Load flow analysis with a neuro-fuzzy model of an induction motor load

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This paper appears in: AFRICON, 2009. AFRICON '09.
Issue Date: 23-25 Sept. 2009
On page(s): 1 - 4
Location: Nairobi
Print ISBN: 978-1-4244-3918-8
INSPEC Accession Number: 10963658
Digital Object Identifier: 10.1109/AFRCON.2009.5308308
Date of Current Version: 03 November 2009

ABSTRACT

In the conventional load flow study, the active and reactive powers of all load buses are generally specified. Although the constant power model is applicable for approximate studies, it may not be suitable for the motors because the reactive power is very sensitive to the voltage variations while the active power is dependent upon the torque being driven. This paper proposes to solve the load flow equations using a neuro-fuzzy model of an induction motor. Both the active and reactive powers of the motor are estimated at each iteration using neuro fuzzy techniques. The efficiency is estimated using the IEEE 30 bus system. The results indicate that the inclusion of induction motor loads has an effect on the convergence characteristic of the active and reactive power mismatches of the modified load flow.

LOAD FLOW WITH A NEURO-FUZZY INDUCTION MOTOR MODEL

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Abstract

In the conventional load flow study, the active and reactive powers of all load buses are generally specified. Although the constant power model is applicable for approximate studies, it may not suitable for the motors because the reactive power is very sensitive to the voltage variations while the active power is dependent upon the torque being driven. The paper proposes to solve the load flow equations with neuro fuzzy induction motor models. Both the motor active power and reactive power are estimated at each iteration using neuro fuzzy techniques. The efficiency is estimated using the IEEE 30 bus system. The results indicate that the inclusion of induction motor loads has an effect on the convergence characteristic of the active and reactive power mismatches of the modified load flow.

Keywords-component; induction motor loads, neuro-fuzzy, load flow

I. INTRODUCTION

Power flow calculations provide a starting point for most power system analysis. For example, the problems related to transient and voltage stabilities due to dynamic behavior of induction motor loads have been a major area of attraction for power system planners and operation engineers all over the world. In the conventional load flow study, the active and reactive powers of all load buses are generally specified [1].

To solve the load flow equations with IM loads, the motor active power is assumed to be fairly constant [4, 5]. This assumption is valid when the motors are operated in the vicinity of small changes of the supply voltage, not below the stalling point while running a constant load. Reference [6] analyzes the significance of exact calculation of equivalent-circuit impedances and adequate handling with load power-slip characteristics of individual motors in induction motor aggregation.

Induction motor modeling is a complex problem because of the non linear relationships between the power and the parameters affecting them. Reference [7] shows the capability of Artificial Neural Networks [ANN's] to emulate known load models is examined. However, the individual relations between the input variables and the output variables are not developed by engineering judgment so that the model tends to be a black box or input/output table without analytical basis. This paper considers the combination of neural nets and fuzzy logic for load modeling.

In this paper, the conventional load flow algorithm has been upgraded and modified to incorporate the nonlinear characteristics of an aggregated induction motor load. The modified load flow incorporates a neuro-fuzzy induction motor model that estimates the scheduled active and reactive power adjustable during each iteration process. The impact of the aggregated induction motor on the convergence characteristics of load flow are investigated using the IEEE-30bus standard test system.

II. METHODOLOGY

A. *INDUCTION MOTOR AGGREGATION*

In large industrial plants a significant portion of power system load is comprised of many induction motors. For large utility power systems the analysis of transient stability must also be performed taking into account realistic representation of induction motor loads, particularly if the problem to be investigated *is* very susceptible to such kind of load [8]. In this case, simulation studies become computationally feasible only if groups of individual motors can be aggregated in a single equivalent model. In this paper the transformer-type equivalent circuit is used to represent an induction motor. The equations used to obtain the aggregate motor can be found in [3].

B. *NEURO-FUZZY INDUCTION MOTOR MODEL*

Figure 1 shows the equivalent circuit of the aggregated induction motor load.

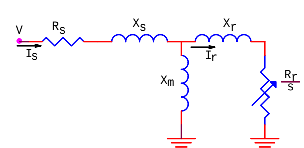

Figure 1. Per Phase equivalent circuit (squirrel-cage)

where the parameters $\boldsymbol{R_s}$ (stator resistance), $\boldsymbol{X_s}$ (stator reactance), $\boldsymbol{X_m}$ (magnetizing reactance), $\boldsymbol{R_r}$ (rotor resistance), and $\boldsymbol{X_r}$ (rotor reactance) are known. The rotor slip is indicated by **s.** Fig.2 shows the slip curves derived at different load bus voltages for the aggregated Induction Motor.

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The power developed is assumed to be equal to the mechanical power. Based on the aggregated Induction Motor Model, the active power and reactive power consumed at the operating slip were trained using the Artificial Neuro-Fuzzy Inference System.

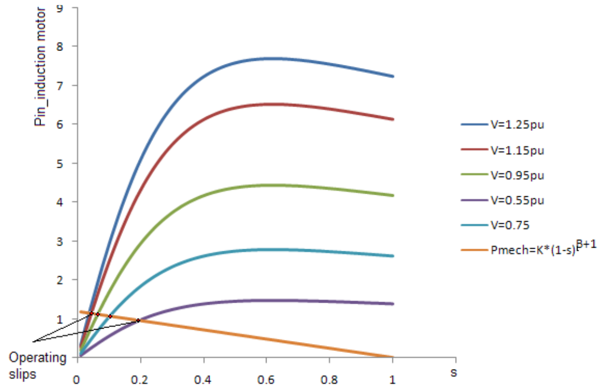

Figure 2. Electrical and Mechnical Power Slip Curves

The voltage was the input of the fuzzy inference system while the active and reactive powers were the output.

The power balance at the operating slip is give by

$$P_e - P_{mech} = 0 \tag{1}$$

where,

$$P_e = I_r^2 R_r \frac{1-s}{s} \tag{2}$$

$$P_{mech} = K(1-s)^{\beta+1} \tag{3}$$

K, β are real constants that define the type of load.
I_r^2 denotes the magnitude of the rotor current, which is also a function of slip and can be calculated from the equivalent-circuit in Figure 1. The operating slip at each voltage was estimated in this paper using a combination of bisection method and the Newton Raphson method. The ANFIS was then used to optimize the rules.

C. MODIFIED NEWTON-RAPHSON LOAD FLOW ALGORITHM WITH NEURO-FUZZY IM MODEL

This paper used the neuro-fuzzy induction model to estimate the active and reactive power demand for each adjustment in the voltage through out the iterative process. The investigations were carried out using an IEEE standard system. The procedure for the Newton-Raphson load flow analysis with the neuro-fuzzy induction motor can be summarized as follows:

1. For load buses where P_i scheduled and Q_i scheduled are specified, use a flat where $|V_i| = 0$ and $\delta_I = 0$
   For load buses with induction motors,
   $$P_i = fuz\_p(V_i) \tag{4}$$
   $$Q_i = fuz\_q(V_i) \tag{5}$$
   where fuz_p and fuz_q are Sugeno-type fuzzy scalar mapping.

   For a PV bus where V_i and P_i an initial estimate $\delta_I = 0$ is given.
2. For the load buses, the injected powers P_i^k and Q_i^k are calculated at k^{th} iteration. Since P_i and Q_i are given then the power mismatches are determined.
3. For voltage regulated buses, P_i^k and ΔP_i^k is determined.
4. The elements of the Jacobean matrix are calculated.
5. The linear simultaneous equations obtained are solved directly using triangular factorization and Gauss elimination.
6. The new voltage magnitude and phase angles are computed.
7. The process is continued until the power mismatches are less than a specified accuracy. For the load buses with induction motors the active and reactive scheduled powers are updated using equations (4) and (5) respectively.

III. TEST RESULTS

A. THE AGGREGATED INDUCTION MOTOR LOAD

The scheduled active power (*Pm*) at bus 26 was 3.497MW. It was calculated from the individual sum of 165 numbers of the 25HP-motor input powers at the rated voltage. Based on [2, 3] the aggregate motor model and parameters where obtained as shown in Table 1(last row).

Table 1. Induction Motor Parameters based on individual HP

HP	Rs	Rr	Xs	Xr	Xm	rpm
25	0.022	0.047	0.05	0	1.95	1695
100	0.011	0.047	0.053	0.1	2.51	1705
4125	0.021	0.047	0.05	0.05	1.95	1695

B. NEURO-FUZZY INDUCTION MOTOR MODEL

The obtained aggregate motor was then modeled using Artificial Neuro Fuzzy inference system (ANFIS). The resulting surface for mapping the reactive power is shown in figure 3. Seven rules where optimized.

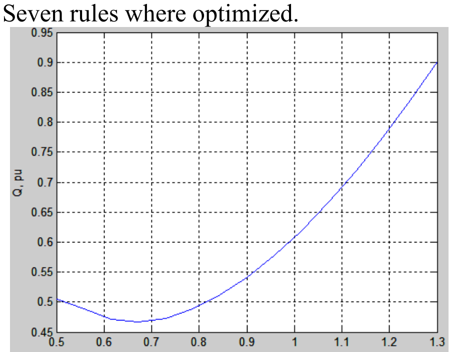

Figure 3 Surface view for Reactive Power Mapping

C. LOAD FLOW TEST

In this section, the IEEE-30bus standard network was used in order to show, quantitatively, how the modified load flow with the induction motor load performed. In this study, the network was modified to include 25 horsepower (HP) induction motors at bus 26. The motor's data are given in Table 1. After the load flow study successfully converged to the mismatch tolerance of 1.0E-10, the final iterative solutions are summarized in

Table 2. The motor terminal voltage (1.002pu) and reactive power (1.877MVAR) at bus 26. Using 100HP motors in place of the 25HP led to a reduction in reactive power. This observation is true in light of the fact that larger motors operate at lower slips and hence consume less reactive power.

Table 2. Converged Load Flow Solution Results for Load buses

Bus No	Vmag pu	Angle Deg	Load MW	Load MVAR	Generation MW	Generation MVAR
1	1.06	0.00	0	0	261	2.623
2	1.033	-5.36	21.7	12.7	40	22.66
3	1.019	-8.03	2.4	1.2	0	0
4	1.009	-9.70	7.6	1.6	0	0
5	1	14.38	94.2	19	0	32.73
6	1.009	11.47	0	0	0	0
7	0.998	13.20	22.8	10.9	0	0
8	1.01	12.23	30	30	0	39.05
9	1.049	14.51	0	0	0	0
10	1.043	16.10	5.8	2	0	0
11	1.082	14.51	0	0	0	16.94
12	1.056	15.38	11.2	7.5	0	0
13	1.071	15.38	0	0	0	11.5
14	1.041	16.27	6.2	1.6	0	0
15	1.036	16.36	8.2	2.5	0	0
16	1.043	15.96	3.5	1.8	0	0
17	1.038	16.27	9	5.8	0	0
18	1.026	16.96	3.2	0.9	0	0
19	1.024	17.13	9.5	3.4	0	0
20	1.028	16.93	2.2	0.7	0	0
21	1.03	16.55	17.5	11.2	0	0
22	1.031	16.54	0	0	0	0
23	1.026	16.75	3.2	1.6	0	0
24	1.02	16.92	8.7	6.7	0	0
25	1.018	16.53	0	0	0	0
26	**1.002**	**17.00**	**3.479**	**1.877**	**0**	**0**
27	1.024	16.00	0	0	0	0
28	1.009	12.14	0	0	0	0
29	1.005	17.23	2.4	0.9	0	0
30	0.993	18.11	10.6	1.9	0	0

D. CONVERGENCE TEST

In this section, the load flow convergence characteristics are investigated using the IEEE- 30bus system. The behavior of the maximum absolute mismatches of active and reactive powers of the test system is shown in Figure 4 as a function of iteration numbers.

This power mismatch was the key factor that greatly influenced the number of iterations. The solutions of the modified power flow slowly converged in 5 iterations, starting from a flat voltage profile, after the reactive power mismatch was below the specified tolerance (1.0E-10).

The convergence characteristics of both conventional (normal) and modified load flows were also compared.

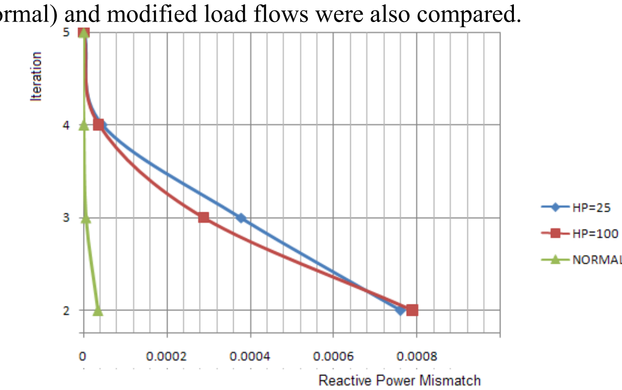

Figure 4 Reactive Power Mismatch at bus 26 of the Modified Load Flow with 25HP and 100HP induction motors

E. CONCLUSION

In this paper, the conventional load flow algorithm has been upgraded to incorporate the non-linear neuro-fuzzy model of induction motor load. The algorithm efficiency has been illustrated through the numerical example using the IEEE-30bus standard system. The modified load flow calculation gives the exact amount of the reactive power required by the induction motor loads.

The artificial admittance added into the motor load bus is not necessary for adjusting the difference between the actual and scheduled reactive powers, when the voltage and transient stabilities are analyzed. However, modified load flow algorithm looses the quadratic convergence characteristic of the conventional load flow program.

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