3.2 TRANSFORMER AGEING EQUATIONS

Abnormal conditions, such as overloading, providing power to non- sinusoidal loads or exposure to higher ambient temperature higher than the norm, can accelerate transformer aging and consequently accelerating their life span. The ageing acceleration factor is greater than 1 when the HST is over 110 ºC and less than 1 when the HST is below 110 ºC [19]. The ageing acceleration factor is expressed by Equation (3) for thermally upgraded paper.

$$FAA = e^{\left(\frac{B}{110+273} - \frac{B}{\theta_{HS}+273}\right)_{P.U}} \tag{3}$$

Where, FAA = Ageing acceleration factor, B is a constant.
The HST varies according to the load and ambient temperature. Thus, equivalent aging acceleration factor (in hours or days) at the reference temperature that will be consumed in a particular period of time for the given temperature cycle is expressed by (4)

$$V_{EQA} = \frac{\sum_{n}^{N} FAA \times \Delta t_n}{\sum_{n=1}^{N} \Delta t_n} \tag{4}$$

Where, V_{EQA} is the equivalent aging factor for the total time period and n is index of the time interval t, N is total number of time intervals, FAA is the aging acceleration factor for the temperature which exists during the time interval Δt_n, Δt_n is the time intervals in hours.

3.3 TRANSFORMER AGEING EQUATIONS

The equivalent loss of life in relation to the total time period is determined by multiplying the equivalent ageing acceleration factor by the time period (t) expressed

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in hours[20]. In this case, the total time period used is 24 hours. Therefore, the percentage loss of life is given by equation. (5):

$$percentage\ loss\ of\ life = \frac{V_{EQA} \times t \times 100}{Normal\ insulation\ life} \tag{5}$$

4. RESULTS AND DISCUSSIONS

4.1 TRANSFORMER PARAMETERS RESULTS

The real-time monitoring data of a three phase prototype distribution transformer can be accessed on the thingspeak server, the acquired data consisting voltages, currents, active power, reactive power, apparent power, power factor, ambient temperature, oil temperature and oil level were stored in the cloud server for two weeks as detailed in [18]. These data was used to evaluate the percentage loss of life for average weekday load consumption on transformer for a 24 hour load cycle as given in Table 2.

TABLE 2.
The percentage loss of life for average weekday load consumption.

TIME (H)	LOAD FACTOR (PU)	θ_{oil}℃	θ_{AMB}℃	$\theta_{\Delta HR}(u)$℃	θ_{HS}℃	AGENING ACCELERATION FACTOR FAA (Weekdays)	CUMMULATIVE AGE HOURS (Weekdays)	PERCENTAGE LOL (Weekdays)
1:00	0.368	20.025	16.711	7.432	44.162	0.000294574	0.000294574	9.42637E-06
2:00	0.327	19.131	17.744	6.025	42.895	0.00024369	0.000538264	8.61222E-06
3:00	0.308	19.023	17.452	5.404	41.874	0.000208908	0.000747172	7.96983E-06
4:00	0.412	21.890	17.633	9.112	48.632	0.000568391	0.001315562	1.05245E-05
5:00	0.409	20.251	18.029	9.017	47.287	0.000467294	0.001782856	1.14103E-05
6:00	0.540	22.148	18.542	14.854	55.534	0.001514188	0.003297045	1.75842E-05
7:00	0.661	25.852	19.852	21.383	67.083	0.007137128	0.010434173	4.76991E-05
8:00	0.753	27.029	20.653	27.000	74.670	0.018688724	0.029122897	0.000116492
9:00	0.775	27.787	21.458	28.455	77.685	0.027081752	0.056204649	0.000199839
10:00	0.660	25.115	21.567	21.309	67.979	0.008014712	0.064219361	0.000205502
11:00	0.503	23.752	23.495	13.073	60.313	0.002913958	0.067133319	0.000195297
12:00	0.512	26.150	25.682	13.505	65.335	0.005682838	0.072816158	0.000194176
13:00	0.470	29.081	28.851	11.570	69.500	0.009743231	0.082559389	0.000203223
14:00	0.422	27.256	28.086	9.519	64.849	0.00533194	0.087891329	0.000200894
15:00	0.487	27.733	29.650	12.322	69.702	0.00999842	0.097889749	0.000208831
16:00	0.638	30.782	28.594	20.051	79.421	0.033433278	0.131323028	0.000262646
17:00	0.810	32.451	27.536	30.799	90.779	0.126265281	0.257588309	0.000484872
18:00	0.950	34.882	26.233	41.042	102.152	0.440742296	0.698330605	0.001241477
19:00	1.015	35.144	25.092	46.229	106.459	0.693850876	1.392181481	0.002344727
20:00	1.035	35.633	23.731	47.855	107.215	0.750577964	2.142759445	0.003428415
21:00	0.820	30.314	23.582	31.483	85.373	0.067786086	2.210545531	0.00336845
22:00	0.652	25.783	22.264	20.838	68.878	0.008997308	2.219542839	0.003228426
23:00	0.559	23.879	20.566	15.792	60.222	0.002878506	2.222421345	0.003092064
24:00	0.430	21.218	19.636	9.852	50.692	0.000764859	2.223186203	0.002964248

Table 2 illustrates the hourly percentage loss of life of a distribution transformer under weekday load conditions. During the early morning hours (1:00–4:00), the load factor remains low (0.30–0.4 pu), resulting in hot-spot temperatures below 49 °C and negligible aging acceleration factors (FAA < 0.0006). As the load increases between 7:00 and 12:00, hot-spot temperatures rise to 65–78 °C, with FAA values climbing to 0.017–0.083, indicating a clear acceleration of insulation degradation. The most critical stress occurs during evening peak demand (17:00–21:00), when the load factor reaches up to 1.035 pu and hot-spot temperatures greater than 100 °C. Under these conditions, the FAA rises sharply, peaking at 0.75 at 20:00. By the end of the day, the transformer accumulates approximately 2.22 hours of equivalent aging, corresponding to a total daily life loss of 0.00296%. Although this value is small in isolation, it aggregates to nearly 0.8% annually, which can consume up to a quarter of the transformer's expected service life over three decades. The findings emphasize that peak load periods dominate thermal aging and highlight the necessity of load management and condition monitoring strategies to prolong transformer life and ensure system reliability.

In order to evaluate the hotspot temperature for every hour, it is required to convert the total load demand for every hour by the residences to per unit value. This is necessary to have a convenient round number and all the values to be in the same unit. Thus, a base value of 5.0539kW is selected for weekdays based on assumption [21]. Therefore, cumulative loss of life was calculated for variable load conditions for weekdays. The outcomes as explained in the following paragraph shows that different days of operating a distribution transformer will produce less or more aging than another day.

The graph in Figure 4 illustrates the daily power consumption of the residences throughout the week. It is evident that the average power usage in each residence sharply rose to about 1.160 kW at 10:00 in the morning and then declined to approximately 0.74 kW by 14:00. Moreover, at 16:00, the average power consumption in each residence increased to nearly 1.120 kW and then sharply peaked at 20:00 in the evening before decreasing for the rest of the day.

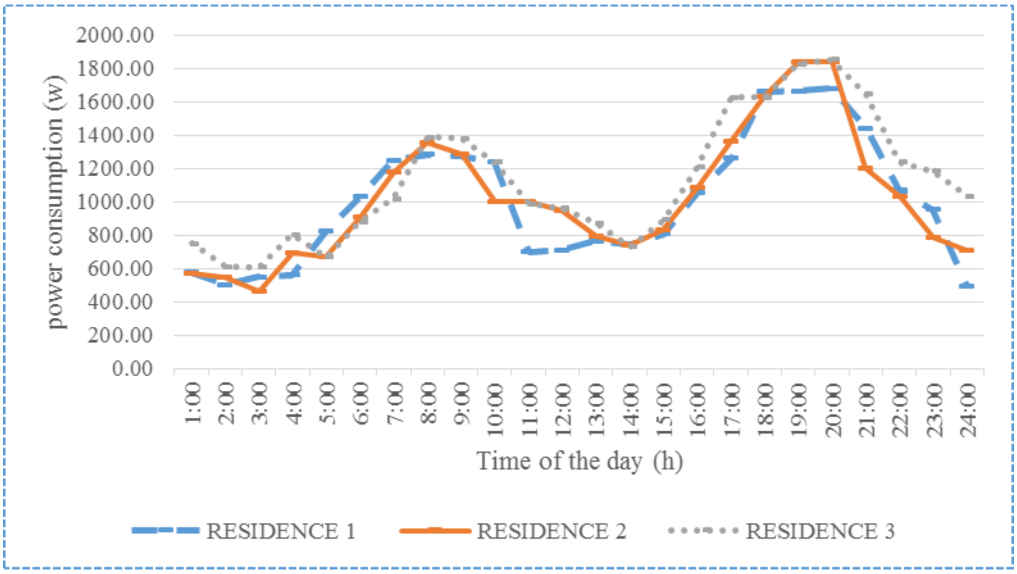

FIGURE 4. Average weekdays power consumed by the consumer in the residents for 24hours load cycle

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Figure 5 illustrates the average power consumption during weekdays and weekends in a 24-hour load cycle. Between 1:00 and 5:00 hours, the power consumed remains relatively consistent for both cases, with a notable change occurring at 6:00 hours. Over the weekends, power consumption steadily increases from approximately 4 kW at 8:00 hours to around 5.5 kW at 13:00 hours, then gradually drops to 2 kW at 24:00 hours. Conversely, on weekdays, power consumption sharply rises from 1.8 kW at 2:00 hours to 4 kW at 8:00 hours, before decreasing to nearly 2 kW at 14:00 hours. Furthermore, on weekdays, power consumption peaks at 5.3 kW at 20:00 hours. Consequently, weekend power consumption rises in the afternoon compared to weekdays, which experience increased power consumption during the evening.

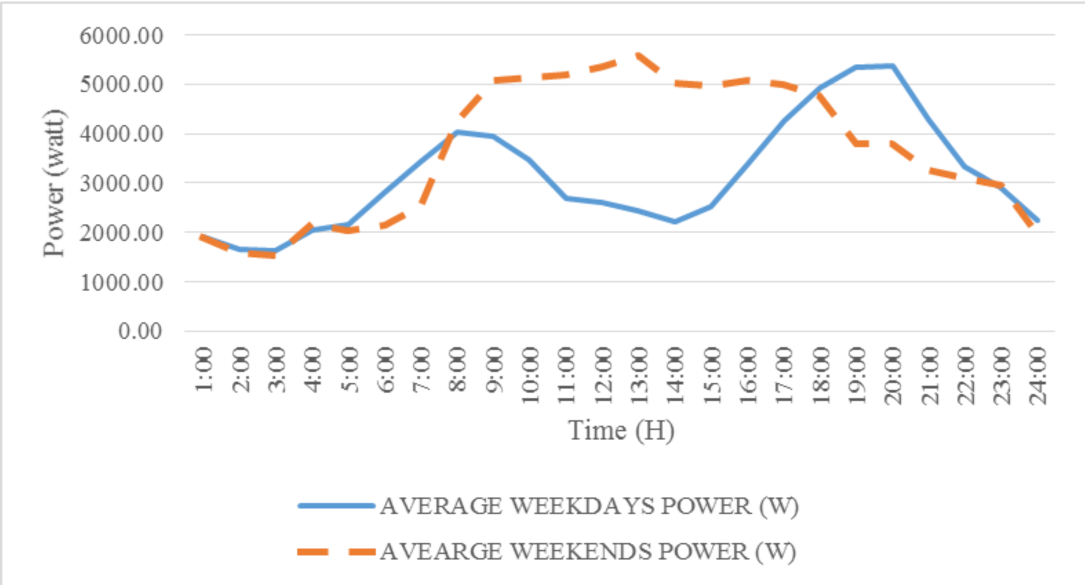

FIGURE 5. Average weekdays and weekends power consumed by the 3 residents for 24 hours load cycle

The weekday's graphical representation of hot spot temperature for a day including the variation of the load factor, ambient temperature and top oil temperature rise over ambient temperature is shown in Figure 6.

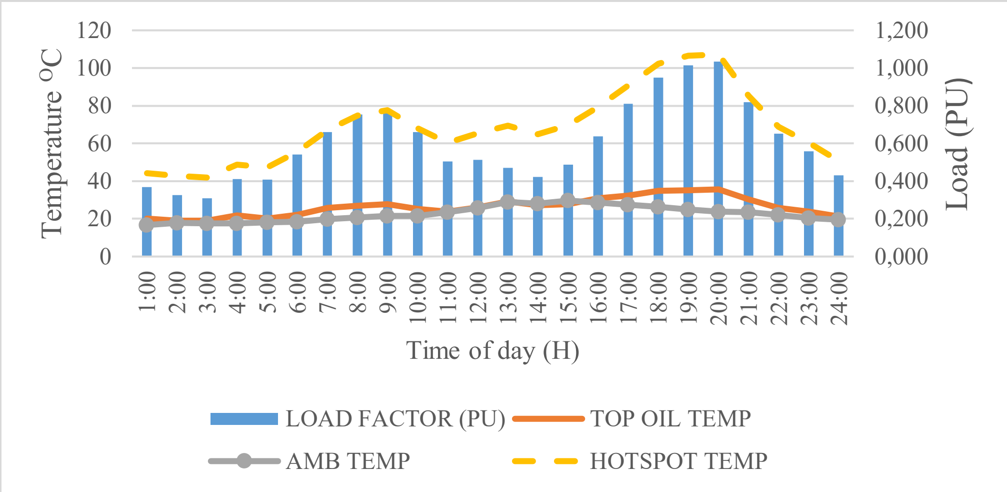

FIGURE 6. Graphical representation of hot spot temperature, load factor, top oil temperature rise and ambient temperature for 24hours (Weekdays).

The hot spot temperature follows the load changes, indicating that the curve representing the hot spot temperature is directly dependent on the load change, oil temperature and the ambient temperature. The hotspot temperature at 3:00 rose gradually from nearly 40^0C to around 78^0C at 8:00. However, the hot spot temperature virtually remained constant from 10:00 at 65^0C till around 15:00 at 70^0C. Furthermore, the hotspot temperature peak of 107^0C was observed at the hours of 20:00 which later dropped for the rest of the hours. Likewise, to evaluate the hotspot temperature for every hour during the weekends as a result of heat dissipated due to various losses, it is required to estimate the total load demand for every hour by the residences. The load demand values were further converted to per unit value. This is necessary in order to have a convenient round number and all the values to be in the same unit as shown in Table 3 [21]. Therefore, a base value of 5.3534kW was chosen based on assumption for weekend's power consumption in order to make the calculation easy. In addition, the cumulative loss of life was calculated for variable load conditions for weekends. The results shows that the ageing of transformer varies for different days of operation. Figure 7 shows the weekend graphical representation of the hot spot temperature for a day including the variation of the load factor, ambient temperature, and top oil temperature rise over ambient.

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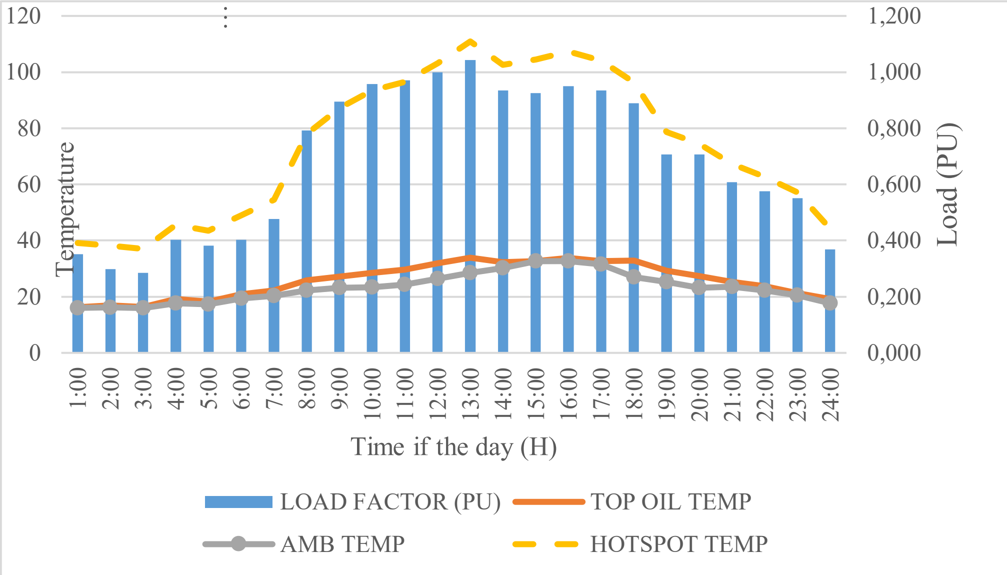

FIGURE 7. Graphical representation of hot spot temperature, load factor, top oil temperature rise and ambient temperature for 24hours (Weekends).

Observations from Figure 7 reveal a direct correlation between the hot spot temperature and the load pattern. The curve representing the hot spot temperature demonstrates its dependence on changes in load, oil temperature, and ambient temperature. At 4:00 hours, the hot spot temperature gradually increased from approximately 42°C to around 85°C by 8:00 hours. Subsequently, from 10:00 hours onwards, the hot spot temperature remained relatively constant at 980°C until around 12:00, after which it peaked at 110°C at 13:00 hours and gradually decreased thereafter.

Assuming a normal insulation life of 20.55 years or 180,000 hours at the reference temperature [22], the percentage loss of life is computed for various load conditions, as illustrated in Table 3. These tables highlight that the percentage loss of life is higher during weekends compared to weekdays, attributed to increased loads leading to elevated hot spot temperatures. This, in turn, influences the aging acceleration factor, resulting in a premature loss of life for the transformer. In conclusion, exceeding thermal limits for transformer temperature can significantly reduce its life expectancy below the specified normal duration.

TABLE 3
The percentage loss of life for average weekends load consumption.

TIME (H)	LOAD FACTOR (PU)	θ_{oil}°C	θ_{AMB}°C	$\theta_{\Delta HR}(u)$°C	θ_{HS}°C	AGENING ACCELERATION FACTOR FAA (WEEKENDS)	CUMMULATIVE AGE HOURS (WEEKENDS)	PERCENTAGE LOL (WEEKENDS)
1:00	0.352	16.25	16.02	6.878	39.148	0.000137813	0.000137813	4.41E-06
2:00	0.299	16.85	16.21	5.110	38.170	0.000118484	0.000256297	4.10075E-06
3:00	0.285	16.27	16.05	4.698	37.018	9.90596E-05	0.000355356	3.79047E-06
4:00	0.403	19.24	17.63	8.781	45.651	0.000367453	0.000722809	5.78248E-06
5:00	0.382	18.25	17.22	7.961	43.431	0.000264075	0.000986884	6.31606E-06
6:00	0.402	20.84	19.37	8.727	48.937	0.000594105	0.00158099	8.43195E-06
7:00	0.476	22.21	20.42	11.833	54.463	0.00130417	0.00288516	1.31893E-05
8:00	0.793	25.92	22.32	29.646	77.886	0.027751694	0.030636854	0.000122547
9:00	0.946	27.22	23.09	40.708	91.018	0.129728041	0.160364896	0.000404701
10:00	0.958	28.51	23.36	41.654	93.524	0.171958872	0.332323768	0.000914499
11:00	0.971	29.55	24.27	42.681	96.501	0.239126116	0.571449885	0.001527002
12:00	0.999	31.85	26.38	44.887	103.117	0.488335578	1.059785463	0.00270198
13:00	1.042	33.89	28.55	48.480	110.920	1.098375907	2.158161369	0.00519783
14:00	0.935	32.35	30.28	39.905	102.535	0.459105249	2.617266619	0.00587594
15:00	0.925	32.73	32.65	39.117	104.497	0.564978	3.182244618	0.006689497
16:00	0.950	33.78	32.59	41.050	107.420	0.766730398	3.948975016	0.007804864
17:00	0.934	32.69	31.53	39.831	104.051	0.539089579	4.488064596	0.008360511
18:00	0.890	32.88	27.03	36.486	96.396	0.236372457	4.724437053	0.008316256
19:00	0.706	29.24	25.29	24.040	78.570	0.03015911	4.754596163	0.007929353
20:00	0.707	27.33	23.09	24.117	74.537	0.018381008	4.772977171	0.007562295
21:00	0.608	25.25	23.58	18.369	67.199	0.007245925	4.780223096	0.007213227
22:00	0.577	23.75	22.26	16.701	62.711	0.004018513	4.784241609	0.006891198
23:00	0.551	21.27	20.56	15.413	57.243	0.001917824	4.786159433	0.006594249
24:00	0.369	19.22	17.63	7.484	44.334	0.00030225	4.786461683	0.006319892

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Furthermore, the analysis presented in Tables 2 and 3 highlights that the hot spot temperatures reach 107.215°C at 20:00 hours on weekdays and 110.920°C at 13:00 hours on weekends, coinciding with peak loads of 1.035 p.u. and 1.042 p.u., respectively. These elevated temperatures significantly impact the aging acceleration factor, leading to a reduction in the transformer's service life. Figure 8 illustrates the aging acceleration factor under weekday and weekend conditions.

Notably, the highest ageing acceleration factor on weekends occurs in the afternoon at 0.8 p.u., attributed to a sudden load increase at 13:00 hours. On weekdays, the peak aging acceleration factor is approximately 0.75 p.u. at 20:00 hours. This observation suggests that an increase in load contributes to a higher aging acceleration factor, consequently contributing to the loss of life of the transformer. Therefore, it is observed that the aging acceleration factor peaks during weekdays at night due to heightened load demand, whereas on weekends, it occurs in the afternoon in response to increased load demand.

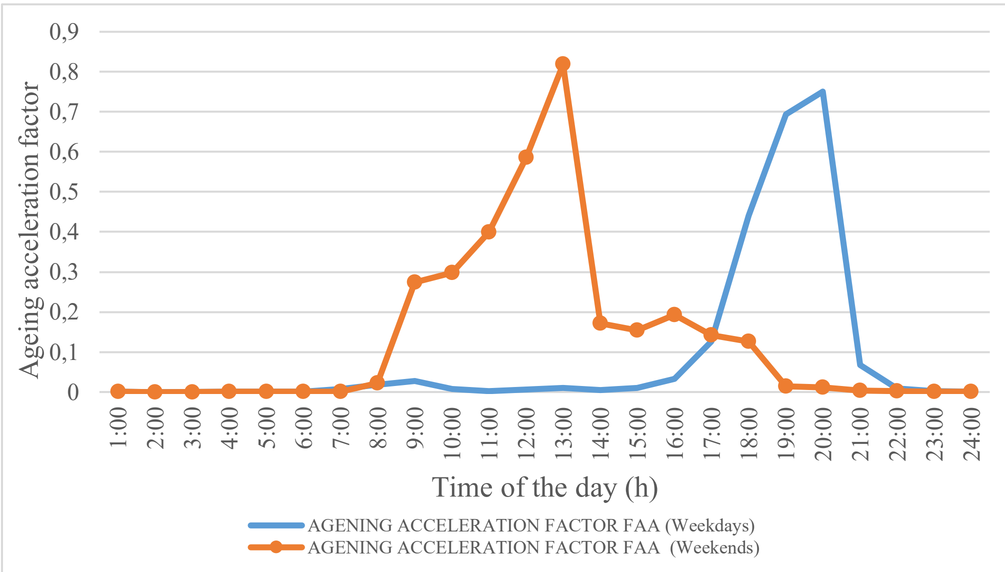

FIGURE 8. Aging acceleration factor of transformer for 24hours load cycle.

In Figures 9 and 10, the cumulative age hours and percentage Loss of Life (LOL) for a transformer in a 24-hour load cycle are illustrated. On weekdays, the transformer has operated for 2.223 hours, with a LOL percentage of 0.002964248%. On weekends, the operational time increases to 4.786 hours, accompanied by an estimated LOL percentage of 0.006319892%. These figures indicate a higher power consumption on the transformer during weekends in comparison to weekdays.

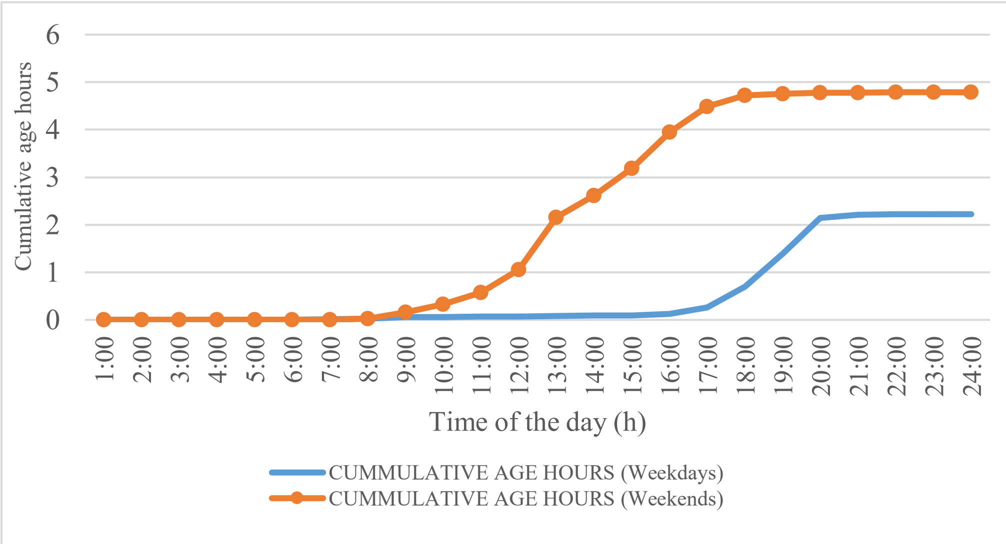

FIGURE 9. Cumulative age hours of transformer insulation life for 24hours load cycle.

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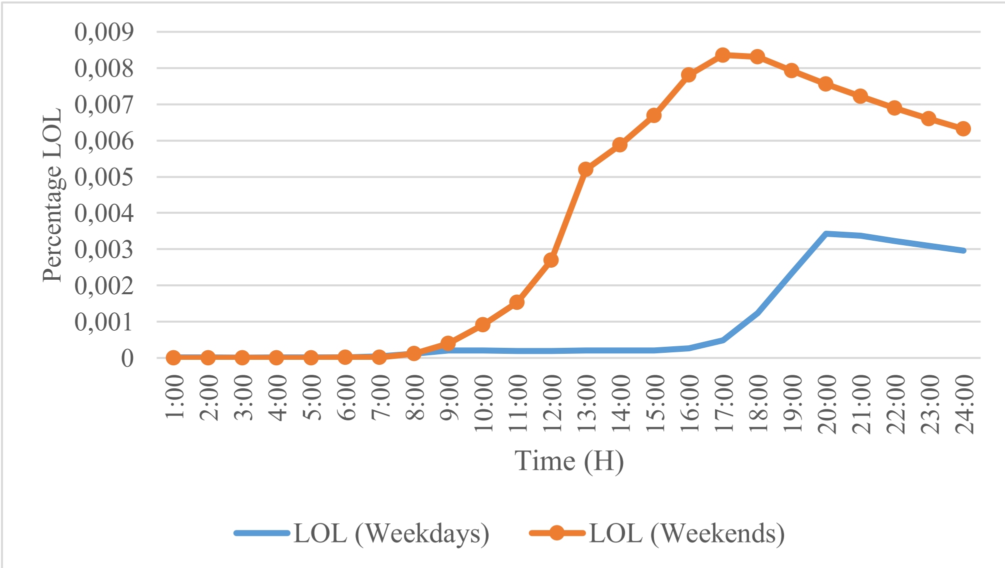

FIGURE 10. Percentage loss of life of transformer for 24-hour load cycle.

4.2 TRANSFORMER LOSS OF LIFE DUE TO THE IMPACT OF LOAD FACTOR

Table 4 illustrates the life loss outcomes resulting from the application of a peak load factor of 1.43 p.u to the transformer for one hour at 13:00 pm. The sudden increase in load leads to elevated temperatures in the transformer oil, initiating a sustained rise in hot spot temperature. This temperature increase ultimately results in insulation failure, leading to a higher cumulative loss of life. This effect induces aging hours exceeding 24 hours.

TABLE 4.
The percentage loss of life due to the impact of peak load

TIME (H)	LOAD FACTOR (PU)	θ_{oil}℃	θ_{AMB}℃	$\theta_{\Delta HR}(u)$℃	θ_{HS}℃	AGENING ACCELERATION FACTOR(FAA) (Weekdays)	CUMMULATIVE AGE HOURS (Weekdays)	PERCENTAGE LOL (Weekdays)
1:00	0.368	16.25	16.71	6.878	44.162	0.000294574	0.000294574	9.42637E-06
2:00	0.327	16.85	17.74	5.110	42.895	0.00024369	0.000538264	8.61222E-06
3:00	0.308	16.27	17.45	4.698	41.874	0.000208908	0.000747172	7.96983E-06
4:00	0.412	19.24	17.63	8.781	48.632	0.000568391	0.001315562	1.05245E-05
5:00	0.409	18.25	18.02	7.961	47.287	0.000467294	0.001782856	1.14103E-05
6:00	0.540	20.84	18.54	8.727	55.534	0.001514188	0.003297045	1.75842E-05
7:00	0.661	22.21	19.85	11.833	67.083	0.007137128	0.010434173	4.76991E-05
8:00	0.753	25.92	20.65	29.646	74.670	0.018688724	0.029122897	0.000116492
9:00	0.775	27.22	21.45	40.708	77.685	0.027081752	0.056204649	0.000199839
10:00	0.660	28.51	21.56	41.654	67.979	0.008014712	0.064219361	0.000205502
11:00	0.503	29.55	23.49	42.681	60.313	0.002913958	0.067133319	0.000195297
12:00	0.512	31.85	25.68	44.887	65.335	0.005682838	0.072816158	0.000194176
13:00	***1.430***	***33.89***	***28.85***	***48.480***	***143.598***	***23.53610976***	***23.60892592***	***0.058114279***
14:00	0.422	32.35	28.08	39.905	64.849	0.00533194	23.61425786	0.053975447
15:00	0.487	32.73	29.65	39.117	69.702	0.00999842	23.62425628	0.050398413
16:00	0.638	33.78	28.59	41.050	79.421	0.033433278	23.65768956	0.047315379
17:00	0.810	32.69	27.53	39.831	90.779	0.126265281	23.78395484	0.044769797
18:00	0.950	32.88	26.23	36.486	102.152	0.440742296	24.22469714	0.043066128
19:00	1.015	29.24	25.09	24.040	106.459	0.693850876	24.91854801	0.041968081
20:00	1.035	27.33	23.73	24.117	107.215	0.750577964	25.66912598	0.041070602
21:00	0.820	25.25	23.58	18.369	85.373	0.067786086	25.73691206	0.039218152
22:00	0.652	23.75	22.26	16.701	68.878	0.008997308	25.74590937	0.037448595
23:00	0.559	21.27	20.56	15.413	60.222	0.002878506	25.74878788	0.035824401
24:00	0.430	19.22	19.63	7.484	50.692	0.000764859	25.74955274	0.034332737

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Figure 11 illustrates the cumulative age hours of the transformer when subjected to a peak load factor of 1.43 for one hour on weekdays. This scenario leads to a more significant increase in cumulative age hours and consequently, a higher percentage loss of the transformer's operational life compared to its normal operation.

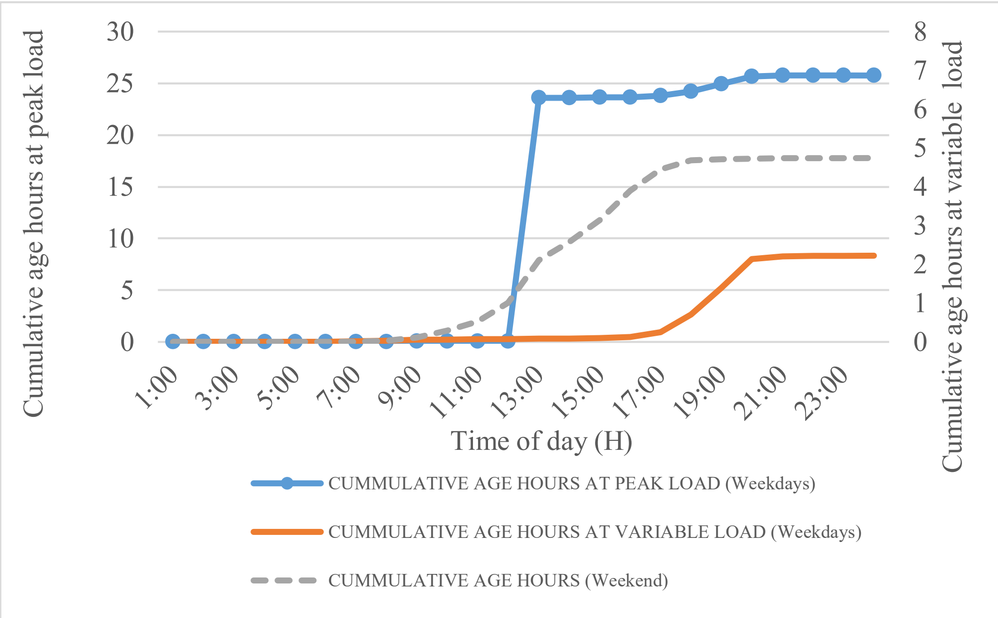

FIGURE 11. Cumulative age hours of transformer for 24hours load cycle.

4.3 TRANSFORMER LOSS OF LIFE DUE TO DIFFERENT OPERATING CONDITIONS

Table 5 provides a comprehensive overview of cumulative age hours and the percentage loss of life for various operating conditions applied to the transformer. The data indicates that running the transformer under different load and temperature conditions over a 24-hour period results in distinct cumulative aging hours and percentage loss of life. This variability is attributed to the transformer load variations, leading to elevated transformer oil temperatures and subsequently increased hot spot temperatures. This phenomenon significantly impacts the aging acceleration factor, resulting in varying cumulative age hours. It is important to note that each day of operating a distribution transformer may lead to either lesser or greater aging compared to another day.

For example, operating the transformer at higher loads during weekends accelerates the loss of life in comparison to weekdays with lower transformer loading. Moreover, the impact of operating the transformer at peak loads substantially affects the aging acceleration factor, reducing the transformer's service life by 1.0725%.

TABLE 5.
The loss of life due to different operating conditions.

S/N	OPERATING CONDITION	CUMMULATIVE AGEING HOURS FOR 24HOURS	PERCENTAGE LOSS OF LIFE
1	Operating the transformer at variable load condition for 24hours during the weekdays	2.22	$0.29*10^{-2}$
2	Operating the transformer at variable load condition for 24hours during the weekends	4.79	$0.63*10^{-2}$
3	Operating the transformer at a peak load for one hour	25.75	$3.43*10^{-2}$

5. CONCLUSIONS

The study minimizes the risk associated with earlier rise in temperature, prolong overloading and thermal degradation of the transformer. So that transformer may last up to its expected life without failure. This was achieved by the evaluation of the transformer loss of life based on the data acquired from the prototype distribution transformer. The former monitors and records the operating parameters of the prototype transformer. On the other hand, the latter acquire the transformer parameters data and uploaded to the cloud in real time.

These data were further analysed to calculate the cumulative age hours and percentage loss of life for different loading condition on the distribution transformer. The study indicate that the aging of distribution transformer varies for different days of operation, due to the connected loads on the transformer which is proportional to the oil temperature. An increase in oil temperature beyond thermal limit affect the transformer insulation, consequently affect the aging acceleration factor and reduce transformer service life.

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