APPLICATION OF FULLY INFORMED PARTICLE SWARM OPTIMIZATION IN SMART TRANSMISSION GRID

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ABSTRACT—*Smart transmission grid is envisioned to operate more efficiently as compared to the existing grid. About 10% of the total generation is dissipated in the form of transmission losses. Future load growth demands installation of new generation plants which can be deferred through released capacity from the efficient operation of the existing grid. This paper demonstrates the application of fully informed particle swarm optimization (FIPSO) in transmission loss reduction. The control parameters considered to achieve this objective include generator voltage magnitude control, generator active power control, static var compensators (SVCs) reactive power control, and on-load tap changers (OLTCs) tap-position control. The simulation study is performed using Ward-Hale 6-bus system and standard IEEE 30-bus system. Comparison with other algorithms suggests the FIPSO as a potential candidate for the future operation of the transmission grid.*

Index Terms— Fully informed particle swarm optimization (FIPSO), Heuristic search methods, Optimal power flow (OPF), Power transmission loss, Smart transmission grid.

I. INTRODUCTION

The transmission system is meant to transmit electrical energy from the generation plants to the load centers. Generation plants can be located several hundred kilometers far from the load centers. Resistance of the transmission line increases linearly with the length. Therefore, the power loss occurring across the transmission lines increases. Transmission losses are typically 10% of the total generation [1]. New generation plants needs to be installed in order to cater the future load growth. Smart transmission grid [2] is envisioned to release the capacity by operating efficiently. This efficient operation will reduce the power transmission losses and will defer the need of immediate installation of new generation plants. Additionally, revenue of transmission companies will be increased as they will purchase less power from the generation companies.

Energy management system (EMS) [3] is the real-time monitoring and decision support tool for the transmission systems. It receives the time-stamp input monitoring signals from the phasor measurement units (PMUs). Decision support tool will compute the required control actions using optimal power flow (OPF). The OPF [4] is an important optimization problem in the electric power system. It can be single- or multi- objective optimization problem. Some of the potential optimization objectives include minimum shift of generation from some optimum point, reduction of fuel emissions, reduction of transmission losses, and reduction of generation cost. According to [5], the process of reducing the resistance for power transmission loss reduction using physical changes such as reconductoring and installation of additional transmission circuits is a costly solution and requires longer time to implement. The paper suggested the OPF based voltage related adjustments as an effective solution.

The fully informed particle swarm optimization (FIPSO) was introduced in 2004 [6]. It is the variant of conventional particle swarm optimization (PSO). The PSO is one of the most prominent heuristic optimization algorithms available. It has the ability of parallel computation which makes it fast, robust, and an ideal candidate for the real-time or near real-time applications. The FIPSO differs from the conventional PSO in the sense that it updates its velocity in each iteration by accounting the information available from all the neighborhood particles rather than considering only the best particle. This strategy makes it fully informed.

The objective function of the OPF problem can be computed using analytical techniques as well as heuristic optimization techniques. Differential evolution PSO [7], which is a blend of PSO and differential evolution methods, is used for reducing transmission losses in the power system. Here, differential evolution PSO resulted in high quality solution with small computational time as compared to several other heuristic and conventional methods. Similarly, the cost minimization [8] is performed by using the conventional PSO. The interior point method [9], an analytical technique, can be used for the solution of constrained optimal power flow. The OPF [10] incorporating flexible AC transmission system (FACTS) devices can optimize the power flow without requiring the generation rescheduling.

This paper presents the application of FIPSO for transmission losses reduction. The control variables considered are generator voltage magnitude control, generator active power control, static var compensators (SVCs) reactive power control, and on-load tap changers (OLTCs) tap-position control. The simulation studies are performed using Ward-Hale 6-bus system [11] and IEEE 30-bus system.

II. PROBLEM FORMULATION

Power losses are distributed over branches in the transmission system. Simple addition of losses occurring in each branch will result in total losses occurring in the entire transmission system. Mathematically, it can be expressed as:

$$P_{Loss} = \sum_{i=1}^{N} P_i \qquad (1)$$

where P_{Loss} is total transmission losses, N is the total number of branches in transmission lines, and P_i is the *ith* branch loss.

Equation (1) is subjected to various equality and inequality constraints. Equality constraints include active and reactive power flow equations. Performing load flow analysis will ensure the compliance of the equality constraints. Inequality constraints on control variables include generator voltage limits, generator active power limits, SVCs' reactive power limits, and OLTCs' tap-position limits. The deviations of the state variables from the desired values can be accounted for by using penalty function approach which can be added in

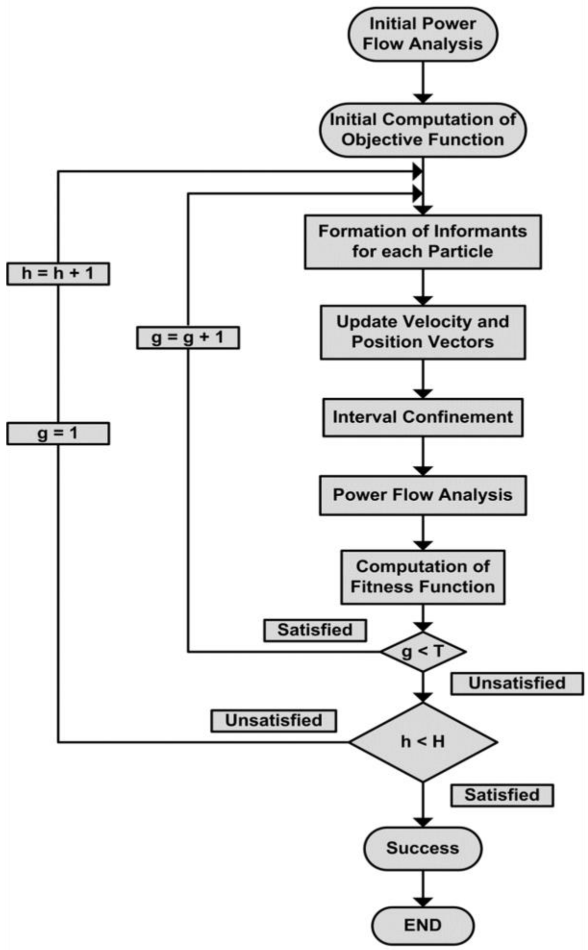

Fig. 1. Complete Flowchart of FIPSO-OPF

(1).

The particles in conventional PSO update their position and velocity vectors by considering the information provided by the single best informant in their neighborhood. Over trusting the single best informant can lead to sub-optimal solution. The FIPSO was introduced as a variant of PSO in 2004. In FIPSO, the particle updates its velocity by considering each and every particle present in the swarm rather than just the best one. The velocity update equation for k^{th} particle and d^{th} dimension can be mathematically expressed as:

$$vv_{k,d} = cc\left[vv_{k,d} + \sum_{i=1}^{M} \frac{U(0,\delta)\ (PP_{k,d(n)} - p_{k,d})}{M}\right] \qquad (2)$$

where *cc* is the constriction coefficient, *M* is the total number of informants, *U(0,δ)* is the uniformly distributed random numbers between 0 and constant δ, and $pp_{k,d(n)}$ is the best position attained by i^{th} informant of particle *k* so far.

III. INTEGRATING FIPSO WITH OPF

The OPF has objective function along with control variables, state variables, and fixed parameters of the transmission system. The control variables can be adjusted to any value within their limits. Following the adjustments of the control variables, the state variables will adjust themselves accordingly and their current values can be determined by running the load flow program. The active power transmission loss can be computed after the determination of the values of the control variables, state variables, and fixed parameters. The fixed parameters include various entities such as reactance of transmission line.

The OPF handles the inequality constraints on control and state variables. The set-to-middle approach (SMA) is used for control variables during limit violations. The SMA will put the control variable in the middle of its lower and upper limits. This approach seems to yield better results as compared to the conventional approach of putting the variable to either at upper or lower limit. After executing SMA, the velocity of the corresponding particle will be set to zero value. Penalty function can be used to tackle the inequality constraints on state variables.

The centralized control scheme is used. It is assumed that all the monitoring signals will be fed to central controller under EMS. The optimization engine of the EMS will use the FIPSO-OPF to determine the optimal values while satisfying the equality and inequality constraints. The optimal values of control variables will result in minimum power transmission loss.

A comprehensive flowchart depicting the integration of FIPSO with OPF is shown in fig. 1. Total number of iterations is indicated by *H*, swarm size is indicated by *T*, current particle is represented by *g*, and current iteration is represented by *h*.

The objective function will be evaluated multiple times during the optimization process as is apparent from fig. 1. The stopping criteria can be either the maximum number of iterations or the computation of tolerance after each iteration. In case of maximum number of iterations as a stopping criterion, the total number of computation of objective function is equal to the product of total number of particles and the total number of iterations.

Table I
FIPSO-OPF for Ward-Hale 6-bus System

Iter.	T	SD	AVG	MAX	MIN
5	15	0.0969	7.8853	8.1429	7.7541
	30	0.0798	7.8166	7.9766	7.6920
	40	0.0545	7.8017	7.8872	7.6896
15	15	0.0456	7.7308	7.8530	7.6698
	30	0.0242	7.6954	7.7351	7.6464
	40	0.0198	7.6893	7.7192	7.6422
25	15	0.0449	7.7064	7.8131	7.6548
	30	0.0434	7.6982	7.8150	7.6462
	40	0.0238	7.6654	7.7079	7.6020
35	15	0.0519	7.6966	7.8482	7.6309
	30	0.0420	7.6539	7.7133	7.5383
	40	0.0394	7.6556	7.7133	7.5598
45	15	0.0631	7.6691	7.8300	7.5787
	30	0.0377	7.6456	7.7243	7.5735
	40	0.0442	7.6377	7.7036	7.5450

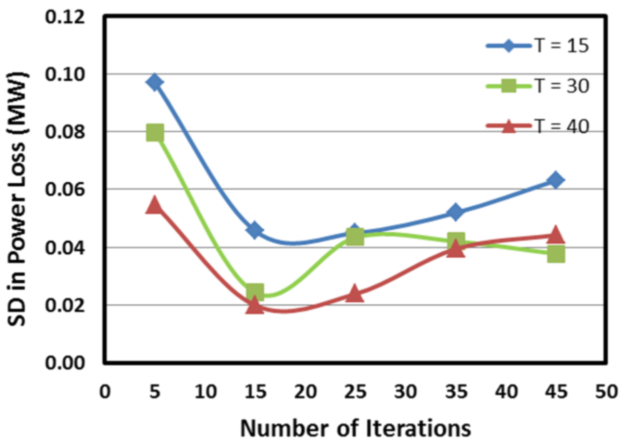

Fig. 2. Characteristic of FIPSO-OPF w.r.t SD in power loss

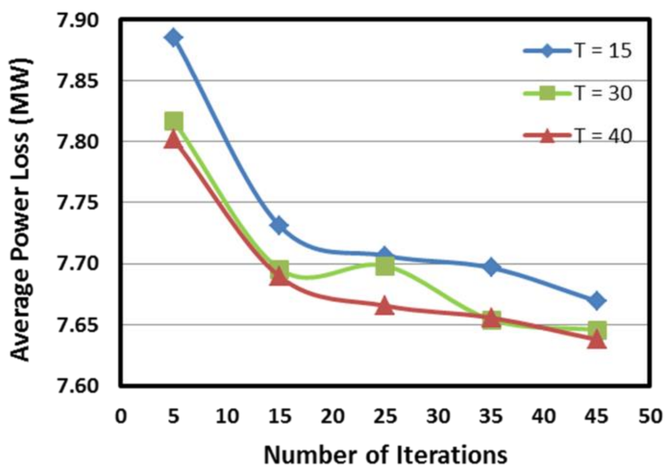

Fig. 3. Characteristic of FIPSO-OPF w.r.t average power loss

IV. SIMULATION STUDIES AND RESULTS

The simulation studies are performed to test the FIPSO-PSO algorithm using Ward-Hale 6-bus system and standard IEEE 30-bus system. The authenticity of the computed results is ensured by performing twenty successive trials for each instance. We performed successive trials as these include all the worst and best results rather than performing more than twenty trials and selecting the best twenty among them.

Possible criteria for performance evaluation of FIPSO-OPF include minimum power loss, maximum power loss, average power loss, and standard deviation (SD) in power loss. Considering standard deviation (SD) or average power loss alone can lead to misleading interpretation of results. We have considered both average power loss and SD in power loss for the performance evaluation. The implementation of FIPSO-OPF algorithm is meant to decrease the power losses occurring in the transmission system. Initial active power loss was 15.29MW and 17.59MW for Ward-Hale 6-bus system and IEEE 30-bus system respectively.

The results of FIPSO-OPF for Ward-Hale 6-bus system are summarized in Table I. Several distinct number of iterations and swarm sizes are used to compute the results. All the power losses are mentioned in MW. The minimum power loss of 7.5383MW occurs for swarm size of 30 at iteration 35. The minimum value of average power loss is 7.6377MW for swarm size of 40 at iteration 45. This depicts the efficiency of FIPSO-OPF algorithm as it reduced the power loss from the initial value of 15.29MW.

Fig. 2 shows the relationship of SD in power loss with swarm size and number of iterations. It is apparent from the graph that increasing the swarm size decreases the SD in power loss. The smaller the SD in power loss is, the consistent the results of FIPSO-OPF algorithm is. It is well known that FIPSO will result in near-global solution as compared to the global one. In case of analytical or deterministic approach, we can get absolute global solution while heuristic techniques like FIPSO will yield near-global result. Smaller value of SD will ensure that FIPSO-OPF will yield near-global solution almost each time.

Fig. 3 shows the relationship of average power loss with swarm size and number of iterations. It is apparent from the graph that increasing the swarm size decreases average power loss. Moreover, increasing the number of iterations up to 15 results in a very rapid fall of average power loss. After iteration 15, the increase in the number of iterations results only in modest decrease in power loss. The swarm size of 20 to 40 is suggested to be sufficient for every type of optimization problem [12]. Considering the swarm size more than 40 will most probably result in the increase of computational time with only slight improvement in performance. This demands a trade-off between computational time and desired level of improvement in result. This trade-off becomes critical for real-time or near real-time operations.

The results of FIPSO-OPF for IEEE 30-bus system are summarized in Table II. Again, several distinct number of iterations and swarm sizes are used to compute the results. All the power losses are mentioned in MW. The minimum power loss of 3.7319MW occurs for swarm size of 30 at iteration 25. The minimum value of average power loss is 3.8987MW for swarm size of 40 at iteration 45. The minimum value of maximum power loss is 4.0887MW for swarm size of 30 at iteration 45. This depicts the efficiency of FIPSO-OPF algorithm as it reduced the power loss from the initial value of 17.59MW.

Table II
FIPSO-OPF for IEEE 30-bus System

Iter.	T	SD	AVG	MAX	MIN
5	18	0.3150	4.6931	5.2510	4.2843
	30	0.2172	4.6298	4.9815	4.2981
	40	0.2257	4.4702	4.8179	3.9906
15	18	0.0871	4.1127	4.2601	3.9354
	30	0.1297	4.0652	4.3431	3.8412
	40	0.1315	4.0606	4.3223	3.8243
25	18	0.1358	4.0996	4.3842	3.8234
	30	0.1125	3.9874	4.1499	3.7319
	40	0.1118	3.9648	4.2090	3.7320
35	18	0.1008	4.0003	4.2125	3.7992
	30	0.0979	3.9700	4.0989	3.7943
	40	0.0891	3.9601	4.1208	3.8059
45	18	0.0893	4.0000	4.1602	3.8406
	30	0.0989	3.9304	4.0887	3.6908
	40	0.0913	3.8987	4.1268	3.7371

Fig. 4 shows the relationship of SD in power loss with swarm size and number of iterations. It can be observed that increasing the swarm size decreases the SD in power loss. The smaller the SD in power loss is, the consistent the results of FIPSO-OPF algorithm is. Fig. 5 shows the relationship of average power loss with swarm size and number of iterations. It can be seen that increasing the swarm size decreases average power loss. Moreover, increasing the number of iterations up to 15 results in a very rapid fall of average power loss. After iteration 15, the increase in the number of iterations results only in modest decrease in power loss. When comparing it with fig. 3, it is interesting to note that the pattern is almost similar for both Ward-Hale 6-bus system and IEEE 30-bus system. This comparison also indicates the accuracy of the implementation as well as the suitability of FIPSO-OPF algorithm for practical power system operation.

The optimal settings of control variables required to achieve the minimum power transmission loss in Ward-Hale 6-bus system are summarized in Table III. Similar optimal settings for IEEE 30-bus system are summarized in Table IV. These settings are of practical nature. By configuring the power system control to these values will result in minimum power loss provided the same load is existing as was used during this simulation study. These control settings will be changed with load variations.

V. DISCUSSION

The twenty successive trials for the computation of each instance indicate the authenticity of the results computed. It is established that increasing the number of iterations resulted in lower value of power transmission loss. Similarly, increasing the swarm size also resulted in lower value of power loss. The consistent and reliable results are required for the OPF as it is a real-time optimization problem. The consistency can be established by having the lower value of standard deviation in power loss. The reliability can be ensured by having the lower value of average power loss. Combine analysis of SD and average power loss will indicate the true picture of the performance of FIPSO-OPF.

A comparison with other optimization techniques can indicate the potential of FIPSO for OPF problem. For IEEE 30-bus system, reference [13] computed 6.49MW, 4.27MW, and 4.98MW of minimum power loss using EP, PSO, and NCPSO respectively. These results are much greater than 3.7319MW using FIPSO-OPF. Similarly, reference [8] used PSO to compute minimum power loss of 6.23MW for IEEE 30-bus system which is greater than FIPSO-OPF result. For Ward-Hale 6-bus system, reference [11] used Power Loss Minimization (PLM) and computed 8.47MW of minimum power loss which is on higher side as compared to 7.5383MW using FIPSO-OPF. These improved results are depicting the efficiency of FIPSO as well as the effectiveness of set-to-middle approach used in this research work instead of set-to-limit approach for control variables violating the limits.

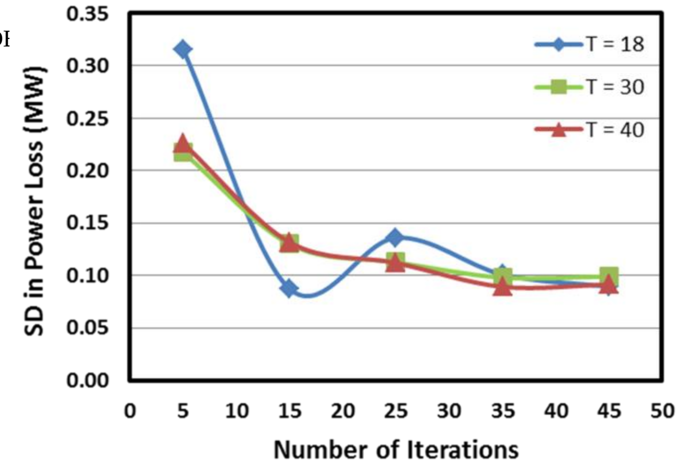

Fig. 4. Characteristic of FIPSO-OPF w.r.t SD in power loss

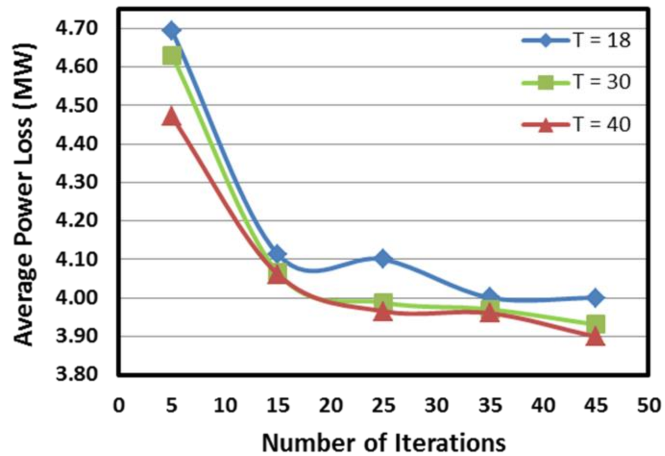

Fig. 5. Characteristic of FIPSO-OPF w.r.t average power loss

VI. CONCLUSION

Smart transmission grid is envisioned to operate more efficiently as compared to the existing grid. This paper demonstrates the application of fully informed particle swarm optimization (FIPSO) in transmission loss reduction. The control parameters considered to achieve this objective include on-load tap changers (OLTCs) tap-position control, static var compensators (SVCs) reactive power control, generator active power control, and generator voltage magnitude control. The simulation study is performed using Ward-Hale 6-bus system and standard IEEE 30-bus system. Comparison with other algorithms suggests the FIPSO as a potential candidate for the future operation of the transmission grid. Sufficient power

Table III
Settings of Control Variables for Ward-Hale 6-bus System

T	15	30	40
P_{loss} (MW)	7.6523	7.5787	7.5703
$P_{GEN,\,2}$ (p.u)	0.2816	0.2776	0.2964
V_2 (p.u)	1.0676	1.0811	1.0701
T_6	1.00	0.94	0.96
T_4	1.00	0.99	1.00
$Q_{comp,4}$ (p.u)	0.30	0.35	0.24
$Q_{comp,6}$ (p.u)	0.44	0.34	0.47

Table IV
Settings of Control Variables for IEEE 30-bus System

T	18	30	40
P_{loss} (MW)	4.0019	3.9522	3.8497
$Q_{comp,10}$ (p.u)	0.2200	0.2200	0.2700
$Q_{comp,24}$ (p.u)	0.2600	0.2000	0.2000
T_{28}	0.9800	0.9800	0.9900
T_4	0.9800	0.9800	0.9800
T_6	0.9800	0.9800	0.9800
T_9	0.9800	0.9800	0.9700
V_{13} (p.u)	1.0250	1.0250	1.0250
V_{11} (p.u)	1.0250	1.0250	1.0250
V_8 (p.u)	1.0250	1.0250	1.0250
V_5 (p.u)	1.0250	1.0250	1.0250
V_2 (p.u)	1.0250	1.0250	1.0250
$P_{GEN,\,13}$ (p.u)	0.3745	0.3195	0.3816
$P_{GEN,\,11}$ (p.u)	0.2806	0.2906	0.2523
$P_{GEN,\,8}$ (p.u)	0.5422	0.4867	0.5347
$P_{GEN,\,5}$ (p.u)	0.4937	0.4860	0.4992
$P_{GEN,\,2}$ (p.u)	0.5114	0.7799	0.7657

loss reduction as compared to the other techniques advocates the FIPSO to be integrated into the OPF problem. We can conclude that FIPSO is an ideal candidate for OPF problem.

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