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Maintenance Scheduling Algorithm for Transformers in Tanzania Electrical Secondary Distribution Networks

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Abstract

The drive by the government of Tanzania to electrify every village has resulted into expansion of the electrical secondary distribution networks (ESDNs). Therefore, maintenance management is of the highest priority for the smooth operation of the ESDNs to reduce unscheduled downtime and unexpected mechanical failures. Studies show that condition-based predictive maintenance (CBPdM) method allows the utility company to monitor, analyze and process the information obtained from ESDNs transformers. Thus, this study adopts the CBPdM method to develop a maintenance scheduling algorithm that can predict the transformer state, forecast maintenance time based on transformer load profile and schedule its maintenance using a knowledge-based system (KBS). Applying the challenge driven education approach, the requirements for developing an algorithm were established through an extensive literature survey and engagement of the key stakeholders from the Tanzania utility company. Our study uses the Dissolved Gas Analysis tool to collect the transformer parameters used in algorithm design. The parameter analysis was performed using Statistical Package for Social Sciences software. Results show that the designed KBS algorithm minimizes human-related maintenance errors and lowers labour costs as the system makes all the maintenance decisions. Specifically, the proposed maintenance scheduling algorithm reduces downtime maintenance costs by 1.45 times relative to the classical inspection-based maintenance model while significantly saving the maintenance costs.

Keywords: Electrical power network, Forecasted load consumption, Knowledge-Based System, Maintenance Scheduling, Predictive Maintenance, Secondary Distribution.

Introduction

The global energy systems are changing, driven by technological advancements in the generation, transmission, distribution, and management of energy. Likewise, the Tanzania energy system is expanding due to the government's efforts in electrifying every village by 2025 (URT 2020). The current transformations also catalyze the changes in living styles and standards accommodated by a massive number of power-hungry devices needing quality and reliable power supply. The transformations cause management challenges to utility companies. Other challenges include expansion of the distribution network due to increasing demands, ageing assets, rising operational, downtime and maintenance costs, and growing user expectations (Butt et al. 2021). The ever-growing electrical secondary distribution network (ESDN) needs effective maintenance and planning to accommodate these demands effectively (Colak et al. 2016).

Despite the emergence and use of smart grid technologies in managing electrical power networks, most utility companies, such as Tanzania Electric Power Supply Company (TANESCO), still employ informed human decision-making in the maintenance scheduling process. This approach takes a long time with a high probability of human-related errors. In addition, the approach imposes losses to end-users and to the utility because human-related errors may introduce unnecessary costs (Asadzadeh and Azadeh 2014). To facilitate proper and cost-effective maintenance scheduling in ESDN, we need predictive maintenance scheduling that monitors, analyses, and predicts equipment conditions before faults occur. This method allows timely maintenance action to prevent long downtimes and minimizes the cost of an unexpected failure of the equipment in the power system (Rivas et al. 2020). According to the United States Department of Energy, a maintenance program that uses predictive maintenance can result in savings of 8% to 12% of maintenance costs over a program using other maintenance schemes (de Wilde et al. 2011). In most ESDNs, especially those of Tanzania, maintenance schedules are time-based preventive maintenance. In this scheme, the maintenance is performed based on the time interval specified regardless of the condition of the equipment (Figure 1). This process may introduce unnecessary costs to utility companies due to the replacement of the equipment prematurely (De Faria et al. 2015). Considering the latter, researchers have proposed the use of predictive maintenance in the transformer maintenance scheduling process.

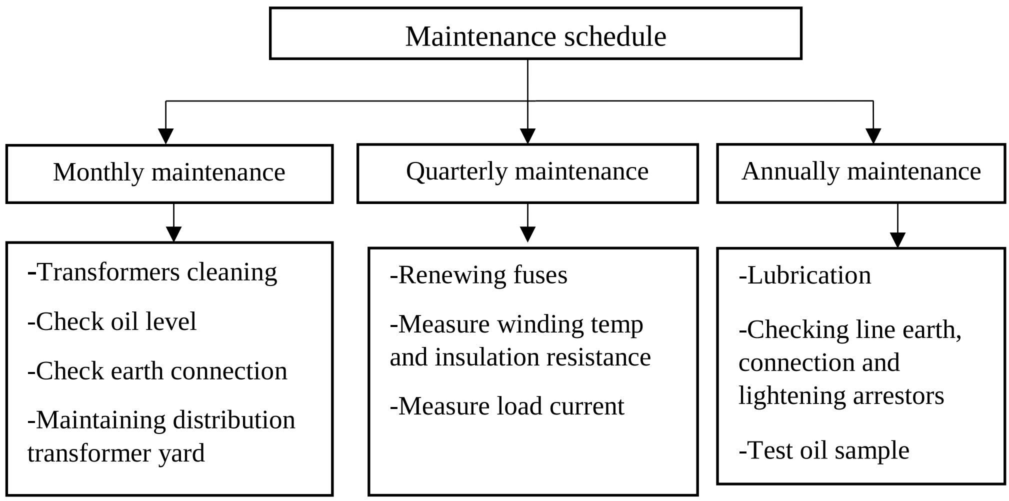

Figure 1: TANESCO transformer maintenance scheduling process.

Transformer maintenance scheduling has been extensively studied to enhance power reliability and to reduce maintenance costs in utility companies. The study by Samadi et al. (2019) proposed the inspection-based maintenance (IBM) model for a maintenance schedule to improve equipment reliability. To estimate the reliability and availability of transformers, the authors proposed a method that uses the Markov model approach with total dissolved combustible gas (TDCG) and breakdown voltage (BDV) parameters (Afandi et al. 2020). The study proposed that the transformer maintenance schedule be conducted twice annually. This recommendation complies with the time–based preventive maintenance approach, where equipment maintenance is performed based on the time interval specified regardless of the condition of the equipment (De Faria et al. 2015). The recommended fixed maintenance schedule, however, may result in high downtime and unplanned maintenance. The authors Xu et al. (2020) proposed maintenance scheduling with rescheduling capability. Their method is condition-based maintenance, where the condition of the equipment is monitored, and the maintenance decision is made based on the current status of the transformer. The authors Sarajcev et al. (2020) proposed a maintenance scheduling decision that considered the utility expected maintenance cost and transformer health state for preventive maintenance. In the proposed method, the expected profit was analyzed, and more parameters were used to realize the health status of the transformer based on the Bayesian model. Finally, the authors used expected profit in the maintenance decision-making process. However, the accuracy of the Bayesian model is moderate compared with the high accuracy of the Multi-Layer Artificial Neural Network (MLANN). The use of MLANN in predictive maintenance increases the accuracy of the decision-making process.

Artificial Neural Networks (ANNs) is a data processing tool consisting of many simple and highly interconnected processing units called neurons (Elsheikh et al. 2019). ANNs acquire sensory datasets to detect equipment faults and classify their health status. The essential characteristic of ANN is its ability to model processes and systems from actual data with high-speed data processing. This characteristic makes ANN an excellent tool for predicting and modelling different systems with irregular time series data (Carvalho et al. 2019). The integration of the prediction and maintenance scheduling process requires a tool for the prediction and maintenance scheduling process. The study by Zhu et al. (2018) indicated the high accuracy of the knowledge-based system (KBS), such as artificial neural networks, in the mapping process, making KBS an excellent tool for maintenance schedules.

The KBS, also called an expert system, is a decision-making tool that mimics the intelligence of human expertise in solving problems. The tasks of KBS include perception, interpretation, learning, reasoning, communication, and decision-making for a specific issue. KBS, a cost-effective way of transferring expert knowledge within a utility company or organization (Leo Kumar 2019), comprises three elements, namely database, expert knowledge, and inference engine (Figure 2) (Naser and Almursheidi 2016). This system can incorporate utility-based knowledge into existing maintenance scheduling theories, making it the most important part in practical applications (Yunusa-Kaltungo and Labib 2021). KBS requires high-quality knowledge that may partly be achieved through Challenge-Driven Education (CDE), as applied in this study (Kalinga et al. 2017).

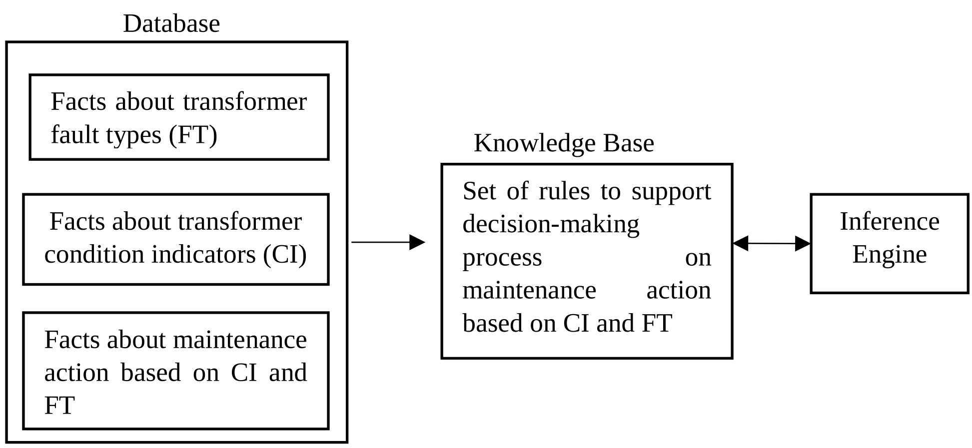

Figure 2: Block diagram of a knowledge-based system for maintenance decision-making (Leo Kumar 2019).

CDE is the research method that considers the opinion of key stakeholders in all research procedures, including problem formulation in developing practical solutions (Ibwe et al. 2018). In this study, the key stakeholders involved are distribution and maintenance engineers from TANESCO, representatives from the Ministry of Energy, and researchers from the College of Information and Communication Technologies at the University of Dar es Salaam in Tanzania. The authors conducted several meetings and discussions and, finally, the challenge of unreliable power supply in ESDNs was identified. Several factors, including unplanned maintenance, cause unreliable power supply in ESDNs.

Therefore, researchers proposed a predictive maintenance method in electrical power distribution networks to reduce downtime and minimize maintenance costs of transformers. In the existing predictive maintenance scheduling methods, the effects of fault types and forecasted load profiles are not considered in the maintenance decision-making process (Liu et al. 2021). This limitation may introduce unnecessary costs to the utility company and limit the implementation of such methods in real applications. In this study, the maintenance scheduling algorithm is designed based on the transformer state, fault type, and forecasted load profile to overcome the challenge. The time for maintenance action is determined based on the forecasted load profile. The time slot with a low load profile based on the predicted transformer status is selected for maintenance action. The chosen time reduces the maintenance cost by reducing the downtime loss acquired during peak hours. The study aims to minimize the overall maintenance cost for the transformer in ESDN. Total maintenance cost ($C_{T(at)}$) is shown in Equation (1).

$$C_{T(at)} = C_{m(t)} + C_{L(t)} + C_{D(t)} \qquad 1$$

where $C_{m(t)}$ denotes summation of material cost, $C_{L(t)}$ denotes labour cost, and $C_{D(t)}$ denotes downtime cost.

In our observational survey from workers of TANESCO, we noted that the maintenance cost is computed based on the material and labour costs. The downtime cost is neglected in the maintenance decision-making process. Relying on the two components (material and labour cost) in computing the total maintenance cost is not feasible in a real application. Therefore, there is a need to include downtime costs in selecting maintenance time with minimum possible maintenance costs.

The theoretical and practical contributions of this work are as follows:

(1) Establishment of the maintenance scheduling algorithm that significantly reduces downtime maintenance costs;
(2) Establishment of the predictive model for maintenance scheduling of transformers in Tanzania secondary distribution networks; and
(3) Establishment of benchmarks of downtime saving costs per year for different classical methods.

Materials and Methods

This section presents the procedures used to design a maintenance scheduling algorithm. The section also presents the methods used in each step and the area in which the research was conducted.

Research design

The primary and secondary data were collected for a maintenance scheduling algorithm design, training, and testing. The primary data were collected for designing a knowledge-based system through interviews with maintenance personnel at TANESCO. The secondary data were the historical data for training and testing the Transformer Status Prediction (TSP) and Forecast Maintenance Time (FOMT). The data analysis was performed based on a quantitative approach. After data analysis, the accuracy of the most popular existing prediction models was tested. These models are support vector machine (SVM), kernel support vector machine (KSVM), and MLANN. Next, the authors designed TSP, KBS, and FOMT algorithms to schedule the time for maintenance action. Thereafter, the proposed algorithm for maintenance scheduling based on TSP-FOMT-KBS was designed following the transformer maintenance requirements from TANESCO. Figure 3 shows the procedure for research design.

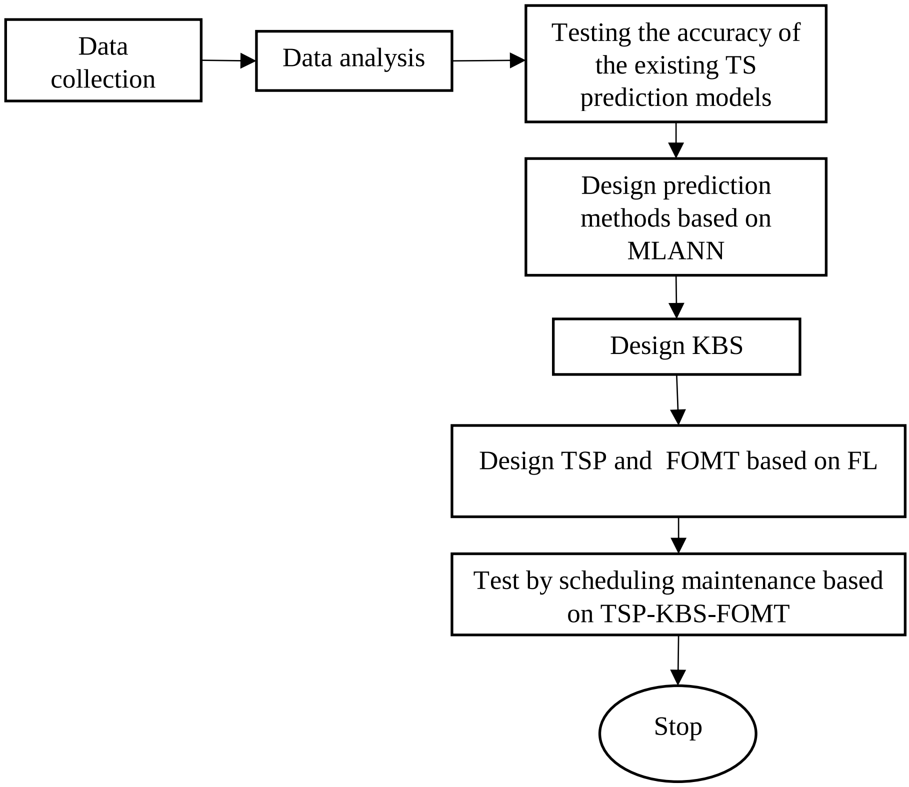

Figure 3: Maintenance scheduling design process.

Study area and data description

The study was conducted at Kinondoni-North Electrical Secondary Distribution Network (ESDN) with 1,297 low voltage transformers. The three ESDN transformers, with power ratings of 315 kVA, 200 kVA, and 100 kVA, were selected as a pilot site for designing a maintenance schedule algorithm. In this area (Kinondoni-North), the time-based preventive maintenance approach is still being used by maintenance personnel to clear transformer faults, which are usually caused by overload, short currents, welding defects, and contact faults. Due to the limitation of this approach, we propose a predictive maintenance method to be applied in ESDN.

Data collection

We collected 143 historical data measured by a dissolved gas analysis tool from 2016 to 2020. The measured data are presented in parts per million (ppm) using the weight of gas or moisture divided by the weight of oil. These data were used for transformer state prediction (TSP) and fault identification process. To achieve the design of the load forecasting algorithm, a total of 105193 load data in kWh was recorded from 2015 to 2019 using electrical meter readings. Other information recorded by interviewing four engineers from a Tanzania utility company was about the maintenance schedule practice of the transformers in ESDNs. The information obtained was the maintenance schedule decision variables presented in Table 1.

Table 1: Decision variables for maintenance schedule

Decision variables	Description	Expected maintenance time frame
Normal	N	No maintenance schedule
Caution	C	Schedule maintenance within 3 days
Warning	W	Schedule maintenance within 24 hours
Critical	Cr	Schedule maintenance immediately

Based on inclusion criteria, electrical power distribution engineers and maintenance engineers from TANESCO were involved. Interviews were conducted at the Msasani site and lasted three hours for distribution engineers and two hours for maintenance engineers at TANESCO head office, Ubungo. Answers from the respondents were recorded in a notebook and sound recorder. The obtained information was then analyzed and used to design a knowledge-based system, as shown in Table 2.

Table 2: Fault types with corresponding maintenance actions

Fault category	No	Fault type	Description	Actions
A	1	PD	Partial discharge	1-Off load oil. 2-Check connection point. 3-Inspection (Internal connection) 4-Identify loose point/winding breakage. 5-Repair (Tight the loose point) 6-Check winding paper move (change position). 7-Return to the original position (perform Frequency Response Analysis -FRA). 8-Perform further analysis (test every month).
	2	D1	Low energy discharge	
	3	D2	High-energy discharge	
B	4	T1	Thermal fault T>300 ℃	1-Improve cooling system (Load < 3/4 of maximum load). 2-Improve load profile (Load > 3/4 of maximum load). 3-Change transformer location. 4-Degasing/Oil filtration
	5	T2	Thermal T>300 ℃ – 700 ℃	
	6	T3	Thermal fault T>700 ℃	
C	7	CDA	Paper deterioration due to ageing	1-Degasing/oil filtration 2-Perform further analysis (close monitoring after every month). 3-Replace transformer.
D	8	CDF	Cellulose deterioration due to other factors (stress faults)	1-Check material used in transformer manufacturing. 2-Check load profile (load>3/4 of maximum load). 3-Check water content.
E	9	CIT	Contamination in tank	1-Check contamination in tank and clean.
F	10	Leaks	Water leaks into the oil	1-Check leakage in tank and repair.

Data processing

The collected load data were used to design a load forecasting algorithm that forecasts load profiles every 20 minutes (Bakiri et al. 2021). In this study, the data were transformed to forecast the load hourly. The interpolation technique based on the multivariant imputation by chained equation methods was applied using the R statistical computing software version 4.0.5 to acquire adequate transformer data for prediction. After obtaining the adequate transformer data, the outliers were removed from the dataset to smooth the normalisation process (Pearson 2002). The min-max normalisation method was used for normalisation (Patro and Sahu 2015).

Transformer state prediction algorithm design

The transformer state prediction (TSP) algorithm was designed to achieve a high accuracy prediction of the transformer health status in ESDN; the general TSP design procedure is presented in Figure 4.

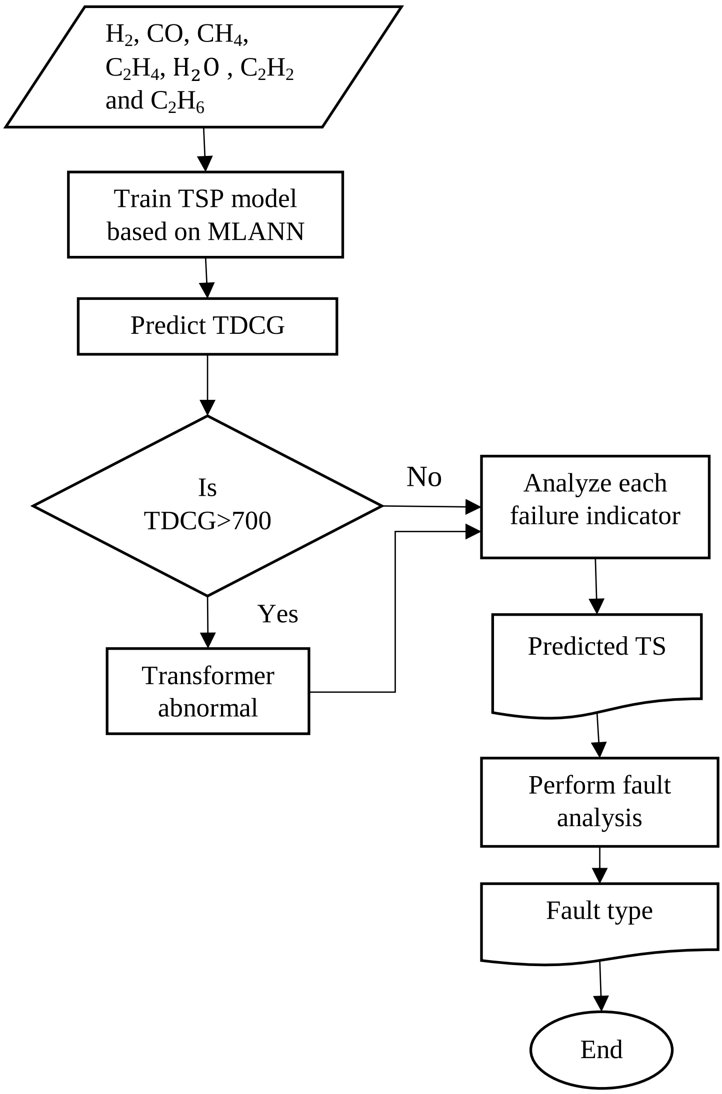

Figure 4: The architecture of the proposed TSP model.

In TANESCO, the transformer state (TS) is divided into four categories: Normal, Caution, Warning, and Critical. To ensure high-level prediction accuracy of the TSP algorithm, all typical transformer failure parameters (TFP) that are frequently used to flag the condition of this type of transformer, which include hydrogen (H_2), carbon monoxide (CO), methane (CH_4), ethylene (C_2H_4), water (H_2O), acetylene (C_2H_2), ethane (C_2H_6), and TDCG have been used in an algorithm design (Bustamante et al. 2019). The TSP algorithm is built on the top MLANN model due to its high accuracy (97.53%) compared with SVM (96.72%) and KSVM (97.50%).

The proposed TSP algorithm predicts the transformer's health status and uses the real-time failure indicator to identify the fault types (See Table 1). TDCG limit values are specified by the Tanzania utility company, whereby the standard TS value is below 700 ppm, and any value above 700 ppm is abnormal.

Design of a knowledge-based system

The knowledge-based system (KBS) is designed to allow flexibility in the maintenance scheduling process. The expert knowledge presented in Table 1 is transferred into the system application to guarantee its availability. The input of the proposed KBS is the transformer status and fault type from the TSP algorithm. Fault types have been categorized into six, represented by letters A to F. Maintenance action ranges from A1-8, B1-4, C1-2, D1-3, E1, and F1. For example, if the predicted transformer status is warning and the fault type is in category B (thermal fault), the system will recommend performing maintenance action D1-3 (Table 1). The KBS designing process is presented in Figure 5.

Design of the forecasted maintenance time algorithm

The forecasted maintenance time (FOMT) algorithm minimizes downtime during the maintenance process. The FOMT algorithm is intended to forecast the time with the lowest possible load profile and feed the KBS information for maintenance scheduling to minimize maintenance costs. The design process is presented in Figure 6.

The input in the FOMT algorithm is TS, load profile, time, and date of fault. The algorithm for load forecasting is based on an extended multivariant non-linear regression model presented in Bakiri et al. (2021). The FOMT algorithm extracts the predicted TS and computes the maintenance action time based on the forecasted load. The lowest possible load profile is scheduled for maintenance to reduce the downtime cost. Reducing downtime costs minimizes the total maintenance cost of the transformer (Equation 1).

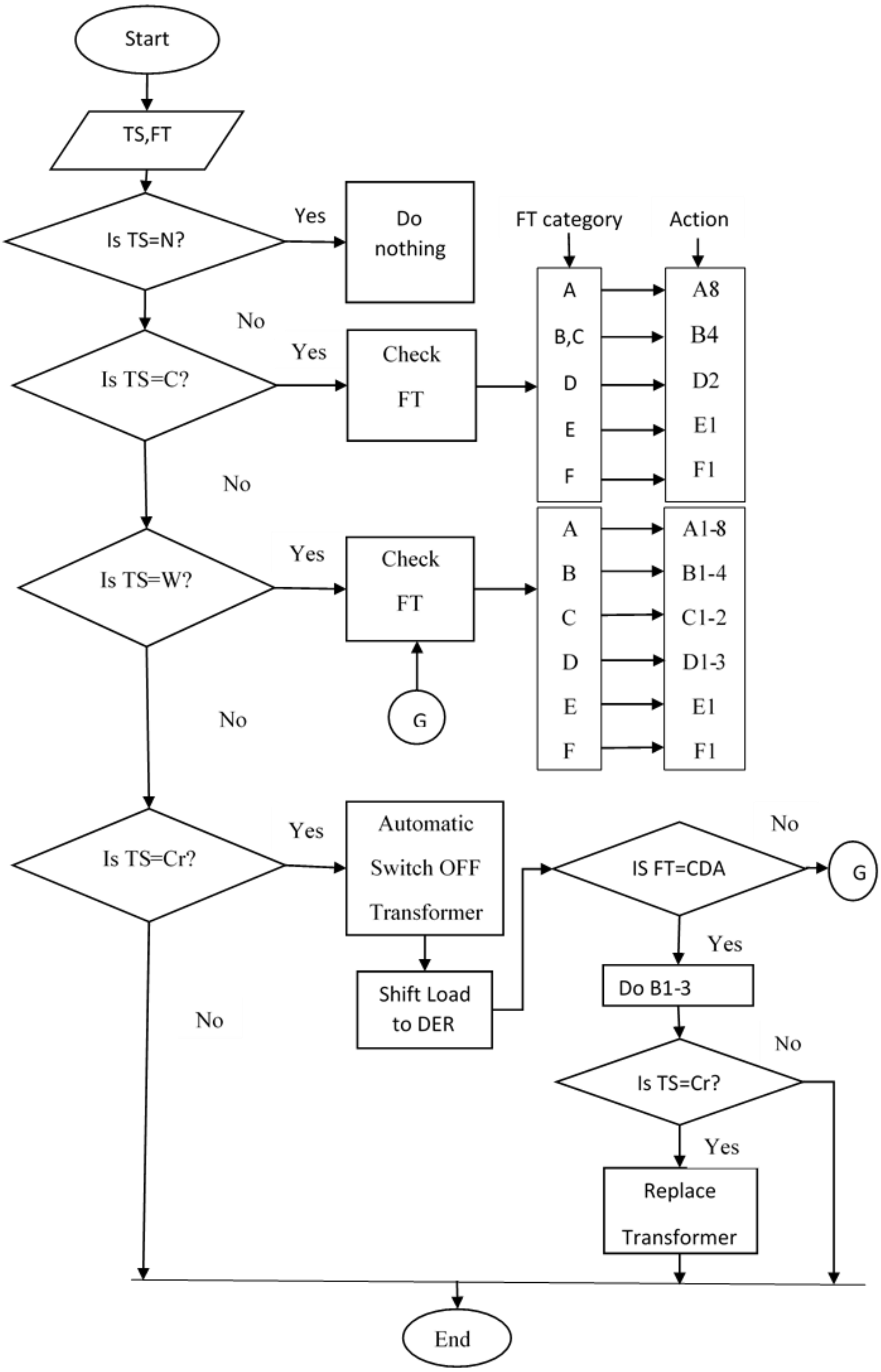

Figure 5: Decision–making process of the proposed KBS.

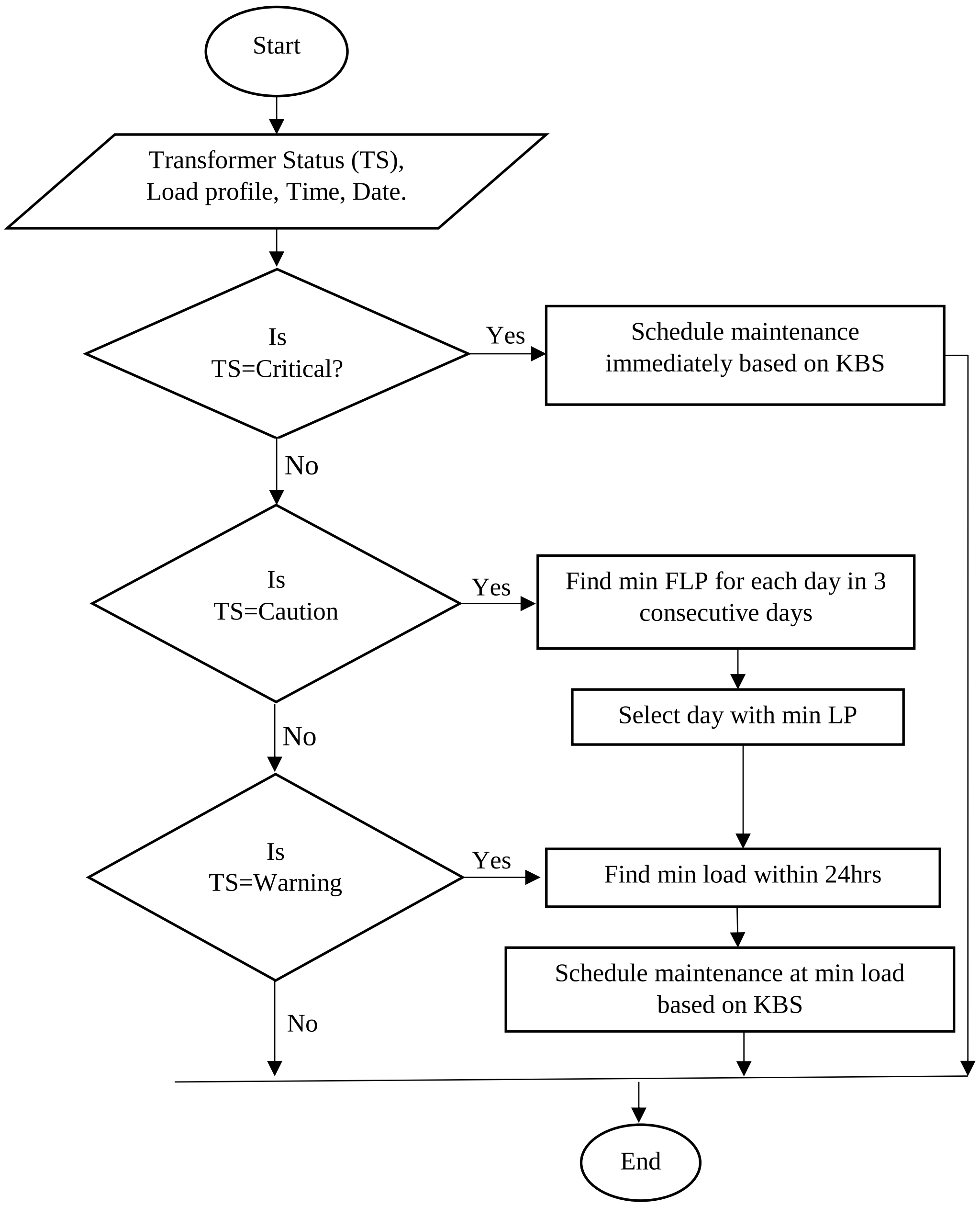

Figure 6: The FOTM design process.

Design of a TSP-FOMT-KBS algorithm

The TSP-FOMT-KBS algorithm integrates three different algorithms to design the transformer maintenance scheduling in an ESDN: TSP algorithm that predicts the transformer status and identifies the fault type; FOMT that forecasts the time with minimum load based on predicted transformer status; KBS algorithm that decides maintenance action, and time is based on the predicted transformer status, fault type, and forecasted maintenance time. The architecture design of TSP-FOMT-KBS is presented in Figure 7. The algorithm for the proposed TSP-FOMT-KBS is shown in Table 3.

Table 3: The TSP-FOMT-KBS algorithm

The algorithm 1:TSP-FOMT-KBS	
1	Receive the real-time TFPs, Load profile, maintenance actions, and possible maintenance time-frame
2	Predict TS by using MLANN
3	Compute FT, Fault-time, and Fault-date
4	Compute the time for maintenance action using FL, Fault-time, Fault-date and maintenance time-frame
5	Produce scheduled date, time, and maintenance action
6	End

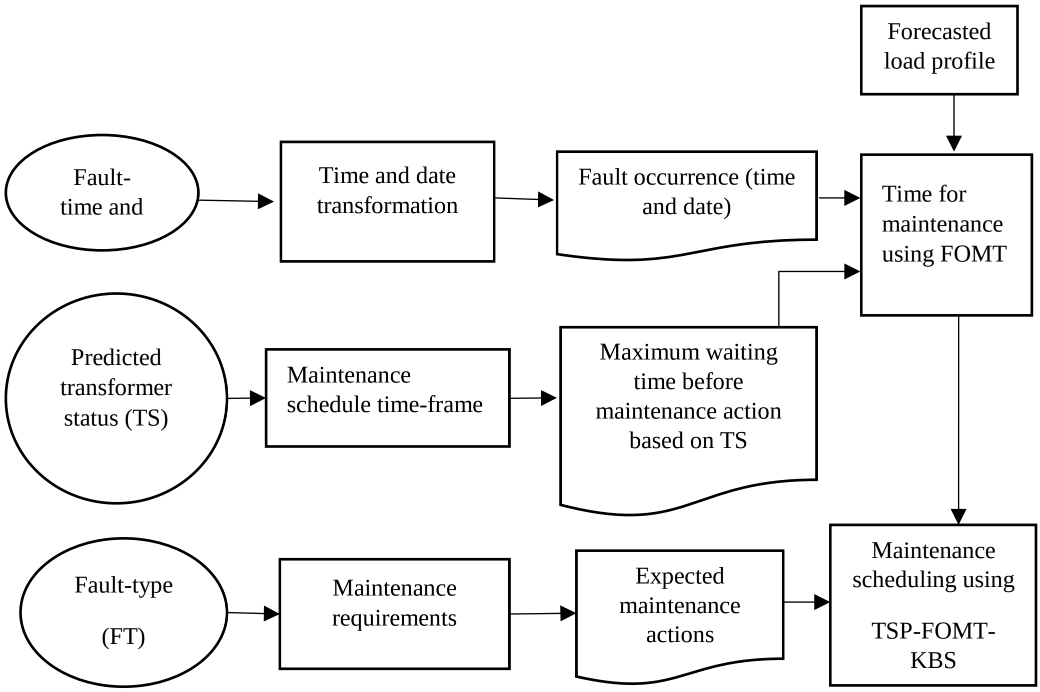

Figure 7: The architectural model of the proposed TSP-FOMT-KBS for MS in SDN.

Results and Discussion

The proposed FOMT algorithm in Figure 5 was implemented using the R software environment. The ability of the FOMT algorithm to forecast the time for maintenance action was then validated. The inputs (predicted TS, load profile, fault-time, and date) were passed into the algorithm, and two scenarios were tested. The first scenario is when the transformer status is in a warning condition where the maintenance should be arranged within 24 hours. Assuming the fault occurred at 7 hours, the algorithm forecasted the load consumption in the next 24 hours (Figure 8). After that, the algorithm selects the time with minimum load consumption for maintenance scheduling. Based on the forecasted load consumption profile, the time for the maintenance schedule was arranged in 8 hours, with the lowest load consumption of about 19 kWh. The cost of losing 1 kWh in a Tanzania residential area is TZS 355; therefore, the lowest downtime cost for this scenario is TZS 6,745 per hour.

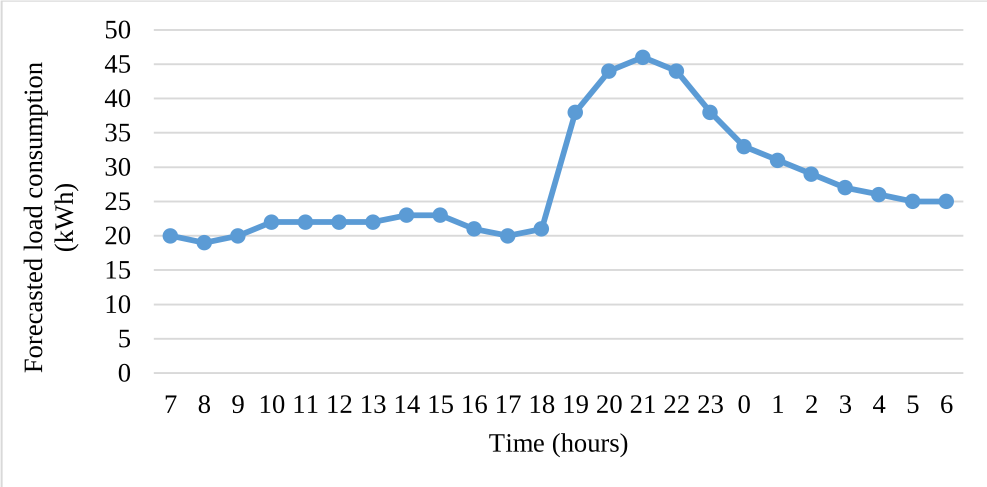

Figure 8: The time for maintenance schedule based on the FOMT model (TS: Warning).

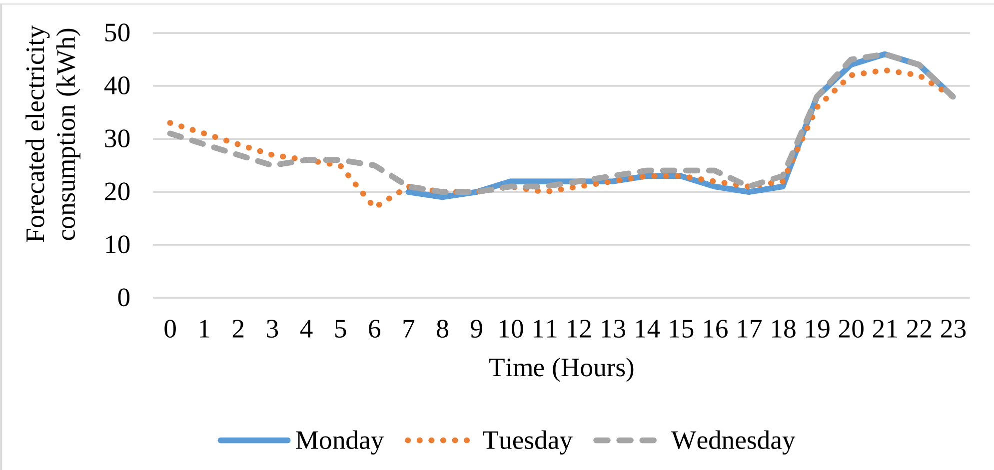

Figure 9: The time for maintenance schedule based on the FOMT algorithm.

The second scenario is when the transformer state is caution, where the maintenance action should be arranged within three days. Assuming the fault occurred on Monday at 7 hours, the algorithm forecasts the load consumption profile for three days starting on the same day at 8 hours, Tuesday, and Wednesday (Figure 9). Then, the algorithm finds the time for the maintenance schedule within three days. Based on the load consumption profile, the lowest load consumption was on Tuesday at 6 hours. Therefore, the maintenance was scheduled on Tuesday at 6 hours to minimize the downtime cost.

The objective of the TSP-FOMT-KBS is to minimize the overall maintenance cost for transformers in the ESDN. Since the load consumption is directly related to the downtime cost as shown in Figure 10, monitoring the load consumption profile before the maintenance schedule becomes necessary. The TSP-FOMT-KBS model was tested to realize its capability in an R software environment. The TSP-FOMT-KBS algorithm was tested using the R software to realize its capability. Results showed that the model could schedule maintenance on Monday at 8 hours; also, the model shows the action to be done based on the transformer status and fault type as shown in Figure 11.

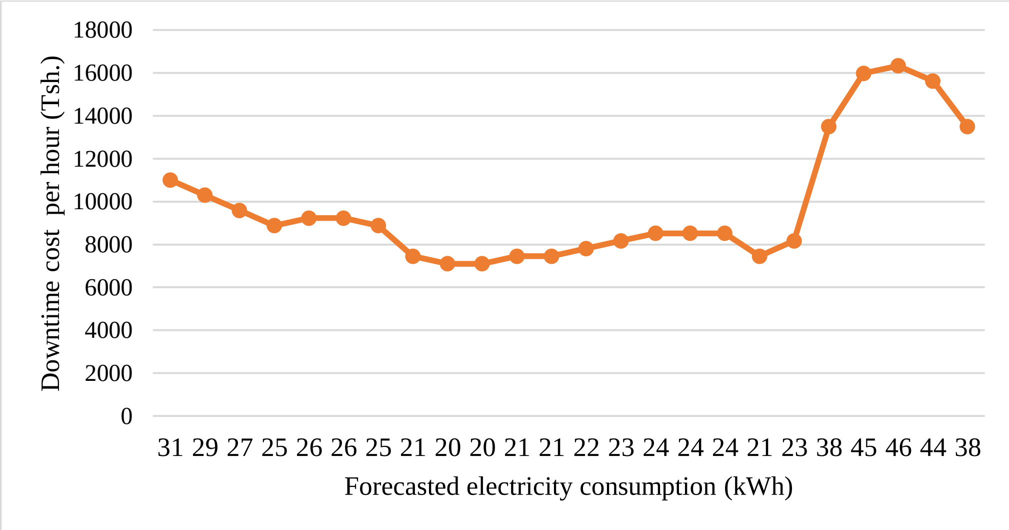

Figure 10: The downtime cost based on the forecasted electricity consumption in ESDN.

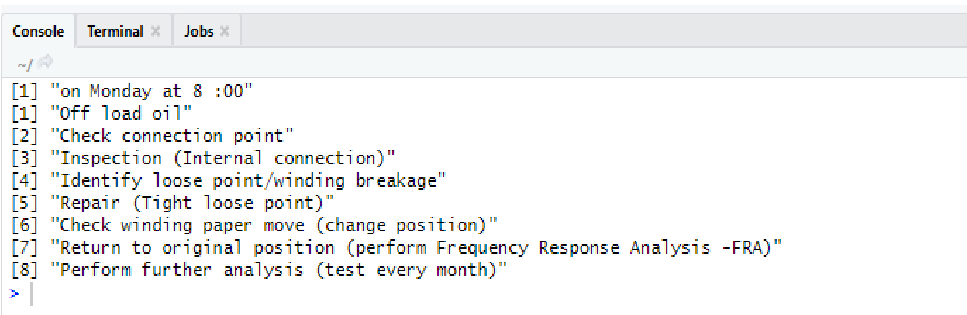

Figure 11: Screenshot for maintenance scheduling based on TSP-FOMT-KBS.

The time-based preventive maintenance (TBM) method schedules maintenance at a fixed time interval regardless of the state of the transformer and the residential customer load consumption. This approach may cause unplanned downtime hence introducing high downtime costs as shown in Table 4. Predictive maintenance reduces unplanned downtime and minimizes the downtime maintenance costs. Therefore, the total maintenance cost of the equipment is minimized since the downtime maintenance costs add up in calculating the total maintenance. Given the average downtime costs in Table 4, the downtime maintenance cost decrease can be calculated using Equation 2. Based on the downtime maintenance cost analysis, the TPS-FOMT-KBS algorithm saves downtime maintenance costs up to 58% per hour.

Table 4: Downtime cost analysis for maintenance scheduling approaches

No	Maintenance scheduling approach	Average downtime cost per hour (TZS)
1	TBM	15,795
2	TSP-FOMT-KBS	6,627

$$Percentage\ decrease = [(Downtime\ cost_{old}\ Downtime\ cost_{new})/Downtime\ cost_{old}] \times 100\% \qquad 2$$

Monitoring the health states of distribution transformers has been considered crucial in the condition-based predictive maintenance process. Different condition monitoring techniques are available in utility companies, such as oil analysis through DGA, temperature monitoring and vibration analysis. The research indicates that chemical detection techniques such as DGA are widely used to diagnose and predict the conditions of the transformer (Li and Li 2017). Different classification and prediction models have been used in the condition-based predictive maintenance process. It has been shown that MLANN achieves a high accuracy level (about 97.53%) compared to some existing models published by different authors. The proposed MLANN model uses both regular and irregular time series data for transformer state prediction.

In addition, this paper proposed a method for maintenance scheduling based on the transformer health state prediction (MLANN prediction). It predicts the health state of the transformer; for abnormal conditions, further analysis is performed to identify the fault type. After that, the time for maintenance scheduling is minimized using the forecasted load profile and downtime cost analysis. Finally, the knowledge-based system is used for maintenance decision making. The KBS has been designed to incorporate the knowledge from utility company expertise. The use of the KBS system minimizes the human maintenance-related error in ESDN. The proposed TSP-FOMT-KBS model has shown great ability in the maintenance decision-making process based on the predicted transformer status and fault type compared with existing methods (Table 5).

The maintenance schedule aims to reduce maintenance costs and unplanned downtime costs. The proposed PdM costs 58% less than the traditional time-based preventive maintenance used by TANESCO. The utility company can use the forecasted downtime cost for the maintenance schedule at the lowest possible maintenance cost. It gives flexibility to utility to prepare spare parts and labour. It can be used in preparing the spare parts inventory system for future use.

Table 5: Comparison with the benchmarks

Author	Method	Load variations	TSP	FT	KBS	Downtime cost saving/year
Yin and Lu (2009)	BPSO	√	×	×	×	33%
Arab et al. (2015)	SDP	×	×	√	×	39%
Samadi et al. (2019)	IBM	√	×	×	×	40%
Moslemi et al. (2018)	CBM	×	×	√	√	36%
Yang et al. (2019)	ABC	×	×	√	×	18.9%
Behnia and Akhbari (2019)	GTEMS	×	×	√	×	10.1%
This work	CBPMS	√	√	√	√	58%
√-Included	×-Not included					

Conclusion and Recommendations

A predictive maintenance algorithm has been proposed to minimize the maintenance downtime costs in Tanzania ESDN. The PdM approach usually uses the predicted status of the equipment in the maintenance decision-making process. Several data-driven models have been proposed for transformer state prediction. Based on the nature of available transformer data, MLANN has shown promising results compared with other existing methods. Therefore, the prediction engine of MLANN was integrated into the knowledge-based system (KBS) to enhance the maintenance scheduling process. The forecasted maintenance time (FOMT) model was introduced to minimize downtime maintenance costs. The model estimates the time with the minimum possible maintenance downtime cost to support KBS in deciding the maintenance schedule. This work focuses on the transformer maintenance scheduling process, and scholars may extend the work to include other electrical equipment, such as circuit breakers, lines conductors, and other distribution components. The proposed prediction model has been tested using irregular time series data; therefore, further study can be conducted with the regular time series data to justify its accuracy.

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