Transactions on Energy Systems and Engineering Applications

Article

FACTS placement for reactive power planning with weak node constraints using an improved symbiotic search algorithm

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Received: 9 June 2023; Accepted: 20 November 2023; Published: 14 December 2023

Abstract: In this paper, an Improved Symbiotic Organisms Search (ISOS) algorithm is proposed for effective Reactive Power Planning (RPP) as an Optimal Power Flow (OPF) issue on an IEEE 57 bus network. The objective of the work is two-fold: to reduce the energy loss and to enhance the voltage profile within the prescribed limit by ensuring the economic operation and reduced investment cost of Flexible AC Transmission Systems (FACTS) in the system. Furthermore, the optimal position of FACTS is determined by including the existing system controlling variables like reactive power generators output, transformer tapping, and capacitors connected at shunt. Here, two FACTS devices, Static Var Compensator (SVC) and Thyristor-Controlled Series Controller (TCSC), have been taken into consideration. The power flow method is used to determine the optimal positions for SVCs and TCSCs. The performance of the ISOS algorithm is compared with that of three other state-of-the-art optimization techniques: Symbiotic Organisms Search (SOS), Differential Evolution (DE), and Teaching-Learning-Based Optimization (TLBO). The ISOS algorithm yields a significantly more economical system than other algorithms applied for RPP. Non-parametric tests such as the Signed test, Wilcoxon signed rank test, and Friedman test is conducted for statistical analysis to investigate the superiority of the ISOS algorithm over other techniques.

 https://doi.org/10.32397/tesea.vol4.n2.524

How to cite this article: Kumar Gupta, Vikash; Kumar Mishra, Sudhansu; Babu, Rohit. FACTS placement for reactive power planning with weak node constraints using an improved symbiotic search algorithm. *Transactions on Energy Systems and Engineering Applications*, 4(2): 524, 2023. DOI:10.32397/tesea.vol4.n2.524

1. Introduction

1.1. Overview

With the increased load capacity of transmission lines due to the restructuring of the power industry and deregulation in the electricity market, the need for the operation of power networks closer to their stability limits has become a major challenge. The power-carrying capacity of the existing transmission networks is one of the major bottlenecks of any system. It is also infeasible to build and design another system to meet the rising demand for energy, because of major factors like large capital investment, environmental clearance, land acquisition, and more. To fulfill the power demand, power system equipment is pushed to its most extreme limit. Therefore, a small disturbance or sequence of voltage instability results in a voltage collapse in the system. This will lead to uneven distribution of power, resulting in congestion in some lines of the transmission network while the other lines will be underutilized. The phenomenon of voltage instability in any system is described by a monotonic voltage drop that is delayed at first and gets a sudden breakdown after a certain period. As a solution, power electronic devices, like Flexible AC Transmission Systems (FACTS), are employed in power systems to meet the load demand more reliably and efficiently while meeting the stability criterion. All the abbreviations and nomenclature are listed in Table 1 to enhance the readability of the paper.

1.2. Related Work

S. Perez-London et al. have proposed contingency ranking by considering the Fast Voltage Stability Index (FVSI) and the Simplified Voltage Stability Index (SVSI) [1]. An evaluation of voltage stability for a multi-bus electrical network in [2] used a pi-network model, considering all the line losses as an Optimal Power Flow (OPF) problem. The Bus Voltage Stability (BVS) method was developed by Damina O. Dike and Satish M. Mahajan to mitigate power outages through the compensation of reactive power [3]. The Artificial Bee Colony (ABC) algorithm has been implemented to solve the OPF dispatch problems [4]. The use of a fractal search algorithm to optimize the reconfiguration of the electrical distribution system of Algeria with FACTS was proposed in [5]. Particle Swarm Optimization (PSO) and Differential Evolution (DE) were successfully implemented in two test systems to minimize the operating cost and power loss [6]. Saurav Raj and Biplab Bhattacharyya [7] demostrated that effective positioning of shunt capacitors and proper planning of existing reactive sources result in loss minimization, improved bus voltage, and reduced power system operating costs. The Lyapunov control method was proposed to improve the transient stability with the Unified Power Flow Controller (UPFC) [8]. Optimizing the control parameters results in a reduction of real power loss, as verified in [9]. Raj and Bhattacharyya applied series and shunt FACTS devices along with the Whale Optimization Algorithm (WOA) to solve the RPP problem [10]. To implement the reactive dispatch for power planning, the generation pricing and line load elements were taken into account, along with other conditions, in [11]. The SOS algorithm was utilised by A. K. C. Saha and P. Das [12] to obtain the solution of static Optimal Power Flow (OPF) and Economic Load Dispatch (ELD) using a valve point. The transmission expansion planning model and second-order cone programming were proposed in [13] to achieve high wind energy penetration. Gomes and Saraiva have proposed a two-stage technique for the transmission expansion design in AC dynamic systems [14].

R. V. Rao et al. introduced TLBO as a powerful tool for solving various optimization problems [15]. PSO and Genetic Algorithm (GA) were used for VAR strategic planning for reactive power to reduce the system's operating costs with FACTS in [16]. A hybrid Chaotic Chimp Optimization Algorithm (CCOA) is implemented by Saurav Raj et al. for the security of the power system [17] to address the reactive power dispatch issue. The authors' primary goal in [18] was to optimize reactive power flow using the GA in an HVDC test system. In [19], hybrid soft computing techniques, such as the oppositional-based marine

Table 1. Abbreviations and Nomenclatures

Abbreviations		Nomenclature	
ISOS	Improved Symbiotic Organisms Search	i, j	node i and j
OPF	Optimal Power Flow	X_{ij_new}	Line reactance with TCSC
FACTS	Flexible AC Transmission Systems	X_{ij_old}	Line reactance without TCSC
SVC	Static Var Compensator	X_{TCSC}	Reactance of TCSC
TCSC	Thyristor-Controlled Series Controller	E_{Loss}	Energy loss in a transmission network
SOS	Symbiotic Organisms Search	L	Total number of transmission lines
DE	Differential Evolution	g_k	Conductance of k^{th} line
TLBO	Teaching-Learning-Based Optimization	V_i, V_j	Voltage at i^{th} and j^{th} bus
FVSI	Fast Voltage Stability Index	$\cos\theta$	Cos of angle between i^{th} and j^{th} bus
SVSI	Simplified Voltage Stability Index	$Cost_{SVC}$	Cost occurred by SVCs in \$/kVar
BVS	Bus Voltage Stability	$Cost_{TCSC}$	Cost occurred by TCSC in \$/kVar
ABC	Artificial Bee Colony	$Cost_{Loss}$	Cost due to energy loss
PSO	Particle Swarm Optimization	$F1$	Operating value of SVC
UPFC	Unified Power Flow Controller	$F2$	Operating value of TCSC
WOA	Whale Optimization Algorithm	P_{Gi}, Q_{Gi}	Active and reactive power generation at i^{th} bus
ELD	Economic Load Dispatch	P_{Di}, Q_{Di}	Active and reactive power demand at i^{th} bus
GA	Genetic Algorithm	G_{ij}, B_{ij}	Real and imaginary components of the bus admittance matrix
CCOA	Chaotic Chimp Optimization Algorithm	δ_{ij}	Phase angle between i^{th} and j^{th} bus
HVDC	High Voltage DC	$V_{Gi}^{min}, V_{Gi}^{max}$	Minimum and maximum limit of voltages at generator bus
OMPA-HHO	Oppositional-based marine predators' algorithm with Harris Hawks' optimization	$Q_{Gi}^{min}, Q_{Gi}^{max}$	Minimum and maximum limit of reactive power at generator bus
GWSO	Glow Worm Swarm Optimization	V_i^{min}, V_i^{max}	Minimum and maximum limit of voltages at i^{th} bus
GWO	Grey Wolf Optimizer	Tap_i^{min}, Tap_i^{max}	Minimum and maximum limit of transformer tapping
MHSO	Modified harmony search optimization	SVC_i^{min}, SVC_i^{max}	Minimum and maximum limit of SVC
CSA	Cuckoo Search Algorithm	$TCSC_i^{min}$, $TCSC_i^{max}$	Minimum and maximum limit of TCSC
MSCA	Modified Sine-Cosine Algorithm	P_i	Random organisms selected in an ecosystem
HHOPSO	Harris Hawk-Particle Swarm Optimizer	P_{best}, N_{iter}^{max}	Best organism in an ecosystem and maximum no. of iterations respectively.
VCRPP	voltage constrained reactive power planning	$P_{i,new}, P_{j,new}$	New organisms created from the parent organisms P_i and P_j
PV	Photovoltaic	N_{iter} and bf_1, bf_2	
ECED	Environment Constrained Economic Dispatch	$\forall N_{iter} \leq N_{iter}^{max}$ and $\forall N_{iter} \leq N_{iter}^{max}$	Early stage of algorithm and late stage of algorithm; η: Improved boundry search from (-1,1)

predators' algorithm with Harris Hawks' optimization (OMPA-HHO), were implemented by Mahapatra et al. to solve RPP. Several optimization techniques, such as the Jaya Algorithm, Glow Worm Swarm Optimization (GWSO), TLBO, Modified TLBO, meta-heuristic algorithm, Grey Wolf Optimizer (GWO), and DE were discussed in [20–25] to get a satisfactory solution to the OPF problem. The OPF using a Hybrid TLBO in [26] increases the system's power transfer capacity for stability enhancement with UPFC. Adaryani M. R. and Karami A. implemented the ABC algorithm to find the best settings of the control variables for multi-objective OPF problems in a multi-objective framework [27]. Transmission loss minimization with thyristor-controlled series compensator (TCSC) using modified harmony search optimization (MHSO) at different bus systems was presented in [28] and [29].

The solution for single and multi-objective problems using the Cuckoo Search Algorithm (CSA) was presented in [30]. In [31] and [32], the authors used the Modified Sine-Cosine Algorithm (MSCA) for the solution of the OPF issue. The Harris Hawk-Particle Swarm Optimizer (HHOPSO) is discussed in [33] as a potential solution to the Voltage Constrained Reactive Power Planning (VCRPP) problem. Thukaram and Yesuratnam utilized the network's reactive power sources to improve the voltage profile with FACTS for the DC link operation [34]. Kataoka and Shinoda have considered generators' reactive power output constraints and loadability to maintain the voltage stability limit [35]. S. Nandkishor Dehedkar and S. Raj [36] presented the voltage collapse proximity index method for the placement of a photovoltaic (PV) system to estimate active and reactive power loss as well as voltage profile improvement. Voltage stability analysis on a three-phase unbalanced system compared with the continuation three-phase power flow through PV curves, was discussed in [37]. B. Dey et al. [38] presented a fair trade-off strategy to resolve the Environment Constrained Economic Dispatch (ECED) problem. The use of a nonlinear least square improvement calculation to improve the voltage stability margin is discussed in [39]. A Fuzzy logic approach was presented in [40] for detecting weak buses.

1.3. Motivation

The main objective of this work is to present an innovative method for solving the RPP problem. Reactive power planning is important in power systems to ensure the efficient and reliable operation of electrical grids. One of the main motivations for reactive power planning is to maintain system voltage within acceptable limits. Another motivation is to improve the efficiency of the power system. By managing the reactive power flow, the overall power system losses and operating costs can be reduced. Overall, the motivation for reactive power planning is to ensure the efficient, reliable, and cost-effective operation of power systems. According to the literature review, researchers have used several techniques to solve the RPP problem. However, the majority of them are based on the application of evolution and swarm intelligence to optimize parameters for their efficacy. Among these, certain algorithms have specialised control parameters. For instance, GA utilizes crossover rate and mutation, and PSO uses inertia weights and cognitive parameters. Improper tuning of these parameters can significantly impact the performance of the optimization algorithm, and results may even diverge. With these considerations in mind, we have applied the Improved Symbiotic Organisms Search (ISOS) algorithm, which does not depend on control variables.

1.4. Unique Contributions

The following are the overall contributions of this research work:

1. The objective function is considered to be a combinatorial one, which consists of two functions: minimization of energy loss and the cost of FACTS.
2. Two approaches, namely voltage sensitivity indicator and reactive power flow, are used to locate the weak nodes to decide the appropriate place for FACTS.

3. Comparative analysis is conducted with three other widely used algorithms, i.e., SOS, TLBO, and DE, considering the total energy loss and percentage reduction in loss.
4. A non-parametric statistical analysis is conducted to assess the dominance of the proposed ISOS approach over others.

The remaining sections of this research are organized as follows: Section 2 presents the static representation of TCSC and SVC. Section 3 describes the problem formulation with FACTS, while Section 4 explains the SOS and ISOS algorithm. The validation of the proposed methodology with numerical data is presented in Section 5, and Section 6 provides the conclusions derived from the case studies and analyses.

2. Static Representation Of TCSC And SVC

FACTS is an abbreviation for Flexible Alternating Current Transmission Systems. FACTS devices are advanced power electronics devices that are used to enhance the controllability and flexibility of power systems and also improves the performance of power systems, including voltage stability and power flow control. The optimal placement of SVC and TCSC also resolves the congestion issue in the transmission network.

2.1. Thyristor-Controlled Series Controller (TCSC)

The addition of TCSC changes the line impedance, restricts power flow in the network, and raises the system's power transfer limit. The TCSC static model is shown in Figure 1. The line reactance after the installation of TCSC is represented as

$$X_{ij\_new} = X_{ij\_old} - X_{TCSC}. \tag{1}$$

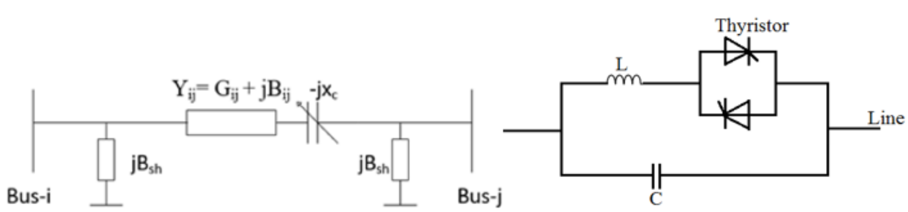

Figure 1. Basic model of TCSC.

2.2. Static Var Compensator (SVC)

SVC is a static power electronic device used to regulate the voltage of the power system and provide dynamic reactive power compensation. For system stability, SVC has the ability to absorb or supply reactive power as needed. Figure 2 depicts a static model of SVC.

2.3. Weak Node Selection for FACTs Placement

The voltage profile of the buses in the network is improved by using FACTS, thereby lowering energy loss, reducing the power flows in congested lines, and reducing the overall operating costs for reactive power planning even at higher loads. To identify the system's vulnerable buses, the L-index approach is employed for SVCs placement, and TCSCs are placed in lines with a lot of reactive power flowing. Operating costs can be reduced by the proper coordination of FACTS with the existing generators' reactive power generation, transformer tapping, and shunt capacitors of the network. SVCs were strategically

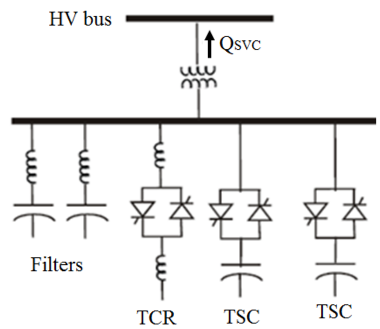

Figure 2. A static model of SVC.

placed on the 18^{th}, 25^{th}, 31^{st}, and 57^{th} buses to inject sufficient reactive power and enhance the network's performance. To reduce the overall reactance of the line, TCSCs are installed on the 37^{th}, 59^{th}, and 65^{th} lines. So, for the IEEE 57 network, four SVCs and three TCSCs were selected in this work to optimize the operating cost after the inclusion of FACTS.

3. Problem Formulation With Facts

The main objective of this work is to achieve the optimal coordination of FACTS devices to solve a non-linear RPP problem in order to minimize both energy loss and system operating costs with the proper coordination with the existing sources of reactive power. The generation of reactive power by generators and the adjustment of transformer tap positions within predefined limits do not incur additional system costs. Consequently, our cost considerations are concentrated on two main components: the cost associated with energy loss in the system, and the cost of FACTS devices, such as SVC and TCSC. The objective function of this optimization process is to minimize the overall operating cost, which encompasses these two major cost factors.

Energy loss in a transmission network can be mathematically expressed as

$$E_{Loss} = \sum_{k=1}^{L} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos\theta) \ , \tag{2}$$

and overall operating cost can be expressed as

$$Cost_{TOTAL} = Cost_{SVC} + Cost_{TCSC} + Cost_{Loss} \ . \tag{3}$$

The costs incurred by SVCs and TCSCs can be expressed by equations

$$\text{Cost of SVCs: } Cost_{SVC} = 0.0003(F1)^2 - 0.305(F1) + 127.38 \text{ (\$/kVar)} \ , \tag{4}$$

and

$$\text{Cost of TCSCs: } Cost_{TCSC} = 0.0015(F2)^2 - 0.7130(F2) + 153.75 \text{ (\$/kVar)} \ . \tag{5}$$

Cost due to energy loss can be mathematically expressed as

$$Cost_{Loss} = 0.06 \times 8760 \times 10^5 \times E_{Loss} \text{ (\$/kVar)} \tag{6}$$

The cost functions expressed in Equations 4 to 6 were taken from [41].

3.1. Equality Constraints

The power flow balance equations for the equality constraints is as follow:

$$\text{Real power load demand: } P_{Gi} - P_{Di} = V_i \sum_{j=1}^{N_B} V_j [G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}] \tag{7}$$

and

$$\text{Reactive power load demand: } Q_{Gi} - Q_{Di} = V_i \sum_{j=1}^{N_B} V_j [G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}] \tag{8}$$

3.2. Inequality Constraints

The inequality constraints encompass several factors like generator voltages, transformer tapping ratio, power injection by SVCs, and new reactance value by placing TCSCs. The inequality constraints are mathematically expressed as

$$\begin{cases} \text{Generator voltage limit:} & V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \\ \text{Reactive generation of generator limits:} & Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \\ \text{Voltage limits:} & V_i^{min} \leq V_i \leq V_i^{max} \\ \text{Transformer tapping limits:} & Tap_i^{min} \leq Tap_i \leq Tap_i^{max} \\ \text{SVC's limits:} & SVC_i^{min} \leq SVC_i \leq SVC_i^{max} \\ \text{TCSC's limits:} & TCSC_i^{min} \leq TCSC_i \leq TCSC_i^{max} \end{cases} \tag{9}$$

4. Proposed Algorithm

4.1. Symbiotic Organism Search (SOS)

Cheng and Pragyo [42] proposed the Symbiotic Organisms Search (SOS) algorithm, developed by exploiting the interactions among different organisms in an ecosystem. The popularity of SOS has grown due to its ease of use and effectiveness in a wide range of applications while requiring little computational effort. The areas of applications of SOS include congestion management, scheduling of hydrothermal generators, and cloud computing, among others [43]. Mutualism, Commensalism, and Parasitism are three stages of SOS briefed as follows.

Mutualism: An example of mutualism is the interaction between bumblebees and flowers, where both organisms benefit from each other. Flowers provide food to bumblebees in the form of nectar. In return, the bees help in the pollination process of flowers by carrying nectar from one flower to another. In this phase of interaction, for an organism P_i, P_j is chosen randomly from the rest of an ecosystem. P_{best} denotes the best organism present in an ecosystem. A mutual vector is created based on the formula

$$MutualVector = \frac{P_i + P_j}{2} \ . \tag{10}$$

Two new organisms are created from the parent organisms $P_{i,new}$ and $P_{j,new}$ as follows:

$$P_{i,new} = P_i + \text{rand} \times (P_{best} - MutualVector \times bf_1) \tag{11}$$

and

$$P_{j,new} = P_j + \text{rand} \times (P_{best} - MutualVector \times bf_2) \ . \tag{12}$$

The creation of new organisms represents the process of adaptation among the existing organisms to increase their fitness in the ecosystem. The level of adaptation is determined by the benefit factors. The new organisms replace the parent organisms if their fitness is found to be better than the parents'.

Commensalism: In this process, one participating organism is benefitted by the interaction, whereas, the other organism remains unaffected. The interaction between Barnacles and Whales presents an interesting example of such interactions. Barnacles depend on sea waves to bring food as they cannot move from one place to another. To enhance the chances of getting food, they attach themselves to the bodies of whales, because of which they get access to food, and fit themselves to cope with the changing environments. For an organism P_i, present in the environment, another organism P_j is selected as a new organism for updating P_i as follows:

$$P_{i,new} = P_i + \text{rand} \times (-1, 1) \times (P_{best} - P_j) \ . \tag{13}$$

If a new organism's fitness is found to be better than that of the parent organism, then it is accepted in the ecosystem, replacing the parent organism.

Parasitism: The Parasitic interactions harms one of the participating organisms, whereas the other organism gains from it. The prime example of such a situation is the interaction between the Plasmodium falciparum parasite and humans. The parasite lives inside the human body to nourish itself, and its presence causes malaria in human beings. In the ecosystem, an organism P_i is selected to generate the parasite. Then, the parasite is generated by modifying P_i along different dimensions. Another organism P_j is chosen and its fitness value is compared with that of the parasite vector. If the parasite vector's fitness is superior to that of P_j, it replaces P_i in the ecosystem. Otherwise, if the parasite vector is not well suited as P_j, its existence in the ecosystem ends.

4.2. Proposed Improved SOS Algorithm in Power System Applcation

The effectiveness of the control parameters in the SOS algorithm is influenced by various controlling factors. During the mutualism phase, the benefit factor is selected randomly as 1 or 2, which may create a new solution in the unworkable region, decreasing the stability and dependability of the algorithm because of the increase in the variance of the objective function between the optimum organism and the overall ecosystem. Also, in the commensalism phase, the search limit in the optimization process is too wide due to an excessively large interval of random elements, which ultimately reduces the algorithm's ability to converge quickly and effectively. Based on the abovementioned findings, the Improved SOS (ISOS) algorithm has been proposed to produce a better solution in an effort to overcome the shortcomings of the original algorithm by modifying the controlling parameters.

4.2.1. Improvement in benefit factor

In the mutualism phase of our proposed Improved SOS algorithm, we've incorporated an adaptive benefit factor, which allows biological individuals to interact with one another and gain proportionate benefits more effectively. If the benefit factor is set to $bf_1 = bf_2 = 2$ in the early stages, each individual will benefit the most from the other, broadening the search space for biological organisms and generating more distinct organisms. When the benefit factor is set to $bf_1 = bf_2 = 1$ in the later stages, it ensures that each organism gets an equal share of the gain during the interaction. The mathematical expression of the adaptive benefit factor is

$$\begin{cases} bf_1 = bf_2 = 2, \forall N_{iter} \leq N_{iter}^{max}/2 \\ bf_1 = bf_2 = 1, \forall N_{iter} > N_{iter}^{max}/2 \end{cases} \ . \tag{14}$$

4.2.2. Random number selection in Commensalism phase

In ISOS, a set of random numbers within a specific range is replaced by a diminishing range, which is adjusted depending on the number of iterations used. As a result, the search range's boundary value gradually decreases as the number of iterations increases, accelerating the algorithm's convergence speed. To make sure that the method is accurately optimised and accelerates the algorithm's convergence speed, the boundary value is given by the equation

$$\eta = 1 - 0.5\frac{N_{iter} - 1}{N_{iter}^{max}} \ . \tag{15}$$

Hence, in the commensalism phase, the enhanced mathematical approach for creating new beings can be written as

$$P_{i,new} = P_i + rand(-\eta, \eta) \times (P_{best} - P_j) \ . \tag{16}$$

The flowchart of improved SOS algorithm is shown in Figure 3.

4.3. Advantages of Implementation of ISOS

The following are some of the important capabilities of the proposed ISOS algorithm in the abovementioned optimization problem, considering all the equality and inequality constraints:

1. ISOS converges quicker than SOS, which can be crucial in RPP and maintaining voltage stability.
2. ISOS can also optimize large networks more effectively, allowing for better reactive power allocation.
3. ISOS has automated mechanisms for parameter tuning, making it simpler for power system engineers and operators to use.
4. Certain aspects of the ISOS algorithm make it easier to understand and implement, which reduces complexity.

5. Results and Discussion

The IEEE 57 bus test system was used to assess the ISOS algorithm for the Reactive Power Planning (RPP) problem. The assessment was conducted in MATLAB R2017b software in a device with 3.10GHz, 32 GB RAM, and an Intel Core i9 CPU. The system consists of 57 buses, 80 transmission network lines, 6 generators, 15 transformer tapping, and 4 shunt capacitors. Table 2 shows the optimal position for SVCs and TCSCs in the transmission network.

Table 2. Optimal position for FACTs in the network.

SVCs on buses	TCSCs on lines
18^{th}, 25^{th}, 31^{st} and 57^{th}	37^{th}, 59^{th} and 65^{th}

The positions of SVCs in buses were obtained using the L-index method, while the placement of TCSCs in lines was obtained through the power flow method. After the installation of FACTS, various optimization algorithms, such as ISOS, SOS, DE, and TLBO, were performed for 500 iterations with a population size of 80 for each technique. Table 3 shows the Q-flow in network lines both before and after the placement of FACTs.

After installing the FACTs, the reactive power flow at the heavily loaded lines is reduced due to power re-despatch by implementing the ISOS compared to SOS, DE, and TLBO. There is also a reduction in the

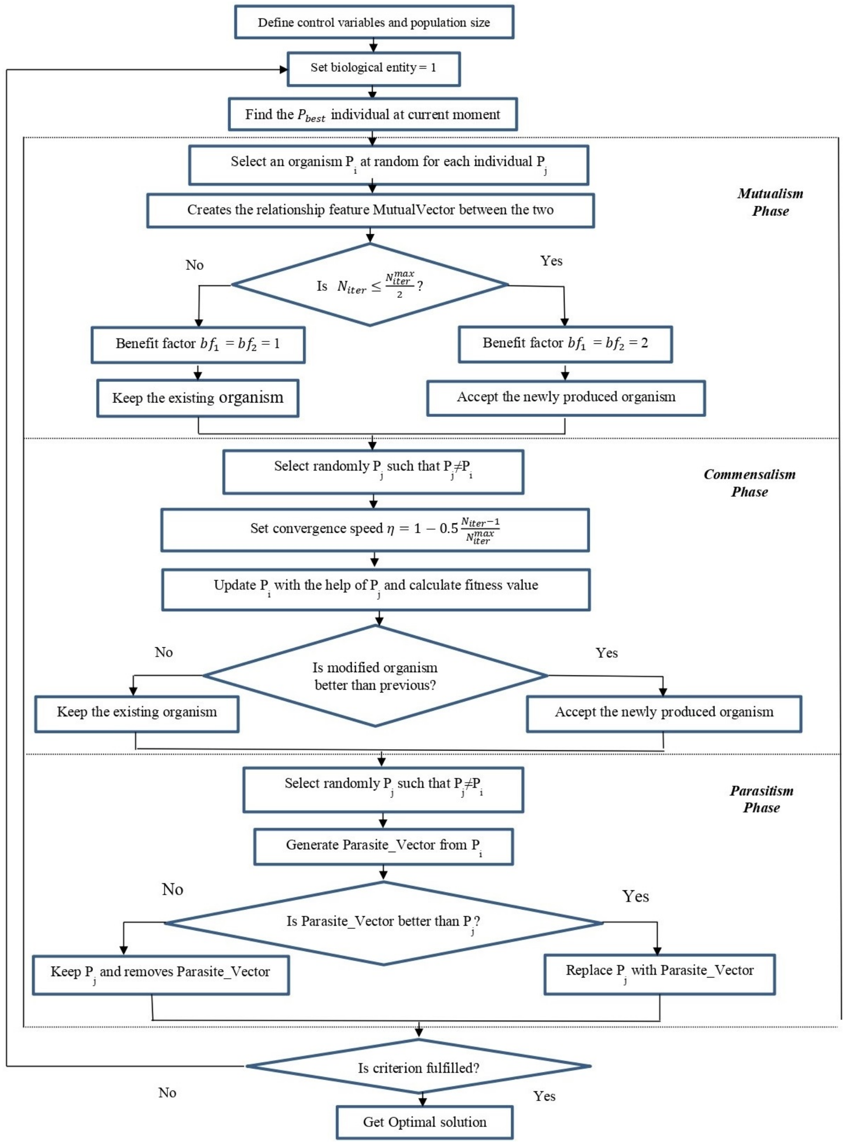

Figure 3. Flowchart of the Improved SOS algorithm.

net reactive power flow. Table 4 presents the bus voltages in the network before and after the installation of FACTs.

Table 3. Q-flow by TLBO, DE, SOS and ISOS techniques.

Line No.	100%					150%				
	Without	TLBO	DE	SOS	ISOS	Without	TLBO	DE	SOS	ISOS
37	0.8189	0.8614	0.6776	0.4900	0.4708	0.9142	0.9711	0.7049	0.5762	0.5390
59	0.9825	0.8107	0.7108	0.6319	0.6147	1.1514	0.9152	0.7650	0.7587	0.7500
65	1.0128	0.5879	0.7515	0.4081	0.3809	0.9635	0.5879	0.8653	0.6795	0.6551
$\sum$	2.8142	2.2600	2.1399	1.5300	1.4664	3.0291	2.4742	2.3352	2.0144	1.9441

Table 4. Bus voltage at weak nodes with increased loading by various techniques.

Bus No.	100%					150%				
	Without	TLBO	DE	SOS	ISOS	Without	TLBO	DE	SOS	ISOS
18	1.0017	1.0567	1.0412	1.0632	1.0357	0.9853	1.0567	1.0653	1.0669	1.0517
25	0.9828	0.9742	1.0790	1.0854	1.0594	0.9243	0.9742	1.0103	1.0641	1.0426
31	0.9361	0.9381	1.0325	1.0587	1.0482	0.8658	0.9254	0.9532	1.0403	1.0278
57	0.9642	1.0176	1.0140	1.0264	1.0156	0.9259	0.9726	0.9806	1.0153	1.0107

It was found that installing SVC at the optimal locations results in the improvement of bus voltages, maintaining them within acceptable limits even under higher loading conditions. Table 5 shows the optimal magnitudes of the controlling parameters obtained using the ISOS, SOS, DE, and TLBO optimization techniques. It is evident from Table 5 that all the values of the controlling parameters lie within the constraints.

Table 5. Controlling parameter rating with increased loading by TLBO, DE, SOS and ISOS.

Control Variables	100%				150%			
	TLBO	DE	SOS	ISOS	TLBO	DE	SOS	ISOS
Qg2	0.1596	0.5	0.5103	0.5328	-0.1924	0.5	0.5418	0.5376
Qg3	0.2155	0.4943	0.4479	0.3408	0.2790	0.4702	0.3712	0.3708
Qg6	-0.0209	0.1803	0.0016	0.0009	0.3740	0.1030	0.0529	0.0421
Qg8	0.2825	0.4616	-0.0240	-0.0040	0.0143	0.5671	0.5813	0.5644
Qg9	0.0859	0.09	0.1137	0.1900	0.3671	0.09	0.1174	0.1329
Qg12	0.2470	-0.3930	0.2792	0.1302	-0.2258	-0.2887	0.7407	0.7309
Tap4-18	0.9710	10.500	10.500	10.500	0.9544	0.9994	10.825	10.825
Tap4-18	0.9500	0.9600	0.9500	0.9500	0.9505	10.113	0.9500	0.9500
Tap20-21	0.9638	10.078	10.800	0.9500	0.9534	10.122	0.9500	0.9547
Tap24-25	0.9766	10.186	0.9500	0.9500	0.9500	10.500	0.9500	0.9586
Tap24-25	0.9833	10.500	0.9500	0.9500	0.9664	0.9961	0.9500	0.9425
Tap24-26	0.9997	10.378	0.9500	0.9500	0.9554	10.500	0.9500	0.9487
Tap7-29	0.9973	0.9811	0.9500	0.9500	0.9522	0.9728	0.9500	0.9500
Tap32-34	10.023	0.9687	0.9500	0.9500	0.9558	0.9832	0.9500	0.9500
Tap11-41	0.9951	0.9500	0.9500	0.9500	0.9910	0.9500	0.9509	0.9500
Tap15-45	10.011	0.9500	0.9500	0.9500	0.9582	0.9500	0.9541	0.9500
Tap14-46	0.9960	0.9500	0.9680	0.9500	10.403	0.9500	0.9500	0.9500
Tap10-51	10.324	0.9670	0.9500	0.9500	0.9500	0.9657	0.9509	0.9500
Tap13-49	0.9867	0.9500	0.9500	0.9500	0.9545	0.9500	0.9476	0.9500
Tap11-43	10.034	0.9500	0.9500	0.9500	10.503	0.9500	0.9512	0.9500
Tap40-56	10.136	10.007	0.9500	0.9500	0.9500	0.9863	0.9500	0.9502
Tap39-57	10.438	0.9500	0.9530	0.9500	0.9529	0.9539	0.9502	0.9505
Tap9-55	10.291	0.9684	0.9500	0.9500	0.9500	0.9785	0.9503	0.9500
SVC49	0.1464	0.0169	0.0479	0.0333	0.1401	0.0531	0.1309	0.1309
SVC25	0.1124	0.0795	0.0917	0.0878	0.0450	0.0302	0.0493	0.0493

SVC38	0.2593	0.0486	0.0915	0.0975	0.1985	0.0732	0.1067	0.1067
TCSC24-26	0.0277	0.0453	0.0217	0.0116	0.1324	0.0449	0.0442	0.0434
TCSC14-46	0.0027	0.0032	0.0098	0.0096	0.0342	0.0039	0.0127	0.0119
TCSC10-51	0.0051	0.0	0.0022	0.0020	0.2913	0.0	0.0519	0.0438

Table 6 depicts the energy loss in the system before and after the installation of the FACTs. Notably, the system obtains a significant loss reduction when using ISOS instead of SOS, DE, and TLBO. At base loading, the ISOS technique achieves a 10.8% reduction in the loss, surpassing TLBO, DE, and SOS, which achieve only 4.08%, 8.24%, and 9.14% reduction, respectively. Similarly, at 150% of base loading, ISOS attains a 9.19% reduction, while TLBO, DE, and SOS attain 7.4%, 8.33%, and 8.69% in loss reduction.

Table 6. Total energy loss and percentage of loss reduction using TLBO, DE, SOS and ISOS with increased loading.

Reactive Loading	Initial loss (p.u.)	Energy loss (p.u.)				Energy Loss Reduction (%)			
		TLBO	DE	SOS	ISOS	TLBO	DE	SOS	ISOS
100%	0.2789	0.2675	0.2559	0.2534	0.2487	4.08	8.24	9.14	10.8
150%	0.3013	0.2790	0.2762	0.2751	0.2736	7.4	8.33	8.69	9.19

Table 7 shows the total operating costs before and after SVC and TCSC placement under two different loading conditions. The total system operating expenses are reduced to a great extent after using ISOS instead of SOS, DE, and TLBO, even after considering the expense of FACTS. There is a net saving in the operating cost of 1.562 M$ and 1.565 M$ for two cases of loadings using the ISOS technique.

Table 7. Operating Cost using TLBO, DE, SOS and ISOS with increased loading.

Q- Loading (in %)	Initial operating cost (in M $)	Optimization methods	Reduced operating cost with optimization methods (in M $)	Total net saving (in M$)
100	14.65	TLBO	13.741	0.929
		DE	13.55	1.12
		SOS	13.27	1.38
		ISOS	13.108	1.542
150	15.83	TLBO	14.648	1.182
		DE	14.56	1.27
		SOS	14.48	1.35
		ISOS	14.265	1.565

Table 8 shows the statistical metrics obtained in this analysis after applying all four optimization techniques.

Since all three optimization techniques consider various randomly initialized parameters, the simulation output also varies in each run. Two well-recognized statistical tests, the Sign test and the Wilcoxon Signed rank test, were also conducted for pairwise comparison among these approaches, ensuring a fair comparison of performance. These two tests were executed to demonstrate the superiority of the proposed ISOS algorithm over others. We ran all four optimization techniques 25 times each, and the performance metrics

Table 8. Statistical Analysis.

Loading	Techniques	Best	Worst	Mean	Standard deviation	Standard Deviation Error
100%	TLBO	1.3513	1.3576	1.384099	0.025847	0.002585
	DE	1.3465	1.3554	1.362498	0.016392	0.001639
	SOS	1.3283	1.3318	1.348965	0.025791	0.002579
	ISOS	1.3012	1.3042	1.326922	0.032126	0.003213
150%	TLBO	1.4621	1.4821	1.498701	0.059198	0.00592
	DE	1.4509	1.4617	1.469728	0.03556	0.003556
	SOS	1.4327	1.4563	1.461327	0.031784	0.003178
	ISOS	1.4105	1.4274	1.43683	0.028838	0.002884

were recorded every time. Table 9 displays the minimum number of wins required to achieve significant levels of α=0.05 and α=0.01 by running the algorithms 5 to 25 times.

Table 9. Minimum number of wins needed to attain significance levels of α=0.05 and α =0.01.

No. of cases	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
α=0.05	5	6	7	7	8	9	9	10	10	11	12	12	13	13	14	15	15	16	17	18	18
α=0.01	5	6	6	7	7	8	9	9	10	10	11	12	12	13	13	14	14	15	16	16	17

Table 10 compares all four optimization algorithms by considering the PSNR value as a victorious parameter.

Table 10. Using PSNR as the winning parameter, critical values for the two tailed sign tests were attained for α=0.05 and α=0.01.

ISOS	SOS	TLBO	DE
Wins (+)	20	18	17
Loss (-)	0	2	3
Detected difference	α=0.05	α=0.05	α=0.05

According to the Sign Test, the ISOS algorithm has a considerable advantage over the other algorithms with a magnitude of α=0.05, as shown in Table 11.

Table 11. Sign test using PSNR as winning parameters by applying all four optimization techniques.

Comparison	p-value	h-value
ISOS to SOS	0.0008	1
ISOS to TLBO	0.0006	1
ISOS to DE	0.0004	1

By considering the same PSNR value as the triumphant parameters, the p-value and h-value the resulting from the Wilcoxon signed test are presented in Table 12.

Table 12. Wilcoxon signed test using PSNR value as winning parameter by applying all four optimization techniques.

Comparison	p-value	h-value
ISOS to SOS	0.0002	1
ISOS to TLBO	0.0025	1
ISOS to DE	0.0001	1

Additionally, the ranking and parameters for the Friedman test, which is employed to detect the dominance between the two algorithms, are depicted in Tables 13 and 14.

Table 13. Ranking table for the Friedman test.

Methods	ISOS	SOS	TLBO	DE
Mean Ranks	16.8	5.2	17.2	18

Table 14. Parameter for the Friedman test.

Source	Sum of Squares	Degrees of Freedom	Mean Square	Chi-Square	Critical value (p)
Column	142.2	3	34.163	55.45	1.782E-11
Error	57.9	75	0.785		
Total	198	100			

Figures 4 and 5 depict the convergence characteristics for energy loss under base load and 150 percent of base load, respectively, employing various optimization techniques. As can be seen, the ISOS technique converges much faster than other competitive optimization techniques.

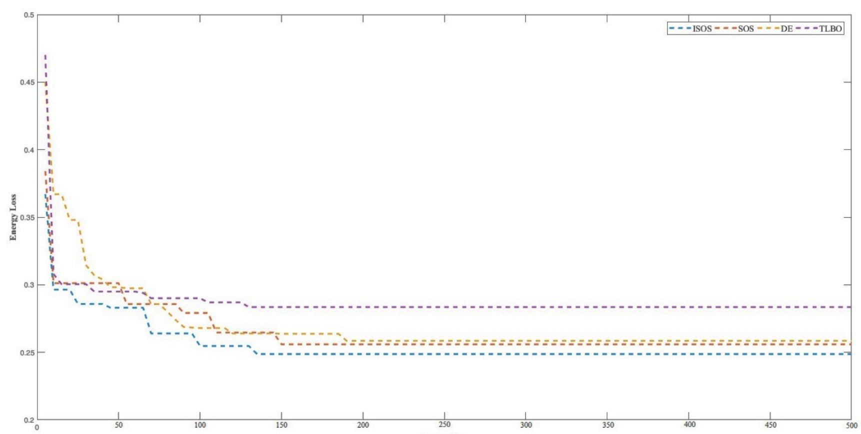

Figure 4. Energy loss with respect to generation at base loading.

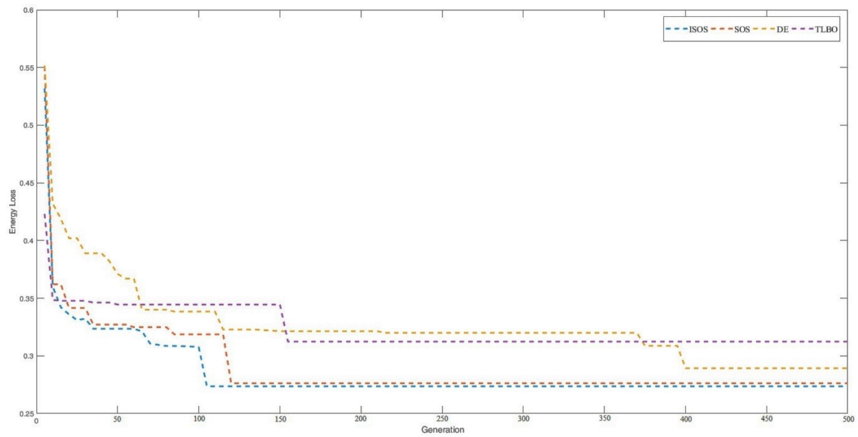

Figure 5. Energy loss with respect to generation at 150% of base loading.

Figures 6 and 7 show the convergence characteristics for the operating cost under base load and 150 percent of base load, respectively, using all four optimization techniques. It is evident from the data presented in these figures that the ISOS technique demonstrates notably faster convergence compared to the other optimization methods. It can be concluded from simulation studies that the proposed ISOS approach is superior to alternative approaches in terms of accessibility, operating cost minimization, and energy loss reduction.

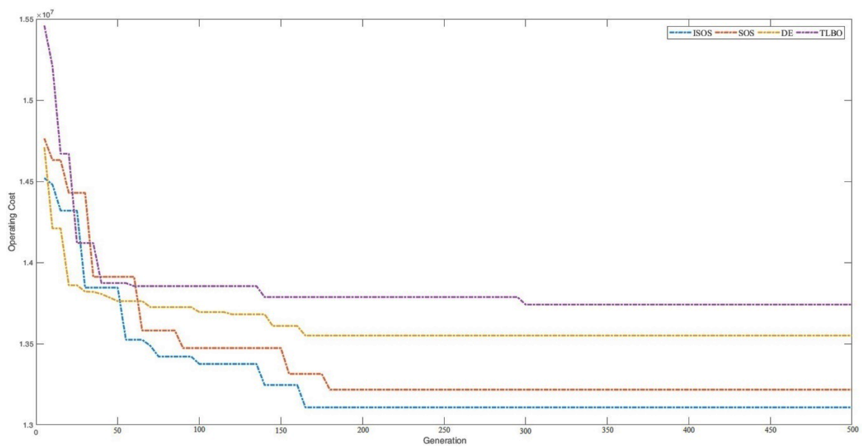

Figure 6. Operating cost with respect to generation at base loading.

6. Conclusions

This paper presents the implementation of the ISOS optimization technique for effective reactive power management on the IEEE 57 bus system. The proposed approach successfully mitigates energy loss and reduces the overall system cost by optimizing power flow distribution in congested transmission lines through the strategic allocation of Flexible AC Transmission Systems (FACTS) devices. The proposed ISOS algorithm was compared with other state-of-the-art optimization techniques: SOS, DE, and TLBO. It is observed that the proposed approach outperforms others by requiring fewer evaluation functions because it eliminates the need for tuning parameters. The application of the ISOS algorithm resulted in improved system performance and substantial cost savings of 1.562 M$ and 1.565 M$ for the base load scenario and 150% of the base load, respectively. Notably, the versatility of the ISOS technique extends beyond

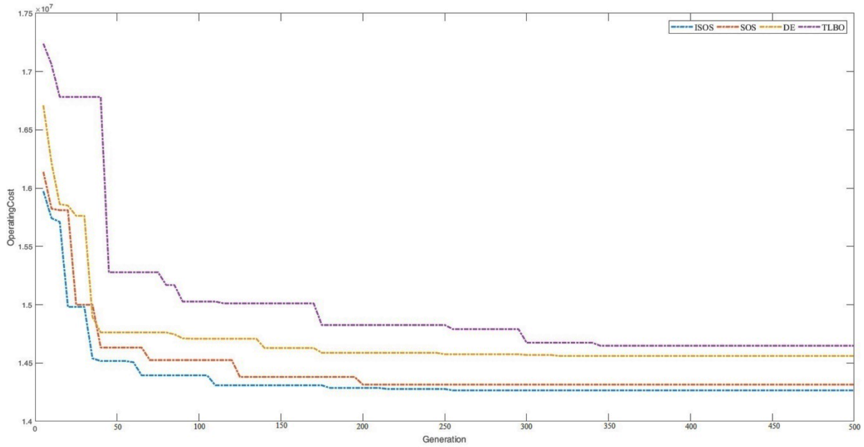

Figure 7. Operating cost with respect to generation at 150% of base loading.

its application in reactive power management, as it can be employed in various engineering domains to attain superior solutions with enhanced responsiveness and local search capabilities. Additionally, we validated the superiority of the ISOS algorithm over the other three optimization techniques by conducting rigorous statistical tests, including the Signed test, Wilcoxon signed rank test, and Friedman test. In the future, the reactive power management capability of the proposed approach for any other bus system may be investigated. Hybridization of the ISOS algorithm with other recently proposed swarm and evolutionary optimization techniques could be explored to enhance the performance.

Funding: This research received no external funding.

Author contributions: Conceptualization, V.K.G.; Writing – Review & Editing, R.B.; Supervision, V.K.G.

Disclosure statement: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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