Internet of things based metaheuristic reliability centered maintenance of distribution transformers

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Abstract. The transformer is a vital component of the power system. Continuous stress on the transformer due to overload, transient and faults will lead to physical damages. The isolation of the transformer causes significant revenue loss and inconvenience to the consumers at the distribution level. This invites the need to achieve a reliable power supply to the consumers and to perform maintenance activity appropriately. Optimized and predictive maintenance strategies are evolved to improve power availability for consumers. The model considers dispersive generation at the customer end, namely solar photovoltaics standalone system, diesel generation, and vehicle to load capabilities. Incipient or critical status of transformers’ functional parameters are observed through the transformer terminal unit and sent to the internet of things platform. The remote processing unit acquires the information from all the distribution transformer and generates the optimized and reliability-centered maintenance schedule. In the proposed work, new reliability indices concerning the consumer dispersive generation are defined. The maximization of the reliability problem is solved using the coconut tree optimization technique. The highest reliability of power supply to the consumer and maintenance schedule are obtained. Economic facet of the estimated maintenance schedule exhibit benefit for both utility and consumer as it encapsulate time of use tariff. The heuristic dataset is used to synthesize the trained model by the machine learning algorithm and future maintenance schedule is predicted. The comparative study is made for the outcome of time-based optimized and predicted maintenance schedules against reliability.

Keywords: Reliability centered maintenance, Distributed generation, Machine Learning, Optimization

1. Introduction
Electrical, mechanical and thermal causes and operations can damage the transformer. The failure of the distribution transformer would lead to an outage for the consumers and revenue loss for the supply utility [1]. The incipient or critical damages may occur at winding, core, tap changer, insulation, bushing, protection unit, measurement units and cooling system. The failure and its effect causes poor power quality and lower the reliability of supply [2]. Different types of maintenance procedures, namely, routine, planned, corrective, periodic, overhaul, condition-based and predictive maintenance, are used to safeguard transformer for a longer time [3]. Among all the maintenance procedures, the
hybrid maintenance model composed of predictive, proactive and reliability centric provides benefit to the consumers compared to other standalone methods [4]. The reliability-centred maintenance method has been applied in power sector very effectively [5,6,7]. Hence RCM is inherited and brought in to the maintenance of transformer considering dispersive generation such as diesel generation, solar PV standalone system, vehicle to load capabilities. The prosumer oriented objective is achieved through optimization techniques. The optimized parameters are continuously passed to the database. The remote RCM client prepares the trained model using FMEA and prosumer data. The predictions are retrieved from the trained model as and when required. The schedule is prepared, considering all the micro to the macro level of features of prosumers and power system components. The state of the art in this work is, obtaining the highest reliability of power supply to the consumer and optimized maintenance schedule for the transformer using novel coconut tree optimization and machine learning techniques. New reliability indices are defined considering multiple energy sources namely grid, solar, vehicle to load and diesel generator. Internet of things platform is developed and utilized to fetch consumer parameters and to publish maintenance schedule.

2. Objectives

The objectives of the work are as follows,

- Maximize the reliability of power supply to the consumer considering multiple sources.
- Obtain reliability centered maintenance schedule for transformer using optimization technique.
- Prepare machine learning model using past dataset (maintenance schedule). Predict the RCM schedule for the future instant.

3. Transformer Reliability Indices

Transformer operation is vital in providing reliable power supply to the customers. Similar to distribution utility indices such as SAIFI, SAIDI and AENS I [3], transformer reliability indices namely Transformer Unavailability Index (TUI) and Transformer Reliability Indices (TRI) are defined to optimally schedule the maintenance activity.

3.1. Transformer Unavailability Index (TUI)

It the ratio of total revenue loss for the distribution utility nullifying the income at the time of dispersive generation at the load end to the total number of customers connected to the distribution transformer. This index considers only flat rate tariff.

3.1.1. TUI with grid energy only.

It is the ratio of cumulative revenue loss to the total number of consumers during outage condition as shown in Equation (1). \( t_s \) and \( t_e \) are start time and end time of the outage. \( \lambda \) is cost grid power at the time of interruption. \( \bar{L} \) is the consumer demand. \( i \) is an interruption instance number. \( C \) is the number of consumers affected at \( r \)th instance.

\[
TUI = \frac{\sum_{i=1}^{n} \bar{L}_i (t_{ei} - t_{si}) \lambda_i}{\sum_{i=1}^{n} C_i}
\]  

3.1.2. TUI with grid, solar and electric vehicle energy.

It the ratio of total revenue loss for the distribution utility nullifying the income at the time of solar PV system and electric vehicle to load capability utilization at the load end to the total number of customers connected to the distribution transformer as shown in Equation (2)-(3). \( \bar{U} = t_{ei} - t_{si} \) is utility interruption duration. \( U' = t_{ei} - t_{si} \) is solar PV system backup time. \( \bar{L} \) is solar PV system power capability, \( U'' = t_{ei} - t_{si} \) is V2L (Vehicle to Load) backup time. \( \bar{L} \) is V2L power capability. \( \alpha_1, \alpha_2, \alpha_3 \) and \( \alpha_4 \) are participation factors decided or agreed by the utility and consumer mutually.
3.1.3. TUI with grid, solar, electric vehicle and diesel generator energy.

It the ratio of total revenue loss for the distribution utility nullifying the income at the time of solar PV system, electric vehicle to load capability and diesel generator utilization at the load end to the total number of customers connected to the distribution transformer as shown in Equation (4)-(5).

\[ U''' = t_{ei} - t_{si} \text{ is diesel generator backup time. } \]

\[ L_{di} \text{ is diesel generator power capability.} \]

\[ TUI = \frac{\sum_{i=1}^{n} L_{i} (U_{j}) \lambda_{i} - \sum_{i=1}^{n} L_{si} (U'_{i}) \lambda_{i} - \sum_{i=1}^{n} L_{ei} (U''_{i}) \lambda_{i}}{\sum_{i=1}^{n} C_{i}} \quad (4) \]

\[ TUI = \frac{\sum_{i=1}^{n} L_{i} (U_{j}) \lambda_{i} - \sum_{i=1}^{n} L_{si} (U'_{i}) \lambda_{i} - \sum_{i=1}^{n} L_{ei} (U''_{i}) \lambda_{i}}{\sum_{i=1}^{n} C_{i}} \quad (5) \]

3.2. Transformer Time Space Unavailability Index (TTSUI)

It the ratio of sum of transformer unavailability indices at all the time instances to the total number of time instances as shown in Equation (6) and (7). Additionally variable cost or time of use tariff is considered in this case.

\[ TTSUI = \frac{1}{m} \sum_{j=1}^{m} TUI_{j} \quad (6) \]

\[ TTSUI = \frac{1}{m} \sum_{j=1}^{m} \frac{1}{\sum_{i=1}^{n} C_{i}} \left[ \sum_{i=1}^{n} \lambda_{ij} (\alpha_{1} L_{ij} - \alpha_{2} L_{si} - \alpha_{3} L_{ei} - \alpha_{4} L_{di}) t_{ei} \right] \quad (7) \]

3.3. Transformer Reliability Index (TRI)

Sum of reliability and unavailability is equal to one as per the definition. Therefore, transformer reliability index is defined as shown in Equation (8).

\[ TRI = 1 - TUI \text{ or } 1 - TTSUI \quad (8) \]

4. Reliability Centered Maintenance

The outcome of reliability centered maintenance is expected to be beneficial for both consumer and utility. The cost gain or saving with grid power reliability is the expectation of consumers. Profitability, power system stability and socio-political agenda fulfilment is the expectation of the
utilities. These two expectations are fulfilled by the proposed reliability centered maintenance system. The workflow of proposed system is shown in Figure 1.

5. Failure Modes and Effect Analysis (FMEA)
Failure modes and effect analysis is performed for distribution transformers by constructing iterative tableau consisting of component of transformer, functionality of the component, mode of failure, local and end effects. These descriptive failures are mapped to factors namely severity (SEV), probability (OCC) and detectability (DET) of failure. Risk parity factor (RPF) is the product of severity, probability and detectability. Once the recommendations are incorporated revised RPF is estimated to attain better lifespan of component [8,9,10].

6. Internet of Things based RCM
RCM service receives customer details and FMEA data from IoT platform. The trained model and dataset are used to retrain and predict the schedule. The transformer maintenance and load curtailment are executed as per the schedule to attain maximized TRI. The work flow is shown in Figure 2.
7. Optimization Techniques

The TRI shown in Equation (8) is a linear combination of start and stop time, which needs to be estimated. The system boundaries and requirements are constraints. Linear programming and coconut tree optimization can be used to estimate the schedule or for better time performance.

7.1. Linear Programming

Maximization of TRI is achieved by using linear programming technique. The general steps involved in linear programming is shown Algorithm 1.

| Algorithm: 1 Linear Programming |
|---------------------------------|
| **Step 1** | Introduction of slack or surplus variables to every inequality and objective functions. Formulation of simplex tableau. |
| **Step 2** | Identification of entering and leaving variable to mark pivot element. Perform elementary row operation to make non-pivot elements in the column zero. |
| **Step 3** | Note basic and non-basic solution. |
| **Step 4** | If all the elements in the last row is 0 or positive then go to step 2, else go to step 5 |
| **Step 5** | Record basic and non-basic solution by decoding tableau and stop the process. |

7.2. Coconut Tree Optimization

Maximization of TRI is achieved by using coconut tree optimization technique. The general steps involved in CTO is shown Algorithm 2.

| Algorithm: 2 Coconut Tree Optimization Technique |
|--------------------------------------------------|
| **Step 1** | Input parameters for the algorithm Objective function, constraints, rib length, leaflet length, equality constraints tolerance and boundaries. |
| **Step 2** | Estimation of initial solution or root position Swing randomly around the initial point to get multiple neighbourhood points and select better initial point compared to all root point. |
| **Step 3** | Estimation of fruit and end positions Search multiple points around root point to get fruit position. |
| **Step 4** | Evolution of local solution Create end point, search along and orthogonally in each leaf. Store best among each leaf as local optima. |
| **Step 5** | Determination of best among all local optima to get global optima. |

8. Machine Learning

There are many machine algorithm techniques available in the literature. Each algorithm plays a more significant role in the prediction of response from the predictors. Support Vector Machine (SVM) is also one such machine learning algorithm. The steps are shown in Algorithm 3.

| Algorithm: 3 SVM Technique |
|---------------------------|
| **Step 1** | Mark all the data points in the vector space |
| **Step 2** | Create hyperplanes which separates data. Select the hyperplane which separates optimally. This hyperplane is more away from every vectors. |
| **Step 3** | Increase the separation margin until hyperplane encounters support vector from each subspace. |
| **Step 4** | Generate predictors for regression test. Mark the predictors on the vector space. Find the Euclidean distance for each candidate. Compare with input-output dataset to output accuracy of the model |
9. Problem Formulation

The optimization problem is an unavailability minimization of the power to the consumer. In other words, reliability maximization of the power supply to load considering three types of dispersive generation. In this work, maintenance schedule are estimated for time of use tariff. The maintenance schedule is provided for the prosumer requirement as in Equation (9)-(15).

\[
\min f(x) \Rightarrow \min TUI \Rightarrow \max 1 - TUI \Rightarrow \max TRI \Rightarrow \min - TRI
\]  

\[
\min \frac{1}{m} \sum_{j=1}^{m} \left\{ \sum_{i=1}^{n} \lambda_{ij} \left( \alpha_1 L_{ij} - \alpha_2 L_{sij} - \alpha_3 L_{eij} - \alpha_4 L_{dij} - \alpha_4 L_{dij} \right) t_{ei} \right\}
\]

Subject to,

\[
L_{ij} \left( t_{ei} - t_{sij} \right) + L_{sij} \left( t_{ei} - t_{stij} \right) + L_{eij} \left( t_{ei} - t_{sij} \right) + L_{dij} \left( t_{ei} - t_{sij} \right) = E^T_{ij}
\]

\[
t_{ei} - t_{sij} = U_{ij}
\]

\[
t_{sij} - t_{ei} \leq 0
\]

\[
t_{sij} + U \leq t_{sij+h} \forall h : -n \rightarrow n \in \mathbb{Z}, h \neq 0
\]

\[
\begin{bmatrix} 0 \\ 0 \end{bmatrix} \leq \begin{bmatrix} t_{sij} \\ t_{ei} \end{bmatrix} \leq \begin{bmatrix} U_{ij} \\ U_{ij} \end{bmatrix}
\]

### Parameters Description

- \( \sum_{i=1}^{n} \lambda_{ij} \left( \alpha_1 L_{ij} - \alpha_2 L_{sij} - \alpha_3 L_{eij} - \alpha_4 L_{dij} - \alpha_4 L_{dij} \right) t_{ei} \)
  - Bill amount for the energy usage from \( t_s \) to \( t_e \).
  - The \( n \) number of interruption is considered.
  - \( m \) time instances are considered.
  - \( i \) and \( j \) represents the interruption and time instant number.

- \( \sum_{i=1}^{n} \lambda_{ij} \left( \alpha_2 L_{sij} + \alpha_3 L_{eij} + \alpha_4 L_{dij} - \alpha_1 L_{ij} \right) t_{si} \)
  - It is the energy balance equation.
  - \( E^T_{ij} \) is the total energy demand from the consumer which has to be supplied by the three sources considered.

Equation (12) is an equality constraints provides the maintenance time duration (\( U \)) required for the specific type of instance. Equation (13) is inequality constraint infer starting instant is before ending. Equation (14) convey that the maintenance tasks shouldn’t be schedule at same slot. Every maintenance task should be taken up one after other. Equation (15) is the time boundary.

10. Results and Discussion

The optimized maintenance schedule obtained in comparison with the unoptimized schedule is shown in Figure 3(a). The machine learning accuracy or confidence for the miniature dataset is captured in the confusion matrix and region of convergence curves.

10.1. Case Study

The algorithms are validated for the following case data and results are provided in the next section.

| Parameters                 | Description                                                                 |
|----------------------------|-----------------------------------------------------------------------------|
| Number of consumers        | 20 for all DTCs                                                             |
| Cost characteristics for ToU tariff | Random integer from 0 to 10 for all DTCs                                   |
| Power demand               | Random integer from 8 to 12kW for all DTCs                                  |
| Solar, V2L and DG capacity | 10kWh each with random availability                                         |
| Energy demand              | 20kWh, 30kWh, 40kWh, 35kWh                                                  |
| Outage duration            | 2h, 2.5h, 3h and 4.5h for each DTCs                                         |
| Participation factor       | Unit random number                                                          |
10.2. **RCM for ToU tariff (With and without optimization)**

The maintenance chart and consistency of methods for the time of use tariff structure are shown in Figure 3(a) and 3(b) respectively. It is observed that reliability increases with the proposed methods.

![RCM Schedule for ToU](image1)

![Reliability deviation with respect to RCM](image2)

**Figure 3.** RCM Schedule and normalized reliability indices

10.3. **RCM with Machine learning for ToU rate**

An accuracy of 88.6% is obtained after training ToU dataset. The confusion matrix and RoC for multiband optimized dataset are shown in Figure 4(a) and 4(b). The model generated almost provides a true response. The true response is the start time of the maintenance schedule.

![Confusion Matrix](image3)

![RoC: RCM](image4)

**Figure 4.** Confusion matrix and RoC for ToU tariff RCM using SVM technique

11. **Conclusion and Future Scope**

In this work, transformer reliability indices are defined considering prosumer data and infrastructure. The dispersive generation available at the load end, improved the reliability of supply to the customer around 3%. It also helped in predictive maintenance of transformer. The optimization problem is formulated and solved using linear and coconut tree optimization. An optimized maintenance schedule is obtained using optimization techniques and machine learning techniques. The accuracy of the trained model for the time of use tariff is 88.6% for the system under consideration.

The work can be extended by providing failure details of all the components to get a generalized diagnostic model. The real-time transformer functional parameters are provided to the learned system. The non-technical, environmental and managerial constraints and data modelling enhance the applicability of the proposed method on site.
Appendices

IoT Platform

The details of the IoT platform and APIs used are given below,

| URL | http://openioe.herokuapp.com |
|-----|------------------------------|
| APIs | Get XML | http://openioe.herokuapp.com/api/showxml/uid/pin |
|     | Post XML | http://openioe.herokuapp.com/api/updatexml/uid/pin/[xml] |

The FMEA, consumer and utility details are stored in the IoT platform. The XML is constructed and stored in the cloud database. It is fetched and then parsed for the utilization in program to obtain optimal schedule.

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