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# DESIGN OF AN OPTIMIZED ALGORITHM FOR PARAMETER MONITORING OF DISTRIBUTION TRANSFORMERS IN A SMART GRID.

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## ABSTRACT

Distribution transformers are currently monitored manually where a person periodically visits a transformer site for maintenance and recording the parameters. This type of monitoring cannot provide information about occasional overloads and overheating of transformer oil and windings. In this thesis, an optimized algorithm for parameter monitoring of distribution transformers in a smart grid based on HI analysis was developed. The HI was formulated based on the measured (online) data of the distribution transformer obtained from the work by Gajanan et al (2017). The experimental setup adopted is similar to the work by Gajanan et al (2017). This work was also used to validate the results obtained in this work. Results obtained showed that the overall HI obtained by the method developed in this work is 99.89%, while the overall HI obtained by the GA technique employed by Gajanan et al (2017) was 99.78%. This shows a 0.11% improvement when compared to the benchmark performance of 100% obtained by Numerical Method. To obtain the HI, a number of iterations were required to ensure that the obtained results were accurate. Results showed that, under typical circumstances, it took the algorithm employed in this work about 45 iterations before the HI stayed constant, while the work by Gajanan et al (2017) required about 48 iterations to achieve their result. This points to show a conservation of processing resources by the model used in this work. The HI of the DT was also computed when the system was operated under abnormal conditions with faulty sensors, and the overall HI obtained by the method developed in this work for this scenario was 99.70%, while the overall HI obtained by the GA technique employed by Gajanan et al (2017) was 99.53%.

**KEYWORD:** Smart grid, Health Index, Distributed Transformer, Genetic Algorithm

## I. INTRODUCTION

Distribution transformers have a long service life if they are operated under good and rated conditions. However, their life is significantly reduced if they are overloaded, resulting in unexpected failures and loss of supply to a large number of customers thus effecting system reliability. Overloading and ineffective cooling of transformers are the major causes of failure in distribution transformers [1].

Distribution transformers are currently monitored manually where a person periodically visits a transformer site for maintenance and recording the parameters. This type of monitoring cannot provide information about occasional overloads and overheating of transformer oil and windings. All these factors can

significantly reduce transformer life [2]. In order to improve the overall monitoring and protection of a transformer, it is necessary to analyze these parameters. Abnormality in distribution transformer is accompanied with variation in different parameters like Winding temperature, Top and bottom oil temperatures, Ambient temperature, Load current, Oil flow (pump motor), Moisture in oil, dissolved gas in oil, Bushing condition, Oil level, etc.

Online monitoring system consists of embedded system, GSM modem, mobile-users and GSM networks and sensors installed at transformer site Sensors are installed on transformer side which reads and measures the physical quantity from the distribution transformer and then it converts it into the analog signal. The embedded module is located at the transformer site. It is utilized to acquire, process, display, transmit and receive the parameters to/ from the GSM modem. By employing real time monitoring of transformers many operational problems will be identified before any catastrophic failure, thus resulting in a long life service for transformers. It also has the advantages of significant cost savings and greater reliability.

Optimization techniques have become the most popular strategies for solving different electrical problems such as the parameter estimation of electrical elements such as electric machines, transformers, power lines, fuel cells and photovoltaic modules, batteries, management of electrical distribution system with soft open point, optimal power flow problems. In order to determine the transformer parameters, the traditional method based on short-circuit and open-circuit tests is used in transformers, which require disconnecting the system, making it impractical since they are used by multiple users in the distribution grids. In advanced non-invasive systems, employing optimized techniques for transformer parameter monitoring, there is a drawback in that such systems are complex and depends on expert analysis to interpret results. Observing this panorama, this research work arises from an interest in monitoring these parameters through measurements that are already taken in said systems and using this data to determine the health index of the transformers under different operating conditions while using noninvasive tests parameters with an improved optimization technique.
In this paper, an optimized algorithm for parameter monitoring of distribution transformers in a smart grid is proposed.

## II. REVIEW OF RELATED LITERATURE

Several research works have been done in this research area, in this section, a review of these works is done. The work by [3] paper described a fault sensing method which could be used for detection of inter-turn fault in transformers. The work by [4] presented a smart online condition monitoring system for distribution transformer monitoring and condition analysis. With the world facing the urgency of energy transition, the development of efficient and quiet electrical infrastructures is of topical importance in the construction of the environment of the future. The paper by [5] overviewed the issue of the low-frequency noise generated by electrical substations, from the experimental characterization of the source to the possible mitigation measures at the source, along the propagation path and at the receiver. As the acoustic method is known as one of the noninvasive and nondestructive testing methods, the work by [6] proposed a new approach of the classification method for defect identification in power transformers based on the acoustic measurements. In the paper by [7], the noise radiated by an electrical power transformer was predicted using an end-to-end multi-physics modelling solution. The paper by [8] proposed a method of automatic detection of parameters of a distribution transformer (model, type, and power) from a distance, based on its low-frequency noise spectra. The work by [9] studied and developed lifetime estimation methods for power transformers and how these could be used for asset management purposes. The work by [10] proposed a machine learning-based method for developing PHM models from sensor data to perform fault diagnostic for transformer systems in a smart grid. The study by [11] presented an online condition monitoring system (OCMS) for transformers which was useful to replace reactive and preventive maintenance of transformers by predictive maintenance.

Diverse methods such as dissolved gas analysis, sweep frequency response analysis, and partial discharge analysis were reviewed for transformer condition analysis. These methods are not suitable for monitoring distribution transformers considering economics associated with cost of transformer and monitoring method. In other works, temperature measurement techniques were used for the determination of HI. Expert system such as fuzzy logic and artificial neural network were used for condition assessment. However, there is a drawback in the formulation of common framework for these artificial intelligence–based methods. This suggests the necessity for the development of a system independent of expert analysis, and simultaneously, it is compatible with utility

rules and regulations. In this thesis an optimized algorithm that uses data from sensors such as voltage, current, temperature, and oil level, to compute the health index (HI) of the transformer is designed.

## III. METHODOLOGY

The method that would be adopted in this research would be based on simulations and experimentations carried out using Matlab. The research flow would follow the step-wise approach illustrated below:

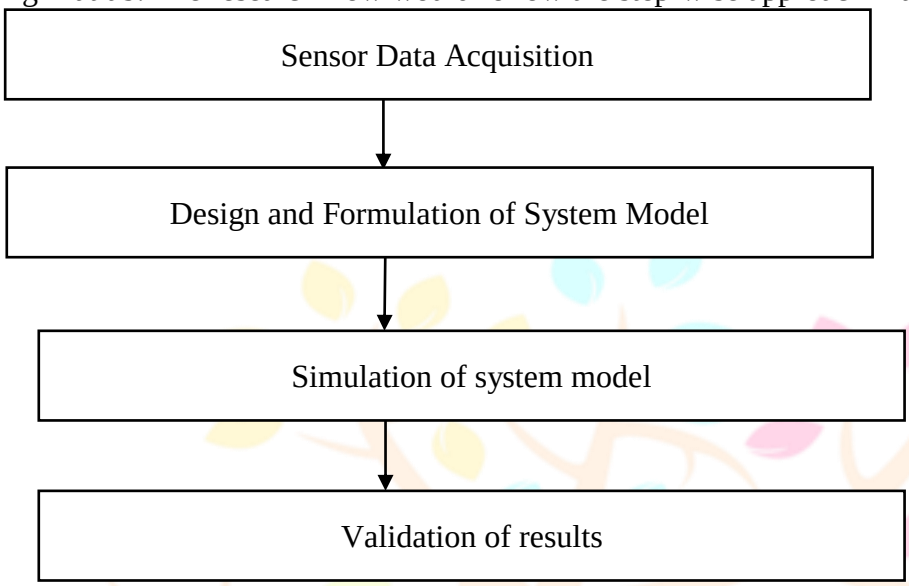


Figure 1: Research Approach block diagram

### i. Sensor Data Acquisition

The goal of sensor data acquisition is to collate sensor data from the communication channel of the smart grid. With the smart grid operation at distribution level, active control of remote stations and transformers is possible by use of the communication layer of the smart transformer system. This work presents a comprehensive monitoring system that uses data from sensors such as voltage, current, temperature, and oil level. The sensors are as follows:

a) **VOLTAGE SENSOR:** Voltage sensors are used to monitor or measure, calculate and determine the supply of voltage. With the help of this sensor, we can determine the AC or DC voltage level. The voltage sensor used is the ZMPT101B AC voltage sensor.
b) **CURRENT SENSOR:** Current transformers (CTs) are sensors are for measuring alternating current. They are particularly useful for measuring whole building electricity consumption (or generation for that matter). The split core type such as the SCT-013-000 used in this work can be clipped to either the live or neutral wire coming into the building without having to do any high voltage electrical work.
c) **TEMPERATURE SENSOR**: A temperature sensor is a device used to measure temperature. This can be air temperature, liquid temperature or the temperature of solid matter. The temperature sensor used in this work is the PT100 temperature sensor.
d) **OIL LEVEL SENSOR**: Oil level sensor is a device which is used to check the oil level in the transformer's conservator tank. The sensor used is the JSN-SR0T4-2.0 ultrasonic distance measurement module, which provides 20cm to 600cm non-contact distance sensing function, with an accuracy of up to 2mm.

### i. Design and Formulation of System Model

In order to provide information about the transformer's state of health and detect incipient faults, the monitoring system's must perform measurements and analyze the results in the context of given environmental conditions. Health Indices (HI) methods are practical tools to aggregate the results of multiple operating observations, field inspections, and site and laboratory testing into a single objective index that quantifies overall health of the distribution transformer [4].

HI represents the change in health condition of transformer (health diagnostics). In this work, the HI is formulated based on the measured (online) data of the distribution transformer. The overall health index is presented in the following equation [4]:

$$HI_{NM} = \frac{\sum_{i=1}^{n=4} S_{P_i} W_{P_i}}{S_{max} \sum_{i=1}^{n=5} W_{P_i}} \quad (1)$$

Where,

- HI is the health Index metric,
- $S_{P_i}$ is the score of each assessment condition that is identified based on the measured data.
- $S_{max}$ is the maximum score of assessment condition.
- $W_{P_i}$ is the weight of each assessment condition.
- $n$ is the number of the assessment condition.
- $P_i$ refers to the i[th] parameter of the system

In this work, an improved Genetic Algorithm (GA) approach is adopted for the computation of HI after processing the sensor data. Each of the sensor parameter is posed as an objective function, thus leading to a multi-objective function problem. Each of the objective function is obtained as follows:

1) **Voltage:** For a DT, the voltage variation of ±6% is permissible for DT. An increase in the voltage (usually the case of over voltage) causes proportionate increase in the working flux and thereby increases in iron loss of DT. The secondary side measured voltages of DT are $U_a$, $U_b$, and $U_c$, and their rated phase value is 230 V. The average of 3 phase voltage deviation ($\Delta U_{DT}$) at that load between the rated values of phase voltage ($U_{rated}$) and measured value of the phase voltage is given as [4]:

$$\Delta U_{DT} = \frac{1}{3}\left(\left|\frac{U_{rated} - U_a}{U_{rated}}\right| + \left|\frac{U_{rated} - U_b}{U_{rated}}\right| + \left|\frac{U_{rated} - U_c}{U_{rated}}\right|\right) \quad (2)$$

2) **Current:** When operating the DT, if there is an overload condition, the load current crosses its rated value and it results in increased copper losses. These ohmic losses also increase due to poor power factor of the connected load and it is also responsible for excessive voltage regulation. The unbalance of these currents ($\Delta I_{DT}$) can be expressed as [4]:

$$\Delta I_{DT} = \sqrt{\frac{1}{3}\left(|I_a - I_{rated}|^2 + |I_b - I_{rated}|^2 + |I_c - I_{rated}|^2\right)} \quad (3)$$

3) Temperature: The top oil rise over ambient temperature is given as (Gajanan et al, 2017):

$$\Delta\Theta_{TO} = \left(\Delta\Theta_{TO,U} - \Delta\Theta_{TO,i}\right)\left(1 - exp\frac{-t}{\tau_{TO}}\right) + \left(\Delta\Theta_{TO,i}\right) \quad (4)$$

Where $\Delta\Theta_{TO,U}$ is the ultimate top oil rise over the ambient temperature for load in °C and $\Delta\Theta_{TO,i}$ is the earlier top oil rise over the ambient temperature for t = 0, in °C. Here, t is the time duration in hours; $\tau_{TO}$ is the oil time constant of DT for any load L, and any specific temperature difference between the highest top and initial top oil rise. The oil time constant ($\tau_{TO}$) is given as [4]:

$$\tau_{TO} = C_{DT}.\frac{\Delta\Theta_{TO,R}}{P_{L,R}} \quad (5)$$

where $P_{L,R}$ is the total loss at rated load in watts. The term $\Delta\Theta_{TO,R}$ is the ultimate top oil rise over the ambient temperature at rated load (°C), and $C_{DT}$ is the thermal capacity of DT. Hence, minimization of top oil temperature is the objective function of the proposed approach.

4) Oil Level: The thermal capacity of DT is expressed as [4]:

$$C_{DT} = 0.1323W_c + 0.0882W_t + 0.3513\vartheta_{oil} \quad (6)$$

Where,

$W_c$ = The weight of core and coil assembly in kg

$W_t$ = The weight of tank and fittings in kg

$\vartheta_{oil}$ = The volume of oil in liters in DT. #

Note that the volume of oil is expressed in terms of maximum volume ($\vartheta_{oil\_max}$) of oil and volume of oil wasted due to oil leakages ($\vartheta_{oil\_leakage}$) as shown in equation (7).

$$\vartheta oil = \vartheta oil\ max - \vartheta oil\ leakage \quad (7)$$

The maintenance of an appropriate oil level is very important, consequently, the minimization of oil losses or oil leakage is one of the objective functions considered. Thus the objective function is given as [4]:

$$\vartheta_{oil\ leakage} = |\ \vartheta_{oil\ level\ set} - \vartheta_{oil\ level\ obsereved}| \qquad (8)$$

From (3.8), $\vartheta_{oil\ level\ set}$ and $\vartheta_{oil\ level\ obsereved}$ are the set value and actual values of oil level, respectively.

From the foregoing, a general formulation for a linear scalarization of the multiobjective optimization is obtained by combining equations (1) to (3) and (8). This is given as:

$$minimize\ f_i(t) = (\Delta U_{DT} + \Delta I_{DT} + \vartheta_{oil\ leakage} \times \Delta\Theta_{TO}) \qquad (9)$$

$$subject\ to \begin{cases} \Delta U_{DT} \leq \Delta U_{DT(S)}, \\ \Delta I_{DT} \leq \Delta I_{DT(S)}, \\ \vartheta_{oil\ leakage} \leq \vartheta_{oil\ leakage\ (S)}, \\ \Delta\Theta_{TO} \leq \Delta\Theta_{TO(S)} \end{cases}$$

From equation (9), the terms $\Delta U_{DT(S)}$, $\Delta I_{DT(S)}$, $\vartheta_{oil\_leakage(S)}$, and $\Delta\Theta_{TO(S)}$ are the specified values for voltage deviation, load current, volume of oil, or oil level due to leakage and top oil temperature rise over the ambient temperature for the DT. The limits for voltage variation and permissible load currents are set according to IEEE standards as contained in [12] and[13] respectively. Limits for oil level and top oil temperature are set based on the data obtained from manufacturer data sheet pertaining to individual DT. By means of optimization, it is possible to assess the condition of distribution transformer more effectively. To solve the optimization problem, Genetic Algorithm (GA) is used.

A GA is a search heuristic that is inspired by Charles Darwin's theory of natural evolution. GA is a search-based optimization technique based on the principles of Genetics and Natural Selection. It is frequently used to find optimal or near-optimal solutions to difficult problems which otherwise would take a lifetime to solve. It is frequently used to solve optimization problems, in research, and in machine learning. Nature has always been a great source of inspiration to all mankind. GAs are a subset of a much larger branch of computation known as Evolutionary Computation. In GAs, we have a pool or a population of possible solutions to the given problem. These solutions then undergo recombination and mutation (like in natural genetics), producing new children, and the process is repeated over various generations. Each individual (or candidate solution) is assigned a fitness value (based on its objective function value) and the fitter individuals are given a higher chance to mate and yield more "fitter" individuals. This is in line with the Darwinian Theory of "Survival of the Fittest". In this way we keep "evolving" better individuals or solutions over generations, till we reach a stopping criterion.

The basic structure of a GA is such that it starts with an initial population (which may be generated at random or seeded by other heuristics), select parents from this population for mating. Apply crossover and mutation operators on the parents to generate new off-springs. And finally these off-springs replace the existing individuals in the population and the process repeats. In this way genetic algorithms actually try to mimic the human evolution to some extent.

The detailed steps of the improved GA are described as follows:

1. The system searches and isolates faulty DT from previous searches made and also indicates previously blocked faulty sensors for possible replacement or repairs.
2. The algorithm fetches individual transformer nameplate details, reference function curve $f_{ref}$ for each individual measurable parameter, time interval for the determination of HI, GA parameters, power factor ($\cos\varphi$set), current ($I_{set}$), and voltage ($V_{set}$) set values. These values are accessed from the individual communication unit of the DT.
3. In this step, the input data from all the four connected sensors are read and converted into pu value using data recommended by [12]. This online data is used to determine the function $f_{ON}$, which is plotted and compared with the reference function curve $f_{ref}$ to monitor sensor operating condition. This step helps to identify defective sensors so that the data from these sensors are blocked from being processed. The data obtained in this step is used to generate a population of chromosomes.
4. The processor then reads the data from healthy sensors and determines the fitness function. The fitness function ($f_2$) for the proposed algorithm is given as [4]:

$$f_2 = \frac{1}{w}\left[w_1 \frac{\Delta U_{DT} - \Delta U_{DTmin}}{\Delta U_{DTmax} - \Delta U_{DTmin}} + w_2 \frac{\Delta I_{DT} - \Delta I_{DTmin}}{\Delta I_{DTmax} - \Delta I_{DTmin}} + w_3 \frac{\vartheta_{oil\ leakage} - \vartheta_{oil\ leakage\ min}}{\vartheta_{oil\ leakage\ max} - \vartheta_{oil\ leakage\ min}} + w_4 \frac{\Delta\Theta_{TO} - \Delta\Theta_{TO\ min}}{\Delta\Theta_{TO\ max} - \Delta\Theta_{TO\ min}}\right] \quad (10)$$

Where, $w = w_1 + w_2 + w_3 + w_4$

$w_1 = Voltage\ weight,$

$w_2 = Current\ weight,$

$w_3 = Oil\ Level\ weight\ ,$

$w_4 = Oil\ temperature\ weight$

According to the availability of measurable parameters, they are translated into genes and ingrained in chromosome strings. The initial population and its compatible strings are generated randomly as a set of binary set [initial population] like [11010.....010] from the input data.

5. The algorithm estimates the fitness within population by calculating the fitness of all chromosomes. 2 chromosomes from the population are randomly selected and the algorithm Performs crossover and mutates the 2 chromosomes selected. The propagating procedure will continue until generations meet maximum generation limit and/or the solution becomes convergent.
6. If more than 2 sensors data was blocked from step 3, the algorithm estimates the impact of the result obtained based on previously estimated HI, if the deviation is below a set threshold of 65%, then the computation is ignored and produces a trip signal that alerts the utility substation of abnormal readings due to faulty sensors.
7. If the condition in step 5 is not applicable, the system displays the HI results and produces alarm or trip signal if necessary and communicates with the utility substation.

### ii. Simulation of system model

The simulation is carried out using MATLAB as depicted in chapter 4. The simulation parameters are chosen and a series of simulations are carried out to examine the performance of the system.

### iii. Validation of Results

To validate the performance of the system, the results obtained are compared to the results obtained from an already existing design as described in section 4.

## IV. RESULTS AND DISCUSSION

With the smart grid operation at distribution level, active control of remote stations and transformers are possible by use of communication channels. The communication module used by the system is the XG2018 3G module. The module has 3G penta-band communication technology that operates at frequencies 800, 850, 900, 1900 and 2100 MHz.

In this research, MATLAB was used to simulate the communication channels, and for the GA method used in this research, the monitoring system was implemented in C++. A layout of the simulation architecture is as shown in figure 2.

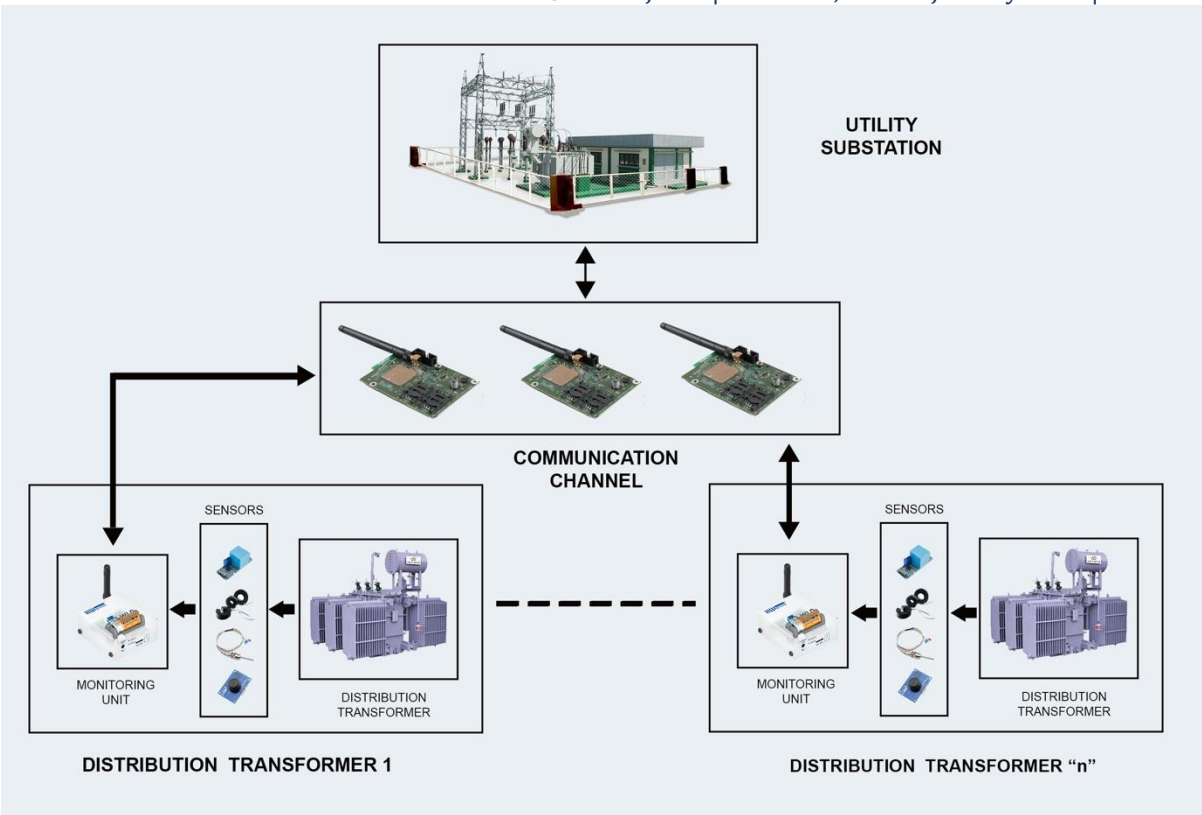


Figure 2: Architecture of the smart transformer system

The experimental setup adopted is similar to the work by [4]. This work is also used to validate the results obtained in this work. The simulation parameters used in this work are as shown in Table 1.

Table 1: Simulation Parameter

| **Parameters** | **VALUE** |
|---|---|
| Rated voltage | 230v |
| Rated load current | 21.65 A |
| Top oil temperature (maximum) | 65 °C |
| Phase Configuration | 3 Phase, 4 wire |

The system performance was analyzed under different scenarios and the following performance metrics were compared with the result obtained by [4].

1. **Normal state with a sound sensor**

The voltage is initially set by the three-phase autotransformer at its rated value with the load on the DT at 50%. 100% of the oil is kept in the DT's main tank. At the ambient temperature of 33.6°C indicated in Figure 3, the top oil temperature kept increasing as the time increased. Figure 3 shows that the top oil temperature steadily rises over time and is influenced by the load that is connected to the transformer.

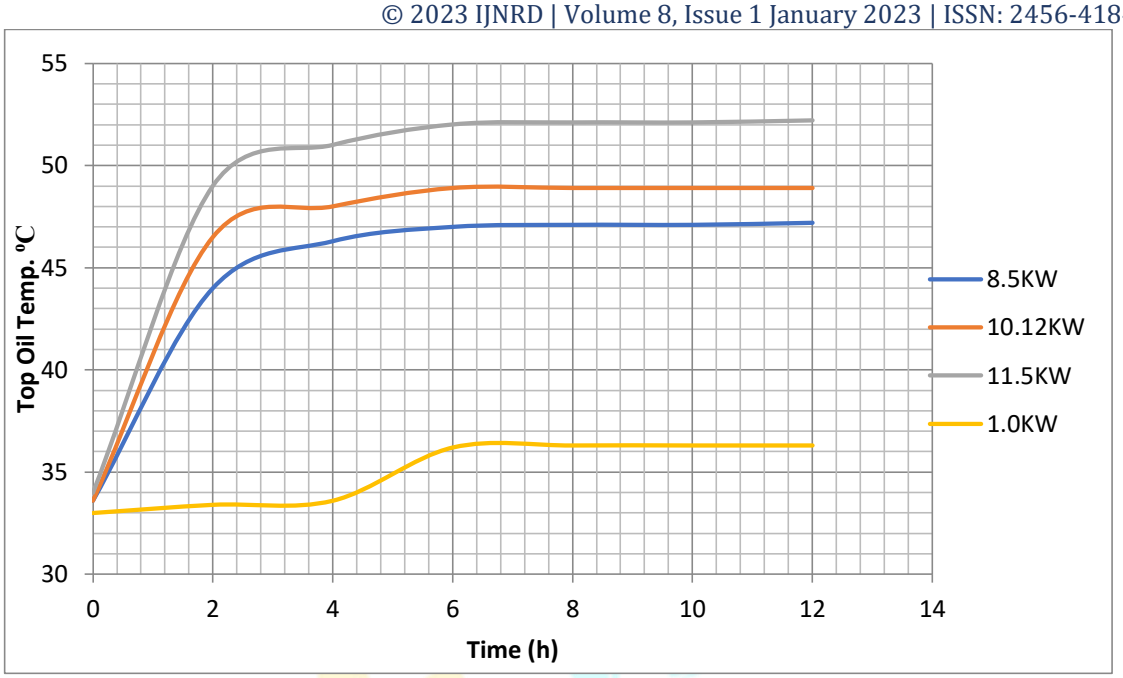


Figure 3: Experimental results for top oil temperature for different load condition

From figure 3, when the load was 1kW, the top oil temperature rose from 33.6°C to 36°C. Higher loading conditions was also considered as shown in figure 3. When the load condition was about 10.12kW, the oil temperature rose to 48.9°C. Figure 4 depicts the experimental findings for temperature fluctuations at various loads and oil levels.

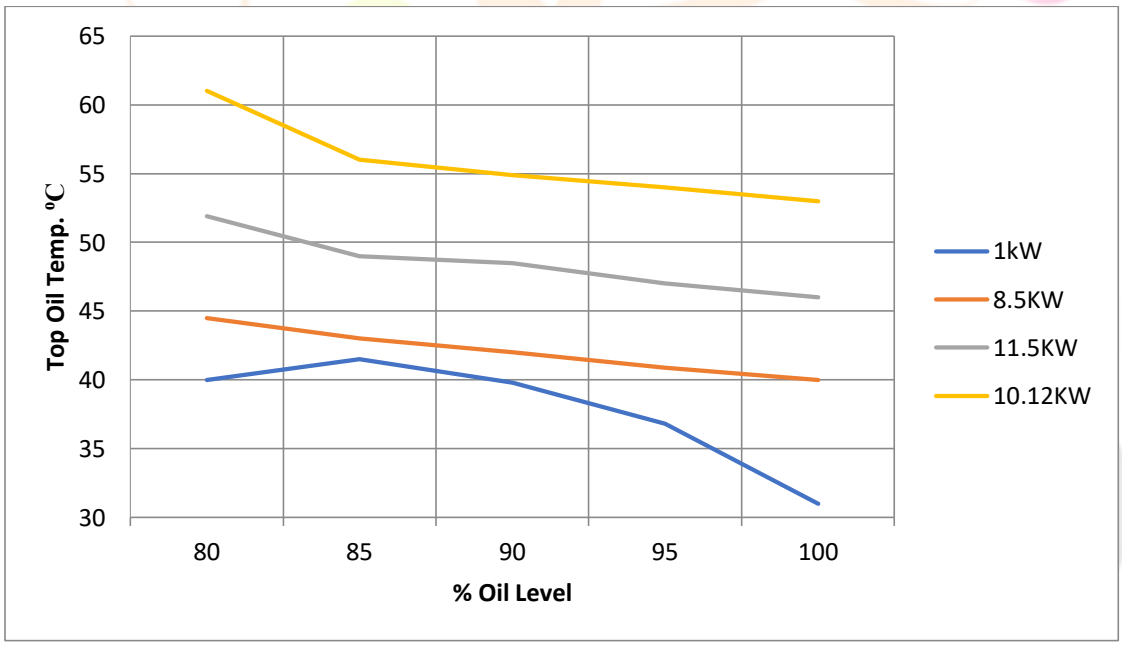


Figure 4: Top oil temperature and oil level

From figure 4, when the oil level was at 90%, and the load condition was 1kW, the top oil temperature was 39.8°C. Also, When the oil level was at 90%, and the load condition was 8.5kW, the top oil temperature was 42°C. The experimental conditions of all the sensors when they were operating in a normal condition was also considered. This analysis is necessary to serve as a baseline for establishing abnormalities when the sensors starts malfunctioning. Figure 5 and figure 6 gives a plot of the experimental characteristics index of the sensors.

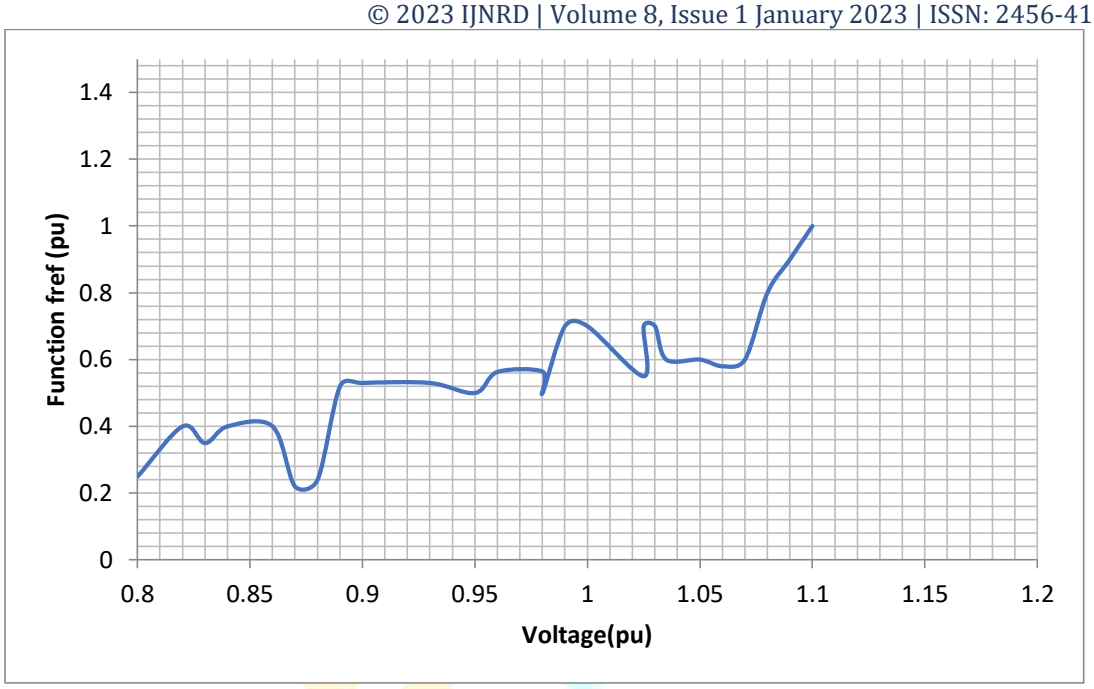


Figure 5: Experimental sensor characteristic curve for Voltage sensor

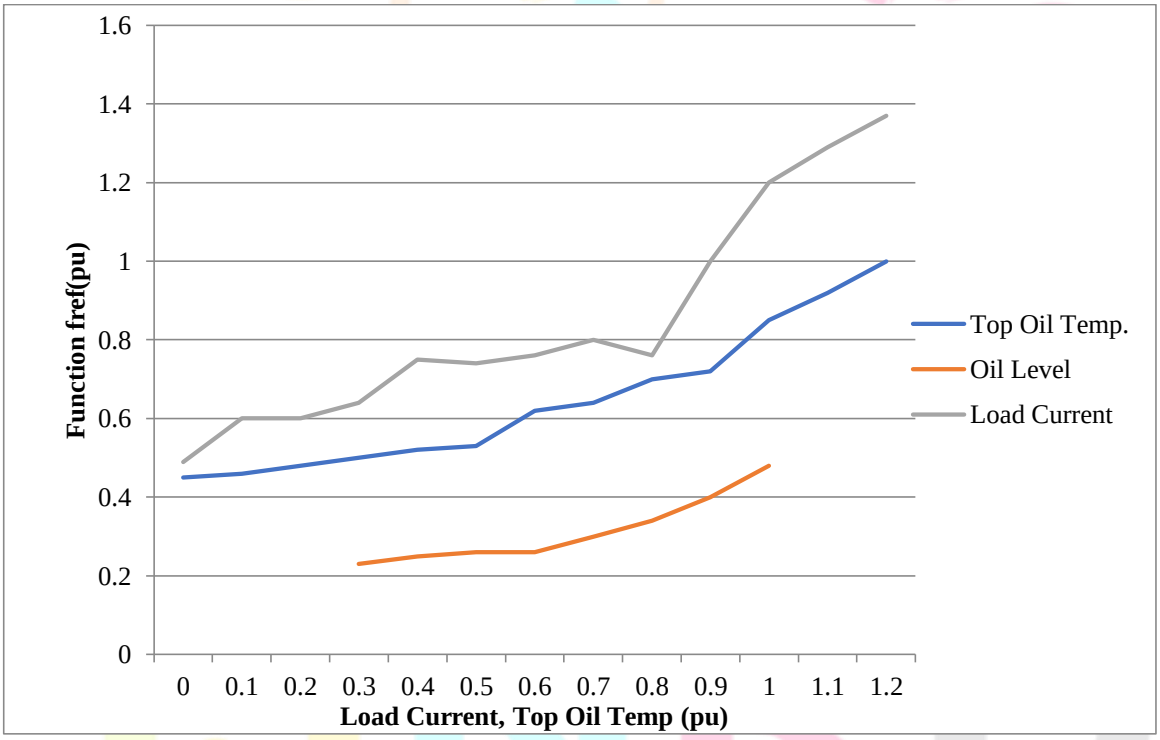


Figure 6: Experimental sensor characteristic curve for load current, oil temperature and oil level sensors.

Under the normal operating condition, the HI of the DT were computed. The overall HI obtained by the method developed in this work is 99.89%, while the overall HI obtained by the GA technique employed by [4] was 99.78%. This shows a 0.11% improvement when compared to the benchmark performance of 100%.

**2. Normal state with a faulty sensor**

In this scenario, the sensors are incorrectly connected intentionally so that inaccurate data is fed to the monitoring unit. In the following analysis, the voltage sensor was incorrectly connected and the data fed in was compared to the reference or baseline performance curve that was captured initially.

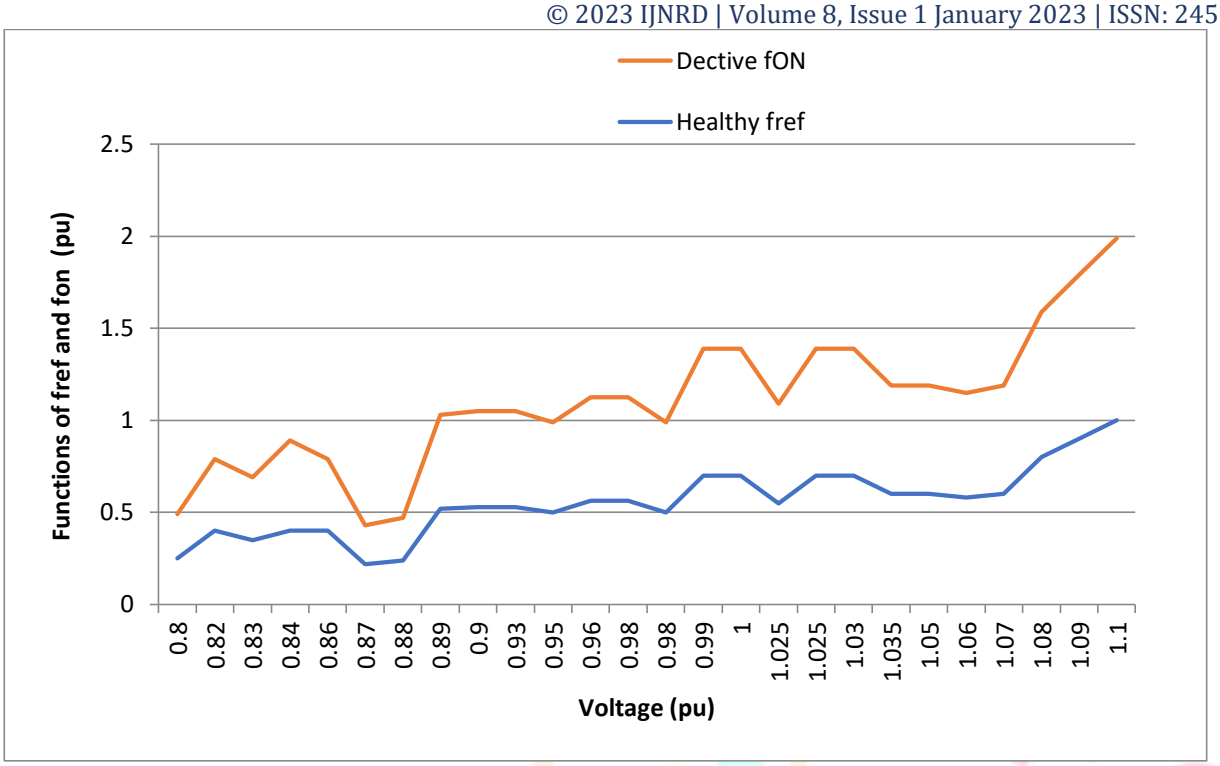


Figure 7: Experimental results for normal condition with a defective voltage sensor

From figure 7, it is seen that the voltage sensor readings did not match with the original reference characteristics captured by the system initially. This is visible by the mismatch of the plot shown in figure 7. Once this happens, the system flags the sensor as being faulty because the online characteristic ($f_{on}$) curve does not match with the previously stored historical characteristics ($f_{ref}$). Also, the HI of the DT was computed. The overall HI obtained by the method developed in this work for this scenario is 99.70%, while the overall HI obtained by the GA technique employed by [4] was 99.53% as shown in figure 8. Note that the drop-in accuracy was as a result of the faulty sensor data that was blocked. It is also noticeable that the impact on the method by [4] was higher than that developed in this work.

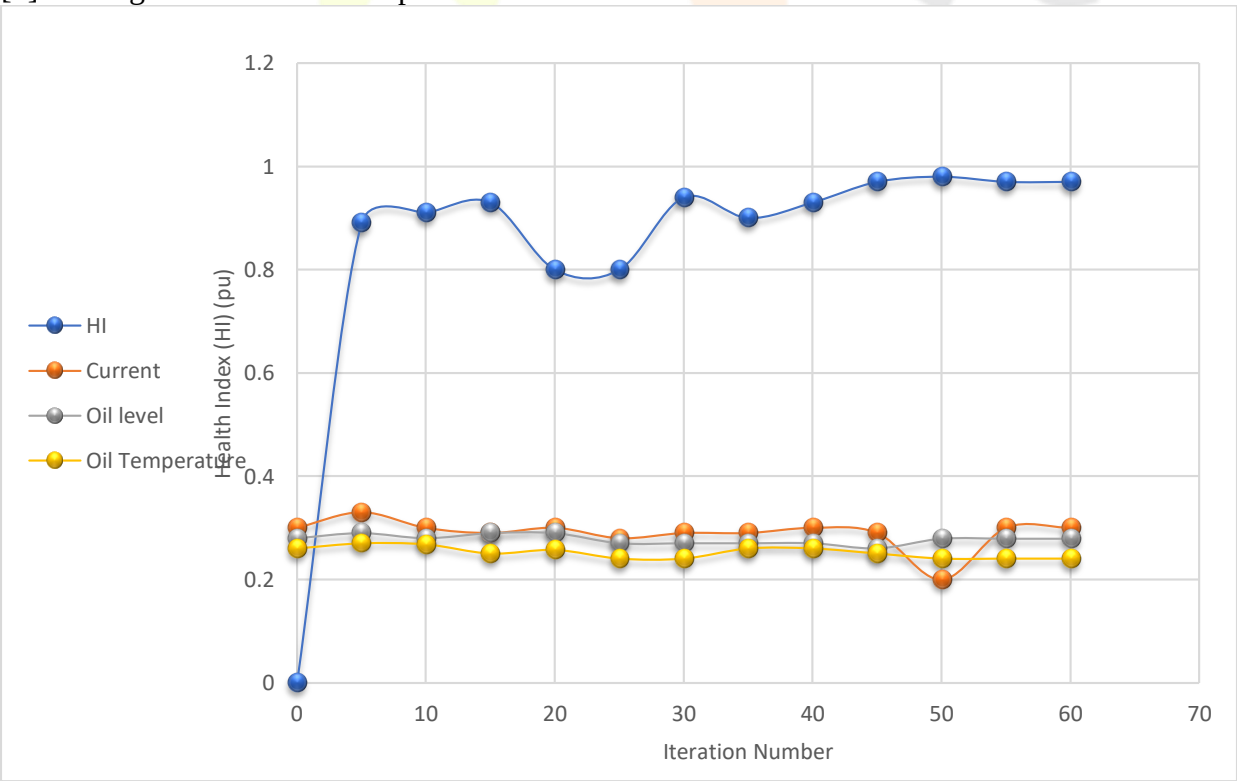


Figure 8: Experimental results for health index and different weights impact

### 3. Abnormal state with a functional sensor

Researchers have looked into how to compute the DT health index in unusual circumstances. The supply voltage fluctuation below and above its tolerance band, the percentage loading of the DT increasing above its rated value, and the DT's oil level decreasing are these abnormal conditions. At first, the oil level is kept at 100%

while the supply voltage is reduced by 1% under a 50% rated load condition. The HI was computed when the top oil temperature was 40.8°C and the current drawn by transformer was 10.16 A. The HI calculated using our method was 99.20%, while the method by [4] was 98.79%.

Also, another scenario was considered when the oil level and the load percentage remain the same but the supply voltage was reduced to 86.08% of the rated voltage. The simulation result showed that the top oil temperature dropped to about 39.8°C. The health index was computed using the developed algorithm, and the obtained Hi for the DT was 81.66%, while the method by [4] was 79.91%. Also, it was observed that the developed model required 50 iterations as seen in Figure 9 to obtained the correct HI, while the experimental performance method by [4] showed that it needed 55 iterations.

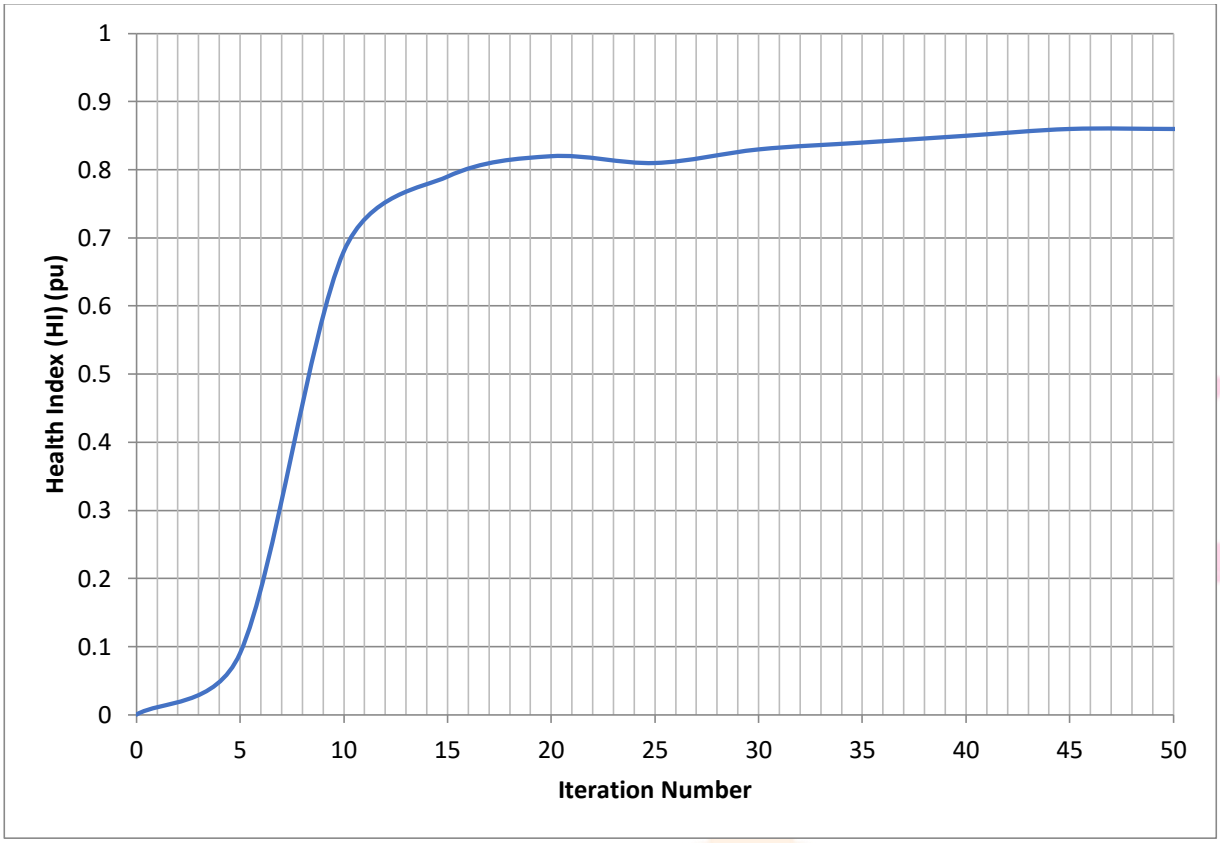


Figure 9: Experimental results for abnormal conditions and healthy sensors

The impact of overloading was also analyzed. It was assumed that an overload condition exists when the DT exceeds a 95% load condition. Under this condition, the oil level was kept at its normal level and the supply voltage was kept within its tolerance. The simulation required that the load was increased gradually from 0% to 120%. This resulted to an increase in the oil temperature until it reached a critical level of about 60.7°C.

## 4. Abnormal circumstance with faulty sensor

The final scenario considered is when the system is operated in an abnormal state and the sensors are all faulty. With faulty sensors and the DT operated with a top oil temperature of about 58.6°C at 160 volts, with overload condition of about 115% at 80% oil level. The HI was calculated using the developed method and the method by [4], the obtained HI respectively, is 51.89% and 49.41%. Figure 10 displays the experimental findings under abnormal circumstances and faulty sensors.

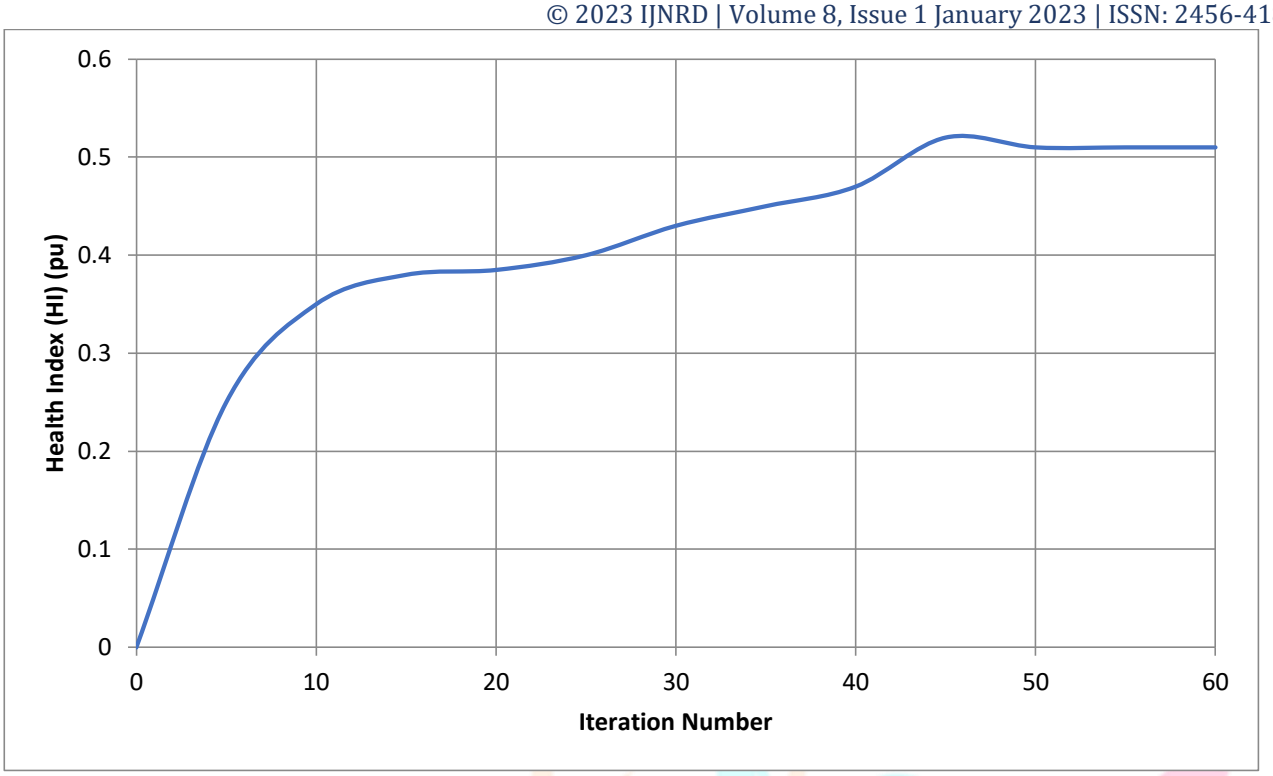


Figure 10: Experimental results for abnormal condition and defective sensors for under voltage

The impact of the weights for each sensor was also analyzed and presented in Figure 11.

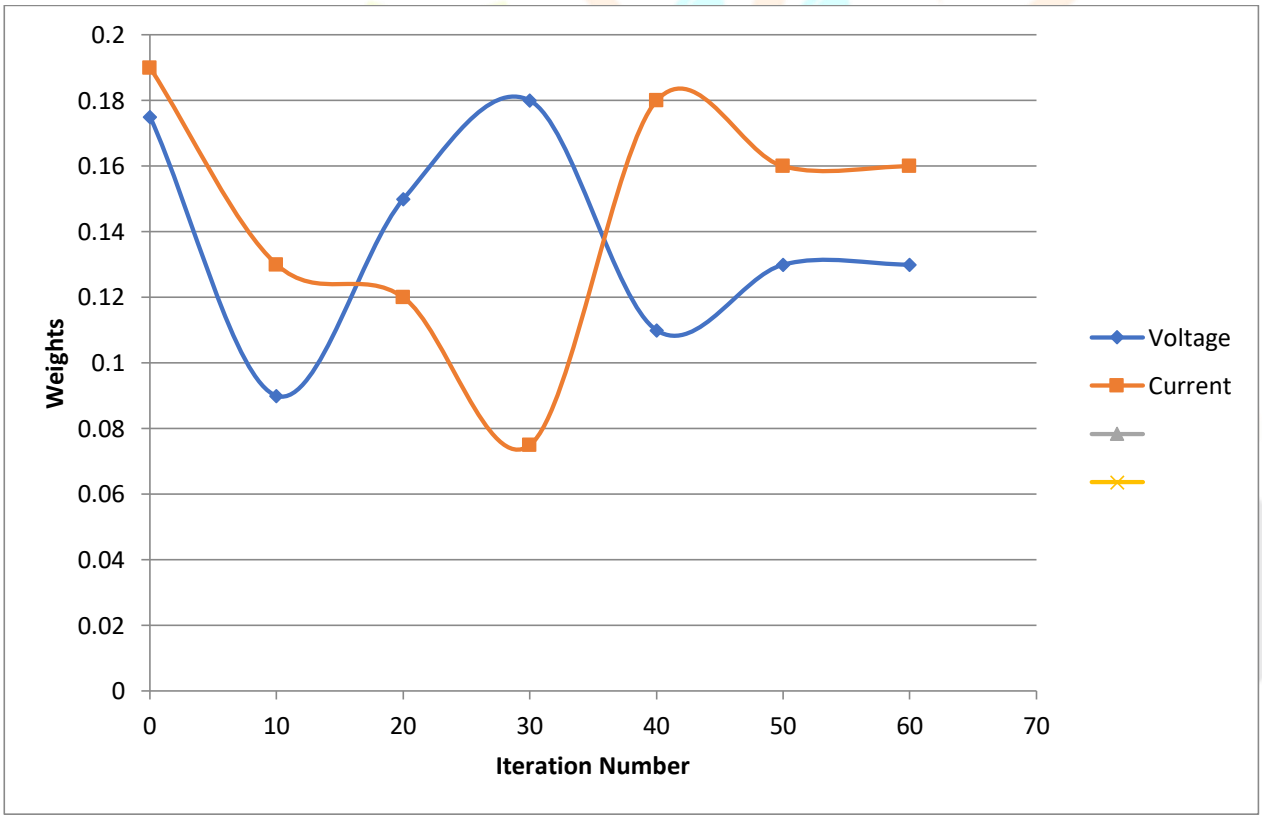


Figure 11: Experimental results of the impact of sensor weights for abnormal condition and defective sensors.

From figure 11 it is observed that the weights for oil level and temperature were blocked because the system detected their readings as very faulty. Thus, they are not allowed to impact on the HI accuracy.

## V. CONCLUSION

Distribution transformers are currently monitored manually where a person periodically visits a transformer site for maintenance and recording the parameters. This type of monitoring cannot provide information about occasional overloads and overheating of transformer oil and windings. Online monitoring system consists of embedded system, GSM modem, mobile-users and GSM networks and sensors installed at transformer site Sensors are installed on transformer side which reads and measures the physical quantity from the distribution transformer and then it converts it into the analog signal. In this paper, an optimized algorithm for parameter monitoring of distribution transformers in a smart grid based on HI analysis was developed. The HI was formulated based on the measured (online) data of the distribution transformer obtained from the work by

[4]. The experimental setup adopted was similar to the work by [4]. This work was also used to validate the results obtained in this work. The system performance was analyzed under different scenarios namely - Normal state with a sound sensor, Normal state with a faulty sensor, Abnormal state with a functional sensor, and Abnormal circumstance with faulty sensor.

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