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ORIGINAL ARTICLE

Optimal reactive power dispatch under coordinated active and reactive load variations using FACTS devices

Sushil Kumar Gupta[1] · Lalit Kumar[1] · Manoj Kumar Kar[1] · Sanjay Kumar[1]

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Abstract In this paper, a solution is provided for solving optimal reactive power dispatch (ORPD) problem by using flexible alternating current transmission (FACTS) devices. The TLBO method is applied on IEEE 14-, 30- and 57- bus test system with optimal positioning of thyristor-controlled series compensator (TCSC) and static var compensator (SVC). The location for TCSC and SVC has been chosen by performing power flow analysis. The ORPD problem is formulated to minimize both active power loss and operating cost. The main objective of this work is to dispatch optimal reactive power considering various loading conditions. The performance of the proposed method is tested under increased reactive loading and simultaneous increased of both active and reactive loading conditions. The proposed method's performance is evaluated under various operating conditions. The obtained results are compared with some of the recent promising techniques such as KHA, BBO and PSO. The simulation results show the efficacy of the proposed method in achieving the better performance of the system in terms of minimum power loss, minimum operating cost and better convergence rate.

✉ Lalit Kumar
2019rsee005@nitjsr.ac.in

Sushil Kumar Gupta
skgupta.ee@nitjsr.ac.in

Manoj Kumar Kar
manojkar132@gmail.com

Sanjay Kumar
sanjay.ee@nitjsr.ac.in

[1] Department of Electrical Engineering, NIT Jamshedpur, Jamshedpur, Jharkhand, India

Keywords Reactive power dispatch · Real power loss · Operating cost · FACTS controllers

1 Introduction

In recent years load demands are dynamically increasing as a result of which some of the transmission lines carries power above the normal capacity. Fulfilling the required demand by constructing new transmission lines or by placing the static capacitors is not feasible due to political and economic factors, also static capacitor once charged suffers from sub synchronous resonance condition. The system capacity may be increased by improving performance of the lines and minimizing the losses. In last few decades, FACTS devices provide the best solution in this aspect due to its unique features such as increased transmission capacity, maintenance of electrical and thermal stability and mitigation of sub synchronous resonance. The ORPD ensures the security, reliability operation of power system. In this work two FACTS devices, namely, Static Var Compensator (SVC) and Thyristor Controlled Series Compensator (TCSC), have been incorporated in IEEE- 14, -30 and -57 bus system.

The existing transmission line become overloaded with day-to-day increased load demand, which causes stability problems in power system. Voltage stability is maintained using SVC and TCSC using sequential quadratic programming (Aghaei et al. 2012). The congestion issue has been solved by optimally coordination of FACTS devices as well as demand response to attain reduced market operation and re-dispatch cost (Yousefi et al. 2012). The control parameter and location of FACTS devices generally varies based on the different approaches. Pricing and sensitivity-based approach with interior point method has been chosen to find the location for the placement of Unified Power Flow controller

(UPFC) and thereby helps to minimize the real power loss and operating cost (Singh 2016). Brain storm optimization algorithm has been applied to find the location of SVC and TCSC for enhancement of voltage profile and stability (Dash et al. 2020). JAYA blended MFO which is a hybrid form of MFO (Moth Flame Optimization) is used in Jordehi (2015) for reducing active power loss. The minimization of cost and maximization of annual benefit is achieved by hybrid PSO using FACTS devices in Wibowo et al. (2011). The efficacy of Moth Flame Optimization (MFO) has been shown over Symbiotic organism Search (SOS) and PSO to reduce real power loss using SVC and TCSC is shown in Kar et al. (2020). Gravitational search algorithm (GSA) has been reduced active loss and cost with increased active and reactive loadings on line of test bus systemin (Bhattacharyya and Kumar 2016). The optimal power flow problem (OPF) has been solved using GSA (Duman et al. 2012). The load ability of lines has been improved using TCSC, SVC and Thyristor controlled phase shifting transformer (TCPST) (Nagalakshmi and Kamaraj 2012). In (Mohanty and Tripathy 2016), teaching and learning based optimization technique (TLBO) has been used to configure and locate distributed generator. The TLBO method has been used to solve bigger size nonlinear problem (Rao et al. 2012). SVC, TCSC, tap settings and var generations have been ameliorated using GSA to reduce congestion (Bhattacharyya and Kumar 2016). GSA and PSO results have been compared for TCSC and SVC values to plan reactive power flow in lines (Bhattacharyya and Kumar 2015). Multiple objectives related to congestion have been optimized using FACTS using pareto solution set in Esmaili et al. (2014). The best VAR reserve for a given period is calculated for a forecasted load using IEEE 6 and 57 bus systems (El-Araby and Yorino 2018), but different loading conditions has not been considered. Using autonomous groups PSO, the ideal location and size of the SVC in IEEE 14 and 30 bus systems has been determined in Shehata et al. 2021. In (Hassan et al. 2013), GA has been used to reduce damping ratio using UPFC by controlling its parameters. The load ability of lines has been improved by optimizing the values of TCSC, TCPST, thyristor controlled var regulator (TCVR) using GA in Gerbex et al. (2001). The optimal power flow problem was handled using multi-FACTS devices (Biswas et al. 2021), which provided a solution for fixed loading but did not consider active or reactive loading. Optimal power flow using multiple UPFC has been achieved using GSA and results are compared with various metaheuristic algorithms (Sarker and Goswami 2014). The hybrid form of multi objective PSO is utilized in Roselyn et al. (2018) to manage the reactive power for stability improvement under the normal and stressed conditions. To investigate the impact of FACTS devices, the OPF problem with the UPFC model was solved via lightning attachment procedure optimization (Taher et al. 2020). The bio inspired optimization techniques were tested under different operation cases such as an increase in load, with and without FACTS and renewable energy sources, and different renewable energy source locations on the network to consider and address the challenges of the OPF in modern power network models (Nusair et al. 2021). The ideal positions of phasor measurement unit (PMUs) are found using a voltage indicator approach in Babu et al. (2020), which is determined using a revolutionary deterministic method based on a linear logic programme model. To reduce the quantity of PMUs in the electrical market, a modified branch and bound algorithm (Babu et al. 2021a) is utilised. Also, a non—linear programming-based approach (Babu et al. 2021b) is proposed to solve optimal PMU location issue for overall power network observability with considering the contingency. Along these lines, to reach their objective the authors have utilized various optimization techniques such as particle swarm optimization (PSO) (Kumar et al. 2021; Kar et al. 2021), biogeography-based optimization (BBO) (Bhattacharya and Chattopadhyay 2011), and Krill heard Algorithm (KHA) (Mukherjee and Mukherjee 2015).

In recent times several methods have been applied to improve the performance of the system in terms of reduction of the power losses and operating cost. But, since these methods are stochastic in nature, there is always a chance of improvement. In this work, the better performance of IEEE -14, -30 and -57 bus system is achieved using the TLBO technique.

2 Objective function

The main aim of this work is to relieve congestion from lines which in this paper is created with two cases of various loading conditions, first case by increasing reactive loading to 1.5 and 2 times the base loading and in second case by increasing both active and reactive loading to 1.1 and 1.2 times of base loading. If lines are freed of reactive power, then more space can be fostered for active power flow which in turn could fulfill demands Also, if our active power loss is reduced then lines transfer capability will be alleviated. FACTS installation is a costly affair, but if overall operating cost of the system is reduced after FACTS placement, then also congestion problem is said to be solved. Loss function is given by Eq. (1),

$$P_L = \sum\nolimits_{x=(m,n)}^{q} g_x \left\{ V_m^2 + V_n^2 - 2V_m V_n \cos \delta_{mn} \right\} \tag{1}$$

P_L is the active power loss of system, where g_x is the conductance of line between buses 'm' and 'n' and δ_{mn} is the phase difference between these buses. Loss is function of line conductance and bus voltages which are influenced by TCSC and SVC. Overall operating cost is given by Eq. (2),

$$C_{total} = C_{system} + C_{SVC} + C_{TCSC} \tag{2}$$

$$C_{SVC} = 0.0003Bsvc^2 - 0.3051Bsvc + 127.38US\$pu \tag{3}$$

$$C_{TCSC} = 0.0015xtcsc^2 - 0.7130xtcsc + 153.75US\$pu \tag{4}$$

where C_{system} is cost due to energy loss which is evaluated as $P_L \times 0.06 \times 100{,}000 \times 8760.$,$C_{SVC}$ is the cost of SVC which depends on the shunt susceptance value *Bsvc* and C_{TCSC} is the cost of TCSC which again depends on its reactance value given by *xtcsc*. Energy cost is taken as 0.06 $/Kwhr and cost is referred from Bhattacharyya and Kumar (2016).

Constraints always come in picture for defining objective function boundaries. Some inequality constraints are shown for active power, reactive power, voltage magnitude, SVC value and TCSC value respectively from Eq. 5, 6, 7, 8, 9 respectively.

$$P^{min} \le P \le P^{max} \tag{5}$$

$$Q^{min} \le Q \le Q^{max} \tag{6}$$

$$0.9pu \le V \le 1.1pu \tag{7}$$

$$0.05pu \le Bsvc \le 0.15pu \tag{8}$$

$$0.01pu \le xtcsc \le 0.06pu \tag{9}$$

3 Proposed approach

Congestion is created by increasing reactive loading for IEEE- 14, IEEE-30 and IEEE-57 bus systems to 1.5–2.0 times base loadings and also by increasing active and reactive loading to 1.1 to 1.2 times base loadings. The Power Flow studies has been achieved using Newton- Raphson's load flow method. From this analysis, the lines carrying the maximum reactive power and weak buses are identified. The TCSC and SVC are placed in these lines and buses respectively. The existing KHA, PSO, BBO and proposed TLBO optimization techniques are used to configure SVC, TCSC, Tap changers and Var generations of generators for minimization of active power loss and operating cost as an objective function.

3.1 Teaching and learning based optimization technique (TLBO)

The problems of Loss and Cost functions are nonlinear functions which could be properly solved by the meta-heuristic optimization technique TLBO. It is based "on the influence of teacher on output of learner in a class" (Rao et al. 2012). Because the TLBO algorithm has few parameters, a fast convergence capability, and a strong global search ability, the basic form of the TLBO algorithm was utilized in this study to answer the research objectives of optimal reactive power dispatch under various operating situations.

Teaching and learning principles define TLBO and output is result secured by students. A good teacher infuses great knowledge to his students who perform better when they properly interact with their mates. TLBO like other nature inspired algorithm is a population-based methodology; here mean result of learners is the considerable factor. First students' population is defined and later mean is calculated from this. The global best value of learner is obtained by calculations from both teacher's and learners' phase (that is both their contributions). Motion induced by other krill individuals (N_i).

3.1.1 Teacher phase

Teacher aims to increase the mean but increasing mean is a random process. X_{teach} is the new mean and it is determined by best learner in class. So, the solution is updated as per the difference between the existing and new mean, this difference is

$$d = r_i\left(X_{teach} - T_f M_i\right) \tag{10}$$

$$T_f = round[1 + rand(0,1)\{2-1\}] \tag{11}$$

T_f is the teaching factor that decides the mean value, r_i is the random number that belongs to the number either 1 or 2. M_i and T_i are the mean and teacher at ith iteration and teacher tries to improve the mean to value X_{teach}.

$$X_{new,i} = X_{o,i} + d \tag{12}$$

$X_{new,i}$ is the modified solution and if it gives better fitness then it will be considered, otherwise it is discarded, $X_{o,i}$ is the previous value of learners. After this, solution is again optimized by learner's phase.

3.1.2 Learner phase

Learner learns fast when he shares his knowledge with fellow mates and it is achieved in this section. Another learner is selected from the population and if it gives better fitness then new solution is updated as

$$X_{new,i} = X_{o,i} + r_i\left(X_j - X_i\right) \tag{13}$$

Otherwise, new solution is

$$X_{new,i} = X_{o,i} + r_i(X_i - X_j) \tag{14}$$

This new solution is again tested for better fitness if it gives better result then, it is accepted least previous value is considered. The flowchart of proposed TLBO method for ORPD problem is depicted in Fig. 1.

3.2 Configuration of TCSC and SVC

The location for placement on IEEE-14, IEEE- 30 and IEEE-57 bus system is determined optimal power flow using Newton- Raphson's load flow method. The lines and buses are keenly observed for maximum reactive flow and minimum bus voltages respectively. For more convergence line that are connected to generator buses are not considered. Once location is ascertained the configuration of parameters are to be defined wisely which is done by optimization techniques. For TLBO, initially population is defined: Var generations of generators, SVC, TCSC and tap changer settings are considered as learners. Mean of the values of population is calculated and the learner who gives minimum loss and minimum cost is considered as teacher. The new

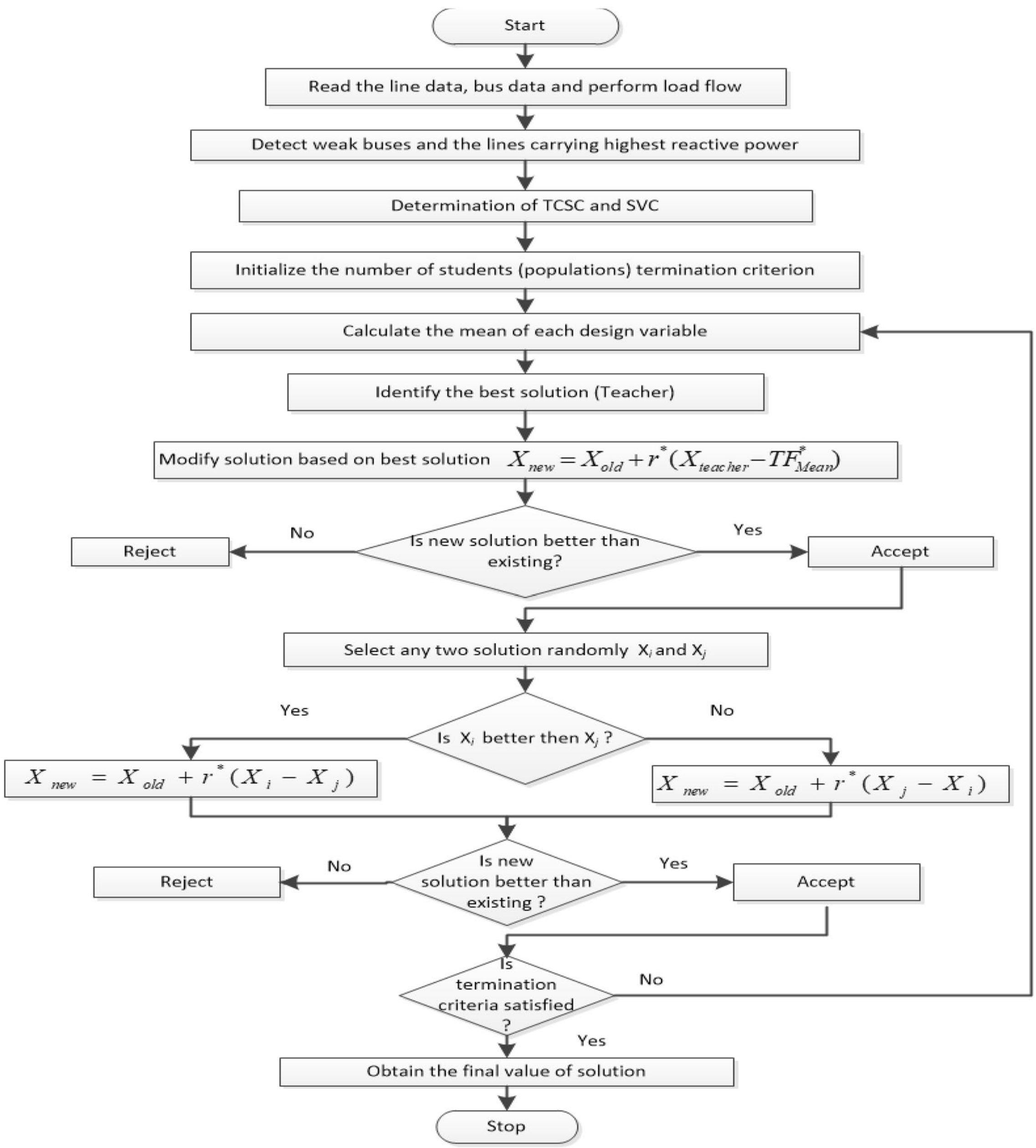

Fig. 1 Flowchart of proposed TLBO method

solution is calculated using Eq. 13 and again tested for better fitness. This ends teacher's phase and for learner's phase again a learner from defined population is compared with current learner to give better result. With respect to this, new solution is calculated using Eq. 13 and 14. Calculation for parameters value is also done using Krill Herd, BBO and PSO techniques to compare the results as to which technique is better in solving the objective function. Results are tested for different reactive loadings that are, 150% and 200% of base reactive loading and also for both active and reactive loading of 110% and 120% of base loading. Variables for 14 bus system 3 tap changer, 4 generators, 3 SVCs on 10,13,14 buses and 1 TCSC on line no. 7, for 30 bus system 4 tap changers, 5 generators, 4 SVCs on 7, 15, 17, 21 buses and 4 TCSCs on 5, 25, 28, 41 lines and for 57 bus system 15 tap changer, 6 generators, 4 SVCs on 32, 25, 42 and 57 buses and 4 TCSCs on 20, 65, 55 and 44 lines.

4 Results and discussions

Table 1, 2 and 3 shows the loss reduction by incorporating FACTS controllers considering base or nominal loading, reactive loading and both active and reactive loadings for IEEE 14, IEEE 30 and IEEE 57 test bus systems respectively. The real power losses are evaluated at base, 150 and 200 percentage of reactive loading, and 110 and 120 percentage of active and reactive loadings. It is concluded from the analysis shown in the table, the TLBO technique outperforms the other methods like as KHA, BBO, and PSO in terms of loss reduction.

Table 4, 5 and 6 shows operating cost in absence and presence of FACTS controllers considering base loading, reactive loading, and active and reactive loading. Since the reactive power is properly optimized in lines and hence the losses are reduced. Net Savings (in \$/p. u) is also shown which is the difference of the overall cost before and after using the FACTS controllers. It is noticed that incorporating FACTS controllers with TLBO technique gives better

Table 1 Real power Loss with various loading scenarios in IEEE 14 bus system

Types of loading	Loading (in %)	Real power loss without FACTS (in p. u.)	Real power loss with FACTS using various methods (in p. u.)			
			KHA	PSO	BBO	TLBO
Base loading	100	0.1346	0.1320	0.1335	0.1321	0.1046
Reactive loading	150	0.1461	0.1322	0.1336	0.1322	0.1105
	200	0.1744	0.1326	0.1337	0.1325	0.1176
Active & Reactive loading	110	0.1709	0.1639	0.1649	0.1640	0.1332
	120	0.2160	0.1998	0.2005	0.1997	0.1646

Table 2 Real power Loss with various loading scenarios in IEEE 30 bus system

Types of loading	Loading (in %)	Real power loss without FACTS (in p. u.)	Real power loss with FACTS using various methods (in p. u.)			
			KHA	PSO	BBO	TLBO
Base loading	100	0.0711	0.0453	0.0448	0.0442	0.0420
Reactive loading	150	0.0742	0.0499	0.0499	0.0498	0.0468
	200	0.0795	0.0572	0.0559	0.0569	0.0541
Active & Reactive loading	110	0.0917	0.0539	0.0540	0.0552	0.0428
	120	0.1263	0.0949	0.0926	0.0929	0.0879

Table 3 Real power Loss with various loading scenarios in IEEE 57 bus system

Types of loading	Loading (in %)	Real power loss without FACTS (in p. u.)	Real power loss with FACTS using various methods (in p. u.)			
			KHA	PSO	BBO	TLBO
Base loading	100	0.2799	0.2298	0.2325	0.2303	0.2239
Reactive Loading	150	0.2999	0.2398	0.2407	0.2381	0.2320
	200	0.3326	0.2581	0.2576	0.2570	0.2567
Active & Reactive loading	110	0.4166	0.3265	0.3202	0.3130	0.3067
	120	0.6107	0.3400	0.3227	0.3174	0.3160

Table 4 Analysis of Operating cost before and after using FACTS for various types of loading in IEEE 14 bus system

Types of loading	Loading (in %)	Operating cost with considering energy loss in $ (A)	Methods	Minimum operating cost after using FACTS devices in $ (B)	Net saving in $ [A—B]
Base loading	100	7,074,576	KHA	6,938,906	135,670
			PSO	7,017,486	57,090
			BBO	6,942,865	131,711
			TLBO	5,497,776	1,576,800
Reactive loading	150	7,679,016	KHA	6,949,673	729,343
			PSO	7,024,603	654,413
			BBO	6,950,516	728,500
			TLBO	5,810,508	1,868,508
	200	9,166,464	KHA	6,970,698	2,195,766
			PSO	7,026,474	2,139,990
			BBO	6,966,009	2,200,455
			TLBO	6,191,568	2,974,896
Active and Reactive loading	110	8,982,504	KHA	8,616,401	366,103
			PSO	8,668,374	314,130
			BBO	8,619,902	362,602
			TLBO	7,000,992	1,981,512
	120	11,352,960	KHA	10,499,557	853,403
			PSO	10,536,406	816,554
			BBO	10,498,521	854,439
			TLBO	08,653,058	2,699,902

Table 5 Analysis of Operating cost before and after using FACTS for various types of loading in IEEE 30 bus system

Types of loading	Loading (in %)	Operating cost with considering energy loss in $ (A)	Methods	Minimum operating cost after using FACTS devices in $ (B)	Net saving in $ [A—B]
Base loading	100	3,737,016	KHA	2.3802×10^6	1,356,806
			PSO	2.3529×10^6	1,384,144
			BBO	2.2345×10^6	1,412,516
			TLBO	2.2082×10^6	**1,514,016**
Reactive loading	150	3,899,952	KHA	2.6239×10^6	1,276,089
			PSO	2.6249×10^6	1,277,462
			BBO	2.6188×10^6	1,281,132
			TLBO	2.4577×10^6	**1,442,238**
	200	4,178,520	KHA	3.0089×10^6	1,116,901
			PSO	2.9368×10^6	1,241,729
			BBO	2.9930×10^6	1,185,549
			TLBO	2.8458×10^6	**1,332,674**
Active and Reactive loading	110	4,819,752	KHA	2.8337×10^6	1,986,055
			PSO	2.9022×10^6	1,917,512
			BBO	2.8358×10^6	1,983,903
			TLBO	2.2513×10^6	**2,568,495**
	120	6,638,328	KHA	4.9867×10^6	1,651,640
			PSO	4.8677×10^6	1,770,651
			BBO	4.8822×10^6	1,756,170
			TLBO	4.6185×10^6	**2,019,839**

Best values are presented in bold

Table 6 Analysis of Operating cost before and after using FACTS for various types of loading in IEEE 57 bus system

Types of loading	Loading (in %)	Operating Cost with considering energy loss in $ (A)	Methods	Minimum operating cost after using FACTS devices in $ (B)	Net saving in $ [A—B]
Base loading	100	1.4712×10^7	KHA	1.2078×10^7	2,633,901
			PSO	1.2220×10^7	2,491,121
			BBO	1.2105×10^7	2,606,822
			TLBO	1.1766×10^7	**2,945,733**
Reactive loading	150	1.5762×10^7	KHA	1.2605×10^7	3,158,156
			PSO	1.2652×10^7	3,110,352
			BBO	1.2513×10^7	3,249,208
			TLBO	1.2192×10^7	**3,571,144**
	200	1.7481×10^7	KHA	1.3565×10^7	3,916,131
			PSO	1.3541×10^7	3,940,530
			BBO	1.3510×10^7	3,971,214
			TLBO	1.3492×10^7	**3,989,345**
Active and Reactive loading	110	2.1897×10^7	KHA	1.7161×10^7	4,735,966
			PSO	1.6831×10^7	5,065,068
			BBO	1.6449×10^7	5,065,068
			TLBO	1.6120×10^7	5,447,223
	120	3.2098×10^7	KHA	1.7868×10^7	**5,776,050**
			PSO	1.6959×10^7	14,230,090
			BBO	1.6684×10^7	15,139,206
			TLBO	1.2078×10^7	**15,414,691**

Best values are presented in bold

savings as compared to other discussed techniques. An approximate of 30–50% savings in cost is achieved when the control variables are optimized using TLBO technique whereas 20–35% savings is obtained by KHA, BBO, and PSO in all the types of loading with IEEE- 14, 30 and 57 test bus system. The cost of FACTS devices configured by TLBO is very cheap while the others method configured FACTS devices are expensive. As cost of FACTS depends on susceptance and reactance value, so smaller values for these parameters are chosen in the TLBO technique.

Table 7, 8 and 9 shows real power loss reduction at various types of loading with different optimization techniques. It is noticed that incorporating FACTS controllers with TLBO technique gives better reduction in losses as compared to other discussed techniques in all the cases such as at base loading, reactive loading or active and reactive loading in all the three-test bus system.

Figures 2, 3, 4, 5 and 6, Figs. 7, 8, 9, 10 and 11 and Figs. 12, 13, 14, 15 and 16 shows the operating cost variation with respect to no. of iteration using KHA, PSO, BBO and TLBO method at distinct loading conditions for IEEE 14, IEEE 30 and IEEE 30 bus system respectively. All the aforesaid techniques are being simulated for 1000 iterations and population no. holds as 40 for both the test bus network.

Table 7 Real Power Loss reduction (in %) at various types of loading with different techniques in IEEE 14 test bus system

Types of loading	Loading (in %)	Loss reduction using various methods (in %)			
		KHA	PSO	BBO	TLBO
Base loading	100	1.96	0.82	1.86	22.28
Reactive loading	150	9.51	8.56	9.52	24.36
	200	23.97	23.34	24.03	32.57
Active & Reactive loading	110	4.11	3.51	4.04	22.06
	120	7.50	7.18	7.55	23.80

Table 8 Real Power Loss reduction (in %) at various types of loading with different techniques in IEEE 30 test bus system

Types of loading	Loading (in %)	Loss reduction using various methods (in %)			
		KHA	PSO	BBO	TLBO
Base loading	100	36.29	36.99	37.83	40.93
Reactive loading	150	32.74	32.74	32.88	36.92
	200	28.05	29.68	28.42	31.95
Active & Reactive loading	110	41.22	41.01	39.80	53.33
	120	24.86	28.81	26.45	30.40

Table 9 Real Power Loss reduction (in %) at various types of loading with different techniques in IEEE 30 test bus system

Types of loading	Loading (in %)	Loss reduction using various methods (in %)			
		KHA	PSO	BBO	TLBO
Base loading	100	17.90	16.93	17.72	20.01
Reactive loading	150	20.04	19.73	20.61	22.65
	200	22.39	22.54	22.73	22.82
Active & Reactive loading	110	21.62	23.14	24.87	26.38
	120	44.33	47.16	48.02	48.25

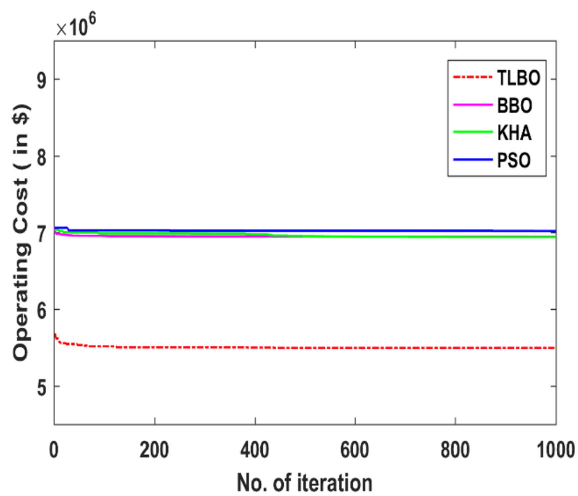

Fig. 2 Operating cost variation with iteration using various algorithms at 100% loading for IEEE 14 bus system

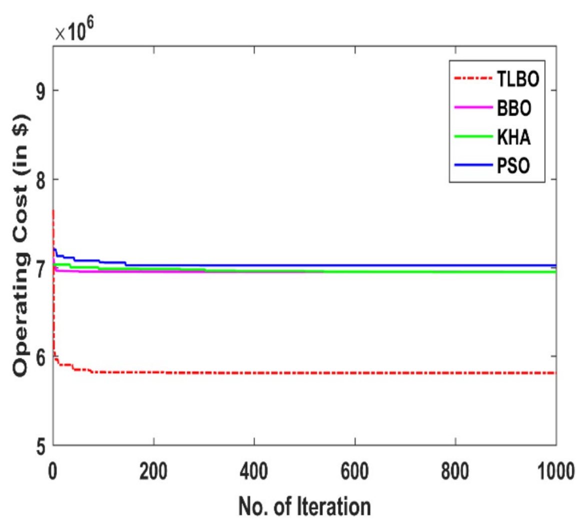

Fig. 3 Operating cost variation with iteration using various algorithms at 150% loading for IEEE 14 bus system

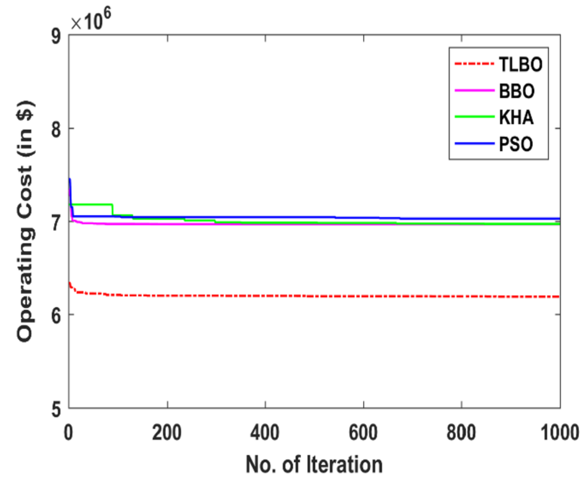

Fig. 4 Operating cost variation with iteration using various algorithms at 200% loading for IEEE 14 bus system

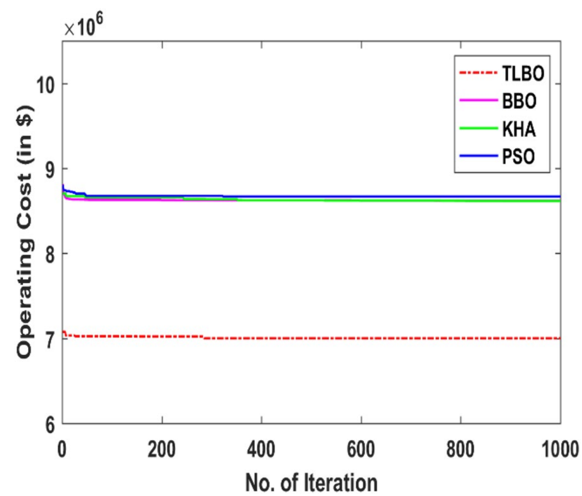

Fig. 5 Operating cost variation with iteration using various algorithms at 110% loading for IEEE 14 bus system

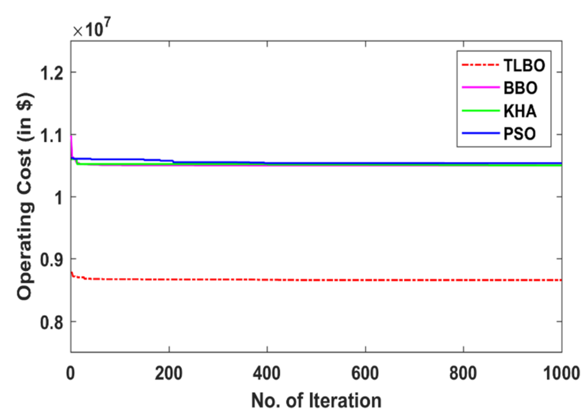

Fig. 6 Operating cost variation with iteration using various algorithms at 120% loading for IEEE 14 bus system

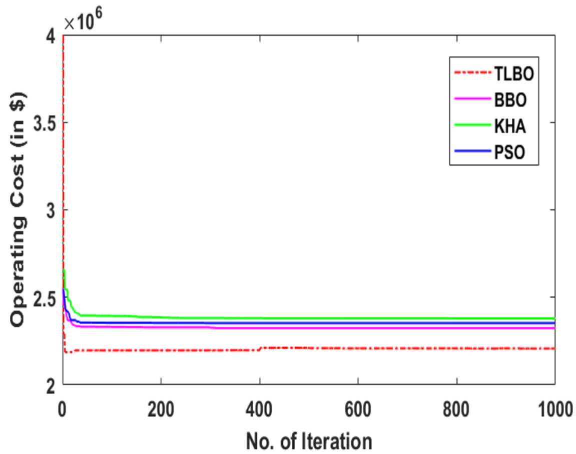

Fig. 7 Operating cost variation with iteration using various algorithms at 100% loading for IEEE 30 bus system

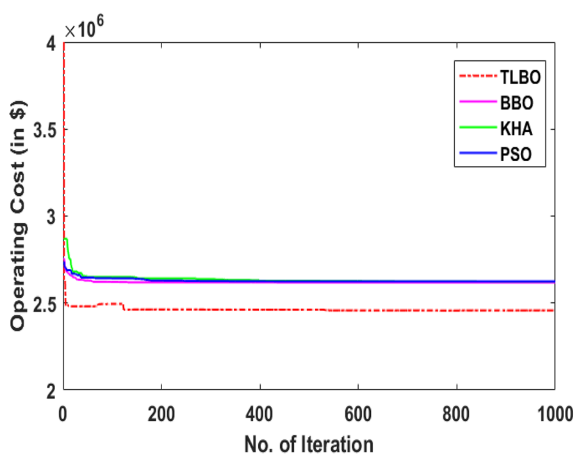

Fig. 8 Operating cost variation with iteration using various algorithms at 150% of reactive loading for IEEE 30 bus system

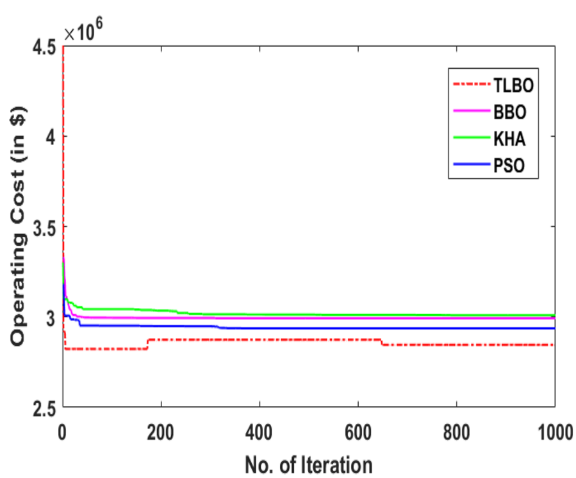

Fig. 9 Operating cost variation with iteration using various algorithms at 200% of reactive loading for IEEE 30 bus system

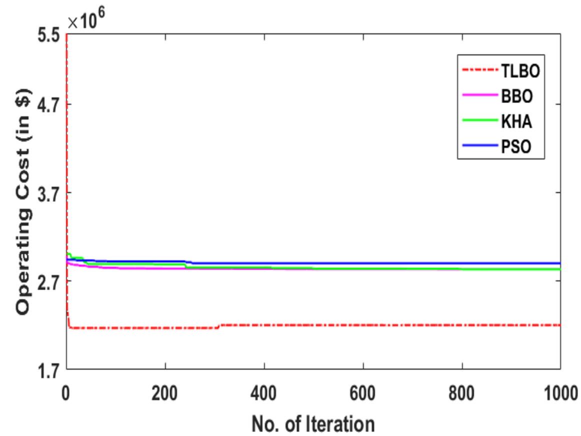

Fig. 10 Operating cost variation with iteration using various algorithms at 110% active and reactive loading for IEEE 30 bus system

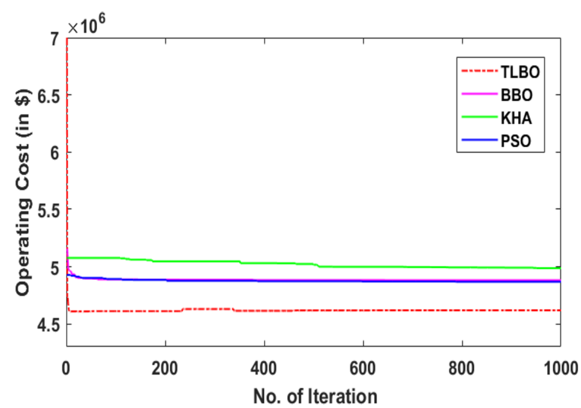

Fig. 11 Operating cost variation with iteration using various algorithms at 120% active and reactive loading for IEEE 30 bus system

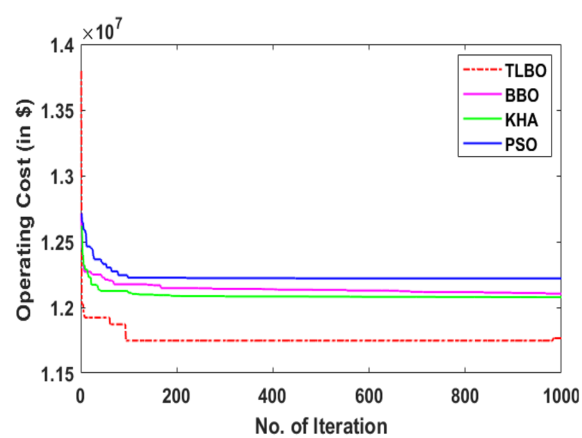

Fig. 12 Operating cost variation with iteration using various algorithms at 100% loading for IEEE 57 bus system

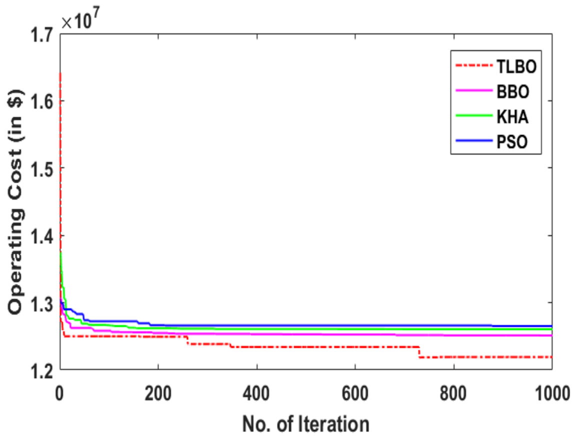

Fig. 13 Operating cost variation with iteration using various algorithms at 150% of reactive loading for IEEE 57 bus system

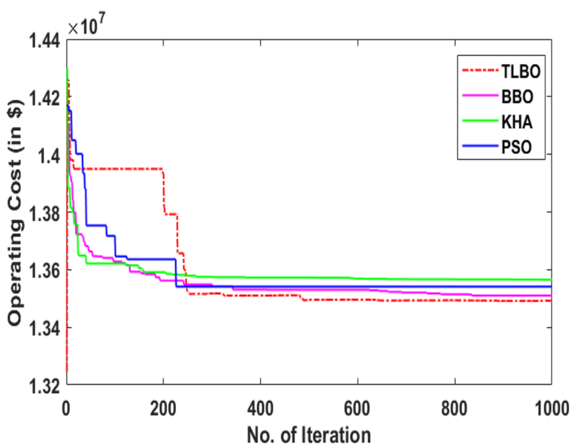

Fig. 14 Operating cost variation with iteration using various algorithms at 200% of reactive loading for IEEE 57 bus system

Here the comparison of operating cost using various techniques are represented. It is clear that TLBO yields better convergence rate as compared with other described techniques in terms of operating cost for all distinct reactive loading conditions as well as distinct active and reactive loading conditions.

5 Conclusion

In this paper, the proposed TLBO technique is implemented on standared IEEE 30 and 57 buses with TCSC and SVC devices for the minimization of active power loss under increased reactive and both active and reactive loading conditions. The supremacy of the proposed method is justified

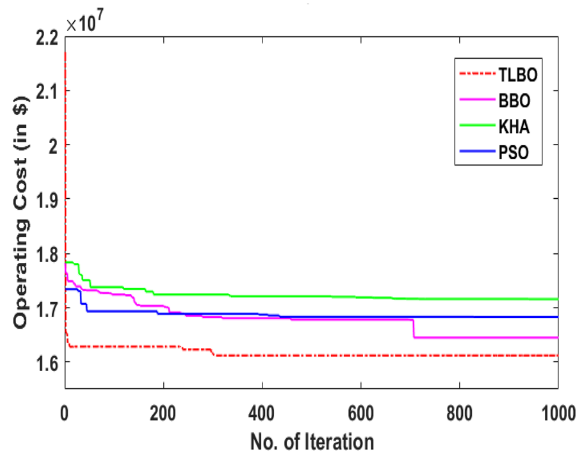

Fig. 15 Operating cost variation with iteration using various algorithms at 110% active and reactive loading for IEEE 57 bus system

by comparing with some of the promising techniques. The

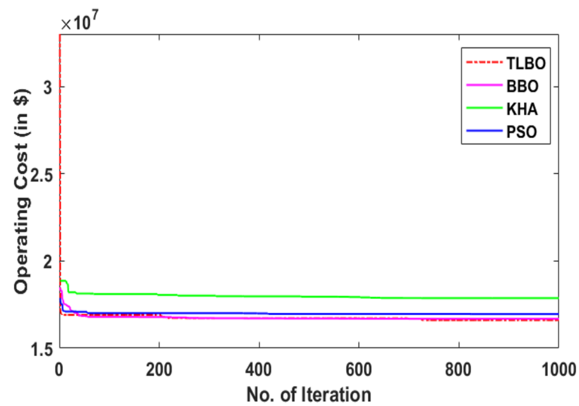

Fig. 16 Operating cost variation with iteration using various algorithms at 120% active and reactive loading for IEEE 57 bus system

simulation result shows that the proposed TLBO technique results minimum active power loss as compared to the other tecniques. It is found that using TLBO method, the active power loss is reduced to 22.28%, 40.93% and 20.01% for IEEE-14, -30 and -57 bus systems respectively. In addition to this, the system operating cost is also found to be reduced. The proposed technique also yields faster convergence rate. The proposed method can be used in future work to solve complicated power system optimization problems. Additionally, this work may be extended with optimal placement of DG sources for better performance. This will help in determining the usefulness and robustness of the proposed method in dealing with a variety of challenging constraints in real world applications.

Declarations

Conflict of interest Authors doesn't have any conflict of interest.

Human or animal rights Research involving Human Participants and/or Animals: Human Participants and/or Animals are not involved in this research.

Informed consent There was no informed consent in this research article.

References

Aghaei J, Gitizadeh M, Kaji M (2012) Placement and operation strategy of FACTS devices using optimal continuous power flow. Sci Iranica 19(6):1683–1690

Babu R, Raj S, Bhattacharyya B (2020) Weak bus-constrained PMU placement for complete observability of a connected power network considering voltage stability indices. Prot Control Modern Power Syst 5(1):1–14

Babu R, Raj S, Dey B, Bhattacharyya B (2021) Modified branch-and-bound algorithm for unravelling optimal PMU placement problem for power grid observability: a comparative analysis. CAAI Trans Intell Technol 6(4):450–470. https://doi.org/10.1049/cit2.12038

Babu R, Gupta VK, Subbaramaiah K (2021) An approach to unravel the optimal PMU placement problem for full observability of power network in view of contingencies. Int J Syst Assur Eng Manag 13(3):1170–1186. https://doi.org/10.1007/s13198-021-01412-4

Bhattacharya A, Chattopadhyay PK (2011) Application of biogeography-based optimisation to solve different optimal power flow problems. IET Gener Transm Distrib 5(1):70–80

Bhattacharyya B, Kumar S (2015) Reactive power planning with FACTS devices using gravitational search algorithm. Ain Shams Eng J 6(3):865–871

Bhattacharyya B, Kumar S (2016) Loadability enhancement with FACTS devices using gravitational search algorithm. Int J Electr Power Energy Syst 1(78):470–479

Bhattacharyya B, Kumar S (2016) Approach for the solution of transmission congestion with multi-type FACTS devices. IET Gener Transm Distrib 10(11):2802–2809

Biswas PP, Arora P, Mallipeddi R, Suganthan PN, Panigrahi BK (2021) Optimal placement and sizing of FACTS devices for optimal power flow in a wind power integrated electrical network. Neural Comput Appl 33(12):6753–6774

Dash SP, Subhashini KR, Satapathy JK (2020) Optimal location and parametric settings of FACTS devices based on JAYA blended moth flame optimization for transmission loss minimization in power systems. Microsyst Technol 26(5):1543–1552

Duman S, Güvenç U, Sönmez Y, Yörükeren N (2012) Optimal power flow using gravitational search algorithm. Energy Convers Manage 1(59):86–95

El-Araby ES, Yorino N (2018) Reactive power reserve management tool for voltage stability enhancement. IET Gener Transm Distrib 12(8):1879–1888

Esmaili M, Shayanfar HA, Moslemi R (2014) Locating series FACTS devices for multi-objective congestion management improving voltage and transient stability. Eur J Oper Res 236(2):763–773

Gerbex S, Cherkaoui R, Germond AJ (2001) Optimal location of multi-type FACTS devices in a power system by means of genetic algorithms. IEEE Trans Power Syst 16(3):537–544

Hassan LH, Moghavvemi M, Almurib HA, Steinmayer O (2013) Application of genetic algorithm in optimization of unified power flow controller parameters and its location in the power system network. Int J Electr Power Energy Syst 1(46):89–97

Jordehi AR (2015) Brainstorm optimisation algorithm (BSOA): an efficient algorithm for finding optimal location and setting of FACTS devices in electric power systems. Int J Electr Power Energy Syst 1(69):48–57

Kar MK, Kumar S, Singh AK, Panigrahi S (2021) Reactive power management by using a modified differential evolution algorithm. Optim Control Appl Methods. https://doi.org/10.1002/oca.2815

Kar MK, Kumar L, Kumar S, Singh AK (2020) Efficient operation of power system with FACTS controllers using evolutionary techniques. In: 2020 7th international conference on signal processing and integrated networks (SPIN) IEEE. pp 962–965

Kumar L, Kar MK, Kumar S (2021) Reactive power management by optimal positioning of FACTS controllers using MFO algorithm. In: 2021 Emerging trends in industry 4.0 (ETI 4.0) IEEE. pp 1–6

Mohanty B, Tripathy S (2016) A teaching learning based optimization technique for optimal location and size of DG in distribution network. J Electrical Syst Inf Technol 3(1):33–44. https://doi.org/10.1016/j.jesit.2015.11.007

Mukherjee A, Mukherjee V (2015) Solution of optimal reactive power dispatch by chaotic krill herd algorithm. IET Gener Transm Distrib 9(15):2351–2362

Nagalakshmi S, Kamaraj N (2012) Comparison of computational intelligence algorithms for loadability enhancement of restructured power system with FACTS devices. Swarm Evol Comput 1(5):17–27

Nusair K, Alasali F, Hayajneh A, Holderbaum W (2021) Optimal placement of facts devices and power-flow solutions for a power network system integrated with stochastic renewable energy resources using new metaheuristic optimization techniques. Int J Energy Res 45(13):18786–18809. https://doi.org/10.1002/er.6997

Rao RV, Savsani VJ, Vakharia DP (2012) Teaching–learning-based optimization: an optimization method for continuous non-linear large scale problems. Inf Sci 183(1):1–5

Roselyn JP, Devaraj D, Dash SS (2018) Voltage-based reactive power pricing in deregulated environment using hybrid multi-objective particle swarm optimisation. Int J Ambient Energy 39(3):285–296

Sarker J, Goswami SK (2014) Solution of multiple UPFC placement problems using gravitational search algorithm. Int J Electr Power Energy Syst 1(55):531–541

Shehata AA, Refaat A, Ahmed MK, Korovkin NV (2021) Optimal placement and sizing of FACTS devices based on autonomous groups particle swarm optimization technique. Arch Electrical Eng. https://doi.org/10.24425/aee.2021.136059

Singh SP (2016) Congestion mitigation using UPFC. IET Gener Transm Distrib 10(10):2433–2442

Taher MA, Kamel S, Jurado F, Ebeed M (2020) Optimal power flow solution incorporating a simplified UPFC model using lightning attachment procedure optimization. Int Trans Electrical Energy Syst 30(1):e12170

Wibowo RS, Yorino N, Eghbal M, Zoka Y, Sasaki Y (2011) FACTS devices allocation with control coordination considering congestion relief and voltage stability. IEEE Trans Power Syst 26(4):2302–2310

Yousefi A, Nguyen TT, Zareipour H, Malik OP (2012) Congestion management using demand response and FACTS devices. Int J Electr Power Energy Syst 37(1):78–85