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Optimum Cost Allocation For Reactive Power Planning In Wind Farms Using Modified Artificial Immune System

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Abstract

Provision of reactive power is considered to be a vital ancillary service in electricity network in order to maintain the voltages at different buses within the prescribed limits. In the earlier systems, the cost of reactive power was assessed and transformed according to the utilization variables and quality based procedure using Particle Swarm Optimization (PSO). The main objective of this paper is to minimize the cost of reactive power through the employment of Static Var Compensator (SVC) in wind farms. To achieve this target, a Modified Artificial Immune System (MAIS) is proposed considering both the static and dynamic variables of the system. MAIS helps to seek out the best global solution among a number of local solutions and provide less iteration with reduction of partial populations. The proposed approach has been tested on practical 75- bus Indian system and the simulation results show that it converges to better solution much faster and MAIS results are compared with Particle Swarm Optimization (PSO), Hybrid Particle Swarm Optimization (HPSO) and a value based approach to prove the performance evaluation of MAIS.

Keywords: Particle Swarm Optimization (PSO), Static Var Compensator (SVC), wind farms, Modified Artificial Immune System (MAIS) , Hybrid Particle Swarm Optimization (HPSO), value based approach.

Introduction

Developing a fair and equitable reactive power cost allocation method has been a hot topic of research, particularly in the new paradigm with many transactions taking place at any time. Reactive power is required for transmission of active power, system voltage control and normal operation of power systems. Reactive power support may be provided by generators, synchronous condensers, shunt capacitors / reactors and Flexible AC Transmission System (FACTS) devices like Static VAr Compensators (SVCs), Static Synchronous Compensator (STATCOM), Unified Power Flow Controller (UPFC) and so on. For improving the performance of ac power systems, this reactive power should be managed efficiently, called as reactive power compensation.

The generators supply reactive power to the grid under a heavy loading condition, whereas they absorb reactive power under light load condition to maintain the system voltage within the specified limits.

SVCs are part of the FACTS device family, regulating voltage and stabilizing the system. To resolve the issue of variations in the voltage conflicts which may lead to poor power quality, there are various solutions provided like regulating the real-time voltage, controlling the load, using voltage regulation devices like capacitors. But, the capacitors don't have enough fastness according to the voltage changes frequently. Therefore, SVCs are suggested as reactive resource, which can be deployed in distributed power systems, even for fast voltage regulations.

The main advantage of SVCs over simple mechanically-switched compensation schemes is their near-instantaneous response to changes in the system voltage. They are, in general, cheaper, higher-capacity, faster and more reliable than dynamic compensation schemes such as synchronous condensers. Typically, an SVC comprises of one or more banks of fixed or switched shunt capacitors or reactors. Elements used to make it are

- Thyristor controlled reactor (TCR), where the reactor may be air- or iron-cored
- Thyristor switched capacitor (TSC)
- Harmonic filter(s)
- Mechanically switched capacitors or reactors (switched by a circuit breaker)

Modeling the operational effects of growing wind generation with respect to regulation, reserve capacity, ramping capability and their effect on planning the future generation portfolios is focused and a new investment planning software called NETPLAN to identify a set of non-dominated national investment strategies taking into account, the unique attributes of variable generation is described. In the case study of U.S. study regions in NETPLAN, the lower bound on arc energy flows is assumed as 0. Further, for the fuel network it can be determined based on existing contracts in the system, and for generation, minimum loading can be utilized [1]. A strong and potentially more accurate Optimal Power Flow (OPF) framework is adopted to perform two-dimensional Locational Marginal Pricing (LMP) which vary spatially and with respect to power factors of loads, under the deficiency of reactive power. The interdependency of active and reactive power loads in the adopted OPF is also taken into account [2]. Pricing computed using power factor penalties is found to be inconsistent and inadequate, which makes the requirement of developing an accurate and feasible method in the electricity market. A new methodology to implement Artificial Intelligence (AI) based optimization for performing load tracing, applying a new hybrid algorithm; Blended Crossover Continuous Ant Colony Optimization (BX-CACO) with simple and easy formulation steps, is adopted in the transmission service pricing to overcome the drawbacks in proportional sharing principle (PSP) like matrix inversion and singularity dependency. However, the improvement of voltage stability is not discussed [3]. A novel genetic algorithms-based optimization method for realistic assessment of techno-economic merits of placing the thyristor-controlled series capacitors (TCSCs) and Static VAr Compensators (SVCs) in a transmission network to facilitate wind power integration and the identification of congested areas is proposed. It is also observed that the network maximum loading does not always leads to maximum profit. If the added load diverts the power away from the congestion, the savings obtained gets reduced [4]. Using simple circuit theory model, the complex problem of bidirectional reactive power flow that prevents the application of power tracing is solved. Calculation of Reactive power pricing depending on power tracing principle using a quadratic reactive cost function for the generators and all other sources are considered to have a fixed cost per unit MVAr supplied, which can be determined from the installation cost of the respective reactive power source is discussed [5]. The link between the nodal active and reactive power demands is recognized in [6] with a linear relationship between the aggregated quantities. A load power factor is assigned for each bus for modelling this functional relationship. But this gross linear representation also does not seem to be very accurate because there can be multiple types of loads at a bus, each with a different power factor. Then the complexity may arise if there are more than one load (or load serving) entities at the same bus. The reason for this is that the mutual consensus between the load entities is then required to decide the load power factor of the respective bus. Simultaneously, the pricing rule suggested in [6] may not be appropriate for the generating entities. A combined dispatch procedure of active and reactive power, expressed through a bilevel optimization problem whose upper and lower level criteria are the minimum opportunity cost and minimum offered price of active power respectively is proposed and the problem is solved using a version of interior point methods with complementary constraints. The most suitable solution for bilevel problem must be tracked among multiple solutions [7]. An improved Artificial Immune System Algorithm is introduced for the first time to overcome its problems of artificial immune system like slow convergence to global optimum and their weak stability [8]. Tracing-compliant min-max fair cost allocation approach to “explicitly” model fairness constraints in the tracing framework considering scalability, numerical stability and termination in finite steps as well as modelling of HVDC lines within the marginal participation scheme is proposed [9]. A Value-based sensitivity approach is proposed to compute both the utilization factor for allocating the reactive power production/absorption cost and the participation factor to compute the VAr reserve to support system security along with the compensation for its utilised capacity. In this approach, all the generators are paying, since the cost incurred for VAr support towards MW load shipment is higher than the net cost [10]. For secure operation of the power system, a new approach is proposed based on tracing algorithm for reactive power pricing taking into consideration, the cost of both active and reactive losses allocated to each generator, all the investment, operation and opportunity costs due to reactive power support [11]. In addition to the calculation of the fixed cost and cost of loss components, a new technique to model the reactive power capability of WFs connected to the grid and determine the lost opportunity cost (LOC) for a WF considering hourly wind variations is proposed. Higher wind speed prediction errors leads to higher payments to WFs for the reactive power service because of the increased LOC component [12]. The wind power variations for every minute are decomposed into slow, fast, and ramp components and the assessment of the effect of each component on power system operation is presented. Detailed, long-term simulation models are performed and extended to include load dynamics and automatic generation control (AGC) time delays to examine the system response for fast wind fluctuations is discussed. However, devising a long term penetration strategy is not preferred from the point of view of system reliability [13]. A fuzzy set theory based modeling technique of wind power generation considering hourly wind speed variations, to effectively assess the generation cost including the neglected generation cost of diesel generators is presented [14]. The general background, objectives, constraints and solution algorithms of reactive power planning with an optimization model is introduced. The objective function is considered as a multiobjective model to compute the weighted sum of various costs like the VAr installation cost, power loss cost, and operation cost (generation fuel cost) as well as the technical merits like minimization of voltage deviation from a given schedule, maximization of voltage stability margin [15]. Both for real and reactive powers, nodal spot pricing have been computed using optimal power flow (OPF) solutions. A sensitivity based approach to optimally locate the unified power flow controller (UPFC) for congestion management in the deregulated power sector and its impact on the nodal spot pricing have been studied [16].

This paper proposes a Modified Artificial Immune System (MAIS) which is a Meta heuristic optimization method employed to optimize the cost of reactive power through the utilization of Static Var Compensator (SVC) in wind farms and the results obtained are compared with evolutionary multi-objective optimization algorithms like Particle Swarm Optimization (PSO) and Hybrid Particle Swarm Optimization (HPSO) and a value based approach to prove its faster convergence.

Mathematical Formulation

In this paper, an optimized reactive power planning model is applied to determine the optimal sizes and locations of SVC installations and the optimal reactive power results of the power system unit. The output of the generators in each stage of power system is included in the power flow constraints to reflect the system impacts. The control variables of the optimization model are sizes and locations of SVCs, and reactive power outputs of the generators under different power systems' power result statuses. The dynamic and static variables are used to represent whether it is optimal to install each SVC at a node.

The main objective is to optimize the cost allocation for reactive power generation. The cost considers the total cost which includes the fixed cost of SVC, reactive power generation cost produced by generators and cost of the loss incurred. It is considered that a network has N number of buses and N_g number of generators.

Objective function is

$$Minimize\ C_T = \sum_{i \in N_g} [C_i(P_{Gi}) + C_i(Q_{Gi})] \qquad -----(1)$$

Subject to the relevant equality and inequality constraints

$$P_{Gi} - P_{Di} - \sum_{j \in N} |V_i||V_j||Y_{ij}|\ Cos(\theta_{ij} + \delta_j - \delta_i) = 0 \qquad -----(2)$$

$$Q_{Gi} - Q_{Di} - \sum_{j \in N} |V_i||V_j||Y_{ij}|\ Sin(\theta_{ij} + \delta_j - \delta_i) = 0 \qquad -----(3)$$

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}\ i \in N_G \qquad -----(4)$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}\ i \in N_G \qquad -----(5)$$

$$|P_{ij}| \le P_{ij}^{max}\ i \ne j\ i, j \in N \qquad -----(6)$$

Where

P_{Gi}, Q_{Gi} are the real power and reactive power generated at $\boldsymbol{i^{th}}$ bus
P_{Di}, Q_{Di} are the real power demand and reactive power demand at i^{th} bus
$C_i(P_{Gi})$ is the cost of the active power at i^{th} bus
$C_i(Q_{Gi})$ is the cost of the reactive power at i^{th} bus
V_i is the voltage at i^{th} bus
V_j is the voltage at j^{th} bus
Y_{ij} is the bus admittance matrix
θ_{ij} is the angle of bus admittance matrix
δ_i is the voltage angle at i^{th} bus
δ_j is the voltage angle at j^{th} bus
P_{ij} is the power flow from i^{th} bus to j^{th} bus

Finally the cost of the real power is computed using the formula

$$C_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \qquad -----(7)$$

and the cost of the reactive power is computed using the following formula:

$$C_i(Q_{Gi}) = \left[C_i(S_{Gi,max}) - C_i\left(\sqrt{S_{Gi,max}^2 - Q_{Gi}^2}\right)\right] K_{Gi} \qquad -----(8)$$

Where a_i, b_i and c_i are the cost coefficients
S_{Gimax} is the maximum value of complex or apparent power at i^{th} bus
K_{Gi} - assumed profit rate for real power generation at i^{th} bus

The total cost of the reactive power support at i^{th} generator, C_{qi} can be represented as

$$C_{qi} = C_{qi}^0 + C_{qi}^{RR} \qquad -----(9)$$

Where C_{qi}^0 is the cost of reactive power from the $\boldsymbol{i^{th}}$ generator and it supports the transportation of real power and supplies reactive loads at certain operating interval.

The cost of the effective reactive power reserve C_{qi}^{RR} from i^{th} generator will be

$$C_{qi}^{RR} = C_q^{rr} Q_{gi-eff}^{RR} \qquad -----(10)$$

Where C_q^{rr} is the unit cost charged to avail the reactive power reserve per $MVArh$ and Q_{gi-eff}^{RR} is the effective reactive power reserve available at the i^{th} generator. It is assumed that the value of C_q^{rr} is decided by the system operator.

Methodology

Artificial Immune System

The Artificial immune system algorithms are Meta heuristic optimization method, which are used for clustering and pattern recognition applications. These algorithms used in multimodal optimization problems are more efficient than genetic algorithms. Artificial immune system uses an idea which is taken from immunology in order to develop systems capable of performing different tasks in various areas of research. The authors are reviewing the clone selection concept together with the affinity maturation process and demonstrate that these biological principles can be very useful for the development of useful computational tools. A major drawback in these algorithms is their slow convergence to global optimum and their weak stability, which needs to be considered while running these algorithms. The artificial immune system optimization technique is implemented in following steps: first the initial values for the reactive power supports are generated randomly. After implementing the load flow, the total system losses are calculated.

Modified Artificial Immune System (MAIS)

The Modified Artificial Immune system is a latest biomedical optimization algorithm used to find the best global solution among a variety of local solutions. The main characteristic of the Immune System (IS) is that it must fight against external intruders (nonself) however should be tolerant with body cells (self). The main characters of IS are

- antigen (Ag): any substance capable of triggering an immune response;
- antibody (Ab): molecule (lymphocytes) that can match and counteract Ag.

The Modified Artificial Immune System is a biologically based optimization method modified from the existing Artificial Immune System. This algorithm considers some immune particles, which is a candidate for finding the solution in the searching space limited by Optimal Power Flow (OPF) constraints. The immune particles try to find the best optimum solution in the dynamic space after a successful mutation and cloning of the entire immune particles. In MAIS, a percentage of non-optimum values are eliminated and new particles are generated randomly for improving the performance of the optimization method, in terms of time, accuracy and new immune particles. Comparing with cloned immune particles, the best solution for the optimized problem is achieved by itself and by the whole group within a time interval and number of iterations.

The MAIS, like the original AIS algorithm was originally proposed for continuous problems and extended to discrete optimization problems as well.

Algorithm of MAIS

- Start
- Initialize Population
- Repeat
- Clone
- Mutate
- Selection
- If [Converge Satisfaction is false] then go to Repeat
- Else Stop

First, the initial values for the reactive power supports are generated randomly. After implementing the load flow, the total system losses are calculated. This technique is repeated until ten values of total losses subject to voltage range are obtained at each bus. As a second step, the size of the reactive power support and losses are cloned. Then, the value of the clone is mutated and the load flow is run again and the new value of total system loss is obtained. The process is repeated until the minimal total system loss is obtained.

Pseudo Code of MAIS

1. Assume P is the number of population and R is the number of iterations.
2. δ is the minimum of P.
3. Set an optimal value of cRa, cRl, cL, cI // which is the obtained optimum value using value based approach.
4. $TC = cRa + cRl + cL + cI$
5. Generate a random population on each individual on P.
6. Due to R, P retrieve 'm' number of individuals which are elected as E.

   Where E $= \{cRa, cRl, cL, cI\}$
7. E should maximize the expected profit
8. E should minimize the production cost.
9. Find out the similarity measurement SM for each individual using objective calculation. Then elect the individuals according to the SM, where the election rate E is proportional to SM.
10. If $(\min(\mathrm{OFV(E)}) < \mathrm{OFV(ValueBased\ Approach)})$,
11. Then $\mathrm{OPTV} = \mathrm{OFV(E)}$ Else $\mathrm{OPTV} = \mathrm{OFV(AIS)}$ and End
12. Change E by pairwise changing or inverse order and find OFV.
13. If $[\mathrm{S(NE)} == \mathrm{S(E)}$ then Eliminate S from $E]$ or Eliminate $\left[\mathrm{Eliminate\ S(E)} == \max\left(\mathrm{OFV(E)}\right)\right]$ and Repeat step 9.
14. Change E by pairwise and find OFV and Repeat step 5.
15. Retrieve next E from P and Repeat step 5, until obtain the best OFV and assign in δ.
16. Display $OFV(\delta)$ with the corresponding individual S, then stop.

Simulation Results

The simulation results obtained from MAIS for complete reactive power, P_{loss}, Q_{loss} MVAr, MW, convergence time for various buses are computed and calculated for 75-bus Indian system as given below.

Table 1: Existing Vs Proposed Global Best Position and Size

Approach	SVC size MVAR	Total P_{loss} MW		Total Q_{gen} MVAR	
		Before SVC	After SVC	Before SVC	After SVC
Existing	40.83	74.948	73.888	330.63	325.11
Proposed	40.83	73.888	72.897	325.11	324.765

Table 1 can also be graphically reproduced as bar charts in Figure 1, which depicts Total real power loss (P_{loss}) in MW and Total reactive power Generation (Q_{gen}) before and after the employment of the same fixed size of SVC in MVAR for both the existing and proposed method. It is observed that the location of an SVC strongly affects controllability of the swing modes. In general the best location is at a point where voltage swings are the greatest. Normally, the mid-point of a transmission line between the two areas is a good candidate for placement. Figure 3 represents the cost analysis charts for Minimum reactive power cost, Maximum reactive power cost, Average reactive power cost and Standard deviation of reactive power cost for various evolutionary multi-objective optimization algorithms like PSO, HPSO and MAIS. It is also inferred that our proposed algorithm (MAIS) has reduced cost of reactive power for various criteria of cost analysis.

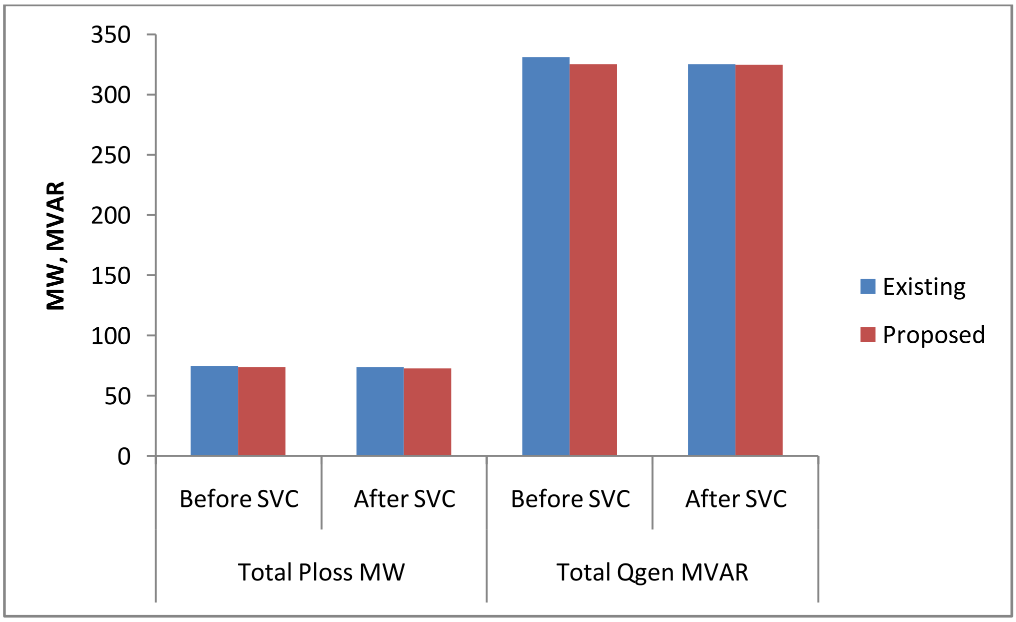

Figure 1: Existing Vs Proposed Global Best Position and Size

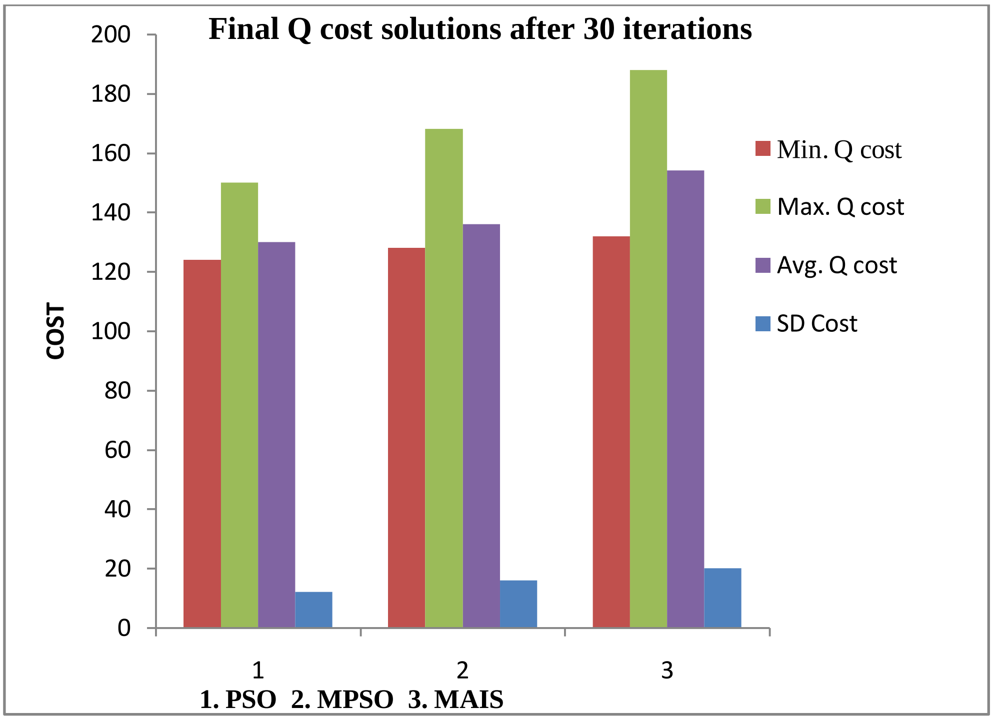

Figure 2: Cost Analysis

Table 2 depicts the parameter values adopted in various algorithms like PSO, HPSO and MAIS. C1 and C2 are the learning factors which play a vital role in obtaining global optimum solutions. Crossover should have a very good convergence characteristics and mutation probability should be very low to obtain the best optimum solution. MAIS evaluate and choose the optimum parameters to obtain optimum cost.

Table 2: Parameter Values for MAIS, PSO and HPSO

Parameters	PSO	HPSO	MAIS
No. of variables	50	50	50
Population Size	50	50	50
No. of iterations	100	100	100
C1	2	2	2
C2	0.3 - 0.95	0.3 – 0.95	0.3 – 0.95
Crossover probability	-	0.5	0.5
Mutation probability	-	0.1	0.1

Case Study

Practical 75-bus Indian System
Figure 3 shows the single line diagram of the practical 75-bus Indian System. The proposed static and dynamic value based cost allocation approach for reactive power support is tested and analyzed on practical 75-bus Indian test system which comprises 15 generators, 97 transmission lines and 60 load buses where it stand for 400, 220 and 132KV network of one of the electricity boards in India.

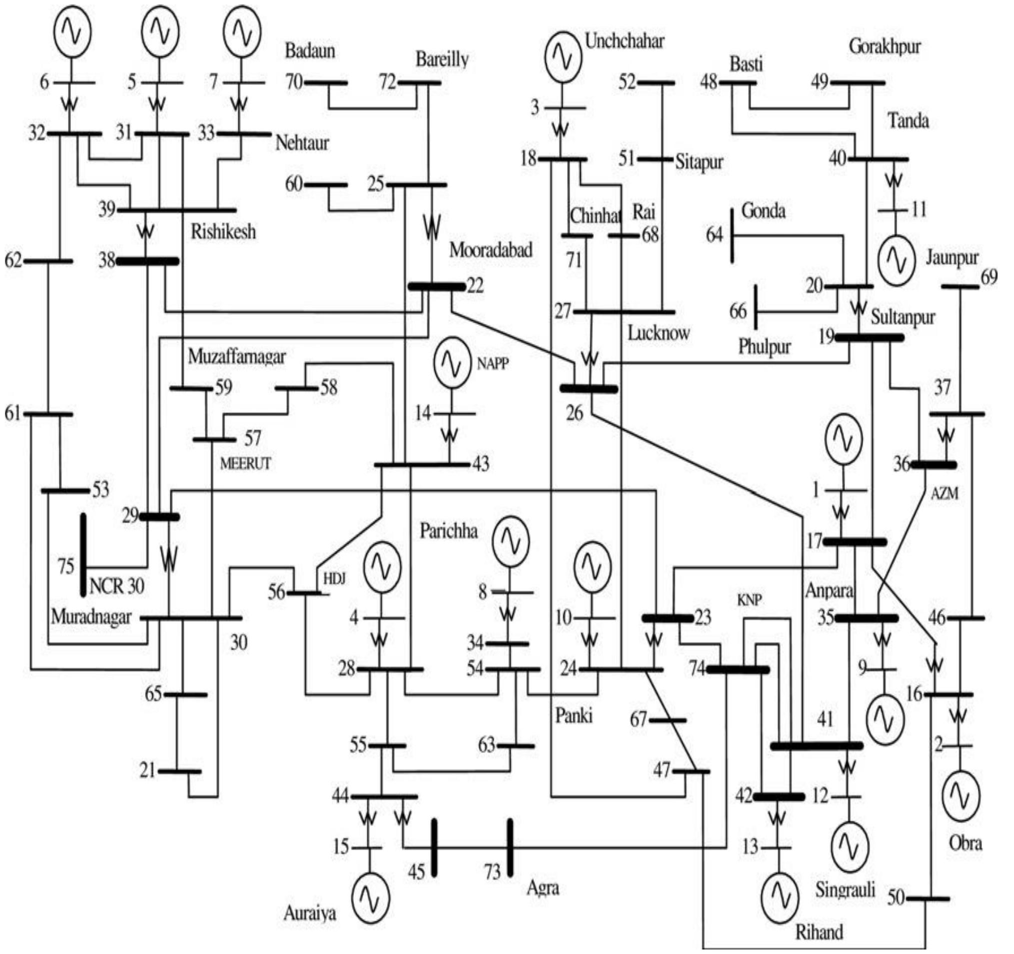

Figure 3: Single Line Diagram of practical 75-bus Indian System

The results obtained from MAIS are compared with the results of the PSO, HPSO and a value based approach and depicted in Table 3.

It is examined and proved that the separation of various cost components for reactive power payments obtained from MAIS is minimum compared to other algorithms like the Value based approach, HPSO, PSO and will provide more transparency to the customers in the electricity market.

Table 3: Cost Based Comparison of PSO, HPSO, Value Based Approach and MAIS

COST	PSO	HPSO	Value Based Approach	**MAIS**
C_q^0, Rs/h	1,22,252.265	1,46,470.00	95 398.19	**95086.35**
C_q^{RR}, Rs / h	2987.765	1876.450	735.20	**591.67**

Conclusion

Numerous algorithms are available for finding the objective functions of reactive power dispatch focused on the technical side of the reactive support like minimizing the power loss. In this paper, the generator cost of reactive support from generation sources are optimized. This paper utilizes MAIS to minimize the total cost of the reactive power support and determines the resultant reactive profile. The compensation using SVC in wind farms (practical 75-bus Indian System) from various LSEs has been determined from the value of their VAr utilization. The MAIS algorithms incorporate the local search technique by removing worst immunes and generating random new immunes for the next iteration of the optimum cost generation. The proposed algorithm applied to practical 75-bus Indian system is compared with a value based approach and evolutionary multi-objective optimization algorithms like PSO and HPSO and observed a faster convergence. Computations performed using the proposed approach provides the optimum cost by concentrating on both dynamic and static variables used in the reactive power resources. It is observed that the cost and the allocations to LSEs at various buses in different time interval are followed in real time functionality. MAIS helps to provide compensation towards valuable reactive reserves to enable the system safety along with the compensation for its utilized capacity which consists of the support for supplying the reactive loads and the additional reactive power transmission losses for MW load shipment. MAIS reduces the cost in terms of useful reserve capacity and the cost of VArs.

References

[1] Krishnan, V. ,Das, T. , Ibanez, E. , Lopez, C.A. et.al, 2013, “Modeling Operational Effects of Wind Generation Within National Long-Term Infrastructure Planning Software,” IEEE Trans. on Power Sys., Vol.28, pp. 1308 – 1317**.**

[2] Vaskar Sarkar and S. A. Khaparde, 2013, “Reactive Power Constrained OPF Scheduling With 2-D Locational Marginal Pricing,” IEEE Trans. on Power Sys., Vol. 28, No. 1, pp. 503 – 512.

[3] Z. Hamid, I. Musirin, M. N. A. Rahim, N. A. M. Kamari, 2012, “Optimization Assisted Load Tracing via Hybrid Ant Colony Algorithm for Deregulated Power System,” WSEAS Trans. on Power Sys., Issue 3, Volume 7, pp.145 – 158.

[4] Faisal B. Alhasawi and Jovica V. Milanovic´, 2012, “Techno-Economic Contribution of FACTS Devices to the Operation of Power Systems with High Level of Wind Power Integration,” IEEE Trans. on Power Sys., Vol. 27, No. 3, pp.1414 – 1421.

[5] Mala De, Swapan K. Goswami, 2012, “Reactive power cost allocation by power tracing based method,” Elsevier, Energy Conversion and Management 64, pp. 43–51.

[6] K. Singh, N. P. Padhy, and J. Sharma, 2011, “Influence of price responsive demand shifting bidding on congestion and LMP in pool-based dayahead electricity markets,” IEEE Trans. Power Sys., vol. 26, no. 2, pp.886–896.

[7] K. C. Almeida, and F. S. Senna, 2011, “Optimal Active-Reactive Power Dispatch Under Competition via Bilevel Programming,” IEEE Trans. on Power Sys., Vol. 26, No. 4, pp.2345 – 2354.

[8] RaminJavadzadeh., Zahra Afsahi and Mohammad RezaMeybodi, 2011, “Improved Artificial Immune System Algorithm with Local Search,” World Academy of Science, Engineering and Technology, International Science Index Vol 5, No. 11, pp. 437 – 440.

[9] M. S. S. Rao, S. A. Soman, Puneet Chitkara, Rajeev Kumar Gajbhiye, N. Hemachandra, and B.L. Menezes, 2010, “Min-Max Fair Power Flow Tracing for Transmission System Usage Cost Allocation: A Large System Perspective,” IEEE Trans. on Power Sys., Vol. 25, No. 3, pp.1457 – 1468.

[10] Parida S.K., Singh S.N. and Srivastava S.C., 2009, “Reactive Power Cost allocation by using a value-based approach,” IET Gen., Trans. & Dist., Vol.3, Issue 9, pp. 872-884.

[11] S. Hasanpour, R. Ghazi, M. H. Javidi, 2009, “A new approach for cost allocation and reactive power pricing in a deregulated environment’, Electrical Engg., Springer 91, pp. 27–34.

[12] Nayeem Rahmat Ullah, Kankar Bhattacharya, Tobrjorn Thiringer, 2009, “Wind Farms as Reactive Power Ancillary Service Providers – Technical and Economic Issues,” IEEE Trans. on Energy Conv., Vol.24, No.3, pp.661-671.

[13] Hadi Banakar, Changling Luo, and Boon Teck Ooi, 2008, “Impacts of Wind Power Minute-to-Minute Variations on Power System Operation,” IEEE Trans. on Power Sys., Vol. 23, No. 1, pp.150 – 160.

[14] Meei-Song Kang, 2007, “Generation Cost Assessment of an Isolated Power System with a Fuzzy Wind Power Generation Model,” IEEE Trans. on Energy Conv., Vol.22, No.2, pp. 397-404.

[15] Wenjuan Zhang, Fangxing Li, and Leon M. Tolbert, 2007, “Review of reactive power planning: Objectives, Constraints and Algorithms,” IEEE Trans. on Power Sys., Vol. 22, No. 4, pp.2177 – 2186.

[16] K. S. Verma and H. O. Gupta, 2006, “Impacts on Real and Reactive power Pricing in Open Power Market using UPFC,” IEEE Trans. on Power Sys., Vol. 21, No. 1, pp. 365 – 371.