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Improvement of Power System Loading Margin with Reducing Network Investment Cost Using SVC

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Abstract **- Under emergency conditions to reduce the harms from environmental deterioration, one of the recently focused developments in the power industry is to make the existing transmission networks sufficiently utilize their capability in power transfer. From the detailed analysis and many studies, voltage instability was found to be the main factor responsible for several blackout events. As an index to indicate the level of static voltage stability of a transmission system, the Loading Margin (LM) or Voltage Stability Margin (VSM), represents the maximum power that can be transferred between generators and loads before voltage collapse point achieved is generally measured in system planning. In this paper, under each contingency with high Risk Index (RI) value, the Modal Analysis (MA) technique is used to determine which buses need Static VAR Compensator (SVC) installation, and with maximum LM and minimum SVC installation cost composed into the multi-objective function. The optimal LM enhancement problem is formulated as a multi-objective optimization problem (MOP) and solved by using the fitness sharing multi-objective particle swarm optimization (MOPSO) algorithm for a Pareto front set. The proposed method may be tested on the IEEE 24-bus reliability test system (RTS) and IEEE 14-bus system.**
Keywords: **Loading Margin, Modal Analysis, Optimal SVC Placement, Multi Objective OPF, Outage Risk Index**

I. INTRODUCTION

Now a day the power system becomes more complex to operate and system becomes less secure for riding through the major outages. The power system must be capable to withstand for the loss of any power system components without disturbing the normal operation. Line outage is commonly used for security analysis of the power system. Based on this criterion, critical contingency lines have been identified and ranking is given. The analysis of optimal power flow problem with outage comes under the security constrained optimal power flow problem .The outage in the power system leads to over loading of lines voltage violation at the buses for secure operation. The facts devices will help to maintain the system security under contingencies by reducing the power flows of heavily loaded lines and maintain the bus voltage magnitude at desired levels.

This is an approach for determining the most suitable locations for installing static VAR compensator (SVC) in order to eliminate lines voltage violations at the buses under contingency analysis. Under urgency to diminish the harms from environmental deterioration, one of the recently focused researches in the power industry is to make the existing transmission networks sufficiently utilize their capability in power transfer [1]–[3]. Through detailed studies, voltage instability was found to be the main factor responsible for several blackout events in the recent years [4]. As an index to indicate the level of static voltage stability of a transmission system, the loading margin (LM) or voltage stability margin (VSM), representing the maximum power that can be transferred between generators and loads before voltage collapse point achieved is generally measured in system planning [5], [6]. The optimal flexible ac transmission systems (FACTS) installation had been researched and discussed widely and several strategies were proposed. In general, the studies are oriented towards technical, economic, or both concerns.

In technical concerns, the method proposed in [3] practically installed different types of FACTS devices on different locations to identify the increase of LM. While in [7], a two-stage SVC installation method is proposed. In stage one, LM is increased on a step-by-step basis and, in each step, to provide sufficient reactive power from an SVC installation, the location and its capacity are determined by using a genetic algorithm (GA), and, in stage two, under different contingencies the control signals to the SVC installation are determined based on various stability indices. The method proposed in [8] used GA to determine the locations and capacities for the respective installations of various types of FACTS devices for LM enhancement.

While in [9], modal analysis (MA) technique and a guaranteed convergence particle swarm optimization (GCPSO) algorithm are used to determine the locations for SVC installation and the capacities to enhance LM. With the compensation of SVC, TCSC, and UPFC installations, in [10], the singular value / Eigen value decomposition analysis of the load-flow Jacobian and the controllability characteristics of an equivalent state model are used to study the voltage instability phenomenon as well as to assess the potential for small-signal voltage stability improvement. Considering contingencies, in [11], tangent vector technique and reactive power sensitivity index were adopted as reference indices to point out the locations suitable for installations of the parallel and series FACTS devices. As specific contingencies are identified to be the main factors that result in voltage instability, [12] expressed line outages with stochastic model and used MA to expect the total participation in all critical modes (TPCM) index value for each bus. The bus with the biggest TPCM index value is selected for a STATCOM installation.

On the other hand, in economic concerns, the total FACTS installation and generation costs were taken as the objective function in [13] and [14], and GA was used to make the decision where to install FACTS devices. The method proposed in [15], comprised of the tabular search (TS) and a nonlinear programming method was used to optimize the FACTS devices investment and recovery. While the method developed in [16] with the proposed performance indices of real power flows was used to seek the optimal locations for FACTS installation. Under the existing FACTS devices installed, in [17], the minimum generation cost-based OPF was solved using the proposed hybrid of TS and simulated annealing (SA) algorithm. While in [18], an optimal approach comprised of CPF and OPF techniques for UPFC installation was proposed to minimize the total generation and installation cost.

Dealing with both concerns simultaneously in the LM enhancement problem for deriving optimal FACTS installation, in [19], the proposed method linearly composed voltage security, system loss, capacities for STATCOM installation and LM into a single-objective function, which was solved by using a PSO algorithm. While in [20] and [21], a single objective function was linearly composed of the installation costs for various types of FACTS devices (UPFC, TCSC, and SVC), system securities, loss and voltage stability indices. The problem was solved by PSO in [20] and GA in [21]. Besides, to possibly reveal the variety of solutions, the optimal SVC installation problem for LM enhancement is formulated as an MOP. A.S. Yome, *et al.,* [22] applied a multi-objective genetic algorithm (MOGA) to the combinatorial optimization problem with the multi-objective function composed of minimum FACTS installation cost and allowable system security limits. The results obtained to release the threats from low voltage and line congestion include the types of FACTS devices used, the installation locations and capacities.

While in [23], the minimum generation costs and allowable system security limits are involved in the multi-objective function, and a bacterial swarming algorithm (BSA) is used to determine the installation locations and capacities for various types of FACTS devices (TCSC, TCPST, TCVR, SVC). The method proposed in [24] composed maximum LM, minimum system loss and voltage deviations at PQ buses into the multi-objective function, and an MOPSO method was used to solve for the locations and capacities for one SVC and one TCSC installations .

From previous reviews, a FACTS installation problem can adopt linearization approaches, or methods with more flexibility including heuristic models and evolutional algorithms. In this paper, both concerns are dealt with at one time. First the risk index (RI) is used to assess the risk level caused by each contingency, and the contingencies with values bigger than the specified are considered for SVC installation. Then, under each considered contingency, MA technique is used to determine which buses need SVC installation, and the LM enhancement problem to determine the capacity of each SVC installation and generation pattern [6] is formulated as an MOP with maximum LM and minimum SVC installation cost involved in the multi-objective function. The fitness sharing MOPSO algorithm is used to solve for a Pareto front set from the MOP for each considered contingency [25], [26]. Also, the performance index, defined as the ratio of the LM to the installation cost, is used to determine a solution from the Pareto front set with LM bigger than or equal to the required LM. Finally, the locations and capacities for SVC installation derived from the union of the solutions for all considered contingencies are taken as the optimal SVC installation for LM enhancement, resulting in that the static voltage stability under each contingency can be maintained for allowable load increases.

According to present day and the expected future situations regarding location of FACTS devices within power systems, it is extremely important to investigate the following issues, which are necessary within the scope of this paper

1. Improvement Of Power System Loadability
2. To reduce network investment cost

II. OPTIMAL POWER FLOW

Load-flow studies are performed to determine the steady-state operation of an electric power system. It calculates the voltage drop on each feeder, the voltage at each bus, and the power flow in all branch and feeder circuits. In this determine if system voltages remain within specified limits under various contingency conditions, and whether equipment such as transformers and conductors are overloaded.

Load-flow studies are often used to identify the need for additional generation, capacitive, or inductive VAr support, or the placement of capacitors and/or reactors to maintain system voltages within specified limits. Losses in each branch and total system power losses are also calculated. Power flow or load-flow studies are important for planning future expansion of power systems as well as in determining the best operation of existing systems.

Optimal power flow (OPF) has been widely used in power system operation and planning. The Optimal power flow module is an intelligent load flow that employs techniques to automatically adjust the power system control settings while simultaneously solving the load flows and optimizing operating conditions with specific constraints. Optimal power flow (OPF) is a static nonlinear programming problem which optimizes a certain objective function while satisfying a set of physical and operational constraints imposed by equipment limitations and security requirements [17]. In general, OPF problem is a large dimension nonlinear and highly constrained optimization problem. So the objective is to minimize the fuel cost and keep the power outputs of generators, bus voltages, shunt capacitors/reactors and transformers tap setting in their secure limits The OPF has been usually considered as the minimization of an objective function representing the generation cost and/or the transmission loss. The constraints involved are the physical laws governing the power generation-transmission systems and the operating limitations of the equipment.

In operation and planning of power systems, operators need to make decisions with respect to different objectives. Hence, several tools have been developed to assist the operators. Optimal Power Flow (OPF) is one of them which help the operators in running the system optimally under specific constraints. A lot of research starting from early 1960s has been done in this field to minimize the total generation cost. After the Clean Air Act Amendments (Kyoto Protocol) in 1990, operating at minimum cost maintaining the security is no longer the sufficient criterion for dispatching electric power. Minimization of polluted gases is also becoming mandatory for the generation utilities in many countries. Hence, OPF problem becomes a multi objective optimization problem.

Many mathematical techniques such as quadratic programming, linear programming, non-linear programming and the interior point method have been applied to solve the OPF problem. All the above mathematical techniques have some drawbacks such as being trapped in local optima or they are suitable for considering a specific objective function in the OPF problem. These shortcomings can be overcome if evolutionary methods are utilized to solve the OPF problem. Particle swarm optimization (PSO) is one of the known optimization algorithms that has been used to solve complicated problems. Also, it is a strong and accurate algorithm that can find high-quality solutions for complicated problems such as the OPF [3].

Main challenges in a multi objective optimization are generation of good quality solutions, generation of uniformly distributed Pareto set, maximizing the diversity of the developed Pareto set, selection of best compromise solution from the Pareto set, computational efficiency, etc. Several methods have been developed to solve mutli-objective optimization problems [18]. By way of example as follows

1. The penalty function method,
2. Weighted sum method
3. e-constrained method
4. Non-dominated sorting genetic algorithm (NSGA) based approach

A. Problem Formulation: The standard OPF problem can be written in the following form [2]:

$$Min.\, F(x,u) \qquad (1)$$

Subject to: $h(x,u)$=0 and $g(x,u) \leq 0$;

Where,

F is the objective function,

h is the equality constraints

g is the inequality constraints

$$x = [V_l^T\ \delta^T\ P_{sg}\ Q_g^T]$$
$$u = [Q_c^T\ Tc^T\ V_g^T\ P_g^T]$$

x is vector of state variables,

u is vector of control variables,

Qc = Reactive power supplied by all shunt reactors

Tc = Transformer load tap changer magnitudes

Vg = Voltage magnitude at PV buses

Pg = Active power generated at the PV buses

Vl = Voltage magnitude at PQ buses

δ = Voltage angles of all buses, except the slack bus

Psg = Active generating power of the slack bus

Qg = Reactive power of all generator units

And ‘u’ is the vector of control variables, the control variable can be generated active and reactive power, generation bus voltage magnitudes, transformer taps etc. However it is the active power generation for problems under consideration.

The equality constraints are the nonlinear power flow equations. The inequality constraints are the functional operating constraints, such as

1. Branch flow limits (MVA, MW or A).
2. Load bus voltage magnitude limits.
3. Generator reactive capabilities.
4. Slack bus active power output limits.

Constraints defines the feasibility region of the problem control variables such as

1. Unit active power output limits.
2. Generation bus voltage magnitude limits.
3. Transformer-tap setting limits (discrete values).

III. SELECTION OF LOCATION

In order to select appropriate bus for placement of FACTS devices in contingency analysis, risk index and modal analysis methods are used.

A. Outage Risk Index: In order to maintain system operating at static voltage stability under each outage, transmission systems need Sufficient LM to avoid voltage instability while accommodating more power transfer. Since contingency events inevitably result in LM decrease, those contingencies with bigger failure probability and resulting in more LM decrease will have bigger values, namely requiring reactive power compensation. Under normal state and without SVC installation, the system LM represented as a loading factor is assumed to be λ_{nor}^*. When contingency (E_i) happens, the LM becomes $\lambda_{E_i}^*$, resulting in a decreased LM expressed as $\Delta_{E_i} = \lambda_{nor}^* - \lambda_{E_i}^*$.

The RI value under contingency E_i is calculated from

$$Risk(E_i) = P_r(E_i) * \Delta\lambda_{E_i} \qquad (2)$$

$$P_r(E_i) = 1$$

Where $P_r(E_i)$ is the failure probability of contingency $(E_i.)$

The failure rate of the contingency is expressed as which can be given in data. It is assumed that the contingency events are independent, and under a contingency, during the period of voltage instability resulted from demand increase, the component is assumed not to be repairable. The failure rate is converted to the failure probability by a Poisson distribution [28]:

Here $P_r(E_i)$ is the average outage probability of contingency (E_i) in a defined time interval T_r (one year). Using the biggest risk index value as base, the line outages with percentages of RI values bigger than 30% are considered for reactive power compensation.

B. Modal Analysis: Reactive power is the most important factor to voltage stability. From the expectation of the impact level on voltage stability from load increase, the signals on which buses the reactive power compensation is necessary for maintaining enough system LM can be obtained. For each contingency, using the Jacobian matrix obtained close to the voltage collapse point during the computation for system LM, the derived first order system equation.

IV. LOAD ABILITY PROBLEM FORMULATION

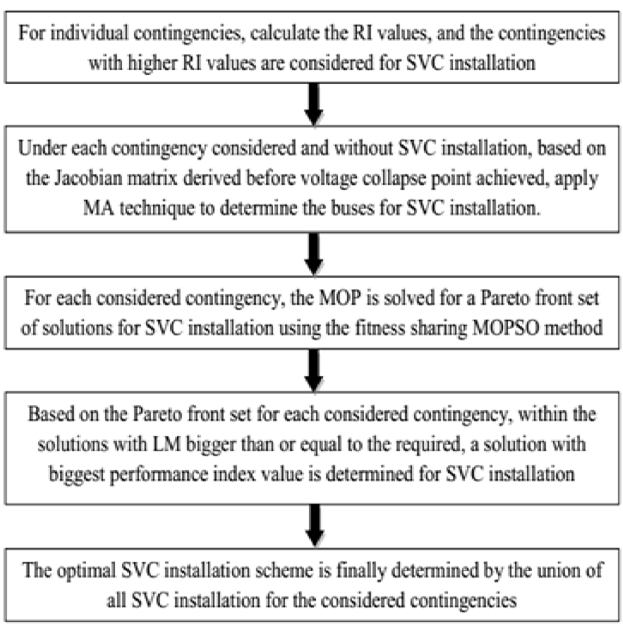

Fig. 1 Proposed LM enhancement strategy

V. RESULTS AND ANALYSIS

To verify the validity of the FS-MOPSO method, the IEEE-24 and IEEE- 14 bus Transmission systems were considered. In order to demonstrate the long term impact of Flexible AC Transmission System (FACTS) devices, a planning period of 5 years have been considered and maintaining same configuration of the network. FACTS Devices installed once will remain in system as long as their performance is satisfactory. Thus the money invested once on FACTS Devices will help investor to harness its benefit throughout its life. The number of FACTS Devices at various locations increase, the investment on FACTS also increases. Investor can be only benefited as long as saving is more than investment. Therefore, there must be some limit on number of FACTS Devices beyond which it may be uneconomical.

A. Example-1: The IEEE 24-bus RTS with bus 13 as the swing bus, 11 generating buses and b and 34 transmission lines is used for testing. The base-case and maximum loading margin case voltage magnitudes and phase angles are given in Table.1.The maximum loading margin is the margin at which voltage limits are violated with increasing load in steps of 0.01 at all load buses.

TABLE I VOLTAGE PROFILE FOR BASE-CASE AND LOADING MARGIN CASE OF IEEE 24 BUS SYSTEM

Bus No	Base case		Loading margin case	
	Voltage		Voltage	
	Magnitude (p.u)	Phase angle (deg)	Magnitude (p.u)	Phase angle (deg)
1	1.0350	-15.5845	1.0350	-22.3455
2	1.0350	-15.7022	1.0350	-22.4579
3	0.9796	-12.2753	0.9616	-18.3894
4	0.9935	-17.3471	0.9432	-23.9290
5	1.0255	-17.7683	1.0080	-23.3726
6	1.0744	-20.4042	1.0443	-26.3726
7	1.0250	-36.1573	0.9322	-45.6789
8	0.9776	-30.8341	0.8980	-39.0127
9	0.9936	-14.4808	0.9640	-19.3381
10	1.0422	-16.8143	1.0100	-21.9100
11	0.9928	-5.8964	0.9775	-8.7847
12	0.9963	-5.1867	0.9767	-7.6687
13	1.0200	0.0000	1.0200	0.0000
14	1.0000	-2.1400	1.0000	-6.3359
15	1.0140	6.1393	1.0140	0.8027
16	1.0170	5.6226	1.0170	0.7159
17	1.0386	9.8924	1.0389	4.6060
18	1.0500	11.1543	1.0500	5.6753
19	1.0231	4.8321	1.0218	0.5544
20	1.0383	6.0663	1.0372	2.5098
21	1.0500	11.8908	1.0500	6.4667
22	1.0500	17.6124	1.0500	12.2419
23	1.0500	7.4396	1.0500	4.3366
24	0.9774	-0.6176	0.9695	-6.1303

From the Table I, it is observed that the voltage magnitude is decrease due to loading margin increased and the voltage deviation is maximum at bus 7 because changed from generator bus to load bus. Also observed that the voltage deviation is minimum at bus 19 because in and around there is a generation support.

B. Selection of Location: In order to select appropriate bus for placement of SVC device in outage risk index and model analysis methods are proposed.

C. Outage Risk Index: For each line outage calculate the corresponding RI value. For this system while calculating the RI for 11th line outage, it is observed that load flow cannot be converged. This is because of the shortage of the power supply. Since, the generator at bus 7 becomes isolated. Hence, for this system line 11 outage is not considered. Using the biggest RI value as base, the percentages of the RI values for individual line outages tabulated in Table II. In the study, except line 11 outage, the line outages with percentages of RI values bigger than 30% are considered for reactive power compensation (i.e., SVC installation).

TABLE II RISK INDEX VALUES FOR VARIOUS LINE OUTAGES, LOAD ABILITY AND FAILURE RATES

Line outage	Loadability	Failure rate	Risk index
1	0.09	0.24	0.0000
2	0.07	0.51	0.0043
3	0.06	0.33	0.0044
4	0.06	0.39	0.0052
5	0.09	0.48	0.0000
6	0.09	0.38	0.0000
7	0.01	0.02	0.0008
8	0.08	0.36	0.0016
9	0.09	0.34	0.0000
10	0.00	0.33	0.0133
12	0.00	0.44	0.0172
13	0.00	0.44	0.0172
14	0.02	0.02	0.0007
15	0.01	0.02	0.0008
16	0.00	0.02	0.0009
17	0.00	0.02	0.0009
18	0.04	0.40	0.0088
19	0.07	0.39	0.0034
20	0.04	0.40	0.0088
21	0.06	0.52	0.0066
22	0.09	0.49	0.0000
23	0.05	0.38	0.0067
24	0.09	0.33	0.0000
25	0.09	0.41	0.0000
26	0.09	0.41	0.0000
27	0.00	0.41	0.0162
28	0.09	0.35	0.0000
29	0.09	0.34	0.0000
30	0.09	0.32	0.0000
31	0.09	0.54	0.0000
32	0.09	0.35	0.0000
33	0.09	0.35	0.0000
34	0.09	0.38	0.0000
35	0.09	0.38	0.0000
36	0.09	0.34	0.0000
37	0.09	0.34	0.0000
38	0.09	0.45	0.0000

The selection range of the buses to install SVC can be defined as the buses which are having RI variation from its base value. If selection range is < 30%, the number of SVC devices at various locations increased. Thereby investment cost is increased. If RI selection range is > 40%, the number of SVC devices at various locations decreased. Thereby investment cost also decreased. But, the lines which are having highest risk factor can be neglected. Therefore RI > 30% is the best range for the minimization of investment cost and risk. From Table II, it is observed that the line outages which has highest RI values are (i.e.4, 10, 12, 13, 18, 20, 23 and 27) selected. And these line outages are involved in the model analysis. Loading margin under the 9 line outages represented as *4,10,12,13,18,20,21,23*.

D. Model Analysis Method: For the above identified each of the 9 line outages, CF value is calculated at all buses. From this CF values greater than 30% of base values are identified and are tabulated in Table III.

TABLE III CF VALUES OF BUSES NECESSARY FOR SVC INSTALLATION UNDER N-1 LINE OUTAGE WITH HIGH RI VALUES

Outage	λ_{Ei}	Contribution factor	Selected buses
4	0.06	Bus 15 / 0.3981 Bus 16 / 0.1833 Bus 17 / 0.2407	14,15,16,17,24
10	0.00	Bus 14 / 0.6660 Bus 15 / 0.3466	
12	0.00	Bus 22 / 2.8145 Bus 23 / 1.5473 Bus 24 / 1.5096	
13	0.00	Bus 24 / 34.8475	
18	0.04	Bus 16 / 0.4057 Bus 17 / 0.2114	
20	0.04	Bus 14 / 0.3943 Bus 15 / 0.2100	
21	0.06	Bus 14 / 0.4848 Bus 15 / 0.2117	
23	0.05	Bus 17 / 0.3769 Bus 18 / 0.2650 Bus 20 / 0.1233	
27	0.00	Bus 14 / 0.6099 Bus 15 / 0.2723 Bus 16 / 0.1857	

The selection range of the buses to install SVC can be defined as the buses which are having CF variation from its base value. If selection range is less than 30%, the number of SVC devices at various locations increased. Thereby investment cost is increased. If CF selection range is greater than 40%, the number of SVC devices at various locations decreased. Thereby investment cost is increased.

If CF selection range is greater than 40%, the number of SVC devices at various locations decreased. Thereby investment cost also decreased. But the buses which are having serious impact of voltage deviation can be neglected.
Therefore CF greater than 30% is the best range for the minimization of investment cost and serious impact of voltage deviation. In considered line outages, the buses

which are repeated at least 2 times are selected for SVC installation. Therefore 14,15,16,17 and 24 buses are best location for SVC. But here buses 15 and 16 are generating buses so they are neglected. Therefore SVC's are placed in load buses called 14, 17 and 24 with size in between limits (0<Qc<1p.u).

E. Multi-Objective Optimization Problem: After calculating location of the SVC, loadability and investment cost are calculated by using Fitness Sharing Multi Objective Particle swarm Optimization (FS-MOPSO) method with 50 populations and 100 iterations are used to solve the multi–objective optimal SVC installation problem. Pareto front set is obtained from FS-MOPSO method.

TABLE IV RESULT OF FS-MOPSO

Line outage	Loadability	Cost	SVC	SVC1	SVC2
4	0.07	361.0866	0.2429	0.5000	0.5000
10	0.00	435.7107	0.5000	0.5000	0.5000
12	0.21	435.7107	0.5000	0.5000	0.5000
13	0.20	435.7107	0.5000	0.5000	0.5000
18	0.09	255.3696	0.5000	0.2830	0.0959
20	0.08	288.9015	0.5000	0.3358	0.1585
21	0.15	300.3725	0.5000	0.5000	0.0340
23	0.24	435.7107	0.5000	0.5000	0.5000
27	0.15	300.3725	0.5000	0.5000	0.0340

The Tables IV given as the line outages in first column and corresponding loadability, investment costs and SVC size are present in 2nd, 3rd and 4th columns respectively. The loadability and investment costs, which are having highest fitness sharing, are selected in Pareto front set of FS-MOPSO method. Performance index (f1 / f2) is calculated for each considered contingency. Highest performance index in FS-MOPSO is selected for optimized values of loadability and investment cost.

Table V given as the highest performance index of FS-MOPSO method that is 0.00055082. And this is highly optimized in line 23 outage, when compared to the remaining line outages. Loadability is 0.24 and corresponding investment cost is 435.7107 are obtained from FS-MOPSO method.

TABLE V OPTIMIZATION OF PERFORMANCE INDEX

	FS-MOPSO
Line outage	23
Loadability (f_1)	0.2400
Cost (f_2)	435.7107
PI ((f_1)/(f_2))	0.00055082

Therefore Load ability is improved from 0(without SVC in contingency analysis) to 0.24 (with SVC in contingency analysis) and corresponding investment cost also optimized.

F. Example-2: The proposed algorithm is applied to test the IEEE-14 bus test system. This system consists of 5 generator units and transmission lines. Throughout all cases, the IEEE14 Bus system base MVA was assumed to be 100 MVA.

G. Selection of Location: In order to select appropriate bus for placement of SVC device analysis, Outage risk index and model analysis methods are used.

H. Outage Risk Index

TABLE VI RISK INDEX VALUES, LOAD ABILITY AND FAILURE RATES FOR VARIOUS LINE OUTAGE

Line outage	Loadability	Failure rate	Risk index
1	0.06	1.0858	0.0234
2	0.03	1.0858	0.0117
3	0.02	1.0858	0.0156
4	0.05	1.0858	0.0039
5	0.05	1.0858	0.0039
6	0.05	1.0858	0.0039
7	0.05	1.0858	0.0039
8	0.05	0.01045	0.0001
9	0.06	0.01045	0.0000
10	0.02	0.01045	0.0002
11	0.05	0.5429	0.0023
12	0.05	0.5429	0.0023
13	0.05	0.5429	0.0023
14	0.0	0.01045	0.0003
15	0.05	0.01045	0.0001
16	0.06	0.5429	0.0000
17	0.05	0.5429	0.0023
18	0.06	0.5429	0.0000
19	0.06	0.5429	0.0000
20	0.05	0.5429	0.0023

For each line outage calculate the corresponding RI value. The line outages with percentages of RI values bigger than 30% are considered for reactive power compensation (i.e., SVC installation). The selection range of the buses to install SVC can be defined as the buses which are having RI variation from its base value. If selection range is < 30%, the number of SVC devices at various locations increased. Thereby investment cost is increased. If RI selection range is > 40%, the number of SVC devices at various locations decreased. Thereby investment cost also decreased. But, the lines which are having highest risk factor can be neglected. Therefore RI > 30% is the best range for the minimization of investment cost and risk. From Table 5.6, it is observed that the line outages which has highest RI values are (i.e.1, 2 and 3) selected. And these line outages are involved in the model analysis. Loading margin under the 3 line outages represented as

I. Model Analysis: For the above identified each of the 3 line outages, CF value is calculated at all buses. From this CF values greater than 30% of base values are identified and are tabulated in Table VII.

TABLE VII CF VALUES OF BUSES NECESSARY FOR INSTALLATION UNDER N-1 LINE OUTAGES WITH HIGH RI VALUES

Outage	λ_{Ei}	Contribution factor	Selected buses
1	0.06	13bus/0.445 14bus/1.0811	10,13,14 buses
2	0.03	10bus/15.6524	
3	0.02	10bus/0.4540 11bus/0.3052 12bus/0.1510 13bus/0.1798 14bus/0.1692	

The selection range of the buses to install SVC can be defined as the buses which are having CF variation from its base value. If selection range is less than 30%, the number of SVC devices at various locations increased. Thereby investment cost is increased. If CF selection range is greater than 40%, the number of SVC devices at various locations decreased. Thereby investment cost is increased.

If CF selection range is greater than 40%, the number of SVC devices at various locations decreased. Thereby investment cost also decreased. But the buses which are having serious impact of voltage deviation can be neglected. Therefore CF greater than 30% is the best range for the minimization of investment cost and serious impact of voltage deviation. In considered line outages, the buses which are repeated at least 2 times are selected for SVC installation. Therefore 10, 13 and 14 buses are best location for SVC.

J. Multi -Objective Optimization Problem: After calculating location of the SVC, loadability and investment cost are calculated by using Fitness Sharing Multi Objective Particle swarm Optimization (FS-MOPSO) method with 50 populations and 100 iterations are used to solve the multi–objective optimal SVC installation problem. Pareto front set is obtained from FS-MOPSO method.

TABLE VIII RESULT OF FSMOPSO

Line outage	Loadability	Cost	SVC		
			SVC	SVC1	SVC2
1	0.25	68.4094	0.1184	0.0000	0.1169
2	0.25	68.4094	0.1184	0.0000	0.1169
3	0.21	73.3460	0.1818	0.0452	0.0253

The Table VIII given as the line outages considered in first column for FS-MOPSO method and corresponding loadability, investment costs and SVC size are present in 2nd, 3rd and 4th columns respectively. The loadability and investment costs, which are having highest fitness sharing, are selected for Pareto front set for FS-MOPS. Performance index (f1 / f2) is calculated for each considered contingency. Highest performance index in this method is selected for optimized values of loadability and investment cost.

Table IX given as the highest performance index of FS-MOPSO is 0.00365. The FS-MOPSO method is highly optimized in line 2 outage, when compared to the remaining line outages. Therefore loadability is 0.25 and corresponding investment cost is 68.4094.

TABLE IX OPTIMIZATION OF PERFORMANCE INDEX USING FSMOPSO

	FS-MOPSO
Line outage	2
Loadability (f_1)	0.25
Cost (f_2)	68.4094
PI [(f_1)/(f_2)]	0.00365

Therefore Load ability is enhanced from 0.03 (without SVC in contingency analysis) to 0.25 (with SVC in contingency analysis) and corresponding investment cost also optimized

VI. CONCLUSION

In this paper, a multi-objective fitness sharing PSO method has been propose for optimal placement of multiple SVC FACTS device to improve the voltage stability. In this multi-objective optimization problem, there are two competitive objectives namely improvement of loadability and to reduce network investment cost. To improve the operation security of power systems while avoiding network expansion by building more transmission lines, it is a good choice to suitably install FACTS devices in existing networks such that they can accommodate more power transfer. The MOP proposed in this paper by considering the most serious contingencies to seek a Pareto front set for each contingency is solved by using the fitness sharing MOPSO method. The proposed performance index is then used to determine an optimal SVC installation scheme for the required LM with the SVC installation locations and capacities derived from the union of the SVC installations for all considered contingencies. From the test results, the achievement of the proposed strategy for SVC installation, that is well consistent with specific economic and technical concerns, is validated. The proposed method has been tested on the IEEE-24 and IEEE-14 bus systems.

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