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ELECTRICITY LOAD FORECASTING USING PARTICLE SWAMP OPTIMISATION TECHNIQUES FOR OPTIMIZATION OF OSOGBO 33BUS SYSTEM IN NIGERIA

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Abstract

Load forecasting for any given day is a difficult task, because it depends not only on the load of the previous days, but it is difficult to model the relationship between the load and the mentioned external factors influencing the load demand, such as weather variations, holiday activities, etc. These are the major factors making the modeling process more complicated. Because the model parameters are decided according to the historical data, some errors may be introduced. An improved method for the short-term load forecasting is presented to improve the forecasting accuracy of daily loads, especially in the scenario where the daily load is affected by weather and date factors seriously. This paper presents a new method for the short-term load forecasting of electric power systems using particle swarm optimization (PSO) techniques. The training samples used in this method are of the same data type as the learning samples in the forecasting process and selected by a fuzzy clustering technique according to the degree of similarity of the input samples considering the periodic characteristics of the load. PSO is applied to optimize the model parameters cost of the electricity load demand

Keywords: PSO, Load Demand. Electricity Forecast, Historical Data

1.0 Introduction

Electricity forecasting is an important component for power system energy management system. Precise electricity forecasting helps the electric utility to make unit commitment decisions, reduce spinning reserve capacity and schedule device maintenance plan properly. Besides playing a key role in reducing the generation cost, it is also essential to the reliability of power systems. The system operators use the electricity forecasting result as a basis of off-line network analysis to determine if the system might be vulnerable. If so, corrective actions should be prepared, such as electricity shedding, power purchases and bringing peaking units on line (Amjady, 2011).

1.1 PROBLEM STATEMENT

1. Inadequate accurate models for electric power load forecasting
2. Low load switching, and infrastructure development
3. Lower electric energy generation, transmission, distribution
4. Automating data access from regional wholesale electricity markets
5. Customizing models using nonlinear regression, nonparametric, and neural network techniques
6. Calibrating models with historical predictors such as weather, seasonality, load, fuel price, and power price

7. Deploying and integrating load forecasting algorithms into enterprise systems

1.2 AIM

To establishing the most suitable component models for the analysis of the power flow for the radial distribution network to be developed on Matlab program

1.3 OBJECTIVES

i. To study and understand the concept of Short Term Electricity Forecasting (STLF) using particle swamp optimization and Data collection
ii. To solve Power flow analysis for radial distribution system based on stage two using Forward/Backward sweep method for analysis of load flow
iii. Development of an algorithm based on multi-objective optimization technique to determine the electricity forecasting base on Particle Swarm Optimization (PSO)
iv. Using PSO algorithm to optimize the existing historical data and minimization of load demand cost by using MATLAB

2.0 Review of Related Works

Charytoniuk(2012) proposed a semi-parametric additive regression methodology that was used to forecast the half hourly electricity one day ahead for the states of Victoria and South Australia in Australia. A separate model is built for each half hour. It uses previous lagged electricity calendar and temperature variables. The forecasting model showed excellent performance on both historical data and when applied in real time on site.

Rule-based forecasting makes use of rules, which are often heuristic in nature, to do accurate forecasting. Expert systems incorporate rules and procedures used by human experts in the field of interest into software that is then able to automatically make forecasts without human assistance.

Cho et al (2010) proposed a knowledge-based expert system for the short-term electricity forecasting of the Taiwan power system. Operators' knowledge and the hourly observation of system electricity over the past five years are employed to establish eleven day-types. Weather parameters were also considered.

Desouky (2013) developed a site-independent technique for short-term electricity forecasting. Knowledge about the electricity and the factors affecting it is extracted and represented in a parameterized rule base. This rule-based system is complemented by a parameter database that varies from site to site. The technique is tested in different sites in the United States with low forecasting errors. The electricity model, the rules and the parameters presented in the paper have been designed using no specific knowledge about any particular site. Results improve if operators at a particular site are consulted.

3.0 Methodology

The research methodologies that will be adopted in this research work are presented in stages as follows:

Stage One: Data collection

Stage Two: Establishing the most suitable component models for the analysis of the power flow for the radial distribution network to be developed on Matlab program

Stage Three: Power flow analysis for radial distribution system based on stage two using Forward/Backward sweep method for analysis of load flow

Stage Four: Development of an algorithm based on multi-objective optimization technique to determine the electricity forecasting base on Particle Swarm Optimization (PSO)

Stage Five: A comparison of the optimized distribution system with the original distribution system

Stage Six: Result validation

3.1: Data collection

The qualitative approach which aims at answering questions from the case companies will be employed. The companies involve are Ibadan Electricity Distribution Company (IBEDC), and National Control Centre (Osogbo). Other sources of data for the research work will include: PHCN publications and internet researches on distribution networks. Moreover, some official of the Distribution Companies will be interviewed about distribution system network.

3.2 Establishing the most suitable component models for the analysis of the power flow for the radial distribution network to be developed on Matlab program

The model for loads, capacitors, Distributed Generators, distribution lines and switches provide relationships between the relevant voltages, currents, and power flows in distribution system.

i Load model: All loads are to draw complex power S = P + jQ. The three phase load may not be balanced, considering node i, $S_i^a, S_i^b and\ S_i^c$ which are the complex power in phase a, b and c can be of different values and even zeros. It can be expressed as (Ranjan et al, 2004):

$$S_i^a = P_i^a + jQ_i^a$$
$$S_i^b = P_i^b + jQ_i^a$$
$$S_i^c = P_i^c + jQ_i^c$$

(3.1)

iii DG model: The DG is simply modeled as constant active (P) and reactive (Q) power generating source. The specified values of this DG are real (P_{DG}) and reactive (Q_{DG}) power output of the DG. The model is shown in figure 5.1.

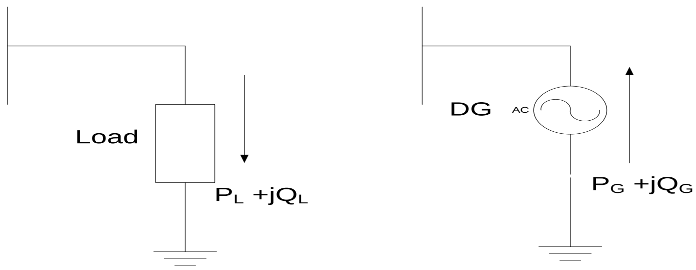

Figure 3.1: The model of load and DG (Fan et al, 2014**)**

The load current injection or equivalent current injection (ECI) $I_{Li}$is computed as a function of the bus voltage Vi.

$$I_{Li} = (P_i - Q_i)/V_i^*, \qquad i = 1,2\ldots n \qquad (3.2.)$$

With DGs modeled as negative loads, the equivalent loads at bus i can be expressed as:

$$P_i = P_{Li} - P_{Gi}$$
$$Q_i = Q_{Li} - Q_{Gi} \qquad (3.3)$$

P_{Li} and Q_{Li} are the constant power loads connected at bus i, P_{Gi} and Q_{Gi} are the real and reactive powers injected by the DG connected at bus i respectively.

iv Reactive Power Balance

The voltage profile of power system operation is determined by reactive power balance.

$$\sum_{i=1}^{NG} QGi + \sum_{i=1}^{NC} QC_i = \sum_{k=1}^{ND} QD_k + Q_L \qquad (3.4)$$

Where:

QGi : The reaction power generation of generator i

QCi : The reactive power generator of the VAR compensation device i such as capacitor

QD_k : The reactive power load at load bus k.

Q L = System reactive power loss.

v Load balancing equation

In order to reach the balance loading condition, the neutral current is given as:

$$I_n = I_{tot}^a + I_{tot}^b + I_{tot}^c \qquad (3.5)$$

The minimization of the neutral current, the better balanced loading condition.

3.3 Power flow analysis for radial distribution system based on stage two using

Forward/Backward sweep method for analysis of load flow

Adaptation of Forward/Backward sweep algorithm for radial electric networks with Distributed Generation and capacitor is considered as constant power (P_i $Q_i$nodes) to which the specified quantities are the constant power and the unknown quantities are the component of voltage. The current through branch i is equal to the sum of the load currents of all the nodes beyond branch i plus the sum of the charging currents of all the nodes beyond branch i plus the sum of all injected capacitor currents of all the nodes and the sum of distributed generator currents at all nodes expressed by (Hwan et al, 2011):

$$I_i = \sum_{j=1}^{n} I_{Lij} + \sum_{j=1}^{n} I_{Cij} - \sum_{j=1}^{n} I_{CCij} - \sum_{j=1}^{n} I_{Gij} \qquad (3.6)$$

The real and reactive power loss of Ith node is given by

$$P_{Li} = real\{V_{Si} - V_{rj}\} \cdot I_i \qquad (3.7)$$

$$Q_{Li} = imag\{V_{Si} - V_{rj}\} \cdot I_i \qquad (3.8)$$

The algorithm for load flow is as follows:

i Read the line data and bus data

ii Initialize the voltage of the slack node to 1.0 p.u and phase angle Zero

iii Perform the backward sweep to obtain the current in each branch from the last node to the starting node

iv Perform the forward sweep to calculate the voltage and the phase angles at each node, starting from the source node to the last node

v Check the convergence criteria. If satisfied, go to (vii) else repeat step (iii) to (v)

vi If yes, print power flow result

vii Compute the power losses

viii Compute the voltage stability index for each of the buses considering each phases of the network

ix Stop

3.4 Forward/Backward Power Flow and Modeling

The backward-forward sweep method has been widely used to solve power flow problems in distribution networks because it converges very fast and consumes less computational memory. The common algorithm of the power flow consists of two basic steps of the backward-forward sweep, which iterates in a loop so that the convergence of the power flow is gained.

The first step in performing the power flow is numbering the branches or the distribution lines. In order to do this, first the network needs to be layered. For layering the network, the proposed strategy starts from the main node and moves forward to the ending nodes. The lines between this node and the next nodes constitute the first layer. The second layer consists of the lines between these layers and the next layers located after them. After the network layering, it starts from main node and the branches are numbered from I to N_b. The number allocated to the branches of the lower is bigger than the number of the upper layer branches (in radial networks, N_b=N-1, where N is the number of nodes and N_b is the number of branches)

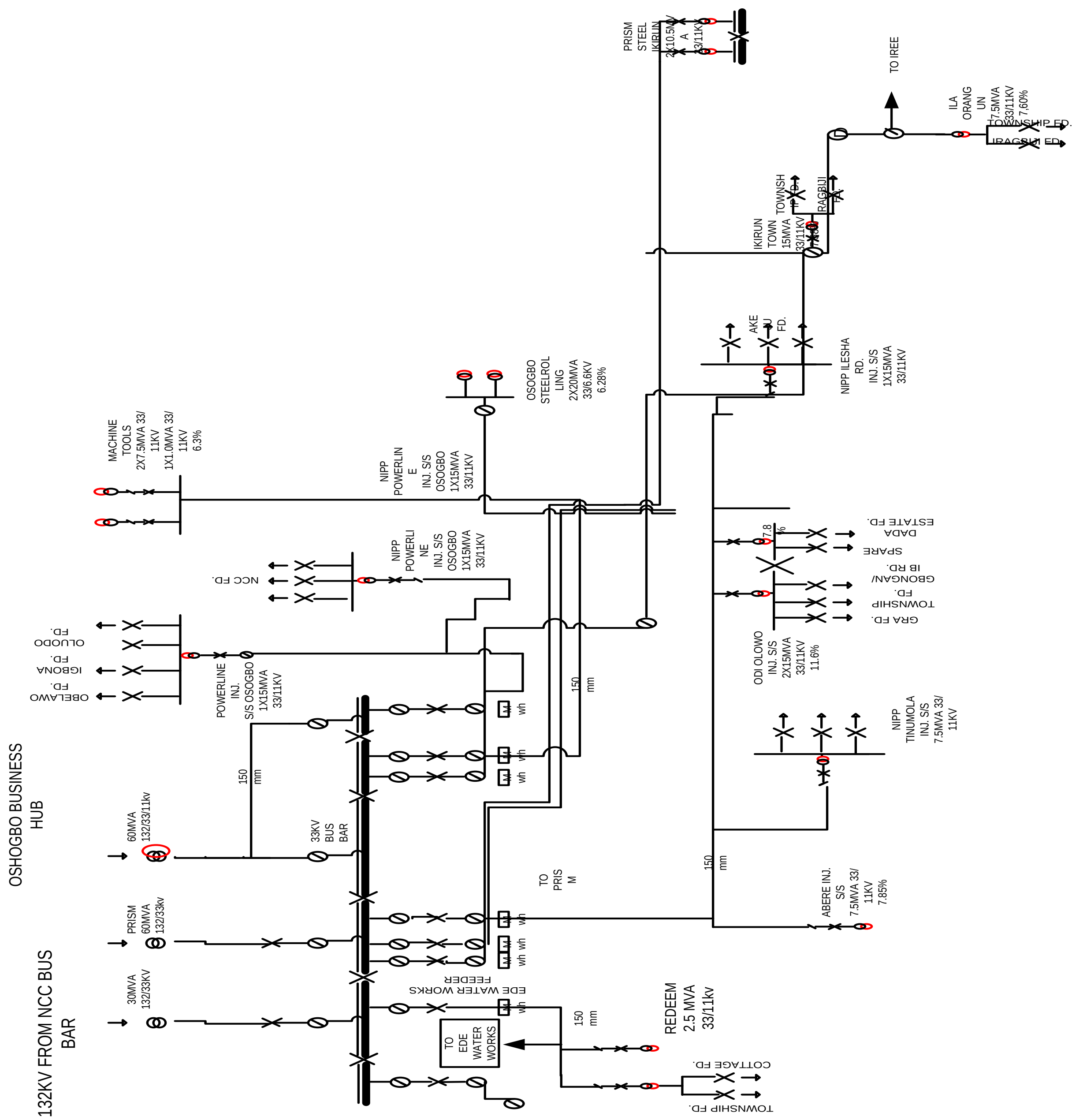

Fig 3.2: Developed Model for osogbo 33 bus system

3.4 Development of an algorithm based on multi-objective optimization technique to determine the electricity forecasting in the system using PSO

Swarm behavior can be modeled with a few simple rules. Schools of fishes and swarms of bird can be modeled with such simple models. Namely, even if the behavior rules of each individual (agent) are simple, the behavior of the swarm can be complicated. The position of eachagent is represented by its x, y axis position and also its velocity is expressed by vx(the velocity of x axis) and vy (the velocity of y axis). Modification of the agent positionis realized by the position and velocity information.Bird flocking optimizes a certain objective function. Each agent knows its bestvalue so far (pbest) and its x, y position. This information is an analogy of thepersonal experiences of each agent. Moreover, each agent knows the best value sofar in the group (gbest) among pbests. Velocity of each agent can be modified by the following equation:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \times \left(pbest_i - s_i^k\right) + c_2 rand_2 \times \left(gbest - s_i^k\right) \quad (3.90)$$

where v_i^k is velocity of agent i at iteration k, w is weighting function, c_j is weightingcoefficients, rand is random number between 0 and 1, s_i^k is current position of agent i at iteration k, $pbest_i$ is pbest of agent i, and gbest is gbest of the group (Kwang and Mohamed, 2008).

The steps to be followed are itemized:

Step 1: Input line and bus data, and bus voltage limits,

Step 2: Calculate the loss using distributed load flow based on backward /forward sweep

Step 3: Randomly generate an initial population (array) of particle with random position and velocities on dimension in the solution space. Set the iterative counter k = 0

Step 4: For each particle, if the bus voltage is within the limits, calculate the loss, otherwise that particle is infeasible

Step 5: For each particle, compare its objective value with the individual best. If the objective value is lower than Pbest, set the value as current Pbest, and then record the corresponding particle position.

Step 6: Choose the particle associated with the minimum individual best, Pbest of all particles, and set the value of this Pbest as the current best Gbest

Step 7: Update the location and position of the generation

Step 8: If the iteration number reaches the maximum limit, go to step 9, otherwise set iteration index k = k+1 and go back to step (4)

Step 9: Print out the optimum solution to the target problem. The best position includes the optimal location and size of DG, and the corresponding fitness value representing the minimum total real power loss.

4.0 Results and Discussion

Table 1: Load forecasting using PSO Method

Time(hour)	Actual Load(MW)	Forecasted Load(MW)	Forecasting Error(%)
0	2096	2084.384	-0.552
1	1983.9	1936.638	-2.372
2	1821.6	1798.668	-1.249
3	1773.4	1673.171	-2.21
4	1710.7	1699.914	-2.094
5	1698.6	1728.872	0.076
6	1773.4	1914.571	-2.711
7	1936.5	2048.185	-1.112
8	2055.6	2589.259	-0.364
9	2637.7	2604.762	-1.737
10	2591.2	2633.87	0.513
11	2650.5	2634.436	-0.617
12	2651.6	2457.95	-0.627
13	2498.6	2521.008	-1.527
14	2608.4	2540.626	-3.25
15	2570.5	2542.728	-1.062
16	2573.2	2597.982	-1.181
17	2642.1	2675.977	-1.66
18	2751.2	2743.891	-2.704
19	2817.2	2910.345	-2.502
20	2864.8	2926.385	1.6
21	2872.3	2675.575	1.883
22	2665.3	2411.68	0.386
23	2396.1	2084.384	0.65

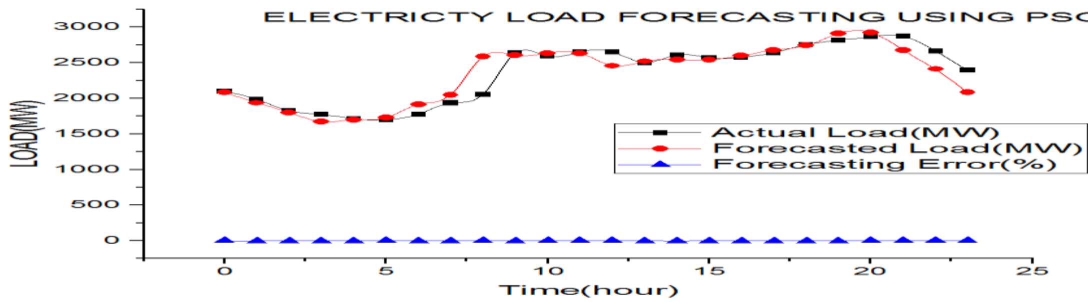

Fig 1: Short Term Load Forecasting using PSO

From figure 1 above, there is an improvement in the actual load due to the developed optimized PSO algorithm apply on the model of osogbo 33 bus system and the historical data. The graph illustrate the daily demand for load. There is highest load demand at the peak hour of the day. Hence the forecasting accuracy of daily load has been increased while the forecasting error is negligible. Advances in different fields such as artificial intelligence (expert systems) have brought different techniques for electricity forecasting. This method is one of the numerous methods which can be used for both long and medium term electricity forecasting. A raw data regarding electricity demand covering a period of six years will be used for this study. In this work, peak electricity for four (4) regions in Nigeria will be used spreading from year 2010 through the year 2014. Two of the region (Shiroro and Kaduna) is from the northern zone of the country while the remaining two (Port Harcourt and Osogbo) from the southern part. Data for each region will be tabulated and a Matlab script will be drafted to compute the power demand in years to come (from 2016 to 2026). Matlab made the realization of power forecasting very simplified in the sense that it gives researcher the freedom to determine the growth of power demand over a range of years using the peak power demand.

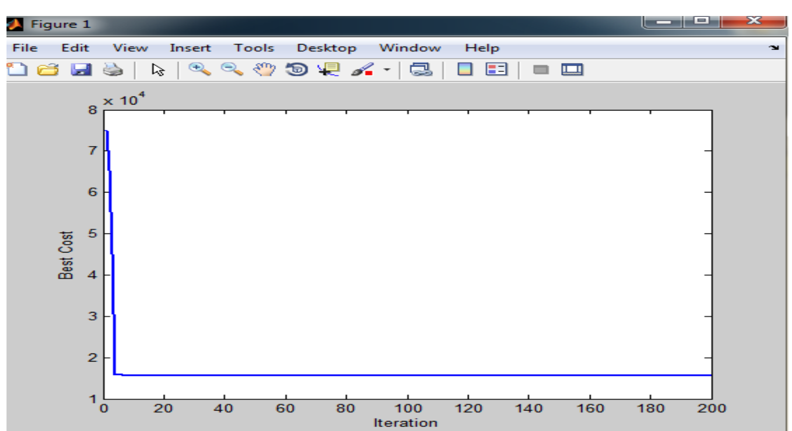

Fig 2: Electricity Load Demand cost using PSO

Fig 4.2 shows the electricity load demand cost for osogbo distribution system. The graph illustrate that at all iteration of the developed algorithm, the cost remain stable which denote the efficiency of the algorithm on load demand curve. It denote that no matter the load demand, the cost will remain stable

4.2 FLOWCHART

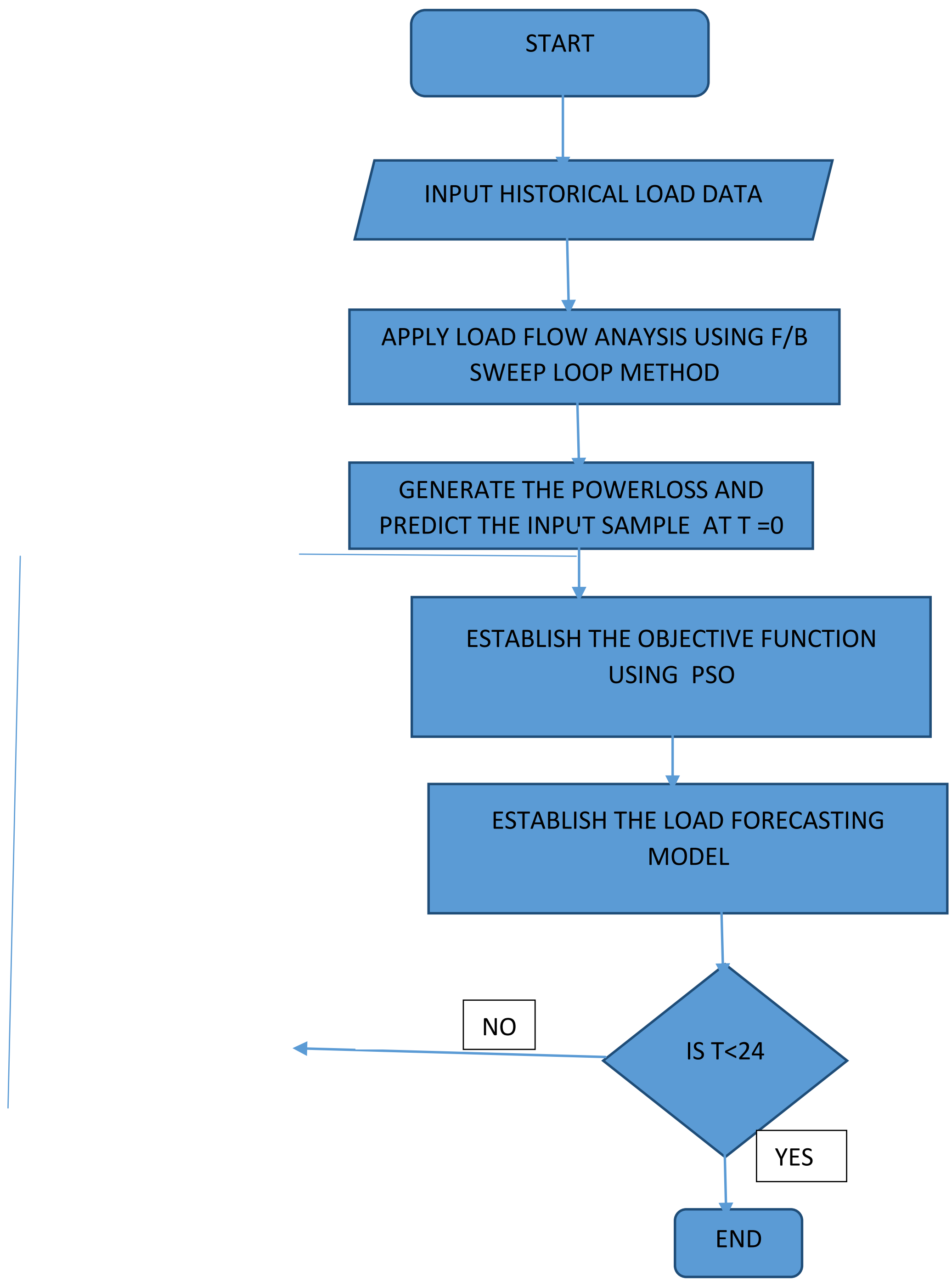

FIG 3: Flowchart of the Electricity Load Forecasting using PSO

5.0 CONCLUSION

Electricity forecasting is very essential to the operation of electricity companies. Itenhances the energy-efficient and reliable operation of a power system. This is a casestudy of short-term electricity forecasting using particle swamp optimization (PSO). This electricity forecasting program gives electricity forecasts half an hour in advance. Historical electricity data obtained from the electricity generation company was use. The main stagesare the pre-processing of the data sets, PSO algorithm, and forecasting. The inputs used for the PSO are one set of historical electricity demand data. Electricity forecasts can be divided into three categories: short-term forecasts which are usuallyfrom one hour to one week, medium forecasts which are usually from a week to a year,and long-term forecasts which are longer than a year. Hence the developed system have greater accuracy in prediction of electricity load demand and also reduce forecasting errors.

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