SCADA ENHANCEMENT FOR EFFECTIVE REHABILITATION STRATEGY OF MV CABLES USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

One of the most important tasks for power utilities is the maintenance and upgrading of their equipments to provide high reliability for their customers. It has significant benefits in terms of customer satisfaction and quality of supply statistics particularly for investment targeting. The basic evaluation steps in condition assessment provide the data for analysis and prioritization methods of power system equipment.

Alexandria Electricity Distribution Company (AEDC) is the electrical power distributor in Alexandria governorate in Egypt. The nominal medium operating voltage is 11KV.Mainly underground cables are used in the network except for some areas located in the outskirts where overhead transmission lines are used. Some of the MV network cables are deteriorated resulting in lengthy and costly outages. A major rehabilitation plan was needed to upgrade the system, including replacement and new design for the MT network.

AEDC implemented SCADA system to provide efficient maintenance strategies thereby reducing the time for maintenance procedures, and increasing its efficiency through the available real-time data, load management applications as well as network connectivity analysis. The data-rich, reliable SCADA system in AEDC was put in service in 1998. Continuous studies are done to leverage the existing SCADA system data to get the best advantage and to provide a reliable strategy to help decision-makers for effective asset management.

This paper presents an application that utilizes the SCADA database and introduces an effective strategy for the rehabilitation of medium voltage underground cables with priority evaluation. The application saves the history of each faulty cable on the network, and is based on a trained back-propagation artificial neural network (ANN) to determine the appropriate weights for the factors affecting the rehabilitation plan. These factors are based on ageing, cable type [XLPE/PILC], loading level, number of cable's faults, number of repairing joints and the strategic path of the cable. The application's output is a full report with the highest-priority cables to be replaced. The application includes additional features for calculating the approximate total cost of replacement for each cable. The application is created using VBA and applied on "Windows" as operating system and "MS ACCESS" as system database.

To demonstrate the effectiveness of the proposed MV cables rehabilitation strategy application, middle control center has been selected for computer simulation. The results show that the application provided a reliable and fast strategy towards an effective rehabilitation plan.

INTRODUCTION

In Alexandria, the MV network is composed of 9818 km of underground cables and 579 km of overhead transmission lines. It is required to provide safe and reliable electrical cable infrastructure that will assure maximum uptime at the lowest possible cost.
Each year the network expands, new cables are added, the previously-installed cables age, some of the cables get deteriorated resulting in lengthy and costly outages, thus reliability of the entire system is at risk. The company replaces around 2.7km of underground MV cables monthly.

To ensure continued reliability, AEDC allocates a certain budget for cable replacement on an annual basis. It makes sense to replace those cables that are near to the end of life immediately, and to defer replacement of other cables that are not in imminent danger of failing. Therefore, an efficient rehabilitation plan was needed to upgrade the system and a scientifically sound method of prioritizing the cable replacement is required.

Some of the major obstacles in the rehabilitation process are:
– Scattered Information from all over the grid
– Diversity of factors affecting the rehabilitation process that require expertise from multi- disciplines
– Absence of a general indexing factor to determine the priority of cables to be replaced.
– Manual analysis/solution takes time and huge effort to reach an optimized rehabilitation plan

Table. 1. MV Cables Failure Statistics at AEDC

Year	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*
Total	938	665	544	223	149	146
Electrical	607	404	387	167	96	104
Splice	101	63	54	15	14	17
Termination	31	13	17	-	-	5
Incidental	199	185	86	41	39	20

In 1998, AEDC installed a Supervisory Control and Data Acquisition (SCADA) system for the monitoring and control of substations. Continuous studies are done for the existing SCADA system to make the full use of its Distribution Management System (DMS) and to leverage it to get the best advantage The DMS database contains the cables information and records the alarms associated with cables' failures and the events associated with cables' maintenance.

This paper presents an application that introduces an effective strategy for the rehabilitation of MV Cables with priority evaluation through calculating a cable rehabilitation index (CRI). It incorporates one of the most popular artificial intelligence techniques namely neural networks.

Neural networks have been used in a board range of applications including: pattern classification, pattern recognition, optimization, prediction and automatic control. Many interesting ANN applications have been reported in power system areas, where they are widely used in load forecasting, unit commitment, economic dispatch, security assessment, fault diagnosis and alarm processing. Neural computing has attractive features, such as its ability to tackle new problems which are hard to define or difficult to solve analytically, its robustness in dealing with incomplete or fuzzy data, its processing speed, its flexibility and ease of maintenance.

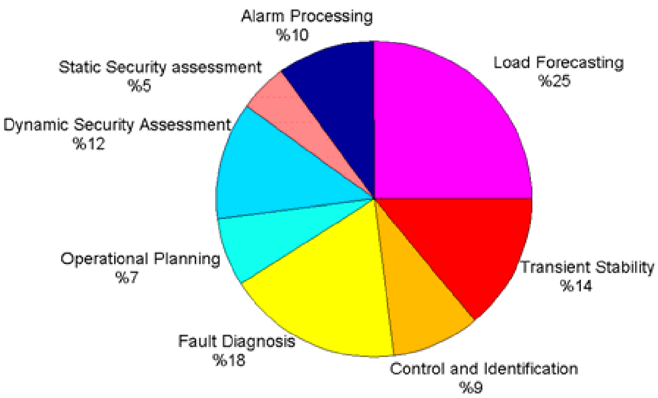


Fig. 1. Neural networks applications for Power Engineering

Most of the applications make use of the conventional multilayer Perception (MLP) model based on back propagation algorithm. Multilayer feed forward can accept several transfer functions, several hidden layers. The application utilizes the top relevant factors in the rehabilitation process and the aggregated data from SCADA [Cables Data-Cables History of faults] to provide a full report with the highest-priority cables to be partially/fully replaced. The application is based on a trained multilayer feed-forward back-propagation neural network to determine the appropriate weights for the factors affecting the rehabilitation plan.

FEEDFORWARD BACKPROPAGATION NEURAL NETWORKS

The use of neural networks offers the following useful properties and capabilities:

1. Nonlinearity. A neural network, made up of an interconnection of nonlinear neurons, is itself nonlinear. Moreover, the nonlinearity is of a special kind in the sense that it is distributed throughout the network. Most real systems, including power system are nonlinear, so this property is very desirable for its applications in power system.

2. Input-Output Mapping. A popular paradigm of learning called learning with a teacher or supervised learning involves modification of the synaptic weights of a neural network by applying a set of labeled training samples or task examples.. The network learns from the examples by constructing an input-output mapping for the problem.

3. Adaptivity. Neural networks have a built-in capability to adapt their synaptic weights to changes in the surrounding environment. Moreover, when it is operating in a non-stationary environment, a neural network can be designed to change its synaptic weights in real time.

4. Fault tolerance. A neural network has the potential to be inherently fault tolerant in the sense that its performance degrades gracefully under missing or erroneous data.

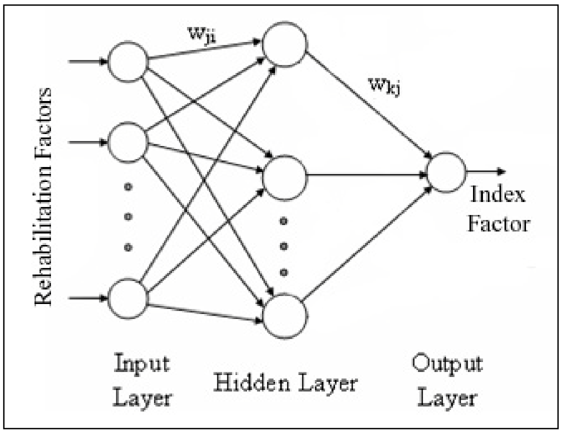


Fig. 2. A three-layered multi-layer perceptron network

The reason is that the information is distributed in the network; the errors must be extensive before catastrophic failure occurs.

Fig.2 illustrates a three-layered multi-layer perceptron network (MLPN). Each layer is composed of a predefined number of neurons. The neurons in the input layer only act as buffers for distributing the input signals x_i to neurons in the hidden layer. Each neuron j in the hidden layer sums up its input signals O_i after weighting them with the signals of the respective connections W_{ji} from the input layer, and

computes its output O_j as a function F of the sum:
$O_j = F (\Sigma W_{ji} O_i - \theta_j)$
where F is the activation function that is necessary to transform the weighted sum of all signals impinging onto a neuron. F is usually a sigmoidal or hyperbolic tangent function.

The outputs of neurons in the output layer are computed similarly. Training a network consists of adjusting its weights using a training algorithm. The network training function updates weight and bias values according to gradient descent momentum and an adaptive learning rate. In our case, we used the backpropagation algorithm.

The Backpropagation Algorithm

- Weight Initialization
  Set all weights and node thresholds to small random numbers.
- Calculation of the activation
  1. The activation level of the input unit is determined by the instance presented to the network.
  2. The activation level O_j of a hidden and output unit is determined by
  $O_j = F (\Sigma W_{ji} O_i - \theta_j)$
  where W_{ji} is the weight from input O_i, θ_j is the node thereshold and F is a sigmoid function :
  $F (a) = 1/(1+e^{-a})$
- Weight Training
  1. Start at the output units and work backward to the hidden layers recursively. Adjust the weights by: $W_{ji} (t +1) = W_{ji} (t) + \Delta W_{ji} (t)$
  where W_{ji} (t) is the weight from unit i to unit j at time t (or the t^{th} iteration) and ΔW_{ji} is the weight adjustment.
  2. The weight adjustment is computed by:
  $\Delta W_{ji} = \eta \delta_j O_j$
  where η is a trial independent learning rate ($0< \eta<1$) and δ_j is the error gradient at unit j.
  Convergence is made faster by adding a momentum term:
  $W_{ji}(t +1) = W_{ji}(t) +\eta\delta_j O_j +\alpha[W_{ji}(t +1)-W_{ji}(t)]$
  where $0 < \alpha < 1$.
  3. The error gradient is given by:
     - For the output units:
       $\delta_j = O_j (1 - O_j) (T_j - O_j)$
       where T_j is the desired target activation and O_j is the actual output activation at output unit j.
     - For the hidden units:
       $\delta_j = O_j (1 - O_j) \Sigma \delta_k W_{kj}$
       where δ_k is the error gradient at unit k to which a connection points from hidden unit j.
  4. Repeat iterations until convergence in terms of the selected error criterion. An iteration includes presenting an instance, calculating activations, and modifying weights.

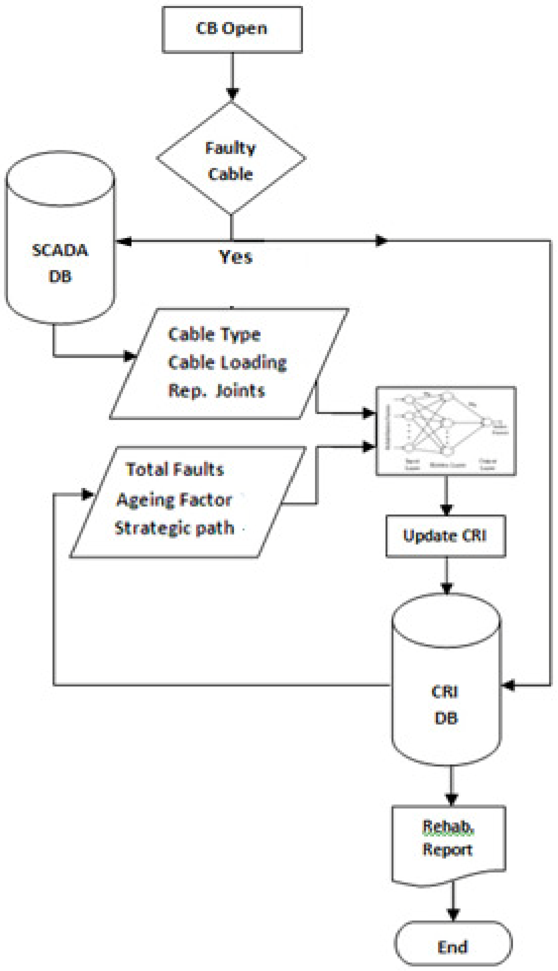


Fig.3. Flow Chart of the CRI application

METHODOLOGY

The neural network has been trained on six factors:

1. Number of cable's faults

The application utilizes the SCADA alarm module that occurs when any circuit breaker is opened due to protection. Investigating the cause of the alarm, whether a false alarm, a kiosk fault or a faulty cable exists. In case of a faulty cable, the cables faults history table in the CRI database gets updated with the new cable details: cable name, date of fault, fault location and fault type (electrical, incidental, splice or termination).
A simple query is added to the application to calculate the total number of faults per cable.

2. The strategic path of the cable

This factor is placed according to the importance of the load with the highest value (priority) given to hospitals, embassies, government locations then factories and industrial locations down to regular residential areas.

3. Ageing

The ageing factor represents the duration of the cable since its first installation and loading in the distribution network in years.

4. Cable type [XLPE/PILC]

Some of the MV underground cables are three core paper insulated lead covered cables (PILC), ranging in size from 150mm2 to 240mm2aluminum. At AEDC, the rehabilitation plan aims for replacing all medium voltage (PILC) feeders and circuit sections by aluminium cross-linked polyethylene (XLPE) shielded cables. Thus this factor places the highest priority to PILC cables over XLPE.

5. Number of repairing joints

The greater the number of repairing joints or splices a cable has, the higher the value of the factor, it portrays how urgent the cable needs to be replaced.

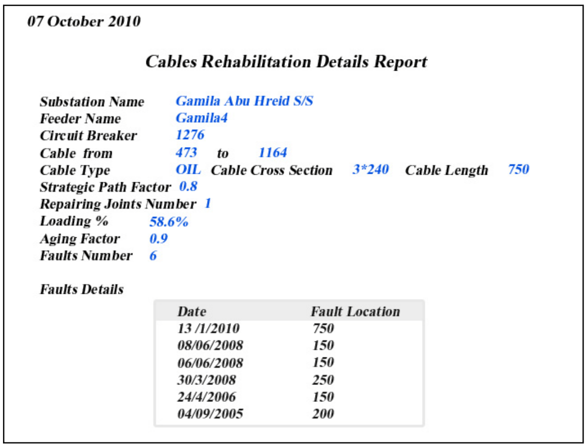
6. Loading Percentage

There have been failures due to overheating caused by increased loading, thus cables heavily loaded are given the highest priority.

After training the MLP neural network, the resulting index value for each faulty cable presents its priority for replacement. The following final step calculates the number of repairing joints with respect to length and the depth of the underground cable to give the final decision whether the cable to be partially or fully replaced.

TEST SYSTEM AND SIMULATION RESULTS

To demonstrate the effectiveness of the proposed MV cables rehabilitation strategy application, middle control center (MCC) has been selected for computer simulation. MCC DMS database contains 2692 MV underground cables records with total length of 1.4kms.


07 October 2010

Cables Rehabilitation Details Report

Substation Name Gamila Abu Hreid S/S
Feeder Name Gamila4
Circuit Breaker 1276
Cable from 473 to 1164
Cable Type OIL *Cable Cross Section* 3*240 *Cable Length* 750
Strategic Path Factor 0.8
Repairing Joints Number 1
Loading % 58.6%
Aging Factor 0.9
Faults Number 6

Faults Details

Date	Fault Location
13 /1/2010	750
08/06/2008	150
06/06/2008	150
30/3/2008	250
24/4/2006	150
04/09/2005	200

Fig. 4. Cables Rehabilitation Details Report

The neural network has been trained on 20 different datasets of faulty cables in the network, where the datasets length ranges from 10-30 faulty cables. Next, the new faulty cables features are fed to the network and the neural network provide the appropriate rehabilitation index value. Accordingly, the cables are sorted and the highest priority cables are rehabilitated.

For each cable, a report can be printed out including the cable's data and the full history of its faults. The application also calculates the approximate cost of the full replacement of the cable.

CONCLUSION AND FUTURE WORK

The application has proved its effectiveness and has reduced the time and the effort consumed in putting the rehabilitation plan by utility experts of several sectors from days to several minutes in an AI model that captures their knowledge and expertise. It can be considered as a reliable inexpensive asset management tool for any power distribution utility.

The advantage of applying the neural network training algorithm keeps it dynamic to implement different policies and the possibility and ease of adding/ removing of the influencing factors then re-training the network and updating the weights is considered a great advantage. Future work includes the addition of surrounding temperature and pollution factors.

It can also be used in developing a failure prediction report by training a second neural network based on collected historical data, cable location and characteristics.

Additional researches are also done to integrate a fuzzy system to act as an expert engineer in assessing cables condition. The aim of the application is to assist maintenance engineers in deciding where to look for possible failures and where preventative maintenance is most needed.

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