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## Heat Transfer and Simulated Coronary Circulation System Optimization Algorithms for Real Power Loss Reduction

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**Abstract.** In this paper, the heat transfer optimization (HTO) algorithm and simulated coronary circulation system (SCCS) optimization algorithm has been designed for Real power loss reduction. In the projected HTO algorithm, every agent is measured as a cooling entity and surrounded by another agent, like where heat transfer will occur. Newton's law of cooling temperature will be updated in the proposed HTO algorithm. Each value of the object is computed through the objective function. Then the objects are arranged in increasing order concerning the objective function value. This projected algorithm time "t" is linked with iteration number, and the value of "t" for every agent is computed. Then SCCS optimization algorithm is projected to solve the optimal reactive power dispatch problem. Actions of human heart veins or coronary artery development have been imitated to design the algorithm. In the projected algorithm candidate solution is made by considering the capillaries. Then the coronary development factor (CDF) will appraise the solution, and population space has been initiated arbitrarily. Then in the whole population, the most excellent solution will be taken as stem, and it will be the minimum value of the Coronary development factor. Then the stem crown production is called the divergence phase, and the other capillaries' growth is known as the clip phase. Based on the arteries leader's coronary development factor (CDF), the most excellent capillary leader's (BCL) growth will be there. With and without L-index (voltage stability), HTO and SCCS algorithm's validity are verified in IEEE 30 bus system. Power loss minimized, voltage deviation also reduced, and voltage stability index augmented.

**Keywords:** optimal reactive power, transmission loss, heat transfer, simulated coronary circulation system.

## 1 Introduction

Power loss minimization and voltage stability enhancement with voltage deviation minimization is the key objectives of this work. Newton's method, interior point method; successive quadratic programming method [1–6]. Nevertheless, there are enormous difficulties found in handling the in-equality constraints. These ten years, there is a massive growth in the swarm and evolutionary algorithms [7–39] for solving the problem. Algorithms like genetic, ant colony, wolf search, cuckoo search, birds swarm, fish swarm, gravitational search, particle swarm optimization, symbiotic organism search algorithm [41–52] are already solved the problem. The central aspect is to maintain the exploration and exploitation in the flow of the process. Many algorithms failed to tradeoff between exploration and exploitation. This paper projects the Heat Transfer Optimization (HTO) algorithm and the Simulated Coronary Circulation System (SCCS)

optimization algorithm to solve the optimal reactive power problem. In the proposed HTO algorithm, every agent is measured as a cooling entity, and it is surrounded by another agent, like where heat transfer will occur. Newton's law of cooling temperature will be updated in the proposed HTO algorithm. Object's temperature is considered the position's position, and the heat energy will be transferred to objects surrounding it. Then new-fangled positions are modernized through new temperature conditions. Each value of the object is computed through the objective function. Then the objects are arranged in increasing order concerning the objective function value. In algorithm Control variable<sub>1</sub> direct the random step size and Control variable<sub>2</sub> organize (1 – t). In the conclusion of the procedure, the value of "t" will be augmented, leading to a linear decrease in arbitrariness and escalating the exploitation. Objects are grouped into two modes concerning temperature as *Temperature*<sub>1</sub>

is ecological one for another object  $Temperature_{\frac{n}{2}+1}$  which is in cooling condition. This paper proposes Simulated Coronary Circulation System (SCCS) optimization algorithm to solve the optimal reactive power problem. SCCS algorithm has been modeled by imitating the actions of human heart veins or coronary artery development. In the projected algorithm, few capillaries which form the preliminary group is designated as the population. Then the main arteries are taken as the variables of the problem. The divergence phase and clip phase are considered as the global search of the procedure. Then the gofer and clip phase is taken as local search in the procedure. The most excellent capillary leader (BCL) is taken as a key leader of the arteries, which will be transformed to a stem through which that coronary tree will expand. A new-fangled solution is obtained from the coronary tree branch, and the objective function cost is obtained from the end of the coronary tree's total cost. Through these for the obtained solution, the Coronary development factor (CDF) will be computed, and it will act as the fitness value of the problem. This work Heart memory parameter (HMP) is taken as a 5.0 and Heart memory parameter considering rate (HMPCR) taken as 0.955, respectively. HMP will save the most excellent solutions, and it will be sequentially modernized iteration by iteration. Proposed HTO, SCCS algorithms evaluated in IEEE 30 bus system with and without L-index. Real power loss and voltage deviation minimized with voltage stability index enhancement.

## 2 Research Methodology

### 2.1 Problem formulation

Power loss minimization is defined by

$$\text{Min } \overline{OBF}(\bar{r}, \bar{u}) \quad (1)$$

subject to

$$L(\bar{r}, \bar{u}) = 0; \quad (2)$$

$$M(\bar{r}, \bar{u}) = 0; \quad (3)$$

$$r = [VLG_1, \dots, VLG_{N_g}; QC_1, \dots, QC_{N_c}; T_1, \dots, T_{N_T}]; \quad (4)$$

$$u = [PG_{slack}; VL_1, \dots, VL_{N_{load}}; QG_1, \dots, QG_{N_g}; SL_1, \dots, SL_{N_T}]; \quad (5)$$

The fitness function ( $F_1, F_2, F_3$ ) is designed for power loss (MW) reduction, Voltage deviation, voltage stability index (L-index) is defined by

$$F_1 = P_{\text{Minimize}} = \text{Minimize} \left[ \sum_{m=1}^{N_{TL}} G_m [VL_i^2 + VL_j^2 - 2 * VL_i VL_j \cos \theta_{ij}] \right]; \quad (6)$$

$$F_2 = \text{Minimize} \left[ \sum_{i=1}^{N_{LB}} |VL_{Lk} - VL_{Lk}^{\text{desired}}|^2 + \sum_{i=1}^{N_g} |QG_k - Q_{kG}^{\text{lim}}|^2 \right]; \quad (7)$$

$$F_3 = \text{Minimize } L_{\text{Maximum}}; \quad (8)$$

$$L_{\text{Maximum}} = \text{Maximum} [L_j]; j = 1, \dots, N_{LB}; \quad (9)$$

$$\begin{cases} L_j = 1 - \sum_{i=1}^{N_{PV}} F_{ji} \frac{VL_i}{VL_j}; \\ F_{ji} = -[Y_1]^{-1} [Y_2]; \end{cases} \quad (10)$$

$$L_{\text{Maximum}} = \text{Maximum} \left[ 1 - [Y_1]^{-1} [Y_2] \times \frac{VL_i}{VL_j} \right]. \quad (11)$$

Equality constraints:

$$0 = PG_i - PD_i - VL_i \sum_{j \in N_B} VL_j [G_{ij} \cos[\theta_i - \theta_j] + B_{ij} \sin[\theta_i - \theta_j]]; \quad (12)$$

$$0 = QG_i - QD_i - VL_i \sum_{j \in N_B} VL_j [G_{ij} \sin[\theta_i - \theta_j] + B_{ij} \cos[\theta_i - \theta_j]]. \quad (13)$$

Inequality constraints:

$$P_{g_{\text{slack}}}^{\text{minimum}} \leq P_{g_{\text{slack}}} \leq P_{g_{\text{slack}}}^{\text{maximum}}; \quad (14)$$

$$Q_{gi}^{\text{minimum}} \leq Q_{gi} \leq Q_{gi}^{\text{maximum}}, i \in N_g; \quad (15)$$

$$VL_i^{\text{minimum}} \leq VL_i \leq VL_i^{\text{maximum}}, i \in N_L; \quad (16)$$

$$T_i^{\text{minimum}} \leq T_i \leq T_i^{\text{maximum}}, i \in N_T; \quad (17)$$

$$Q_c^{\text{minimum}} \leq Q_c \leq Q_c^{\text{maximum}}, i \in N_C; \quad (18)$$

$$|SL_i| \leq S_{L_i}^{\text{maximum}}, i \in N_{TL}; \quad (19)$$

$$VG_i^{\text{minimum}} \leq VG_i \leq VG_i^{\text{maximum}}, i \in N_g. \quad (20)$$

Multi-objective fitness (MOF) function has been defined by

$$\text{MOF} = F_1 + r_1 F_2 + u F_3 = F_1 + \left[ \sum_{i=1}^{N_L} x_v [VL_i - VL_i^{\text{min}}]^2 + \sum_{i=1}^{N_C} r_g [QG_i - QG_i^{\text{min}}]^2 \right] + r_f F_3; \quad (21)$$

$$VL_i^{\text{minimum}} = \begin{cases} VL_i^{\text{max}}, & VL_i > VL_i^{\text{max}}; \\ VL_i^{\text{min}}, & VL_i < VL_i^{\text{min}}; \end{cases} \quad (22)$$

$$QG_i^{\text{minimum}} = \begin{cases} QG_i^{\text{max}}, & QG_i > QG_i^{\text{max}}; \\ QG_i^{\text{min}}, & QG_i < QG_i^{\text{min}}; \end{cases} \quad (23)$$

### 2.2 Heat transfer optimization (HTO) algorithm

Heat transfer characteristics between the objects have been imitated to model the Heat Transfer Optimization (HTO) algorithm. In the proposed algorithm, every agent is measured as a cooling entity, and it is surrounded by another agent, like where heat transfer will occur. Newton's law of cooling temperature will be updated in the proposed HTO algorithm.

Generally, heat exchange coefficient symbolized as "h", and at time  $t=0$  particular objects in highly elevated temperature  $Temperature_0$  has been positioned or surrounded by cooling objects. Then there will be a transfer of heat between the objects  $Tempaerature_b$ . Concerning volume and surface, the heat loss rate is determined by

$$\frac{dq}{dt} = h(Temperature_a - Temperature_b) \text{ surfave area}(SA). \quad (24)$$

In the time  $dt$   $h(Temperature_a - Temperature_b) \text{ surfave area}(SA)dt$  is the heat loss which indicates the decrease in temperature  $dT$  as follows:

$$\text{volume}(v) * \text{density}(\rho) * \text{specific heat}(c) * Dt = -h * SA(Temperature - Temperature_b)dt. \quad (25)$$

Then

$$\frac{\text{Temperature} - \text{Temperature}_b}{\text{Temperature}_0 - \text{Temperature}_b} = \exp\left(-\frac{h * SA}{\text{volume}(v) * \text{density}(\rho) * \text{specific heat}(c)} t\right); \quad (26)$$

$$\beta = \frac{h * SA}{\text{volume}(v) * \text{density}(\rho) * \text{specific heat}(c)}; \quad (27)$$

Then equation (12) can be written as

$$\frac{Temperature - Temperature_b}{Temperature_0 - Temperature_b} = \exp(-\beta t). \quad (28)$$

Then temperature mathematically defined as follows:

$$Temperature = Temperature_b + (Temperature_0 - Temperature_b) \exp(-\beta t). \quad (29)$$

In the exploration of space objects, initial temperature is defined by:

$$Temperature_{initial}^0 = Temperature_{minimum} + random \cdot (Temperature_{maximum} - Temperature_{minimum}). \quad (30)$$

Objects are grouped into two modes concerning temperature as  $Temperature_1$  is ecological one for another object  $Temperature_{\frac{n}{2}+1}$  which is in cooling condition.

Then the value of  $\beta$  (higher or lower) determines the transfer of heat (variation of temperature between objects), and by the status of  $\beta$ , that position will be altered. The  $\beta$  value for each object is computed by

$$\beta = \frac{cost(object)}{cost(poor\_object)}. \quad (31)$$

In this projected algorithm, time “ $t$ ” is linked with iteration number, and the value of “ $t$ ” for every agent is computed by

$$t = \frac{iteration}{maximum\ number\ of\ iteration}. \quad (32)$$

To avoid the solution getting trapped in the local solution ecological temperature of the object has been adjusted as follows:

$$Temperature_i^{ecological} = (1 - (Control\ variable_1 + Control\ variable_2 \times (1 - t)) \times random) \times Previous\ Temperature_i^{ecological}. \quad (33)$$

In equation (33) Control variable<sub>1</sub> direct the random step size and Control variable<sub>2</sub> organize (1 - t). In the conclusion of the procedure, the value of “ $t$ ” will be augmented, leading to a linear decrease in arbitrariness and escalating the exploitation.

Then the new-fangled temperature object is updated by

$$Temperature_i^{new} = Temperature_i^{ecological} + (Temperature_i^{old} - Temperature_i^{new}) \exp(-\beta t); \quad (34)$$

Then  $j$ -th variable agent upper and lower bound defined by

$$Temperature_{i,j} = Temperature_{j,minimum} + random \times (Temperature_{j,maximum} - Temperature_{j,minimum}). \quad (35)$$

a. Start.

b. Agents are initiated by,

$$Temperature_{initial}^0 = Temperature_{minimum} + random \cdot (Temperature_{maximum} - Temperature_{minimum}).$$

c. The objective functional value will be computed.

d. Modernization of population and memory.

e. Grouping of the object is engendered.

f. Value of  $\beta$ ,  $t$  is computed by,

$$\beta = \frac{cost(object)}{cost(poor\_object)};$$

$$t = \frac{iteration}{maximum\ number\ of\ iteration}.$$

g. Ecological values altered by,

$$Temperature_i^{ecological} = (1 - (Control\ variable_1 + Control\ variable_2 \times (1 - t)) \times random) \times Previous\ Temperature_i^{ecological}$$

h. Temperature values are modernized by,

$$Temperature_i^{new} = Temperature_i^{ecological} + (Temperature_i^{old} - Temperature_i^{new}) \exp(-\beta t)$$

$$Temperature_{i,j} = Temperature_{j,minimum} + random \cdot (Temperature_{j,maximum} - Temperature_{j,minimum})$$

i. Is the end condition satisfied? If “yes”, stop the process or else go to step “c”.

### 2.3 Simulated coronary circulation system optimization algorithm

In this work Simulated Coronary Circulation System (SCCS) optimization algorithm has been modeled by imitating the actions of human heart veins or coronary artery development. In the projected algorithm candidate solution is made by considering the capillaries. Then the Coronary development factor (CDF) will appraise the solution, and population space has been initiated arbitrarily. Then the stem crown production is called the divergence phase, and the other capillaries’ growth is known as the clip phase. In the projected algorithm, few capillaries which form the preliminary group is designated as the population. Then the main arteries are taken as the variables of the problem. A new-fangled solution is obtained from the coronary tree branch, and the objective function cost is obtained from the end of the coronary tree’s total cost. Through these for the obtained solution, the Coronary development factor (CDF) will be computed, and it will act as the fitness value of the problem. Then in the whole population, the most excellent solution will be taken as stem, and it will be the minimum value of the Coronary development factor.

The divergence phase and clip phase are considered as the global search of the procedure. In the period at the ending of the stem, the capillary leader will expand, and for iteration “ $t$ ”, there will be  $N_{variable}$ , ( $j = 1, 2, \dots, N_{variable}$ ). Capillaries are the population  $N_{population}$ , ( $i = 1, 2, 3, \dots, N_{population}$ ). Then the  $j$ -th capillaries in the present population is indicated by  $Y_c^{i,j}$ . Through the stem, the most excellent capillary leader (BCL) will be identified. Then for BCL, the Coronary development factor (CDF) is computed by

$$CDF_i^t = \frac{1/fitness_i}{\sum 1/fitness_i}, i = 1, 2, \dots, N_{population}; \quad (36)$$

$$CDF_c^t = \frac{1/fitness_c}{\sum 1/fitness_i}; \quad (37)$$

$$fitness_c = mean(fitness_i). \quad (38)$$

In the divergence phase, the present solution is modernized by

$$Y_{i,j}^{t+1} = Y_{i,j}^t + development\ direction \cdot Divergence\ factor(D_f) \times (Y_{c,j}^t - Random \cdot Y_{i,j}^t), i = 1 \text{ and } N_{population}, j = 1 \text{ and } N_{variable}; \quad (39)$$

$$\begin{cases} development\ direction = -1; & \text{if } CDF_c^t < CDF_i^t; \\ development\ direction & \text{else} \end{cases} \quad (40)$$

$$Y_{c,j} = mean(Y_j^t); j = 1, 2, \dots, N_{variable}. \quad (41)$$

Then the gofer and clip phase is taken as local search in the procedure. The most excellent capillary leader (BCL) is taken as a key leader of the arteries, which will be transformed to stem through the coronary tree will expand. Based on the coronary development factor (CDF) of the arteries leader, the most excellent capillary leader's (BCL) growth will be there, and for this development, the exemplar factor is computed by

$$Y_j^{t+1} = Y_{i,j}^t + \alpha \cdot random \cdot (Y_{best,j}^t - Y_{worst,j}^t). \quad (42)$$

Each capillary leader will explore the newfangled growth as capillaries. Sequentially best (most excellent) and worst are found, and preceding values will be modernized continuously. Then through the Heart memory parameter (HMP) solution which violates the boundary will be identified. HMP possesses the BCL and its CDF values. Heart memory parameter considering rate (HMPCR) varies between 0 and 1 and will select the new-fangled value from the stored values. In this work, HMP is taken as 5.0, and HMPCR is taken as 0.955, respectively. Heart memory parameter (HMP) will save the most excellent solutions, and it will be sequentially modernized iteration by iteration. HMP exploration has been balanced in the projected algorithm.

- a. Start.
- b. In the exploration space, the preliminary position of the capillary leader is arbitrarily initialized by,

$$Y_{i,j}^0 = Y_{minimum} + random \cdot (Y_{maximum} - Y_{minimum}).$$

- c. For every capillary leader, the Coronary development factor (CDF) value is computed by,

$$CDF_i^t = \frac{1/fitness_i}{\sum 1/fitness_i}, i = 1, 2, \dots, N_{population};$$

$$CDF_c^t = \frac{1/fitness_c}{\sum 1/fitness_i}.$$

- d. Heart memory parameter (HMP) will be utilized for storing the most excellent capillary leader and its Coronary development factor (CDF) value. The stored capillary leader will be added to the population, and equivalent to that poor (worst) capillary leader will be removed.

- e. Then the capability of the exploration has been augmented by adding a particular parameter "SP" inside the value of (0, 1), and it also evades the early convergence (during exploration, the beginning value is 0.1, and it increased to 0.3 to induce the superior exploitation), mainly it will specify about the changing the mechanism of the capillary leader, and is defined as follows:

$$SP = \omega_{minimum} + \left( \frac{iteration}{iteration_{maximum}} (\omega_{maximum} - \omega_{minimum}) \right).$$

- f. Apply the equations below when  $Random_i < SP$ ;  
 $Y_{i,j}^{t+1} = Y_{i,j}^t + development\ direction \cdot Divergence\ factor(D_f) \cdot (Y_{c,j}^t - Random \cdot Y_{i,j}^t), i = 1 \text{ and } N_{population}, j = 1 \text{ and } N_{variables};$   
 $\begin{cases} development\ direction = -1; & \text{if } CDF_c^t < CDF_i^t; \\ development\ direction & \text{else} \end{cases}$

$$Y_{c,j} = \frac{\sum_{i=1}^{N_{population}} \frac{Y_j}{fitness_i}}{\sum_{i=1}^{N_{population}} \frac{1}{fitness_i}},$$

$$j = 1, 2, \dots, N_{variable}.$$

or else

$$Y_{i,j} = Y_{minimum,j} + random \cdot (Y_{maximum,j} - Y_{minimum,j}).$$

- g. Concerning the objective function values, the capillary leader will be modernized and classified.
- h. Then the modernization and classification of the capillary leader is done by  
 $Y_j^{t+1} = Y_{i,j}^t + \alpha \cdot random \cdot (Y_{best,j}^t - Y_{worst,j}^t).$
- i. Concerning the objective function values, the capillary leader will be modernized and classified.
- j. Through the heart memory parameter (HMP), the most excellent capillary leader (BCL) will be preserved.
- k. The procedure will be stopped once the predefined value is reached or else go to step "c".
- l. End.

### 3 Results and Discussion

Projected HTO, SCCS algorithms have been tested in the standard IEEE 30 bus system [60]. Tables 1–4 compare values between proposed and reported algorithms for the IEEE 30 bus system. Figures 1–3 give a graphical comparison between the methodologies regarding power loss, voltage stability improvement, voltage deviation, and multi-objective problem formulation. Real power loss reduction has been achieved with voltage stability enhancement with minimization of voltage deviation.

Table 1 – Comparison of total power loss

Method	Power loss (MW)
Hybrid PSO-TS [53]	4.5213
TS [53]	4.6862
Basic PSO [53]	4.6862
ALO [54]	4.5900
QO-TLBO [55]	4.5594
TLBO [55]	4.5629
Standard GA [56]	4.9408
S.PSO [56]	4.9239
HAS [56]	4.9059
S-FS [57]	4.5777
IS-FS [57]	4.5142
SFS [59]	4.5275
HTO	4.5080
SCCS	4.5089

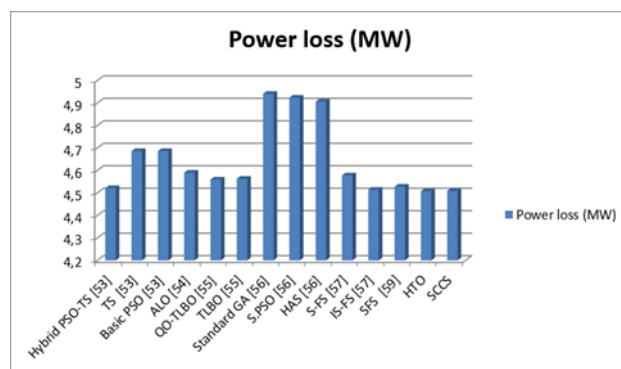


Figure 1 – Comparison of real power loss

Table 2 – Comparison of voltage deviation

Method	Voltage deviation (PU)
BPSO-TVIW [58]	0.1038
BPSO-TVAC [58]	0.2064
SPSO-TVAC [58]	0.1354
BPSO-CF [58]	0.1287
PG-PSO [58]	0.1202
SWT-PSO [58]	0.1614
PGSWT-PSO [58]	0.1539
MPG-PSO [58]	0.0892
QO-TLBO [55]	0.0856
TLBO [55]	0.0913
S-FS [57]	0.1220
ISFS [57]	0.0890
SFS [59]	0.0877
HTO	0.0869
SCCS	0.0867

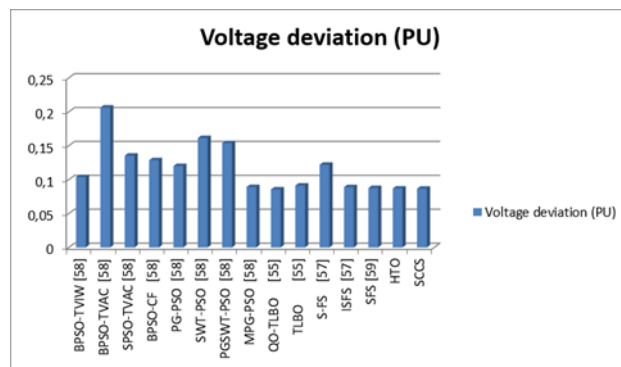


Figure 2 – Comparison of voltage deviation

Table 3 – Comparison of L-Index

Method	L-index (PU)
BPSO-TVIW [58]	0.1258
BPSO-TVAC [58]	0.1499
SPSO-TVAC [58]	0.1271
BPSO-CF [58]	0.1261
PG-PSO [58]	0.1264
SWT-PSO [58]	0.1488
PGSWT-PSO [58]	0.1394
MPG-PSO [58]	0.1241
QO-TLBO [55]	0.1191
TLBO [55]	0.1180
ALO [54]	0.1161
ABC [54]	0.1161
GWO [54]	0.1242
BA [54]	0.1252
S-FS [57]	0.1252
IS-FS [57]	0.1245
SFS [59]	0.1007
HTO	0.1004
SCCS	0.1003

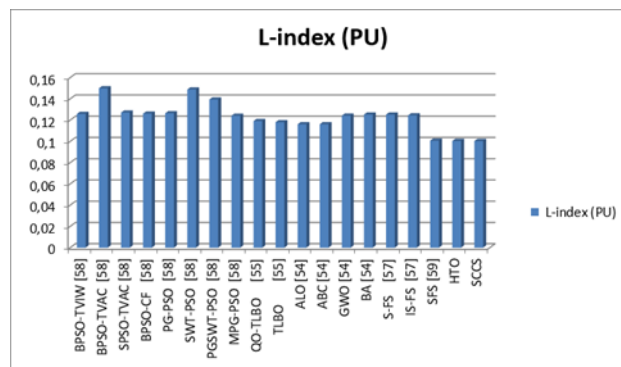


Figure 3 – Comparison of L-index

HTO, SCCS algorithms have been evaluated in IEEE 30 bus system without considering L-index [40]. In Table 4, comparisons of results are presented.

Figure 4 gives a graphical comparison between the methodologies concerning power loss. Power loss reduction has been achieved. Percentage of power loss reduction improved concerning the base case.

Table 4 – Power loss comparison

Parameters	Value of base case [47]	Modified particle swarm optimization [47]	Basic particle swarm optimization [46]	Standard evolutionary programming [45]	Self-adaptive real coded genetic algorithm [45]	HTO	SCCS
Percentage of power loss reduction	0.000	8.400	7.400	6.600	8.300	17.94	17.77
Real power loss, MW	17.550	16.070	16.250	16.380	16.090	14.40	14.43

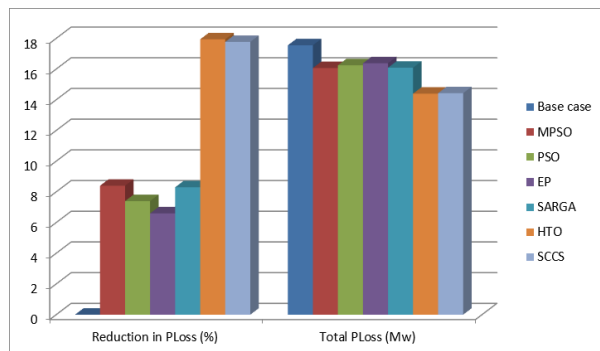


Figure 4 – Comparison of real power loss

From the above results and comparison, it is evident that real power loss has been reduced comparatively. Voltage stability enhancement and voltage deviation minimization are attained. The percentage of power loss reduction has been improved substantially. Overall comparison has been made with standard algorithms – Differential evolution, Gravitational search algorithm, Hybrid Artificial Physics–Particle Swarm Optimization, Modified particle swarm optimization, Basic particle swarm optimization Hybrid PSO-Tabu search (PSO-TS), Ant lion (ALO), quasi-oppositional teaching learning-based (QOTBO), improved stochastic fractal search optimization algorithm (ISFS), harmony search (HS) and improved pseudo-gradient search particle swarm optimization. The projected Heat Transfer Optimization (HTO) algorithm and the Simulated Coronary Circulation System (SCCS) optimization algorithm reduced the power loss effectively.

## 4 Conclusions

In this paper, the heat transfer optimization (HTO) algorithm and simulated coronary circulation system (SCCS) optimization algorithm successfully solved the problem. In HTO object's temperature is considered as the position is its position, and the heat energy will be transferred to objects surrounding it. Then new-fangled positions are modernized through new temperature conditions. Newton's law of cooling temperature will be updated in the proposed HTO algorithm. Then the objects are arranged in increasing order concerning the objective function value. Objects are grouped into two modes concerning temperature as  $Temperature_1$  is ecological one for another object  $Temperature_{\frac{n}{2}+1}$  which is in cooling condition. In the SCCS optimization algorithm, few capillaries which form a preliminary group is designated as the population. Then the main arteries are taken as the variables of the problem.

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Through the Heart memory parameter (HMP) solution which violates the boundary will be identified. HMP possesses the most excellent capillary leader (BCL) and Coronary development (CDF) values. Heart memory parameter considering rate (HMPCR) varies between 0 and 1 and will select the new-fangled value from the stored values. The capability of the exploration has been augmented by adding a particular parameter “SP” inside the value of (0, 1), and it also evades the early convergence (during exploration, the beginning value is 0.1, and it increased to 0.3 to induce the superior exploitation), mainly it will specify about the changing the mechanism of the capillary leader. Proposed HTO, SCCS algorithms verified in standard IEEE 30- bus test system with L-index. Then algorithms are evaluated in the IEEE 30 bus test system devoid of L-index. Power loss minimization, voltage deviation minimization, and voltage stability enhancement have been attained.

## Nomenclature

*OBJF* – minimization of the objective function;  
 $L, M$  – control and dependent variables of the optimal reactive power problem;  
 $r$  – consist of control variables;  
 $(Q_c)$  – reactive power compensators;  
 $T$  – dynamic tap setting of transformers;  
 $(V_g)$  – level of the voltage in the generation units;  
 $u$  – consist of dependent variables;  
 $PG_{slack}$  – slack generator;  
 $V_L$  – voltage on transmission lines;  
 $Q_G$  – generation unit's reactive power;  
 $S_L$  – apparent power;  
 $N_{TL}$  – number of transmission line indicated by the conductance of the transmission line between the  $i^{th}$  and  $j^{th}$  buses;  
 $\emptyset_{ij}$  – phase angle between buses  $i$  and  $j$ ;  
 $V_{Lk}$  – load voltage in  $k^{th}$  load bus;  
 $V_{Lk}^{desired}$  – voltage desired at the  $k^{th}$  load bus;  
 $Q_{GK}$  – reactive power generated at  $k^{th}$  load bus generators;  
 $Q_{KG}^{Lim}$  – reactive power limitation;  
 $N_{LB}, N_g$  – number load and generating units;  
 $Tt$  – transformer tap;  
 $Gen\ volt$  – generator voltage;  
 $DE$  – differential evolution;  
 $GSA$  – gravitational search algorithm;  
 $APOPSO$  – Adapted Particle Swarm Optimization;  
 $MPSO$  – Modified Particle Swarm Optimization;  
 $PSO$  – Particle Swarm Optimization;  
 $EP$  – evolutionary programming;  
 $SARGA$  – self-adaptive real coded genetic algorithm.

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