STATE ESTIMATION AND POWER LOSS MINIMIZATION OF PESCO GRID USING NEWTON-RAPHSON AND PARTICLE SWARM OPTIMIZATION

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https://doi.org/10.26782/jmcms.2019.02.00011

Abstract

This study is targeted for reducing the power losses for a branch of Peshawar Electric Supply Company (PESCO), a small electric power grid in Pakistan, starting from Shahibagh and ending at Hayatabad substation. This study evaluates the current configuration of the transmission network, and then by using Particle Swarm Optimization, the best possible configuration that will ensure maximum throughput and minimum transmission and distribution losses is determined. The study is verified using Newton Raphson Method. Newton Raphson method is used to find the state of the mentioned network and then after the new configuration is proposed, the state estimation is done again to evaluate various parameters of the network and confirm its feasibility. The reconfiguration resulted from the PSO and NR methods have shown electric power losses minimization of the selected grid with 15.021%, amounting to a total of 0.3MW power loss minimization.

Keywords— Power systems, Power system measurements, Power grids, Power system planning, Power transmission

I. Introduction

The Optimal Power Flow Analysis - OPFA contains a group of engineering problems applied to practical life uses in Electrical Power Distribution that contains dispatch as well as transmission line analysis. The goal of OPFA is to make sure that the electric power reaches the consumers at a lowest possible cost. This suggests that there are very little losses in the dispatch and transmission network. In any typical OPFA problem, the goal is to minimize those losses and make sure that the cost of the electricity at consumer side stays as close to the cost of the electricity at production as possible. In a mathematical perspective, such problems are called as Non-Polynomial Hard problems. NP-Hard problems are approached for solutions by researchers using evolutionary algorithms. Of the many algorithms available recently, Particle Swarm Optimization (PSO) is one of the best candidate algorithm for solving NP-Hard
mathematical problems related to Electrical Load Dispatch due to its ease of use and efficient approach. The role of PSO is to determine the best possible set of parameters for a given objective function, that optimizes (either minimize or maximize) the function.

PSO can be used for the optimization of the various parameters inside an OPFA problem, however determining whether the resultant parameters are practically applicable in an electric power grid cannot be determined by it. For this purpose, Newton Raphson method (NR) is used. NR method determines the bus admittance matrix of the network and solves the power flow. Therefore, an automated exchange of information about parameters resulting from PSO to the NR algorithm can determine whether a given set of parameters is practically applicable in a network. The goal of Power Flow Analysis is to satisfy an objective function for a power system such that all the equality and inequality constraints are satisfied [I]. Thus, in this research the objective is to propose a better configuration of PESCO sub-network power grid in which the power losses are decreased than the already existing configuration.

II. Literature Review

OPFA problems fall into the category of NP-hard problems. Optimization is a term used for such problems’ solution approaches, in which the goal is to either decrease or increase a set of variable values, in order to achieve an overall increase in the efficiency of the system under study. As the numbers of inputs to the problem domain are increased, the complexity of the solution of the problem also increases due to the exponentially increasing variable matrix size. There have been many algorithms developed to address the issue of such optimization tasks such as Genetic Algorithm, Ant-Colony Algorithm, and Particle Swarm Optimization algorithm, and Bat and Bee Algorithm in the recent years. Some of these algorithms have been applied to solve and optimize the problems in optimal power flow set. Optimal Power Flow is a set of problems pertaining to the efficiency improvement in the generation and transmission of electrical power.

There are various algorithms for solving NP-hard problems as mentioned in the literature [II] and [III]. Using various algorithms like Particle Swarm Optimization, Ant-Colony Algorithm and Bee Algorithm, researchers have previously found out best possible solutions of the power flow problems like optimal power flow and loss minimization. However, in the recent years, modified algorithms of the original algorithm have been developed that can search the “solution space” more efficiently and find better solutions than the previous researches.

III. Particle Swarm Optimizer

For instance in research [III], author Cui-Ru et al. have developed a modified particle swarm algorithm in order to meet the optimal power flow problem in a more indirect yet efficient way. The algorithm had different solving parameters that enabled the search process to be more robust and find slightly better values. Similarly a more recent research by L. Weibing in 2009 [IV] modified the algorithm used by Cui-Ru and developed a better algorithm that resulted in the solution to be more efficient than the previous solutions. In the recent years, researchers have been
studying that the Lagrangian Relaxation method can be applied to a simplified network model for scheduling and optimal power flow problems using Lagrangian multipliers. However, the only drawback in the Lagrangian multipliers is the difficulty in the designing of the full network and its constituents in the coding environment. The problem encountered in the OPF problems is the difficulty in their convergence to the global minimizer or maximizer.

In the default PSO model, the convergence could not be guaranteed, but in later versions, the convergence problem was removed. The problem of convergence is called as the stagnation problem. In the recent years, hybrid algorithms have emerged in the research market. These algorithms are a combination of particle swarm’s intelligent techniques and another algorithm’s speed. MPSO, MOGA, BIOGA, Hybrid-PSO are a few examples of the lot [V]. This hybridization has improved the speed and agility of the algorithm beyond expectations. These hybrid algorithms are becoming researchers’ focus for PFA and have been applied successfully in a few variations to the economic load dispatch problem [V]. It has been used as a replacement of Genetic Algorithm in various problems and the results [VI] have shown to be better than GA [V]. In [IV] a technique for improvement of the Voltage Var Control (VVC) on different power compensators had been presented. The PSO algorithm was used for reactive power improvement as well as security enhancements. In another research by [VII] Zhao et al., a variation of the PSO called as the Perturb method PSO was tested for viability for future applications in power system improvement. Some tests were done on the IEEE-30 Bus Bar System and a higher quality solution was deducted. For a non-linear input-output relations, Lai et al. [VIII] proposed a variation of the PSO and applied it successfully on IEEE-30 Bus Bar System.

A comparative study was made by Vlachogian in 2006, [IX] for variations of PSO, Local Passive Congregation (LPAC), and General Passive Congregation (GPAC) based on interior point method. The comparative study was done for reactive power dispatch as well as voltage and power stabilization on IEEE 30 Bus Bar System with six generating units, and on IEEE 118 bus System. The results were high quality than the older PSO models. Yang et al. [X] proposed a newer technique in 2006 for a modified PSO addressing the stagnation problem and false reporting for a local minimum. The technique used neighborhood selection strategy and interpret-OPF methods. In his strategy, the fitness function and the constraints were considered separately which made convergence faster than previous approaches. The summary of the technique is that in the swarm, the particles adjusted their speed and direction according to a superior particle in the swarm, thereby avoiding false directions and local minimum stagnation. The technique was tested on IEEE 30 Bus System. In the next year 2007, Pablo et al. [X] presented a novel method for solving OPF with security constraints. In this technique, reconstruction operators sped up the process of convergence. In the year 2009, Gonggui Chen et al. [X] presented a hybrid of PSO and random search algorithms and obtained improved results on IEEE 30 Bus Bar test system. In the same year, Weibing et al. [X] proposed a multi-start approach for the PSO algorithm whereby different swarms were started at different locations to speed up the searching of the problem space. (Tested on IEEE 30 Bus Bar Systems). In the same year, Wannakaran et al. [VIII] distributed Sobal PSO. For convergence and
improvement in the results, Sobal sequence, velocity equation, and swarm size are all initialized uniquely and the results obtained were quite better. This algorithm was tested on IEEE 30 Bus Bar as well as IEEE 6 Bus Bar System. The result of the algorithm is best from all.

In the later years, Fuzzy and Artificial Neural Network techniques made their way into the PSO algorithm. Hence, we saw researched made by different authors trying to merge two techniques. In 2012, Niknam et al. proposed Fuzzy based PSO. In this technique, the searching method was changed into Fuzzy Search and tested. In 2016 [18] we saw last attempt at PSO applied by Rudra et al. on IEEE 30 bus bar, with leader behavior changed in the swarm by an equation. This research aided FACTS devices placement on IEEE 57 Bus bar Test System. In the year 2010 Wannakarn et al. [I] proposed a novel algorithm for the reactive power dispatch problem considering the security enhancements of FACTS devices. His algorithm contained Sobal Method and unique velocity equations, which made the research unique. This algorithm was tested on the IEEE 30 Bus Bar System as well as the six Bus bar System. In [II], the authors have applied the PSO to optimization of the electric vehicles’ energy consumption under unpredictable driving conditions. The authors designed the algorithm for the optimization of the power management techniques and introduced a number of variables for the purpose. In [II], researchers have used another approach for the optimization of the electric grid. The authors used optimal placement of Distributed Generation units for the maximization of the system loadability and minimization and system power losses. In [III], authors have created an extension of the PSO method for the optimization of the power systems in radial distribution systems. The authors have integrated distributed generation system into the radial grid. In [I], the authors have used a neuro-fuzzy and PSO hybrid algorithm for the forecast of wind-power generation system.

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V. Newton Raphson

The Newton Raphson method is a search technique for solving the Jacobians of a matrix. According to the book “Power System Analysis”, written by Stevenson [III], Newton Raphson method is a Taylor Series expansion of a function of two or more variables. Taylor series is expanded mathematically and a square matrix of the partial derivatives of the terms of the original function is obtained. The original function is the objective function that represents the goal for the optimization algorithm, e.g. cost minimization or losses minimization etc. This matrix is called as a Jacobian matrix or J Matrix. This matrix contains the initial solution values of all the parameters of the electrical distribution system as approximate values. These values are just estimates of the original variables. These estimates are called as deltas. These
deltas are put back into the equation again and re-estimated. These estimations are carried out repeatedly until the deltas fall within a threshold provided by the coding.

The Jacobian matrix size depends upon the order of the non-linear equations to be solved. For a second order non-linear equation, the J matrix is 2-by-2. For an nth order equation, the J matrix is n-by-n. The higher the order of the non-linear equation, the higher are the terms and variables involved in the solution and the longer it takes to converge to a solution.

VI. Methodology

Newton Raphson method for Optimal Power Flow can be expressed as:

\[ \psi = \sum_{i=1}^{K} F_i p_i + \lambda (p_{\text{load}} - \sum_{i=1}^{K} p_i) \] (1)

\( \psi \) represents a Jacobian matrix whose second order derivatives create a matrix termed as the Hessian Matrix.

The OPF Problem can be simplified and shown to be formulated in (2):

\[
\begin{align*}
\text{Min } J(x, u), \quad \forall g(x, u) = 0 \\
(2)
\end{align*}
\]

\( g \) is a function that represents the equality constraints or load flow equation parameters while \( h \) represents a function that shows the operating constraints on each of the system variables. System variables are represented by the vector \( x \), which is a set of dependent variables for the system. \( x \) depends on \( u \), which is a set of independent variables of the system under study. For \( N \) number of generators in the network, and \( M \) number of transmission lines, \( T \) number of tap settings, \( G \) number of reactive power outputs in the generators, \( C \) number of compensating devices in the network and \( S \) number of loadings on bus bars, \( x \) and \( u \) can be represented as (3) and (4) respectively:

\[ x(t) = \{ P_{G1}, ..., P_{GN}, V_{L1}, ..., V_{LM}, Q_{G1}, ..., Q_{GG}, S_{L1}, ..., S_{LS} \} \] (3)

Here \( P_{GN} \) is generated power by the \( N \)th generator, \( V_{LM} \) is line voltage for \( M \)th line, \( Q_{GG} \) is the \( G \)th reactive power of the \( N \)th generator, and \( S_{LS} \) is the \( S \)th loading on the \( M \)th line of the network.

\[ u(t) = \{ V_{G1}, ..., V_{GM}, P_{G2}, ..., P_{GN}, T_1, ..., T_0, Q_{C1}, ..., Q_{CY} \} \] (4)

Here \( V_{GM} \) is the generated voltage on \( M \)th line, \( T_0 \) is the number of regulating transformer in the network, and \( Q_{CY} \) is the \( Y \)th shunt compensator in the network.

The total power injection is calculated and represented by the mathematical sum in (5):

\[ P_{GN} - iQ_{GG} = V_{LM} \sum_{m=1}^{M} Y_m V_{Ln} \] (5)

Here \( Y_m \) represents the vector sum of \( M \)th transmission line’s conductance and susceptance.

The power generation cost in a network with \( G \) generating units can be shown to be equivalent to a polynomial quadratic equation:

\[ \text{Cost} = c_G \sum P_M^2 + b_G \sum P_M + a_G \] (6)
Here in equation (6), a, b and c are cost coefficients of the network whereas, P represents the total power flow in the network.

The constraints represented by $h(x,u)$, $g(x,u)$ are described as following:

VII. Generation Constraints

The generators produce electric power in the ranges specified by their capability in the range of a minimum and maximum value. Thus, the generator voltage $V_{GN}$ varies between $V_{GN}^{\text{min}}$ and $V_{GN}^{\text{max}}$ for N number of generators. Similar case is with the generated real power $P_{GN}$ and generated reactive power $Q_{GN}$. Hence, the equality constraints of the generator can be written as shown in (7), (8), and (9).

$$V_{GN}^{\text{min}} \leq V_{GN} \leq V_{GN}^{\text{max}}, \forall N = 1,2,..N$$ (7)

$$P_{GN}^{\text{min}} \leq P_{GN} \leq P_{GN}^{\text{max}}, \forall N = 1,2,..N$$ (8)

$$Q_{GN}^{\text{min}} \leq Q_{GN} \leq Q_{GN}^{\text{max}}, \forall N = 1,2,..N$$ (9)

VIII. Shunt Compensators limits

Shunt compensators $Q_{C1}, Q_{C2} ... Q_{CC}$ are limited by their capacities as shown here in (10):

$$Q_{CC}^{\text{min}} \leq Q_{CC} \leq Q_{CC}^{\text{max}}, \forall C = 1,2,..C$$ (10)

IX. Voltage loading limits

Every transmission line has a maximum and minimum amount of voltage handling capability set by the material used in the transmission line design. Hence the loading voltage value $V_{LM}$ of an $M$th transmission line is restrained by (11):

$$V_{LM}^{\text{min}} \leq V_{LM} \leq V_{LM}^{\text{max}}, \forall M = 1,2,3,...M$$ (11)

Any $M$th transmission line can be loaded with $S$ number of loads. For each bus bar the number of loads are represented by $S$.

X. Objective Function

The objective function can be created from the functions and inequalities shown previously as an augmented matrix which is a sum of the following terms:

$$I_{\text{aug}} = 1 + \lambda_P \sum_{n=1}^{N} |P_{Gn} - P_{G}^{\text{Lim}}|^2 + \lambda_V \sum_{m=1}^{M} |V_{Lm} - V_{L}^{\text{Lim}}|^2 + \lambda_Q \sum_{g=1}^{G} |Q_{Gg} - Q_{G}^{\text{Lim}}|^2 + \lambda_S \sum_{ss=1}^{SS} S_{ss} - S_{ss}^{\text{Lim}}$$ (12)

Here $\lambda_P, \lambda_V, \lambda_Q$, and $\lambda_S$ represent penalty factors of the power system and Limit represent either the minimum or the maximum limit of the corresponding variable accordingly.
XI. Simulation & Results

XI.a. IEEE14 bus bar test system

For testing purposes, the coding is run on IEEE14 bus bar system. The simulation parameters of the PSO and NR method are shown below in Table I:

| Parameter               | Value this research | Value from [25] |
|-------------------------|---------------------|-----------------|
| Swarm Size              | 20                  | 10              |
| NR iterations           | 10                  | 10              |
| Max Iterations          | 3000                | 3000            |
| Inertia Weight (w)      | 0.9, 0.1            | 0.9, 0.4        |
| Acceleration Constants  | $C_1=C_2=1.2$       | $C_1=C_2=1.98$  |
| Convergence Criteria    | $10^{-6}$           | $10^{-6}$       |

The IEEE14 bus bar system is used to test the effectiveness of the PSO algorithm. The parameters of the test system are represented in Table II and III:

| Bus | Type | PD | QD  | VM | VA  | Vmax | Vmin |
|-----|------|----|-----|----|-----|------|------|
| 1   | 3    | 0  | 0   | 1.06 | 0 | 1.06  | 0.94 |
| 2   | 2    | 21.7 | 12.7 | 1.045 | -4.98 | 1.06  | 0.94 |
| 3   | 2    | 94.2 | 19 | 1.01 | -12.72 | 1.06  | 0.94 |
| 4   | 1    | 47.8 | -3.9 | 1.019 | -10.33 | 1.06  | 0.94 |
| 5   | 1    | 7.6 | 1.6 | 1.02 | -8.78 | 1.06  | 0.94 |
| 6   | 2    | 11.2 | 7.5 | 1.07 | -14.22 | 1.06  | 0.94 |
| 7   | 1    | 0  | 0 | 1.062 | -13.37 | 1.06  | 0.94 |
| 8   | 2    | 0  | 0 | 1.09 | -13.36 | 1.06  | 0.94 |
| 9   | 1    | 29.5 | 16.6 | 1.056 | -14.94 | 1.06  | 0.94 |
| 10  | 1    | 9 | 5.8 | 1.051 | -15.1 | 1.06  | 0.94 |
| 11  | 1    | 3.5 | 1.8 | 1.057 | -14.79 | 1.06  | 0.94 |
| 12  | 1    | 6.1 | 1.6 | 1.055 | -15.07 | 1.06  | 0.94 |
| 13  | 1    | 13.5 | 5.8 | 1.05 | -15.16 | 1.06  | 0.94 |
| 14  | 1    | 14.9 | 5 | 1.036 | -16.04 | 1.06  | 0.94 |

The Table II presents the bus data of the system. This is the same data that the “IEEE standards” documents on their page show us about their 14 bus bar system.
This detailed data is published online, and is taken carefully and typed into the algorithm’s data files. The Newton Raphson method runs and estimates the state of the system and presents a summary as is shown in the figure II-IV. Similarly, for the same data, the system branch data is shown in the following Table III.

TABLE III: Branch data for the IEEE14 bus bar system

| From Bus | To bus | R   | X      | B      | Ratio |
|----------|--------|-----|--------|--------|-------|
| 1        | 2      | 0.01938 | 0.05917 | 0.0528 | 0     |
| 1        | 5      | 0.05403 | 0.22304 | 0.0492 | 0     |
| 2        | 3      | 0.04699 | 0.19797 | 0.0438 | 0     |
| 2        | 4      | 0.05811 | 0.17632 | 0.034  | 0     |
| 2        | 5      | 0.05695 | 0.17388 | 0.0346 | 0     |
| 3        | 4      | 0.06701 | 0.17103 | 0.0128 | 0     |
| 4        | 5      | 0.01335 | 0.04211 | 0      | 0     |
| 4        | 7      | 0      | 0.20912 | 0      | 0.978 |
| 4        | 9      | 0      | 0.55618 | 0      | 0.969 |
| 5        | 6      | 0      | 0.25202 | 0      | 0.932 |
| 6        | 11     | 0.09498 | 0.1989  | 0      | 0     |
| 6        | 12     | 0.12291 | 0.25581 | 0      | 0     |
| 6        | 13     | 0.06615 | 0.13027 | 0      | 0     |
| 7        | 8      | 0      | 0.17615 | 0      | 0     |
| 7        | 9      | 0      | 0.11001 | 0      | 0     |
| 9        | 10     | 0.03181 | 0.0845  | 0      | 0     |
| 9        | 14     | 0.12711 | 0.27038 | 0      | 0     |
| 10       | 11     | 0.08205 | 0.19207 | 0      | 0     |
| 12       | 13     | 0.22092 | 0.19988 | 0      | 0     |
| 13       | 14     | 0.17093 | 0.34802 | 0      | 0     |

The results of the power flow calculation done on Newton Raphson Method are shown below in Table IV:
TABLE IV: Newton Raphson state estimation summary for IEEE 14 bus bar system

| Parameter          | Value |
|--------------------|-------|
| Buses              | 14    |
| Generators         | 5     |
| Committed Gens     | 5     |
| Loads              | 11    |
| Fixed              | 11    |
| Dispatch able      | 0     |
| Shunts             | 1     |
| Branches           | 20    |
| Transformers       | 3     |
| Inter-ties         | 0     |
| Areas              | 1     |

In Table V, the summary of the total generation of electrical power, the total load, and losses are shown in the summary. There are 14 buses in the IEEE14 test system and 11 loads. Twenty transmission line branches are present in the system totaling to a 772.4 MW of generation and 259 MW of load with 9.92 MW losses. 32.3 MVar are injected in to the system for compensation.

TABLE V: Newton Raphson state estimation on IEEE 14 bus bar system

| Parameter                  | P (MW) | Q (MVAr) |
|----------------------------|--------|----------|
| Generation Capacity        | 772.4  | -52.0 to 148.0 |
| On-Line Capacity           | 772.4  | -52.0 on 148.0 |
| Generator(actual)          | 268.9  | 60.7     |
| Load                       | 259    | 73.5     |
| Fixed                      | 259    | 73.5     |
| Dispatch able              | 0      | 0        |
| Shunt (injection)          | 0      | 21.4     |
| Losses(I^2Z)               | 9.92   | 40.96    |
| Branch Charging (inj)      | -      | 32.3     |
| Total Inter-tie Flow       | 0      | 0        |
The system has minimum Power Demand at Bus number 3 and maximum Power Demand at Bus No. 8 for 1.01 and 1.09 p.u. respectively. Maximum losses encountered are at line 1-2 for 3.12 MW and reactive power losses of 9.53 MVar at line 1-2.

**XI.b. Peshawar grid selected data**

From the PESCO Grid, the following sub stations were selected due to their closed loop arrangement as shown below.

**TABLE VI: Selected PESCO network’s bus data**

| Name             | Bus | $P_d$ | $V_{t_{\text{max}}}$ | $V_{t_{\text{min}}}$ | $V_{g_{\text{max}}}$ | $V_{g_{\text{min}}}$ |
|------------------|-----|-------|----------------------|----------------------|----------------------|----------------------|
| Dalazak          | 1   | 1.03  | 1.034                | 0.705                | 1.06                 | 0.95                 |
| Jamrud           | 2   | 0.99  | 1.002                | 0.628                | 1.06                 | 0.95                 |
| Hayatabad        | 3   | 1     | 1.036                | 0.633                | 1.06                 | 0.95                 |
| Mattani          | 4   | 1.03  | 1.092                | 0.681                | 1.06                 | 0.95                 |
| Peshawar City    | 5   | 1.02  | 1.032                | 0.809                | 1.06                 | 0.95                 |
| Peshawar Uni     | 6   | 0.99  | 1.024                | 0.621                | 1.06                 | 0.95                 |
| Peshawar Industrial | 7   | 0.99  | 1.035                | 0.617                | 1.06                 | 0.95                 |
| Peshawar Cantt   | 8   | 0.98  | 1.045                | 0.636                | 1.06                 | 0.95                 |
| Peshawar Forte   | 9   | 1.03  | 1.007                | 0.692                | 1.06                 | 0.95                 |
| A R Baba         | 10  | 1.03  | 1.009                | 0.686                | 1.06                 | 0.95                 |
| SakhiCh          | 11  | 0.99  | 1.018                | 0.779                | 1.06                 | 0.95                 |
| ShahiBagh        | 12  | 0.99  | 1.083                | 0.701                | 1.06                 | 0.95                 |
| ShahiBagh New    | 13  | 1.05  | 1.027                | 0.711                | 1.06                 | 0.95                 |
| Warsak           | 14  | 1.01  | 1.096                | 0.717                | 1.06                 | 0.95                 |
| Warsak P         | 15  | 1.01  | 1.006                | 0.722                | 1.06                 | 0.95                 |

In Table VI, $V_l$ represents load voltage, $V_g$ represents generation voltage, and $P_d$ represents power demand on the bus.

![Voltage profile of the selected network before reconfiguration](image)

Fig. I Voltage profile of the selected network before reconfiguration
Fig. I present a summary of the network in the form of voltage demand on each of the included node of the system. The voltage profile is a measure of the system performance and shows the demand of each substation as measured on it with respect to the attached villages. The demand profile is used in optimization of power systems as a measure of the performance the optimizer algorithm. Here we see the demand of each substation in bar-plot. This is just a representation of the data we took from the National Transmission and Dispatch Company Limited - NTDCL report from its latest edition on their website.

In Fig. II, the voltage profile of the network after reconfiguration is shown. The values of voltages on each node of the network can be seen to have decreased from the corresponding values from Fig. III. These values show a decrease in the losses of the network.

In Fig. III, comparison of the network voltage profile before and after the network reconfiguration is shown.
XII. Conclusions

This research is focused on the optimization of a selected set of grids from the Peshawar Electric Supply Company’s (PESCO) substations. The methodology used in this research is a hybrid technique, which is a combination of Particle Swarm Optimizer and Newton Raphson Method, working in combination and succession for testing and reconfiguring the network. The reconfiguration of the network is aimed at minimizing the losses of the network. A 132kV sub-grid of PESCO has been chosen with only one generating station at Warsak location. The data has been manually fed into the algorithm from NTDC five year reports of 2015. Transmission line lengths, Resistances and known values of various components such as Buses, injected real power and injected reactive power, are input. After that, different unknown parameters were found manually using calculation through formulas in textbooks. The complete model is generated and saved in the algorithm folder and the algorithm is run.

The algorithm is not special, just a combination of PSO and NR methods working in cooperation with each other. PSO’s role is to find best values of configuration parameters of the transmission network, while NR affirms the Bus admittance matrix according to those values. The process continues until the maximum iterations are reached or an optimized set of parameters for the selected network is reached.

The transmission line losses are reduced by proposing a better configuration of the flow of power in the network. Our interest is in the total amount of power loss reduction when the new configuration is re-run through Newton Raphson.

In this study, 15.09% reduction of power loss has been observed as compared to a similar study which resulted in 11.0209% power loss minimization. The effectiveness of the PSO and NR working in Unison has been observed in this study and positive results have been observed.

Future researchers are advised to use a mixed algorithm models (called as hybrid algorithms) of PSO and ANN for the same study. The only hurdle in these types of researches is data correctness. Due to the speed of PSO and the learning and applicability of Artificial Neural Network, the future study could prove fruitful.

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