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Optimal Load Dispatch in the South/ South Zone of Nigeria Power System by Means of a Particle Swarm

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Abstract: Solving the optimal load dispatch problem is key in the operation of power system, and several attempts have been made by using different techniques to solve these problems. Several traditional approaches, such as lambda-iteration and gradient method are applied to find out the optimal solution of non-linear problem. More recently, artificial intelligence (AI) computing techniques have received more attention and have been applied in a number of successful and practical applications. The purpose of this work is to apply the evolutionary computing technique known as Particle Swarm Optimization (PSO) to solve the optimal load dispatch problem- using some Power Stations in the Southern part of Nigeria as a case study. PSO is applied using the data of three (SAPELE) and six (AFAM) generating units. In this work, data has been taken from the Power Stations and some published work in which loss coefficients are also given with the max-min power limit and cost function. All the techniques are implemented in MATLAB environment. PSO is applied to find out the minimum cost for different power demand which is finally compared with lambda- iteration method.

Keywords: Particle Swarm Optimization, Power Stations, lambda-iteration, Loss Coefficients, Cost Functions, Artificial Intelligence, Power System

I. INTRODUCTION

Nigeria's Electrical power industry restructuring has created highly vibrant and competitive market that altered many aspects of the power industry. In this changed scenario, there is scarcity of energy resources, increasing power generation cost, environment concern, and an ever growing demand for electrical energy.

The cost of products and services is no doubt a major concern to the engineer; hence the efficient optimum economic operation and planning of electric power generation system have always occupied an important position in the Nigerian electric power industry.

With the large interconnection of the electric networks in the grid, the energy crisis in Nigeria generally and the South/South zone - to be specific- and the ever continuous rise in prices, it is very essential to reduce the running charges of the electric energy. A saving in the operation of the system of a small percent represents a significant reduction in operating cost as well as in the quantities of fuel consumed. The classic problem is the economic load dispatch of generating systems to achieve minimum operating cost.

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This problem area has taken a subtle twist as the public especially in the South region, has become increasingly concerned with environmental matters, so that economic dispatch now includes the dispatch of systems to minimize pollutants and conserve various forms of fuel, as well as achieve minimum cost. In addition there is a need to expand the limited economic optimization problem by incorporating constraints on system operation to ensure the security of the system, thereby preventing the collapse of the entire system due to unforeseen conditions.

The Nigerian Engineers have been largely successful in increasing the efficiency of turbines, generators etc. Any generation plant such as Afam or Sapele may contain different units such as hydro, thermal, gas etc. These plants have different characteristic which gives different generating cost at any load. So there should be a proper scheduling of plants for the minimization of cost of operation. The cost characteristic of the each generating unit is also non-linear. So the problem of achieving the minimum cost becomes an on-linear problem and also a difficult one.

However closely associated with this economic dispatch problem is the problem of the proper commitment of any array of units out of a total array of units to serve the expected load demands in an 'optimal' manner. For the purpose of optimum economic operation of this large scale system, modern system theory and optimization techniques such as PSO are being applied with the expectation of considerable cost savings.

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2.2 APPROACHES ADOPTED IN SOLVING LOAD DISPATCH

2.2.1 The Lambda –Iteration Method:

In Lambda iteration method lambda is the variable introduced in solving constraint optimization problem and is called Lagrange multiplier. It is important to note that lambda can be solved at hand by solving systems of equation. Since all the inequality constraints are satisfied in each trial, the equations are solved by the iterative method as proposed by Zwe-Lee. Gain (2003) and presented in [1].

i) Assume a suitable value of $\lambda^{(0)}$ this value should be more than the largest intercept of the incremental cost characteristic of the various generators.
ii) Compute the individual generations
iii) Check the equality that satisfies (2.1)
iv) If not, make the second guess λ repeat above steps

$$P_d = \sum_{n=1}^{n} P_n \qquad (2.1)$$

2.2.2 The Gradient Search Method:

This method proposed in [2] used by Park J.H et al (1993) works on the principle that the minimum of a function, f(x), can be found by a series of steps that always take us in a downward direction. From any starting point, x0, we may find the direction of "steepest descent" by noting that the gradient f,

$$\nabla f = \begin{matrix} \frac{\partial f}{\partial x} \\ \vdots \\ \frac{\partial y}{\partial x} \end{matrix} \qquad (2.2)$$

always points in the direction of maximum ascent. Therefore, if we want to move in the direction of maximum descent, we negate the gradient. Then we should go from x^0 to x^1 using:

$$x^1 = x^0 - \nabla f \propto \qquad (2.3)$$

Where $\propto$is a scalar to allow us to guarantee that the process of convergence. The best value of
$\propto$ must be determined by experiment
In case of power system economic load dispatch f becomes

$$f = = \sum_{i=1}^{N} Fi \ (Pi) \qquad (2.4)$$

The object is to drive the function to its minimum. However we have to be concerned with the constraints function

$$\phi = (\text{Pload} - \sum_{i=1}^{N} Pi) \qquad (2.5)$$

To solve the economic load dispatch problem which involves minimizing the objective function and keeping the equality constraints, we must apply the gradient technique directly to the
Lagrange function is:

$$\Im = \sum_{i=1}^{N} Fi\ (Pi) + \lambda\ (\text{Pload} - \sum_{i=1}^{N} Pi)$$
(2.6)

And the gradient of this function is

$$\nabla\Im = \begin{matrix} \frac{\partial \Im}{\partial Pi} \\ \frac{\partial \Im}{\partial Pn} \end{matrix} \qquad (2.7)$$

The problem with the formulation is the lack of a guarantee that the new points generated each step will lie on the surface φ
The economic dispatch algorithm requires a starting λ value and starting values for
P1,P2, and P3 .The gradient for $\Im$ is calculated as above and the new values of λ ,P1,and P2 etc, are found from

$$X1 = X^0 - (\nabla\Im)\acute{\alpha} \qquad (2.8a)$$

Where X is a vector

$$X = \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ \lambda \end{bmatrix}$$

2.2.3 Newton's Method:

Newton's method as presented in [3] used by Aravindhababu et al (2002) goes a step beyond the simple gradient method and tries to solve the economic dispatch by observing that the aim is to always drive

$$\nabla\Psi x = 0 \qquad (2.8b)$$

Since this is a vector function, we can formulate the problem as one of finding the correction that exactly drives the gradient to zero (i.e. to a vector, all of whose elements are zero).Suppose we wish to drive the function g(x) to zero. The function g is a vector and the unknown, x are also vectors. Then to use Newton's method, we observe

$$g(x+\Delta x)=g(x)+[g'(x)]\ \Delta x=0 \qquad (2.9)$$

Where g′(x) is the familiar Jacobian matrix. The adjustment at each step is then

$$\Delta X = -[g'(x)]-1\ g(x) \qquad (2.10)$$

Now, if we let the g function be the gradient vector ΔΨx we get

$$\nabla x = -[\frac{\partial}{\partial x}\nabla\psi_x]^{-1}\ \Delta\psi \qquad (2.11)$$

For the economic load dispatch problem this takes the form:

$$\Psi = \sum_{i=1}^{N} Fi\ (Pi) + \lambda\ (\text{Pload} - \sum_{i=1}^{N} Pi) \qquad (2.12)$$

The $\nabla\psi x$ is a Jacobean matrix which has now a second order derivative is called Hessian n-matrix. Generally, Newton's method will solve for the correction that is much closer to the minimum generation cost in one cost in one step than would the gradient method

2.2.4 Economic Dispatch With Piecewise Linear Cost Functions:

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In the method as used by Aravindhababu et al (2002), economic load dispatch problem of those generators are solved whose cost functions are represented as single or multiple segment linear cost functions. Here for all units running, we start with all of them at Pmin, then begin to raise the output of the unit with the lowest incremental cost segment. If this unit hits the right-hand end of a segment, or if it hits P_{max}, we then find the unit with the next lowest incremental cost segment and raise its output.

Eventually, we will reach a point where a units output is being raised and the total of all unit outputs equal the load, or load plus losses. At that point, we assign the last unit being adjusted to have a generation which is practically loaded for one segment. To make this procedure very fast, we can create a table giving each segment of each unit its MW contribution. Then we order this table by ascending order of incremental cost. By search in from the top down in this table, we do not have to go and look for the next segment each time a new segment is to be chosen.

This is an extremely fast form of economic dispatch.

2.2.5 Base Point and Participation Factor:

This method assumes that the economic dispatch problem has to be solved repeatedly by moving the generators from one economically optimum schedule to another as the load changes by a reasonably small amount. It is started from a given schedule called the base point.

Next assume a load change and investigates how much each generating unit needs to be moved in order that the new load served at the most economic operating point.

2.2.6 Linear Programming:

Linear programming (LP) according to Momoh J.A et al (1993) is a technique for optimization of a linear objective function subject to linear equality and linear in-equality constraints. Informally, linear programming determines the way to achieve the best outcome (such as maximum profit or lowest cost) in a given mathematical model and given some list of requirements represented as linear equations. For example if f is function defined as follows

$$f(x_1, x_2, \ldots\ldots\ldots X_n) = c_1 x_1 + c_2 x_2 + \ldots\ldots c_n x_n + d \qquad (2.13)$$

A linear programming method will find a point in the optimization surface where this function has the smallest (or largest) value. Such points may not exist, but if they do, searching through the optimization surface vertices is guaranteed to find at least one of them. Linear programs are problems that can be expressed in canonical form

Maximize $C^T X$

Subject to $AX \leq b$

X represents the vector of variables (to be determined), while C and b are vectors of (known) coefficients and A is a (known) matrix of coefficients. The expression to be maximized or minimized is called the objective function (c^T in this case). The equation $AX \leq b$ is the constraints which specify a convex polyhedron over which the objective function is to be optimized.

2.2.7 Dynamic Programming:

According to reference [4] when cost functions are no-convex equal incremental cost methodology cannot be applied.

Under such circumstances, there is a way to find an optimum dispatch which use dynamic programming method. In dynamic Programming is an optimization technique that transforms a maximization (or minimization) problem involving n decision variables into n problems having only one decision variable each. This is done by defining a sequence of Value functions V1,V2 ,... V n , with an argument y representing the state of the system. The definition of Vi(y) is the maximum obtainable if decisions 1, 2 ...I are available and the state of the system is y. The function V_1 is easy to find. For I=2,...n, Vi at any state y is calculated from V_{i-1} by maximizing, over the I-th decision a simple function (usually the sum) of the gain of decision i and the function V_{i-1} at the new state of the system if this decision is made. Since V_{i-1} has already been calculated, for the needed states, the above operation yields Vi for all the needed states.

Finally, Vn at the initial state of the system is the value of the optimal solution. The optimal values of the decision variables can be recovered, one by one, by tracking back the calculations already performed.

3.0 PSO AS AN OPTIMIZATION TOOL

Particle swarm optimization (PSO) as defined in [5] is a population based stochastic optimization technique developed in 1995, inspired by social behavior of bird flocking or fish schooling (SaumendraSarangi, 2009). PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, flythrough the problem space by following the current optimum particles. The detailed information will be given in following sections. The advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. Unlike Lambda iteration and other traditional methods, PSO takes little iteration to get an optimal dispatch. PSO is a form of Artificial Intelligence which has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control, and other areas.

3.1 ALGORITHM OF PARTICLE SWARM OPTIMISATION:

PSO simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area

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being searched. All the birds do not know where the food is. But they know how far the food is in each iteration. So what's the best strategy to find the food? The effective one is to follow the bird, which is nearest to the food. PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values.

The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.)

This value is called P_{best}. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global be stand called g-best. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called p-best. After finding the two best values, the particle updates its velocity and positions with following equation (3.1) and (3.2).

$$V_i^{(u+1)} = w * V_i^{(u)} + C1 * r\text{ and }(\ ) * (pbest_i - P_i^{(u)}) + C2 * rand(\ ) * (gbest_i - P_i^{(u)}) \quad (2.14)$$

$$P_i^{(u+1)} = P_i^{(u)} + V_i^{(u+1)} \quad (2.15a)$$

The term r and ( )*(pbest i $- P_i^{(u)}$) is called particle memory influence

The term r and ( )*(gbesti$- P_i^{(u)}$) is called swarm influence.

$V_i^{(u)}$ which is the velocity of i_{th} particle at iteration 'u' must lie in the range

$V_{min} \le V_i(u) \le V_{max}$

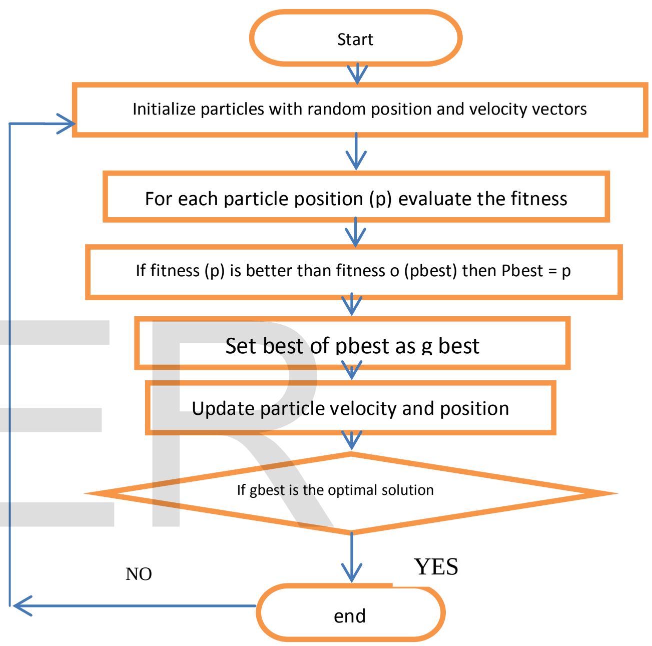
- The parameter Vmax determines the resolution, or fitness, with which regions are to be searched between the present position and the target position
- If Vmax is too high, particles may fly past good solutions. If V minimum is too small, particles may not explore sufficiently beyond local solutions.
- In many experiences with PSO, Vmax was often set at 10-20% of the dynamic range on each dimension.
- The constants C1and C2 pull each particle towards p best and *g best* positions.
- Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement towards, or past, target regions.
- The acceleration constants C1 and C2 are often set to be 2.0 according to past experiences
- Suitable selection of inertia weight 'ω' provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution.
- In general, the inertia weight w is set according to the following equation,

$$W = W_{max} - \left[\frac{W_{max} - W_{min}}{ITER_{max}}\right] \times ITER \quad (2.15b)$$

Where W -is the inertia weighting factor, Wmax - maximum value of weighting factor

Wmin - minimum value of weighting factor, ITERmax- maximum number of iterations

ITER - current number of iteration, The flow chart is as shown below



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3.2 ECONOMIC LOAD DIPSPATCH WITHOUT LOSS:

The economic load dispatch problem deals with the minimization of cost of generating the power at any load demand. The study of this economic load can be classified into two different groups, one is economic load dispatch without the transmission line losses and other one is economic load dispatch with transmission line losses.

3.4.1 ECONOMIC LOAD DIPSPATCH WITHOUT LOSS USING LAGRAGIAN METHOD

The economic load dispatch problem as reported in [6] and stated by Selvakumar and Thanushkodi (2007) is defined as: Min FT = $\sum_{n=1}^{N} Fn$ (2.16)

Subject to

PD $= \sum_{n=1}^{N} Pn$ (2.17)

Where FT is total fuel (or gas) input to the system, Fn the fuel input to nth unit, PD the total load demand and Pn the generation of nth unit.

By making use of Lagrangian multiplier the auxiliary function is obtained as

$$F = FT + \lambda\,(PD - (\textstyle\sum_{i=1}^{N} P_n)) \quad (2.18)$$

Where λ is the Lagrangian multiplier.

Differentiating F with respect to the generation Pn and equating to zero gives the condition for optimal operation of the system.

$$\frac{\partial F}{\partial Pn} = \frac{\partial FT}{\partial Pn} + \lambda(0-1) = 0 \quad (2.19)$$

Since FT = F1+ F2 + F3 + - - - - - - - -+ Fn (2.20)

$$\therefore \frac{\partial F_r}{\partial Pn} = \frac{\partial Fn}{\partial Pn} = \lambda \quad (2.21)$$

And therefore the condition for optimum operation is

$$\frac{\partial F1}{\partial P1} = \frac{dF2}{dP2} = \ldots\ldots\ldots = \frac{\partial Fn}{\partial P^N} = \lambda \quad (2.22)$$

Here = $\frac{\partial Fn}{\partial Pn}$ =incremental production cost of plant n in ₦.per MWhr.

The incremental production cost of a given plant over a limited range is represented by

$$\frac{\partial Fn}{\partial Pn} = FnPn + fn \quad (2.23)$$

Where Fnn = slope of incremental production cost curve

Fn = intercept of incremental production cost curve

The equation (3.5) mean that the machine be so loaded that the incremental cost of production of each machine is same. It is to be noted here that the active power generation constraints are taken into account while solving the equations which are derived above. If these constraints are violated for any generator it is tied to the corresponding limit and the rest of the load is distributed to the remaining generator units according to the equal incremental cost of production.

3.2.1 ELD WITHOUT LOSS USING PSO

When any optimization process is applied to the ELD problem some constraints are considered.

In this work two different constraints are considered. Among them the equality constraint is summation of all the generating power must be equal to the load demand and the inequality constraint is the powers generated must be within the limit of maximum and minimum active power of each unit. The sequential steps of the proposed PSO method are given below.

Step 1:

The individuals of the population are randomly initialized according to the limit of each unit including individual dimensions. The velocities of the different particles are also randomly generated keeping the velocity within the maximum and minimum value of the velocities. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints.

Step 2:

Each set of solution in the space should satisfy the equality constraints .So equality constraints are checked. If any combination doesn't satisfy the constraints then they are set according to the power balance equation.

Step 3:

The evaluation function of each individual Pgi, is calculated in the population using the evaluation function F.

Here F is

$$F = a\times(Pgi)^2 + b\times Pgi + c \quad (2.24)$$

Where a, b, c are constants. The present value is set as the P_{best} value.

Step 4:

Each P_{best} values are compared with the other pbest values in the population. The best evaluation value among the p-bests is denoted as gbest.

Step 5:

The member velocity v of each individual Pg is modified according to the velocity update

Equation

$$Vid^{(u+1)} = W * Vi^{(u)} + C1*rand(\,)*(pbest\,id - Pgid^{(u)}) + C2*rand(\,)*(gbestid - Pgid^{(u)}) \quad (2.25)$$

Where u is the number of iteration according to Saumendra Sarangi (2009).

Step 6:

The velocity components constraint occurring in the limits from the following conditions are checked

$$\left.\begin{array}{l} Vdmin = -0.5 * Pmin \\ Vdmax = +0.5 * Pmax \end{array}\right\} \text{Jeyakumar DN et al (2006)}$$

Step 7:

The position of each individual Pg is modified according to the position update equation

$$Pgid^{(u+1)} = Pgid^{(u)} + Vid^{(u+1)} \quad (2.26)$$

Step 8:

If the evaluation value of each individual is better than previous ***pbest***, the current value is set to be ***pbest***. If the best ***pbest*** is better than ***gbest***, the value is set to be ***gbest.***

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Step 9:

If the number of iterations reaches the maximum, then go to step 10.Otherwise, go to step 2.

Step 10:

The individual that generates the latest **gbest**is the optimal generation power of each unit with the minimum total generation cost.

3.3 ECONOMIC LOAD DIPSPATCH WITH LOSS:

When transmission losses are included and coordinated, the following points must be kept in mind for economic load dispatch solution

1. Whereas incremental transmission cost of production of a plant is always positive, the incremental transmission losses can be both positive and negative.
2. The individual generators will operate at different incremental costs of production.
3. The generation with highest positive incremental transmission loss will operate at the lowest incremental cost of production

3.3.1 ECONOMIC LOAD DIPSPATCH WTH LOSS USING PSO

When the losses are considered the optimization process becomes little bit complicated.

Since the losses are dependent on the power generated of the each unit, in each generation the loss changes. The P-loss can be found out by using the equation below according to Walters DC. (1993)

$$P_L = \sum_m \sum_n P_m B_{mn} P_n \quad (2.27)$$

Where B_{mn} are the loss co-efficient. The loss co-efficient can be calculated from the load flow equations or it may be given in the problem. However in this work for simplicity the loss coefficient are given which are the approximate one. Some parts are neglected. The sequential steps to find the optimum solution are

Step 1:

The power of each unit, velocity of particles, is randomly generated which must be in the maximum and minimum limit. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints.

Step 2:

Each set of solution in the space should satisfy the following equation

$$\sum_{I=1}^{N} Pgi = P D + P_L \quad (2.28)$$

PL calculated by using above (2.27).Then equality constraints are checked. If any combination doesn't satisfy the constraints then they are set according to the power balance equation.

$$P d = P D + P_L - \sum_{\substack{I=1 \\ I \neq d}}^{N} Pi \quad (2.29)$$

Step 3:

The cost function of each individual Pgi, is calculated in the population using the evaluation function F .

Here F is

$$F = a \times (Pgi)^2 + b \times Pgi + c \quad (2.30)$$

Where a, b, c are constants. The present value is set as the pbest value.

Step 4:

Each pbest values are compared with the other pbest values in the population. The best evaluation value among the pbest is denoted as *gbest.*

Step 5:

The member velocity v of each individual Pg is updated according to the velocity update

Equation

$Vid^{(u+1)} = W*Vi^{(u)} + C1*r$ and ( )*(pbest id $- Pgid^{(u)}$) +C2*r and ( )*(gbestid–$Pgid^{(u)}$) (2.31)

Where u is the number of iteration

Step 6:

The velocity components constraint occurring in the limits from the following conditions are checked

$\mathbf{Vd^{min} = -0.5*Pmin}$

$\mathbf{Vd^{max} = +0.5*Pmax}$

Step 7:

The position of each individual Pg is modified according to the position update equation

$$Pgid^{(u+1)} = Pgid^{(u)} + Vid^{(u+1)} \quad (2.32)$$

Step 8:

The cost function of each new is calculated If the evaluation value of each individual is better than previous *pbest;* the current value is set to be *pbest*. If the best *pbest*is better than *gbest*, the value is set to be *gbest*.

Step 9:

If the number of iterations reaches the maximum, then go to step 10.Otherwise, go to step 2.

Step 10:

The individual that generates the latest **gbest** is the optimal generation power of each unit with the minimum total generation cost.

3.3.2 ELD WTH LOSS USING LANGRANGIAN METHOD

The optimal load dispatch problem including transmission losses is defined as

$$\text{Min } FT = \sum_{n=1}^{N} Fn \quad (2.33)$$

$$\text{Subject to } PD + PL - \sum_{n=1}^{N} Pn \quad (2.34)$$

Where PL is the total system loss which is assumed to be a function of generation and the other term have their usual significance.

Making use of the Lagrangian multiplier λ. The auxiliary function is given by

$$F = FT + \lambda\,(PD + PL - \Sigma P\,N) \quad (2.35)$$

The partial differential of this expression when equated to zero gives the condition for optimal load dispatch, i.e.

$$\frac{\partial F}{\partial Pn} = \frac{\partial F_{\cdot}}{\partial P^{n}} + \lambda\left(\frac{\partial Pl}{\partial Pn} - 1\right) = 0 \quad (2.36)$$

$$\frac{\partial F}{\partial Pn} + \lambda\frac{\partial P}{\partial Pn} = \lambda \quad (2.37)$$

Here the term $\frac{\partial Pl}{\partial Pn}$ is known as the incremental transmission loss at plant n and λ is known as the incremental cost of received power in ₦.per MWhr. The equation (2.37) is a set of n equations with (n+1) unknowns' .Here n generations are unknown and λ is also unknown. These equations are known as coordination equations because they coordinate the incremental transmission losses with the incremental cost of production.

To solve these equations the loss formula equation is expressed in terms of generations and is approximately expressed as

$$P_L = \sum_m \sum_n P_m B_{mn} P_n \qquad (2.38)$$

Where P_m and P_n are the source loadings, B_{mn} the transmission loss coefficient. The formula is derived under the following assumptions;

1. The equivalent load current at any bus remains a constant complex fraction of the total equivalent load current.
2. The generator bus voltage magnitudes and angles are constant
3. The power factor of each source is constant.

The solution of coordination equation requires the calculation of

$$\frac{\partial Pl}{\partial P^N} = 2\sum_m B_{mn} P_m \qquad (2.39)$$

Also $\frac{\partial F_n}{\partial P_n} = F_{mn} P_n + f_n$

(2.40)

According to Park J. H. et al (1993) the coordination equation can be rewritten as

$$Fnn \times Pn + Fn + \lambda \sum_m 2B_{mn} P = \lambda \qquad (2.41)$$

Solving for Pnwe obtain

$$P_n = \frac{1 - \frac{fn -}{\lambda} \sum_{m=n} 2B_{mn} P_m}{\frac{F_{mn}}{\lambda} + 2B_{mn}} \qquad (2.42)$$

4.0 RESULTS AND DISCUSSION

The different methods discussed earlier are applied to two cases to find out the minimum cost for any demand. Case I involves three generating units using SAPELE as a case study and Case II involves six generating units using AFAM as a case study.

S/N0	POWER DEMAND (MW)	P1 (MW)	P2 (MW)	P3 (MW)	Ft ₦/Hr	Time in secs
1	450	205.4758	183.2692	61.3158	4.6523e+003	1.2765
2	580	266.5833	232.4072	81.0934	5.7777e+003	1.1297
3	700	322.9862	277.7621	99.3482	6.8384e+003	2.1973
4	800	369.9026	315.4887	114.5328	7.7385e+003	0.9720
5	900	416.8940	353.2756	129.7416	8.6533e+003	0.9619

Results of Particle Swarm Optimization (PSO) are compared with the conventional lambda iteration method. In the first case transmission losses are neglected and then transmission line losses are also considered. All these simulation are done on MATLAB 7.12 environment.

4.1 CASE STUDY 1- SAPELE: THREE UNIT SYSTEM

The three generating units considered are having different characteristics. Their cost function characteristics are given by following equations

F1 = 0.00156P12 + 7.92P1 + 561 ?/Hr
F2 = 0.00194P2 2 + 7.85P2 + 310 ?/Hr
F3 = 0.00482P3 2 + 7.97P3 + 78 ?/Hr
} IEEE Trans. Power Appa. System PAS-90 (1971)

According to the constraints considered in this work among inequality constraints only active power constraints are considered. The unit operating ranges are:

100 MW ≤ P1 ≤ 600 MW
100 MW ≤ P2 ≤ 400 MW
50 MW ≤ P3 ≤ 200 MW

The transmission line losses can be calculated by knowing the loss coefficient. The Bmn loss coefficient matrix is given by

$$B_{mn} = \begin{Bmatrix} 0.000075 & 0.000005 & 0.0000075 \\ 0.001940 & 0.000015 & 0.0000100 \\ 0.004820 & 0.000100 & 0.0000450 \end{Bmatrix}$$

References: IEEE Trans. Power Appa.Syst PAS-90 (1971), Saumendra Sarangi (2009)

4.1.1 ELD WITHOUT TRANSMISSION LINE LOSSES

4.1.1.1 Lambda iteration method

In this method initial value of lambda is guessed in the feasible reason that can be calculated from derivative of the cost function. For the convergence of the problem the delta lambda should be selected small. Here delta lambda is selected 0.0001 and the value of lambda must be chosen near the optimum point, according to Ting T. O. et al.

Table4.1: Lambda Iteration Method without Losses

It is observed that if the lambda value is not selected in the feasible range the cost is not converging. Also, the time taken to converge also depended on the lambda selection and delta lambda value. It nearly takes 1000-2000 iterations to converge according to Momoh J. A. et al.(1999).

4.1.1.2 Particle Swarm Optimization (PSO) method

In this method the initial particles are randomly generated within the feasible range. The parameters c1, c2 and inertia weight are selected for best convergence characteristic. Here c1 =2.01 and c2 = 2.01 Here the maximum value of w is

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chosen 0.9 and minimum value is chosen as 0.4. The velocity limits are selected as Vmax= 0.5*Pmax and the minimum velocity is selected as Vmin= -0.5*Pmin. There are 10 no of particles selected in the population

Table 4.2: PSO method without loss

S/N0	POWER DEMAND (MW)	P1 (MW)	P2 (MW)	P3 (MW)	Ft ₦/Hr	Time in secs
1	450	205.4473	183.2462	61.3065	4.6523e+003	1.2765
2	580	266.5439	232.3755	81.0806	5.7777e+003	1.1297
3	700	322.9408	277.7256	99.3335	6.8384e+003	2.1973
4	800	369.9377	315.5177	114.5446	7.7385e+003	0.9720
5	900	416.9358	353.3090	129.7552	8.6533e+003	0.9619

4.1.1.3 COMPARISON OF COST BETWEEN PSO AND CONVENTIONAL METHODS

The lowest costs obtained in two different methods are compared for five different power demands. It has been observed that for all the demand PSO gives same value of cost which nearly equal to the cost of lambda-iteration method. But in both PSO the cost curve converges within 20 to 40 iterations but conventional method takes more than 1000 iterations, according to Momoh J. A. et al.(1999).

In conventional method selection of lambda value in the feasible range is also required. If it is not selected in the feasible range then it will not converge.

4.3 Comparison of cost in the two different methods

4.1.2 ELD WITH TRANSMISSION LINE LOSSES

4.1.2.1 Lambda iteration method

In this method initial value of lambda is guessed in the feasible reason that can be calculated from derivative of the cost function. For the convergence of the problem the delta lambda should be selected small. Here delta lambda is selected 0.0001 and the value of lambda must be chosen near the optimum point. It has been observed that then minimum cost curve converges after so many iterations than in the no loss case. Here the cost curve converges within the range of 2000to 5000 iterations. The lambda selection is important for convergence of cost curve.

Table 4.4: Lambda iteration method with loss

S/N0	POWER DEMAND (MW)	P1 (MW)	P2 (MW)	P3 (MW)	Loss in (MW)	Ft ₦/Hr	Time in secs
1	450	185.1088	198.6346	67.5762	1.3675	4.6649e+003	0.0603
2	580	239.7541	253.0043	89.4859	2.2968	5.7996e+003	0.1773
3	700	289.9928	303.5003	109.8356	3.3685	6.8716e+003	0.2396
4	800	31.7403	345.8564	126.9058	4.4200	7.7842e+003	0.0841
5	900	373.3016	388.3666	144.0389	5.6136	8.7122e+003	0.0930

4.1.2.2 PSO method

In this method the initial particles are randomly generated within the feasible range. The parameters c1, c2 and inertia weight are selected for best convergence characteristic. Here, c1 =
1.99 and c2 = 1.99. Here the maximum value of w is chosen as 0.9 and minimum value is chosen as 0.4. The velocity limits are selected as Vmax = 0.5*Pmax and the minimum velocity is selected as Vmin = -0.5*Pmin. There are 10 no of particles selected in the population. For different value of c1 and c2 the cost curve converges in the different region. So, the best value is taken for the minimum cost of the problem. If the no of particles are increased then cost curve converges faster. It can be observed that the loss has no effect on the cost characteristic.

Table 4.5: PSO method with loss

S/N0	POWER DEMAND (MW)	P1 (MW)	P2 (MW)	P3 (MW)	Loss in (MW)	Ft ₦/Hr	Time in secs
1	450	204.7077	188.6082	58.0591	1.3750	4.6642e+003	5.3622
2	580	265.8435	239.6414	76.8248	2.3096	5.7981e+003	4.2999
3	700	322.3586	286.9045	94.1244	3.3876	6.8690e+003	5.6332
4	800	369.5131	326.3878	108.548	4.4446	7.7792e+003	4.1134
5	900	416.7222	365.9702	122.9540	5.6464	8.7059e+003	4.0639

4.1.2.3 Comparison of cost in the two different methods

S/N0	Power Demand (MW)	Costs in ₦/Hr Lambda iteration method	Costs in ₦/Hr PSO method	Percentage difference
1	450	4652.3	4652.3	0.0
2	580	5777.7	5777.7	0.0
3	700	6838.0	6838.4	0.99
4	800	7738.5	7738.5	0.99
5	900	8653.5	8653.3	0.99

It has been observed that when transmission line losses are included the minimum cost we found in the PSO method is less than the conventional method.

Table 4.6 Comparison of cost in the two different methods with losses

S/N0	Power Demand (MW)	Costs in ₦/Hr Lambda iteration method	Costs in ₦/Hr PSO method	Percentage difference

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1	450	4664.9	4664.2	1.0%
2	580	5799.6	5798.1	1.0%
3	700	6871.6	6869.0	1.0%
4	800	7784.2	7779.2	1.0%
5	900	8712.2	8705.9	1.0%

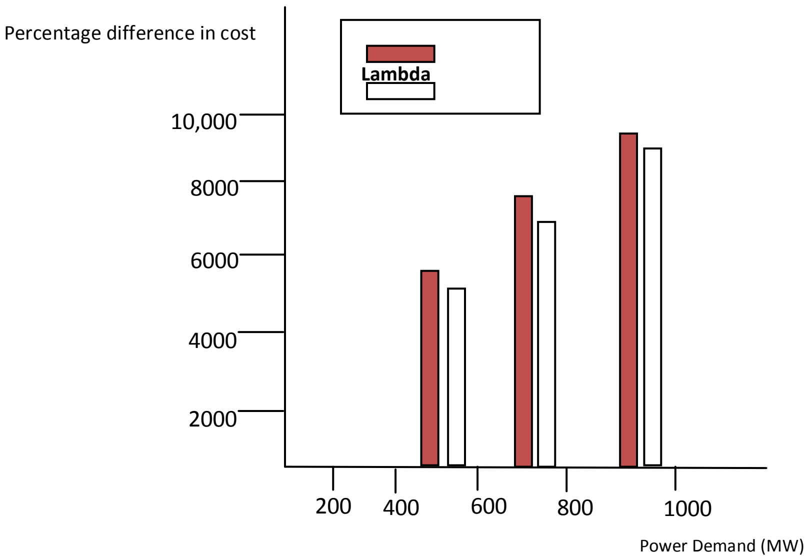

Figure 4.1: Bar chart show the percentage difference for power demands in three unit system

4.2 CASE STUDY 2- AFAM - SIX UNIT SYSTEM

The cost function of the six units are given as follows

$$\left.\begin{aligned}
F1 &= 0.15240P12 + 38.53P1 + 756.79886 \quad N/Hr \\
F2 &= 0.10587P22 + 46.15916P2 + 451.32513 \ N/Hr \\
F3 &= 0.02803P32 + 40.39655P3 + 1049.9977 \ N/Hr \\
F4 &= 0.03546P42 + 38.30553P4 + 1243.5311 \quad N/Hr \\
F5 &= 0.02111P52 + 36.32782P5 + 1658.5596 \quad N/Hr \\
F6 &= 0.01799P32 + 38.27041P3 + 1356.6592 \quad N/Hr
\end{aligned}\right\}$$

Reference: IEEE Trans. Power Appa. System PAS-90 (1971)

The unit operating ranges are

$10 \text{ MW} \leq P1 \leq 125 \text{ MW}$
$10 \text{ MW} \leq P2 \leq 150 \text{ MW}$
$35 \text{ MW} \leq P3 \leq 225 \text{ MW}$
$35 \text{ MW} \leq P4 \leq 210 \text{ MW}$
$130 \text{ MW} \leq P5 \leq 325 \text{ MW}$
$125 \text{ MW} \leq P6 \leq 315 \text{ MW}$

B_{mn} coefficient matrix is given as

$$B_{mn} = \begin{Bmatrix}
0.00014 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\
0.000017 & 0.000060 & 0.000013 & 0.000016 & 0.000015 & 0.000020 \\
0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\
0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.000030 & 0.000025 \\
0.000026 & 0.000015 & 0.000024 & 0.000030 & 0.000069 & 0.000032 \\
0.000022 & 0.000020 & 0.000019 & 0.000025 & 0.000032 & 0.000085
\end{Bmatrix}$$

References: IEEE Trans. Power Appa.Syst PAS-90 (1971), Saumendra Sarangi (2009)

4.2.1 ELD WITHOUT TRANSMISSION LINE LOSSES

4.2.1.1 Lambda iteration method

The initial value of lambda is guessed in the feasible reason that can be calculated from derivative of the cost function. For the convergence of the problem the delta lambda should be selected small. Here delta lambda is selected 0.0001 and the value of lambda must be chosen near the optimum point. In this case also the convergence is largely affected by the selection of lambda and delta value. The time taken for convergence increases than the three unit system.

Table 4.7: AFAM 6-Unit Lambda method without loss

S/N0	POWER DEMAND (MW)	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	Ft ₦/Hr	Time (S)
1	600	21.2237	10	82.0984	94.3804	205.3805	187.0088	3.1445e+004	1.2722
2	700	25.0080	10	102.6736	110.6444	232.7004	219.0667	3.6003e+004	1.4366
3	800	28.7924	10	123.2496	126.9091	260.0213	251.1259	4.0676e+004	1.0977
4	860	31.0628	10	135.5936	136.6666	276.4118	270.3590	4.3535e+004	1.0890
5	900	32.5455	10.8185	143.6555	143.0393	287.1165	282.9201	4.5464e+004	1.1313

4.2.1.2 PSO method

The initial particles are randomly generated within the feasible range. The parameters c1, c2and inertia weight are selected for best convergence characteristic. Here c1=1.99 and c2=1.99.
Here the maximum value of w is chosen 0.9 and minimum value is chosen 0.4.the velocity limits are selected as Vmax= 0.5*Pmax and the minimum velocity is selected as Vmin= -0.5*Pmin. There are 10 no of particles are selected in the population. For different value of c1 and c2 the cost curve converges in the different region. So the best value is taken for the minimum cost of the problem. If the no of particles are increased then cost curve converges faster. It can be

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observed the loss has no effect on the cost characteristic. It has been observed even if the no of units are increased the convergence is less affected.

Table 4.8: Six unit system PSO method without losses

S/N	POWER DEMAND (MW)	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	Ft ₦/Hr	Time in secs
1	600	21.2075	10.0000	182.0915	94.3879	205.3306	186.9824	3.1445e+004	1.2722
2	700	25.0050	10.0000	102.6536	110.6295	232.6774	219.0345	3.6003e+004	1.4366
3	800	28.7768	10.0000	123.3081	126.8297	260.0036	251.0819	4.0676e+004	1.0977
4	860	31.0603	10.0000	135.5660	136.6517	276.3712	270.3508	4.3535e+004	1.0890
5	900	32.3900	11.2864	143.2936	143.0721	287.3322	282.6256	4.5464e+004	1.1313

Table 4.9: AFAM 6-Unit PSO method with loss

S/NO	POWER DEMAND (MW)	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P6 (MW)	Loss in (MW)	Ft ₦/Hr	Time in secs
1	600	23.9071	10.0002	95.6241	100.7082	202.8561	181.1409	14.2365	3.2094e+004	5.9457
2	700	28.3153	10.0013	118.9551	118.6595	230.7771	212.7232	19.4314	3.6912e+004	5.4326
3	800	32.6285	14.4681	141.5402	136.0307	257.6676	242.9956	25.3308	4.1896e+004	5.6267
4	860	35.1904	18.4186	154.9572	146.3244	273.5188	260.8149	29.2244	4.4966e+004	6.0545
5	900	36.8945	121.0830	163.9219	153.2221	284.1644	272.7006	31.9865	4.7045e+004	5.0520

Table 4.10: AFAM 6-Unit Lambda method with loss

S/N0	POWER DEMAND(MW)	P1(MW)	P2(MW)	P3(MW)	P4(MW)	P5(MW)	P6(MW)	PLoss (MW)	Ft (₦/Hr)	Time secs
1	600	24.2556	1.6559	97.5030	102.1451	205.0691	183.7279	14.4509	3.2082e+004	0.2492
2	700	28.4230	8.0125	119.4254	119.0348	231.3208	213.3747	19.4971	3.6916e+004	3.5129
3	800	32.6336	14.4877	141.5599	136.0534	257.6769	243.0241	25.3364	4.1901e+004	3.4349
4	860	35.1851	18.4310	154.9597	146.3424	273.5622	260.8480	29.2315	4.4971e+004	3.4287
5	900	36.8971	21.0809	163.9414	153.2352	284.1824	272.7509	31.9938	4.7050e+004	3.2538

4.2.1.3 Comparison of Cost in Two Different Methods

It has been observed that when the numbers of units are increased the minimum cost we found in the PSO method is less than the conventional method. The performance depends on randomly generated particle in PSO. At all times, PSO gives better result.

Table 4.11 Comparison of cost in the two different methods with losses

S/N0	Power Demand (MW)	Costs in ₦/Hr Lambda iteration method	Costs in ₦/Hr PSO method	Percentage difference
1	600	32082.1	32080.68	0.99
2	700	36916.1	36912.2	0.99
3	800	41901.1	41896.2	0.99
4	860	44971.1	44966.08	0.99
5	900	47050.1	47045.38	0.99

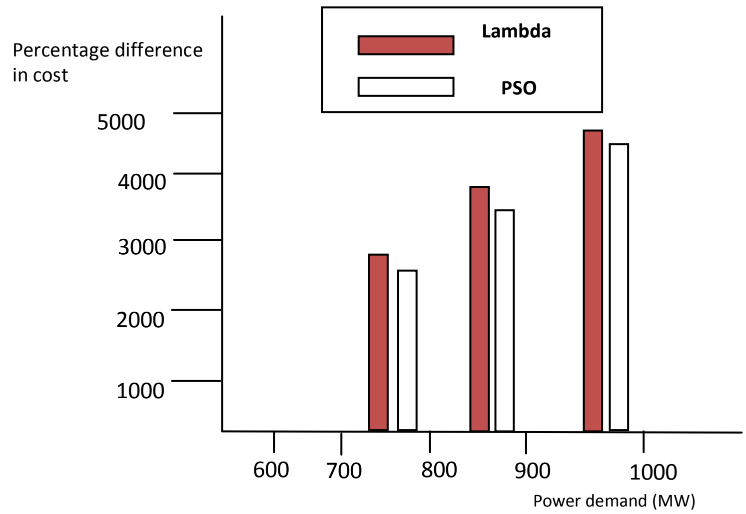

Figure 4.2: Bar chart show the percentage difference for power demands in six unit system

5. CONCLUSION

Economic load dispatch in electric power sector is an important task, as it is required to supply the power at the minimum cost which aids in profit-making. As the efficiency of newly added generating units are more than the previous units the economic load dispatch has to be efficiently solved for minimizing the cost of the generated power.

Load dispatch problem here solved for two different cases. SAPELE with three units in generating stations and AFAM with six units in the generating stations.

Each problem is solved by three different methods in the MATLAB environment.

Before the thesis draws to a close, major studies reported in this work and the general conclusions that emerge out from this work are highlighted. The conclusions are arrived at based on the performance and the capabilities of the PSO application presented here. This finally leads to an outline of the future directions for research and development efforts in this area.

The main conclusions drawn are:

Three unit system:

Both the problem of three units system without loss and with loss is solved by two different methods. In Lambda-iteration method better cost is obtained but the problem converges when the lambda value is selected within the feasible range. But the cost characteristic takes many number of iteration converge. In PSO method the cost characteristic converges in less number of iterations.

When transmission losses are considered PSO method gives a better result than the Lambda iteration method.

In PSO method selection of parameters c1, c2 and w is very much important. The best result obtained when c1 = 2.01 and c2= 2.01 and w value is chosen near 0.8. These results are similar when w is chosen according to the formula used. In PSO better cost is obtained than in the Lambda-iteration method

Six unit system:

The problem of six units system without loss and with loss is solved by two different methods.

In Lambda-iteration method better cost is obtained but the problem converges when the lambda value is selected within the feasible range. The cost characteristic takes many numbers of iterations to converge. In PSO method the cost characteristic converges in less number of iterations. When transmission losses are considered PSO method gives a better result than the Lambda iteration method. In case of Lambda iteration method the number of iterations to converge is also increases. But in PSO method no of iterations are not affected when the transmission line losses are considered. In PSO method the better result depends on the randomly generated particles. So, PSO gives better result.

In PSO method selection of parameters c1, c2 and w is also important like above. The best result obtained when c1=1.99 and c2=1.99 and w value according to the formula used.

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