Simulation of Electrical Load Forecasting in Substation Transformers Using ANFIS

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ABSTRACT

Forecasting models for a daily load curve using ANFIS (Adaptive Neuro-Fuzzy Inference System) data such as power, current, winding temperature, oil temperature and atmospheric temperature etc. After training networks using actual historical load and data properly processed, results indicate that ANFIS forecasting model presented clear superiority with features of simple algorithm, high accuracy and high stability and is more adaptable to the applications in design of load forecasting at substation transformer. The proposed method of a electrical load forecasting with forecasted load management with the work presents a methodology for estimating the maximum power that can be extracted from distribution substation transformers based on Estimated values of future load, current temperature values measured at various locations within the transformer, and transformer reliability requirements.

1. INTRODUCTION

Power systems development and increasing their complexity caused many factors have become much more significant in electric power generation and consumption. In order to meet power systems requirements continually and having sustained economic growth, load forecasting has become a very important task for electric utilities. An accurate load forecast become more imperative in managing utility, developing a power supply strategy, finance planning and electricity market management.

Load forecast should be accomplished over time intervals for economical and efficient operation and also control of power systems. [1, 2]. Power transformers are traditionally protected by differential protection schemes that use voltages and currents to detect abnormalities in the differential zone of protection. For this type of scheme, a short circuit or high magnitude current must be present to initiate a trip. However, this scheme might not be ideal when transformers need to be overloaded to mitigate contingency conditions [3]. Operators can use these ratings until the contingency conditions are mitigated. However, once the transformer has surpassed the short term emergency ratings, the transformer might reach critical temperatures and could possibly sustain damage. Protection engineers can avoid further transformer damage by using the thermal protection principles of the IEEE standard. This paper discusses the fundamental thermal principles of power transformers, philosophies of operations and the implementations of protection system with the help of substation transformer historical parameters [4].

2. CHARACTERISTICS OF PEAK LOAD DATA

Peak Loads are used for short term load forecasting (STLF), and the notable features of this data type are:

a) The available data are the peak load with various parameters from Maharashtra State Electricity Distribution Company for the years 2009 and 20010.

b) The original data takes the shape illustrated in with classification according to the seassion wise

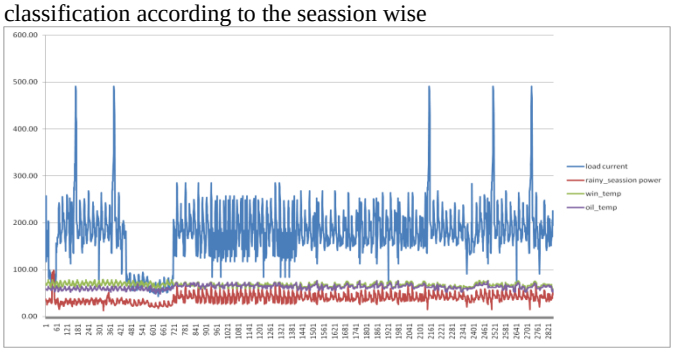


Figure A Rainy session plot shows the continuous variation on the substation transformer and the variation in various parameters.

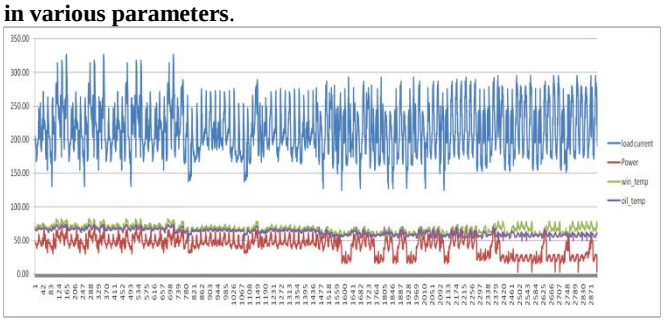


Figure B Winter session plot shows the continuous variation on the substation transformer and the variation in various parameters.

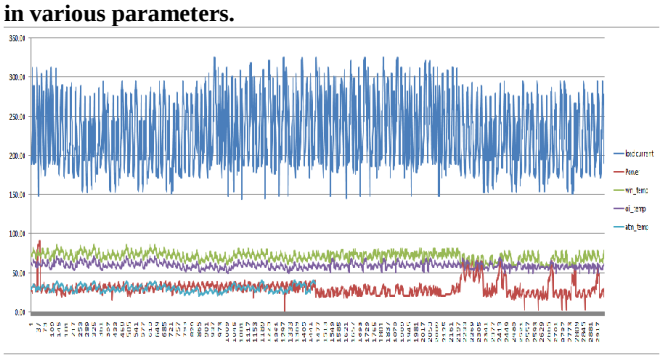


Figure C Summer session plot shows the continuous variation on the substation transformer and the variation in various parameters

3. TRANSFORMER DYNAMIC RATINGS

Under the new North American Electric Reliability Corporation (NERC) standards for rating of power system elements, many utilities have implemented rating methodologies for power transformers. Rating methodologies are bounded by individual utilities' philosophies or criteria and their willingness to sacrifice transformer loss of life. Based on a rating philosophy and the calculations per IEEE C57.91-1995 outlined in this paper, utilities can create thermal dynamic ratings for power transformers. These thermal dynamic ratings can be utilized to set thermal relays, and they can also be applied to real time operating cases for system operators. Regardless of the philosophy employed, rating methodologies have dynamic ratings for four different types of loadings:

• Normal life expectancy loading
• Planned loading beyond nameplate
• Long time emergency loading
• Short time emergency loading

3.1 Operation With Overloads.-

Loads in excess of normal rating may be carried under certain conditions when necessary. Doubtful cases should be reported to the Denver Office, for checking. For operations at loads above normal rating, on a repetitive basis, the cooling system should be maintained at maximum operating efficiency; the windings and oil should be checked to determine that they are reasonably clean and free from excessive amounts of moisture and sludge and that internal obstructions to oil circulation, such as reduced oil duct clearances, of any nature, are not present. Transformer capacity, including over-load capability, may at times be increased by augmenting the cooling air supply with blowers or making other cooling system changes. The transformer manufacturer should be consulted for recommendations and expected hotspot temperatures when cooling system modifications are planned to increase transformer capacity.

3.2 Overload Limitations

The data in this volume cover all types of oil-immersed transformers, except water-cooled transformers built before 1929. The data cover transformers with either of the two commercially available insulation systems: (1) those designed to operate continuously up to 55 °C rise above ambient temperature, and (2) those designed to operate continuously up to 65 °C rise above ambient temperature investigation of the various limitations involved. Among those limitations which should be checked in the field are oil expansion; pressure in sealed- type units; heating of bushings, leads, soldered connections, and tap changers; and heating of associated equipment, such as cables, reactors, circuit breakers, disconnecting switches, and current transformers. any one of which may constitute the practical limit in load carrying ability.

3.3 Transformer Life Expectancy

The life expectancy of transformers, regulators, reactors at various operating temperatures is not accurately known, but the Information in this volume regarding loss of life of is considered to be conservative. "Conservative" is used in the sense that the expected of insulation life for a single recommended load will not be greater than the amount Indicated by data presented herein.

3.4 Aging of Insulation

Aging or deterioration of insulation is a function of time and temperature. Since in most apparatus the temperature distribution is not uniform, that part which is operating at the highest temperature will ordinarily undergo the greatest deterioration. Therefore, it is usual to consider the effects produced by the highest temperature "hottest spot."

$$FAA = \left[\frac{15000}{383} - \frac{15000}{\Theta H + 273}\right]$$

$$FEQA = \frac{\left[\sum_{n=1}^{N} FAAn * \Delta tn\right]}{\sum_{n=1}^{N} \Delta tn}$$

Where:

FEQA	Equivalent aging factor for the total time period
N	Total number of intervals
n	Index of time interval
FAAn	Aging accelerating factor at index n
Δtn	Time interval

A transformer's total loss of life can be derived as a percentage by using the following equation:

$$\text{Loss of Life} = \frac{\text{FEQA x t x 100}}{\text{Normal Insulation Life}}$$

4. METHODOLOGY: PROPOSED MODEL

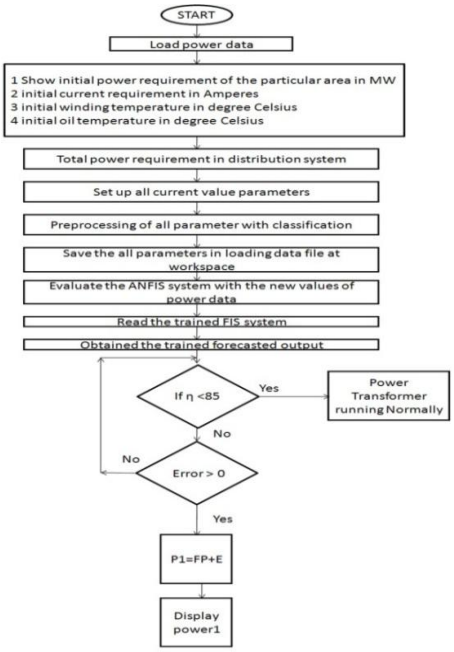


Figure D Load forecasting Flowchart

It consists of software tools developed for this work. The first trains ANFISs based on historical data extracted through the data acquisition system and is executed in offline mode.

The Short Term Load Forecast is fed by a historical data of various parameters, and came out the forecasts using an Adaptive Neuro-fuzzy inference system technique based on Artificial Neural Network and fuzzy logic network, for 50 MVA substation transformers. This procedure is used to define the general operational condition of transformers.1) Normal life expectancy loading 2) Planned loading beyond nameplate 3) Long time emergency loading 4) Short time emergency loading. Supplies short term forecasts along the day aim to provide a procedure which monitors occasional

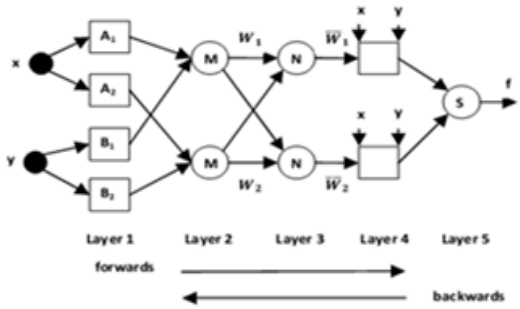
loading variations and accommodates moderate variations along the day. This procedure aims at supplying more accurate conditions of the loading behavior, and provides the loading according to the efficiency of a substation transformer.

The input parameters:

− loading power;
− loading current;
− loading winding temperature (hot-spot temperature);
− loading oil temperature (top oil temperature);
− Ambient temperature.

4.1 Adaptive Neuro-Fuzzy Inference System:-

An ANFIS [7] can help us find the mapping relation between



the input and output data through hybrid learning to determine the optimal distribution of membership functions. Five layers are used to construct this inference sys-tem. Each layer contains several nodes described by the node function. Adaptive nodes, denoted by squares, represent the parameter sets that are adjustable in these nodes, whereas fixed nodes, denoted by circles, represent the parameter sets that are fixed in the system. The output data from the nodes in the previous layers will be the input in the present layer. To illustrate the procedures of an ANFIS, for simplicity, we consider only two inputs x, y and one output f out in this system. The framework of ANFIS is shown in Fig. 2

Figure 2

Layer 1: Every node in this layer is an adaptive node with node function as:

$$O_{1,i} = \mu_{A_i}(x) \quad \text{for} \quad i = 1,2 \qquad (1)$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \quad \text{for} \quad i = 3,4 \qquad (2)$$

where x (or y) is the input of the node, Ai (or Bj) is the linguistic label, l(x) (or l(y)) is the membership function, usually adopting the bell shape with maximum and minimum equal to 1 and 0, respectively, as follows:

$$\mu(x) = \frac{1}{1 + \left(\frac{x - c_i}{a_i}\right)^{2b_i}} \qquad (3)$$

or

$$\mu(x) = \exp\left\{-\left(\frac{x - c_i}{a_i}\right)^2\right\} \qquad (4)$$

Where {ai, bi, ci} is the parameter set. As the values of these parameters change, the bell shaped functions vary accordingly. The parameters in this layer are named premise parameters.

Layer 2: Every node in this layer is a fixed node, marked by a circle and labeled P, with the node function to be multiplied by input signals to serve as output sigma

$$O_{2,i} = \mu_{A_i}(x) \cdot \mu_{B_i}(y) = \omega_i \quad \text{for} \quad i = 1,2 \qquad (5)$$

The output signal xi represents the firing strength of a rule.

Layer 3: Every node in this layer is a fixed node, marked by a circle and labeled N, with the node function to normalize the firing strength by calculating the ratio of the ith node firing strength to the sum of all rules' firing strength.

$$O_{3,i} = \frac{\omega_i}{\sum \omega_i} = \frac{\omega_i}{\omega_1 + \omega_2} = \bar{\omega}_i \quad \text{for} \quad i = 1,2 \qquad (6)$$

Layer 4: Every node in this layer is an adaptive node, marked by a square, with node function

$$O_{4,i} = \bar{\omega}_i \cdot f_i \quad \text{for} \quad i = 1,2 \qquad (7)$$

Where f1 and f2 are the fuzzy if-then rules as follows:

Rule1: if x is A1 and y is B1 then

f1 = p1x + q1y + r1

Rule2: if x is A2 and y is B2 then

f2 = p2x + q2y + r2 and where {pi, qi, ri} is the parameters set, referred to as the consequent parameters.

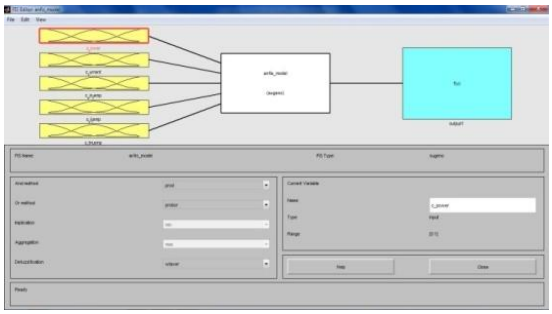
Layer 5: Every node in this layer is a fixed node, marked by a circle and labeled R, with node function to compute the overall output by

$$O_5 = \sum_i \bar{\omega}_i \cdot f_i = f_{\text{out}} \qquad (8)$$

5. LOAD FORECASTING ANALYSIS: ANFIS

It's expected that the substation transformer have to keep the transformer operating safely and established loss of life under control with the help of loading control. We use adaptive Neuro-fuzzy inference system to forecast the future load on substation transformer. With the help of historical loading data parameters such as power, current, winding temperature, oil temperature, atmospheric temperature etc. the results are more heartening and helpful for monitoring the health of power transformer. It can also be used, together with risk calculation for trans-mission lines overload, voltage collapse, voltage out-of-limit, and transient instability to obtain a composite risk as a function of operating conditions. We believe this risk calculation method is helpful in making decisions related to balancing risk against the economic benefits that may result from a transformer loading level.

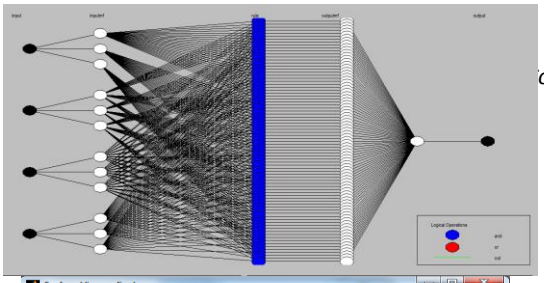
Figure E This figure show the ANFIS window in MATLAB

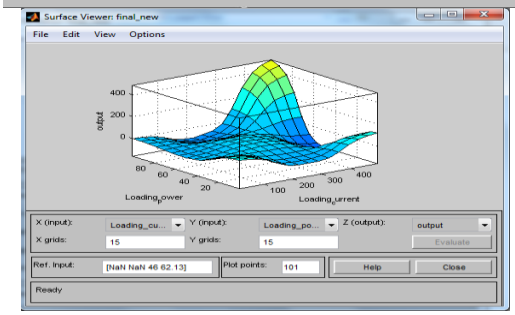


environment with the various parameters like loading power, loading current, loading winding temperature, loading oil temperature and atmospheric temperature as input to the sugeno system

Figure E this figure G shows the after simulation of various parameters obtain the structure of ANFIS which consist of five layers of various nodes, help to understand the each layer with membership function ,fuzzyfication and Defuzzification

Figure H This figure shows the surface viewer of forecasted power to obtain relationship between loading power and loading current. We can see how forecasted power changes with respect to loading parameters.





5.1 Determination of Training Parameters

According to the pre-processing method, specimen set was established based on actual historical hourly load data of various parameters in January, 2009-10 including loading power, loading current, loading winding temperature (hot-spot temperature), loading oil temperature (top oil temperature) and ambient temperature. After training neural network using data, we obtained the hourly load forecasting values. Relative errors comparing the forecasting values with actual values are shown in table1.The forecasting accuracy of the technique was evaluated by the average of absolute percentage errors of the hours in a day. The Absolute Percentage Error (APE) is

$$APE = \frac{|L_a - L_f|}{L_a} \times 100$$

There La and Lf respectively are the actual and the forecast loads in a day. The Mean Absolute Percentage Error (MAPE) is then computed by

$$MAPE = \frac{1}{N_h} \sum_{N_h} APE$$

Table1 ANFIS SYNTHESIS for actual values of Loading Power with Forecasted Power

Hours	ANFIS SYNTHESIS			Hours	ANFIS SYNTHESIS		
	Loading Power In MW	Forecast power	APE %		Loading Power In MW	Forecast power	APE %
1	29.543	23.153	0.2162949	13	40.474	31.52	0.22123
2	30.624	27.048	0.1167712	14	39	30.44	0.21949
3	31.742	31.912	0.0053557	15	36.965	17.713	0.52082
4	35.16	33.295	0.0530432	16	35.743	8.938	0.74994
5	33.14	31.992	0.0346409	17	35.853	9.029	0.74817
6	33.632	29.758	0.1151879	18	35.109	10.246	0.70817
7	34.882	29.211	0.1625767	19	31.727	20.311	0.35982
8	34.478	29.239	0.151952	20	32.814	25.653	0.21823
9	36.997	34.081	0.0788172	21	34.504	31.327	0.09208
10	39.321	33.356	0.1517001	22	33.494	34.301	-0.0241
11	39.836	33.355	0.162692	23	34.899	29.791	0.14637
12	40.197	32.5	0.191482	24	34.043	25.332	0.25588

6. CONCLUSION

This paper presented a work which aims at developing an automated system for local use in Distribution Substations, in order to enable power transformer loading supervising in an optimized way and in real time from the Control Center, by means of loading parameters for controlling the health of substation transformer. According to the historical data we have forecasted power on the substation transformer. This allows a more optimized distribution power reconfiguration, with expressive gains for the operation of the substation transformer. The equipment monitoring and the implementation of automatic platforms in substations tend to less conservative limits of transformer loading. New and more reasonable loading practices, centered on the equipment reliability and on much more during temperature limits have just come up. This is only more safely applicable before the implementation of a more precise transformer loading control process. The developed system has fully reached the expected aims at a first analysis, the results have turned out to be satisfying, and the local system disposes a set of future possibilities of loading condition for each transformer individually, increasing the utilization factor, depending on the operational conditions and on the equipment's history.

The final estimated results are:

Keep under control the established loss of life, keeps the transformer operating safely.

Disconnect non-essential loads only when necessary, and in a minimum quantity;

Avoid the risk of damage to the transformer being loaded in a maximized, continuous way, allowed in a certain time interval.

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