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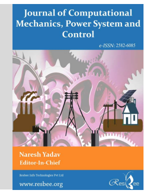

Hierarchical Temporal Memory (HTM)Approach for Fault Detection in Transmission Line

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Abstract: This study was conducted to proposea hierarchical temporal memory (HTM) approach for fault detection in the Onitsha-Alaoji transmission line in Nigeria. Using a mixed research method, the study employed the Hawkins HTM model with two objectives and their corresponding research questions. The study gathered primary and secondary data to detect and evaluate faults in the Onitsha-Alaoji transmission line in Nigeria using HTM and compares its efficacy to current fault detection methods. With the use of simulation and descriptive methods of data analysis, results showed that partial discharge (PD) is the fault type that is being detected and it is commonly found as a fault leading to transmission line errors. More so, fault detection simulations were conducted at 40 km using typical power spectral density analysis. The first fundamental shifted from about 10 kHz to roughly 13 kHz during a fault. The HTM model outperformed sequence learning methods, resulting in a 90% mean test classification accuracy (CA) over extreme learning machine(ELM) and online sequential learning–extreme learning machine (OS-ELM), with OS-ELM performing poorly.The study concluded and recommended that the proposed HTM model be used to identify various PD fault types that plague the Onitsha-Alaoji transmission line in Nigeria. With the increased efficacy and reliability of the proposed model compared to existing methods, it is recommended for future implementation in this transmission line and potentially other fault-prone power transmission lines in Nigeria.

Keywords: Hierarchical Temporal Memory;Partial Discharge;Fault Detection Methods;Transmission Line; Simulation and Descriptive Method.

Nomenclature

Abbreviation	Expansion
HTM	Hierarchical Temporal Memory
GDP	Gross Domestic Product
SDR	Sparse Distributed Representation
VSB	Venezuelan Seismic Bulletin
GDP	Gross Domestic Product
UI	User Interface
OS-ELM	Online Sequential Extreme Learning Machine
CLA	Cortical Learning Algorithm
SPU	Spatial Pooler Unit
TPU	Temporal Pooler Unit
CU	Classifier Unit
HTM-CLA	Hierarchical Temporal Memory-Cortical Learning Algorithm
MAPE	Mean Absolute Percentage Error
NLL	Negative Log Likelihood
PD	Partial Discharge
TL	Transmission Line
PSD	Power Spectral Density

1. Introduction

Power systems rely on the transmission of electrical energy to consumers. However, issues in transmission lines can pose a risk to the safety and stability of the entire power grid. Conventionally, fault detection in transmission lines is carried out using conventional methods that rely on the measurement of current and voltage [12]. These methods have limitations, especially when faults are located far away from the monitoring equipment or in complex network topologies[20]. To overcome these

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limitations, HTM, a machine-learning technique inspired by the human brain, offers a promising solution[5]. HTM can learn complex patterns and make real-time predictions, which makes it suitable for fault detection in complex systems[8]. HTM has three main components: the spatial pooler, the temporal pooler, and the inference layer. The spatial pooler identifies patterns of activity in the input data, while the temporal pooler learns the sequence of patterns and their relationships over time[9]. More so, the inference layer performs the prediction task based on the learned patterns [4].HTM can be applied to fault detection in transmission lines by using voltage and current measurements as input data. One advantage of the HTM approach is its ability to learn and adapt to the changing conditions of the power system[5]. This is crucial in detecting faults in transmission lines because the operating conditions can change rapidly due to changes in load, weather, or other factors[5]. Additionally, the HTM approach can handle incomplete and noisy data, which is often the case with transmission line fault detection. The HTM approach can also be combined with other fault detection techniques to improve their effectiveness[18][9]. By leveraging its ability to learn complex temporal patterns and detect anomalies that may not be apparent through traditional methods, the HTM algorithm can capture dependencies at different levels of abstraction and detect anomalies in complex systems[16].

Statement of the Problem

In Nigeria, like many other developing countries, the problem of fault detection in transmission lines has been a major challenge in the energy sector. Faults in TL are common occurrences that can lead to long periods of energy outage, as it takes time to locate and rectify the fault. The situation has led to a loss of revenue for energy companies due to a decrease in energy delivery to consumers. In addition, the country has suffered a lot of economic setbacks due to the inability to meet up with production targets. According to several reports, it is estimated that the problem of fault detection has reduced the total amount of energy distributed to consumers by up to 40%. This means that the country has not effectively met its energy needs, leading to a decrease in productivity and negatively affecting the country's GDP. To properly address this challenge, there needs to be an investment in modern technologies and infrastructure to ensure efficient monitoring and detection of TL faults. Therefore, the researchers are motivated to propose an HTM approach for fault detection in transmission lines to address this concern.

Aim and Objectives of the Study

This study was aimed at proposinganHTM approach for fault detection in the Onitsha-Alaojitransmission lineinNigeria. Specifically, the objectives were:

1. Identify the fault type that is being targeted for detection and evaluation in the Onitsha-Alaoji transmission line in Nigeria using the proposed HTM technique.
2. Evaluate the reliability and efficacy of the proposed HTM model in comparison to the currently available fault detection methods utilized in the Onitsha-Alaoji TL in Nigeria.

Overall, this study proposed the use of HTM for fault detection in transmission lines, to improve the safety, stability, and viability of the entire power grid.

The following is an outline of this study's main findings: Section 2 covers a Literature review. Section 3 details the Method and Methodology, and Section 4 emphasizes the model of the Existing System. The Proposed HTM System is explained in Section 5. The Results and Discussion are explained in Section 6. Section 7 mentions the Advantages and Disadvantages of the proposed method and section 8 concludes the paper with future work.

2. Literature Review

HTM is an advanced approach that can be used for fault detection in TL, offering significant improvements over traditional methods. This was explained by [15] that HTM is a machine learning algorithm inspired by the structure and functionality of the neocortex, the part of the brain responsible for higher-level cognitive functions. This approach has gained attention in recent years due to its ability to handle complex temporal patterns and its potential for fault detection in various domains. According to research [21], HTM demonstrates superior performance compared to conventional algorithms, providing more accurate and timely fault detection. This is akin to [17] in which the HTM approach incorporates the understanding of temporal patterns, which is critical for fault detection in transmission lines. Traditional methods such as the use of rule-based algorithms or state estimation techniques[22] often struggle to capture the subtle changes occurring over time. On the contrary, [16] observed that HTM models temporal data effectively, utilizing its inherent structure to recognize patterns and anomalies. According to [11], HTM's capability to detect temporal patterns can significantly enhance the accuracy of fault detection in transmission lines. Similarly, IEEE Transactions published that HTM has shown promising results in fault detection applications [2]. The hierarchical structure of HTM allows it to learn complex patterns at multiple levels of abstraction enabling it to capture both short-term and long-term dependencies in transmission line data. This capability is particularly useful for detecting faults that exhibit subtle changes over time or have non-linear characteristics.

Furthermore, [1] pointed out that HTM can adapt to changing conditions and learn from new data without requiring retraining from scratch. This flexibility is crucial in fault detection applications where the operating conditions of transmission lines can vary significantly over time. Moreover, the hierarchical nature of the HTM approach allows for a more comprehensive analysis of fault data[7] [17]. HTM models can capture both short-term and long-term dependencies in the data[23], enabling a better understanding of the context and dynamics of the transmission line. This multi-level analysis provides a more holistic perspective on the fault detection process ensuring higher accuracy and reducing false alarms [3]. Additionally, HTM's ability to handle streaming data in real-time is instrumental in fault detection applications[14]. Traditional methods often rely on batch processing, which can be time-consuming and inefficient for dynamic systems like transmission lines. HTM on the other hand processes data as it arrives, allowing for immediate detection and response to faults. According to [9], this real-time capability of HTM minimizes downtime and improves the overall reliability of the transmission line.

2.1 Review Table

S/N	Study Title	Authors	Year	Objective	Methodology	Key Findings	Contribution
1	Fault classification in double-circuit transmission lines based on the hierarchical temporal memory.	Idonibo yeobu and. Wokom a.	2017	Fault classification in transmission lines.	Hierarchical temporal memory.	Fast and accurate fault detection and classification.	Utilization of extreme learning machine for fault detection and classification.
2	Fast and accurate fault detection and classification in transmission lines using extreme learning machines.	Goni.,*et al.*	2023	Improve fault detection in transmission lines	Use of extreme learning machine.	Enhanced accuracy and speed in fault detection.	Improved reliability in power transmission systems.
3	A comprehensive evaluation of multicategory classification methods for fault classification in series compensated transmission line	Malathi,*et al.*	2010	Evaluate multicategory classification for fault classification.	Using multiclass support vector machine.	New method for fault classification.	Improved fault classification in TL.
4	Improved performance of detection and classification of 3-phase transmission line faults based on discrete wavelet transform and double-channel extreme learning machine.	Haq,*et al.*	2021	Improve detection and classification of faults.	Discrete wavelet transform and double-channel extreme learning machine.	Improved location and classification of faults.	Enhanced performance of fault detection and classification.
5	A novel fault classification technique in series compensated transmission line using ensemble method.	Raval and Pandya	2020	Classify faults in the EHV transmission line.	Using the ensemble method.	Novel approach for fault classification.	A new technique for fault classification in TL.
6	Fault classification, location in a series compensated power transmission network using Online Sequential Extreme Learning Machine.	Garg and Panigrahi	2016	Classify and locate faults in power transmission.	Online Sequential Extreme Learning Machine.	Accurate fault classification and location.	Improved fault detection in power transmission.
7	Fault classification of	Ray,*et*	2016	Classify 3	k-Nearest	Effective fault	Improved fault

	a long transmission line using nearest neighbor algorithm and boolean indicators.	*al*		phase faults in TL.	Neighbor algorithm.	classification in TL.	detection methodology.
8	Ensemble method for fault detection & classification in transmission lines using ML.	Shahid and Azim.	2023	Detect and classify transmission line faults.	Ensemble method, Machine Learning.	Enhanced fault detection and classification.	Advanced fault detection and classification technique.

2.2 Identified Research Gap

This study's approach to identifying the research gap is truly remarkable. It excels at modeling and predicting temporal patterns, making it perfect for detecting faults in transmission lines that heavily rely on temporal data. Specifically focused on the Onitsha-Alaoji transmission line in Nigeria, this study contributes to the scarce literature on fault detection in the Nigerian power grid. By implementing the HTM approach to fault detection in a specific transmission line in Nigeria, this research expands our understanding of a cutting-edge technique that could greatly improve accuracy and efficiency in fault detection. Overall, this research provides valuable insights into an unexplored realm of fault detection, offering thrilling possibilities for advancements in the field.

2.3 Theoretical Framework

The HTM model is an outstanding theory that has immense potential for detecting faults in transmission lines. Jeff Hawkins and his team at Numenta developed this sophisticated model, which offers remarkable advancements compared to traditional approaches[24]. It has shown promising results and could potentially replace existing fault detection systems. HTM model posits that faults are detected through a hierarchical structure of patterns in the data in which anomalies are recognized and flagged. This approach yields more accurate and efficient fault detection making it a highly appealing prospect for the power industry.

3. Materials and Methodology

To achieve the objectives of this research, a systematic approach involvingthe HTM detection process,simulation data for transmission line fault detection, transmission line parameters, model of the existing system as well as a model of the proposed HTM system.

3.1 HTM Detection Process

Initially, the input data at the time interval of t, ie., $I_t = (i_1, i_2, ..., i_n)$ is passed to the encoder. The binary value was then sent to the spatial pooler. The binary representation isconverted into SDR. A temporal memory is used to store data. Finally, the detectionis obtained through SDR prediction. Fig.1 represents the flow of the HTM detection process.

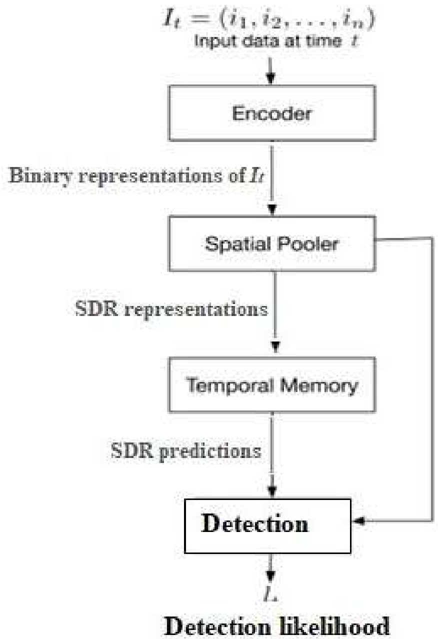

Fig.1. *Visual representation of the flow in the HTM detection process*

3.2 Simulation Data for Transmission Line Fault Detection

For classification purposes, the simulation dataset employed isbased on publicly available data (VSB power line dataset) earlier introduced in Kaggle completion (www.Kaggle.com). In this dataset, there are 8712 samples, where each sample comprises comprising of electrical signals with 800,000 voltage readings kept as numerical figures. The signals are cumulated in a real three-phase power sequence operating within 50Hz main frequency and gathered across a particular full bridge period of about 20ms.Typically, the VSB data collection comprises a feature class that establishes the category of the input signal type.In general, there are8187 normal feature (class) points and 525 feature (class) points inthe abnormal category. A representation of the data set is displayed in Table 1. The full details on the dataset can be obtained from the Kaggle website repository.

Table 1: *VSB Kaggle Dataset Sample*

Signal_id	id_measurement	Phase	Target
0	0	0	0
1	0	1	0
2	0	2	0
3	1	0	1
4	1	1	1
5	1	2	1
6	2	0	0
7	2	1	0

(Source:https://www.kaggle.com/c/vsb-power-line-faultdetection/data)

3.3 Transmission Line Parameters

To effectively apply a fault detection strategy, a transmission line parameter set is needed. In this study, a section of the National Grid located in the SouthernSwamp region of Nigeria was considered. This section is the Onitsha – Alaoji Direct Circuit (T4A), located in Port Harcourt, and is one of the oldest lines in the region. It was built in 1982 and also represents one of the longest TLs as it covers 154km with 306 lattice towers standing along its route. It uses Bison Twin conductors and has two (2) conductors per phase. The conductor cross-section is 350mm^2. Table 2 providesthe key parameters (variance) used in the syntheses of fault detection whereas a one-line diagram is shown in Fig.2.

Table 2: *Onitsha-Alaoji Key TL/Transformer Parameters*

Parameter	Value	Unit
Line Length	154	Km
Conductor Resistance	0.00390	Ω/km
Conductor Inductance	1.11000	mH/km
Conductor Capacitance	0.11100	nF/km
Transformer Inductance	110	mH
Transformer Resistance	0.02	Ω

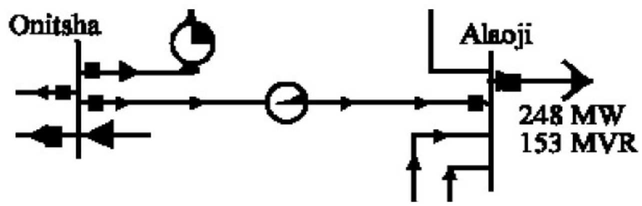

Fig.2. *Line Diagram of Onitsha – Alaoji Direct Circuit (T4A)*

4. Model of Existing System (OS-ELMNeural Model)

Algorithm 1: Initialization Phase:

- Initialize the learning process usinga smallchunk, *k* of initial training data from the given training data set :

○ Chunk→ $N_o = \{(x_i, t_i)\}_{i=1}^{N_o}$

○ Training dataset→ $N = \{(x_i, t_i) \mid x_i \in \Re^n, t_i \in \Re^m, i = 1,...\}, N_o \geq N$

▪ Assignrandom input weights a_i and bias b_i for additive hidden nodes for RBF hidden nodes assign a_i and b_i become a centerand an impact factor, $i = 1,...,N$

▪ Calculate the initial hidden layer output matrix, H_o

$$H_o = \begin{bmatrix} G(a_1, b_1, x_1) & \cdots & G(a_{\tilde{N}}, b_{\tilde{N}}, x_1) \\ G(a_1, b_1, x_{N0}) & \cdots & G(a_{\tilde{N}}, b_{\tilde{N}}, x_{N0}) \end{bmatrix}_{N_0 \times \tilde{N}}$$

▪ Estimate the initial output weight:

$$\beta^{(0)} = P_0 H_0^T T_0,$$
$$P_0 = \left(H_0^T H_0\right)^{-1}$$
$$T_0 = \left[t_{1,\dots,} t_{N0}\right]^T$$

▪ Set *k* = 0.

Sequentiallearning Phase :

○ Present the number of observations in the *(k+1)*th chunk:

$$N_{k+1} = \{(x_i, t_i)\}_{i=\left(\sum_{j=0}^{k} N_j\right)+1}^{\sum_{j=0}^{k+1} N_j}$$

▪ Calculate the partial hidden layer output matrix for the *(k+1)*thchunk of data N_{k+1}, as in [25].

▪ Set $T_{k+1} = \left[t_{\left(\sum_{j=0}^{k} N_j\right)+1}, \dots, t_{\sum_{j=0}^{k+1} N_j} \right]^T$

▪ Calculate the output weight, $\beta^{(k+1)}$

$$P_{k+1} = P_k - P_k H_{k+1}^T \left(I + H_{k+1} P_k H_{k+1}^T\right)^{-1} H_{k+1} P_k$$
$$\beta^{(k+1)} = \beta^{(k)} + P_{k+1} H_{k+1}^T \left(T_{k+1} - H_{k+1} \beta^{(k)}\right)$$

▪ Set k=k+1. Repeat the sequence learning phase

Until *k* is the maximum

End

5.Model of the Proposed HTM System

The HTM model leverages a sparse distributed representation by utilizing the HTM neural network which is based on the CLA. This network employs SDRs to encode input data leading to enhanced noise robustness and flexibility in handling symbolic, numeric, and string data without the requirement of distinct training and testing phases. The CLA enables stable predictions by imitating the brain's regenerative learning processes and generates internal activations that mimic the brain's predictive capabilities. These characteristics make the HTM model relevant for fault prediction purposes. It is illustrated in Fig.3 and depicted in Algorithm 2.

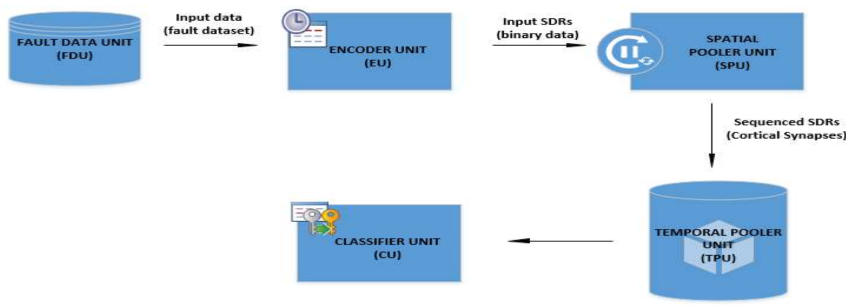

Fig.3. *A diagram showing the model of the proposed HTM system*

Algorithm 2: The Prediction Algorithm of the CLATechnique

procedure DETECT NOVEL PATTERNS
L_t = empty set of all prediction likelihood at time say, t
P_t = empty set of all novel patterns detected at time say, t
while there are unprocessed patterns in the incoming sequence of data **do**
SP_t = fetch new pattern and form SDRs
for each SDR pattern p ϵ SP_t**do**
HTM = find an HTM model corresponding to m, w, task and p
e = t – t_0
d = (t, e, p)
inference i = *HTM.process*(*d*)
s_t = i.*predictScore*
l_t = *predictLikelihood*(s_t)
L_t.*add*(I_t, *p*, *w*, *task*)
if $l_t \geq 1 - \dot{\epsilon}$ then
P_t.add(l_t, m, w, task)
end if
end for
end while
end procedure

The process hypothesizes modelm, which describes a task (the world or observation environment) for a given pattern and considersa winning (success) pattern width. The idea of success patterns or winning width can be considered a core advantage of distributed-tier processing where the solution space is small enough to decipher the issue of a large solution space.

5.1 Description of Proposed HTMSystem Components

5.1.1 SPU

Overlap is calculated by determining the number of active synapses or connections between SDRs and then normalizing this value by the total number of synapses on the winning SDR. This allows the HTM to recognize patterns and calculate future outcomes on the condition of similarities between input data and previously learned representations. Ultimately the SPU playsan important role in the HTM for the functioning of the CLA which is designed to simulate the learning and processing capabilities of the neo-cortex in the human brain.

5.1.2 TPU

TPU on the SDR sequence produced by the SPU is executed by the TPU. In the HTM framework this procedure is managed by applying the "union principle" expounded in [4] and [26] work accompanied by the use of the overlap evaluation metric. By utilizing this principle it becomes possible to scrutinize a prior representation alongside a current one to establish the succeeding batch of projections. If a similarity surpassing a particular limit is detected the most recent forecast will be activated and predicted during the ensuing interval. If there is no match it stays inactive.As recommended in [27] the expected condition of an HTM Cortical Learning net's predictive state at a particular time step t can typically be calculated.

$overlap\ (x, y) \equiv x \cdot y$

Where x and y are two binary SDRs.

For a match to be realized, the overlap score must be greater than a threshold as:

$match\ (x, y) \equiv (x, y) \geq \theta$

$$\pi_{ij}^{t} = \begin{cases} 1 & \text{if } \exists_{d} \parallel \widetilde{D}_{ij}^{d} \circ A^{t} \parallel_{1} > \theta \\ 0 & \text{otherwise} \end{cases}$$

where,

$\widetilde{D}_{ij}^{d}$ = an M×N binary matrix representing the permanence of a connected synapse

d = a cortical segment

i, j = cell and column states

A^{t} = an M×N binary matrix denoting the activation state of the cortical network

θ = the cortical segment activation threshold

N = number of cortical columns

M = number of neurons (cortical faults) per column

5.2.3CU

To assess the effectiveness of the predictive system the CU is utilized to measure its performance using an appropriate metric. In the present study, the MAPE is employed as the performance indicator for the predictive classification simulations which quantifies the percentage difference between the predicted values and the actual outcomes. The desired outcome generated from the HTM-CLA is considered as the objective output while the outcome generated from the simulation is taken as the factual output. This MAPE employs the difference between these outputs in its calculation.

MAPE is computed as:

$$\text{MAPE} = \frac{\sum_{t=1}^{N} |y_t - \hat{y}_t|}{\sum_{t=1}^{N} |y_t|}$$

Where, y_t is the data observed of time t. y is the datum point for the observed data at time t and N is the distance of the data set.MAPE is used because it is less sensitive to outliers (noise).This gives it an advantage in noise rejection.As a good prediction algorithm, it outputs a probability distribution of future elements of the sequence. MAPE considers only the single best prediction from the model and thus does not incorporate other possible predictions from the model.There are tendencies for errors in the MAPE computation, thus: NLL is used as a complementary error metric to address this problem.

If the Sequence Probability can be decomposed into:

$$p(y_1, y_2, \dots \dots y_t) = p(y_1)p(y_2|y_1)p(y_3|y_1, y_2)p(y_t|y_1 \dots y_{t-1})$$

Then, the Conditional Probability Distribution modeled by the HTM based on the previous time step network stated

$$p(y_t|y_1 \dots y_{t-1}) = p(y_t|\text{network state}_{t-1})$$

The NLL of the sequence is then computed as suggested by[27].

$$NLL = \frac{1}{N} \sum_{t=1}^{N} \log P(y_1|\text{model})$$

5.2.4 System Design

A user-friendly UI has been designed specifically to facilitate simulations. It facilitates interactivity enables the loading of data modifications to the HTM Network parameters and ensures the smooth running of CLA simulations. In display component, contains labels where the data entry component and container component are connected.A convenient layout of the UI can be observed in Fig.4.Fig.5 represents the sequential diagram of the Entity Relations of the HTM system.

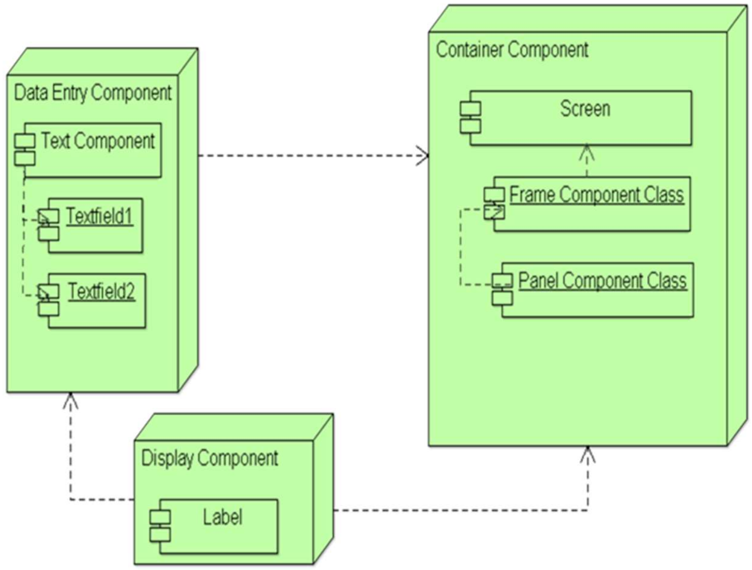

Fig.4. *Cortical Learning User-interface Architecture for Fault Detection Analysis in HTM*

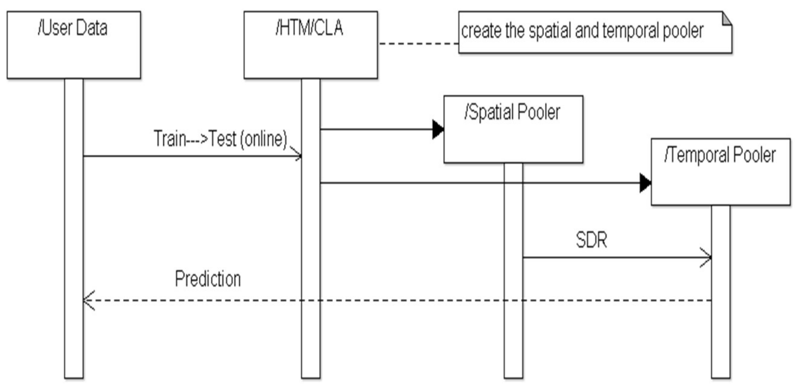

Fig.5. *Sequence diagram showing Entity Relations of the HTM system*

6. Results and Discussions

Research Questions

1. Which fault type is being detected and evaluated using the HTM technique on the Onitsha-Alaoji TL in Nigeria?
2. How does the efficacy and reliability of the proposed HTM model compare to the fault detection methods currently utilized on the Onitsha-Alaoji transmission line in Nigeria?

Answers to Research Questions

Research Question 1: Which fault type is being detected and evaluated using the HTM technique on the Onitsha-Alaoji TL in Nigeria?

The typical approach for detecting faults in transmission linesinvolves utilizing data on PDfaults, measured through a specially designed meter at the faulted line. This method is reflected in the VSB Kaggle dataset, where the point of fault is indicated by the target signature values. The data itself contains the signal ID, a measurement ID, as well as the phase being monitored with a corresponding target label denoting the presence (Signal 1) or absence (Signal 0) of a fault. Our proposed system was put to the test using the fault detection dataset provided by the VSB Fault Line dataset found on Kaggle. Table 3 provides a sample of the dataset utilized in our simulations.

Table 3:*Fault dataset sample*

signal_id	id_measurement	Phase	Target
0	0	0	0
1	0	1	0
2	0	2	0
3	1	0	1
4	1	1	1
5	1	2	1
6	2	0	0
7	2	1	0
8	2	2	0
9	3	0	0
10	3	1	0
11	3	2	0
12	4	0	0
13	4	1	0
14	4	2	0
15	5	0	0
16	5	1	0
17	5	2	0
18	6	0	0
19	6	1	0
20	6	2	0

To achieve the detectionof imminent faults process, a prior and posterior pattern formation based on temporal aggregation is employed [15]. This is shown in Table 4.

Table 4: *Pattern Formation based on temporally aggregated data samples*

Input (prior)	Target (posterior)
0	0
0	1
1	1
0	0
1	1

.

The data in the Tables revealed that PDis the fault type that is being detected in this study. It involves faults arising from insulator damage, wire melting, and vegetation growing too close to cable lines which may cause faults. The PD is commonly found as a fault leading to transmission line errors. Kaggle Dataset established the PD fault diagnosis primarily through target and phase variables, where a target variable value of 0 indicates no fault present and 1 implies a potential fault. The phase variable represents the three-phase power line condition

Research Question 2: How does the efficacy and reliability of the proposed HTM model compare to the fault detection methods currently utilized on the Onitsha-Alaoji TL in Nigeria?

To demonstrate the efficacy and reliability of the proposed HTM model, the simulation results of the experiments performed using the VSB power line Kaggle dataset and the synthesized data of the Onitsha-Alaoji TLare presented while comparing the proposed approach with an existing one.The voltage and current simulations are performed using the developed model for dynamic online fault data synthesis. The simulations for the Onitsha-AlaojiTL fault detection are performed using Typical PSDanalysis at 40km of line length. Figure 6 represents the PSD plots of pre-fault conditions at Onitsha-Alaoji TL and in Figure 7 a total line length of 40Km fault conditions was applied at Onitsha-Alaoji TL.

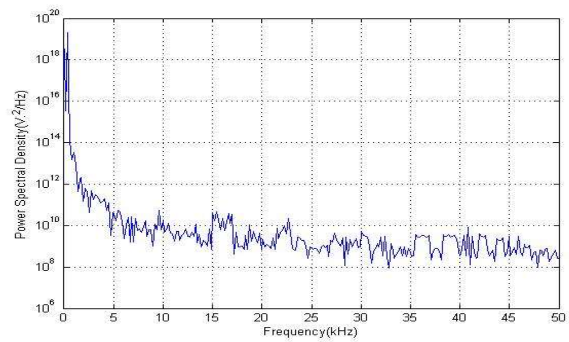

Fig.6. *PSD plots of pre-fault condition at Onitsha-Alaoji TL*

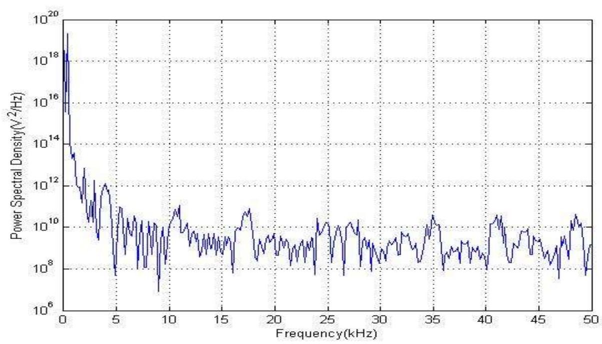

Fig.7. *PSD plots of fault condition at Onitsha-Alaoji TL (fault applied at 40km of total line length)*

From the plot shown in Fig. 6, it was noticed that the first fundamental is formed at a value of about 10 kHz (precisely 9.3 kHz from numerical estimations). Other fundamentals are also formed but are not considered in this study.Furthermore, the plot in Fig.7, shows that during a fault at 40km of the line length, there is a shift of the first fundamental from its previous value to a new state value of about 13 kHz.

6.1 Results Comparing the Proposed HTM Model with Fault Detection Methods Currently Utilized on the Onitsha-Alaoji TL in Nigeria

In the results presented here, the models apply the VSB Kaggle dataset in a data-driven approach to classify the imminent faults that may be experienced in the Onitsha-Alaoji transmission line in Nigeria. The comparative results using the existing dataset on the HTM, ELM, and OS-ELM neural schemes are shown in Tables 5to 7 respectively. Simulations were performed for 100 samples of continuous data sampled five times from the Kaggle VSB dataset for incipient fault classification without repetition.

Table 5: *Results of the proposed HTM sequence learning model*

Trial Sample	HTM CA (%)
1	100.00
2	100.00
3	56.67
4	96.67
5	96.67
Mean:	**90.00**

Table 6: *Results of the ELM sequence learning model*

ELM CAtrain (%)	ELM CAtest (%)
100.00	100.00
100.00	100.00
95.71	56.67
100.00	96.67
82.86	70.00
Mean:	84.66

Table 7: *Results of the OS-ELM sequence learning model*

OS-ELM CAtrain (%)*	OS-ELM CAtest (%)*
20.63	0.05
5.56	0.05
5.14	0.05
4.92	0.03
4.86	0.05
Mean:	0.05

As seen from Tables (5 to 7), the HTM outperformsboth sequence learning techniques with a mean test CA of 90% over the ELM and OS-ELM with approximate calculated values of 84.66% and 0.05% respectively. In particular, the OS-ELM did very poorly on this particular dataset showing the great limitation of this conventional technique for this problem.

6.2 Discussion

The objectives of the study were centered around the identification of the targeted fault types for detection and evaluation in the Onitsha-Alaoji transmission line in Nigeria using the proposed HTM technique, as well as evaluating the reliability and efficacy of the proposed HTM model when compared to the currently available fault detection methods used in the same TL. By gathering both primary and secondary data, it was revealed that PD is typically employed as the fault detection algorithm.

The research focused on faults that were based on the phenomenon of PD, which are natural occurrences that lead to a fault, such as flaws or cracks in insulators, gradual melting of wire, and branches of trees getting close to cable lines. PD phenomenon serves as a signature-based detector and can serve as a prior in determining the likelihood of a fault occurring. Thus, TL faults can be determined by failure probabilities that lead to their occurrence. To achieve the detectionof imminent faults process, a prior and posterior pattern formation based on temporal aggregation is employed, showing its efficiency in comparison to existing algorithms such as OS-ELM and ELM. The VSB Kaggle Dataset was considered a primary source of data for this research, with faults primarily indicated by a fault signature at the target and phase variables. The target value can attain 2 states – a 0 for no-fault likely and a 1 for the likelihood of a fault. The phase variable can attain 3 states corresponding to the three-phase power lines.

To demonstrate the efficacy and reliability of the proposed HTM model, simulation experiments were performed using the VSB power line Kaggle dataset and the synthesized data of the Onitsha-Alaoji TL while comparing the proposed approach with an existing one. Additionally, voltage and current simulations were performed using the developed model for dynamic online fault data synthesis. For the Onitsha-Alaoji TL, simulations for fault detection were performed at 40km of line length using Typical PSD analysis. The first fundamental was formed at a value of about 10 kHz, and during a fault at 40km of the line length, there is a shift of the first fundamental from its previous value to a new state value of about 13 kHz. Overall, the proposed HTM model outperformed both sequence learning techniques with a mean test CA of 90% over the ELM and OS-ELM, with the OS-ELM performing poorly on this particular dataset.

7. Advantages and Disadvantages

Advantages

Improved fault detection efficacy: The HTM approach outperformed sequence learning methods resulting in a 90% mean test CA over other techniques like ELM and OS-ELM.

Increased reliability: It is a more dependable solution for identifying various fault types in the transmission line.

Potential for future implementation: The study recommended the implementation of the HTM model not only in the Onitsha-Alaoji TL but also in other fault-prone power TL in Nigeria indicating its potential for broader application in improving the safety and stability of power grids.

Real-time streaming data analysis: The HTM approach allows for real-time analysis of streaming data, enabling prompt fault detection and reducing false alarms.

Disadvantage

- The HTM approach was not implemented in other domains for fault detection, due to its ability to handle complex temporal patterns and its potential for providing accurate and timely fault detection.

- The performance is evaluated for only PD fault. Different types of faults in transmission lines are not considered.

8. Conclusions and Recommendations

The proposed HTM model outperforms sequence learning methods and achieves 90% mean test classification accuracy. Itcan be used to identify various PD fault types that plague the Onitsha-Alaoji TL in Nigeria. The HTM approach offers significant improvements over traditional methods, providing a more holistic perspective on the fault detection process and enabling real-time handling of streaming data. With the increased efficacy and reliability of the proposed model compared to existing methods, it is recommended for future implementation in this TL and potentially other fault-prone power TL in Nigeria.Future studies could explore the adaptability of the HTM model to changing conditions and its ability to learn from new data without requiring retraining from scratch, which is crucial in fault detection applications where operating conditions of transmission lines can vary significantly over time.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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