

## OPTIMAL VAR PLANNING IN POWER SYSTEMS INCORPORATING DOMESTIC LOAD MODELING USING CHAOTIC TRIGONOMETRIC SEARCH ALGORITHM

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**Abstract.** *In the last couple of years, with the advent of emerging load types, the global electricity markets have been witnessing fast-changing consumption behaviors. Across nearly all load sectors, modern nonlinear power electronic loads constitute a significant portion of the total electricity demand. It is becoming a challenging task for network engineers to maintain an uninterrupted power supply without compromising the network's efficiency and grid controllability. The proposed work presents an innovative planning strategy for optimal reactive power allocation in static load models. This load model utilizes exponent-based representations of active and reactive power, considering the seasonal and temporal variations to simulate their impact on transmission network flows. The objective is to minimize the overall operating cost while adhering to constraints imposed by the network. To ensure economic efficiency, the overall operating cost incorporates various components associated with VAR generation, along with the impact of transformer tap settings. The optimal parameters subjected to reactive power planning (RPP) are obtained by using the proposed CTSA (Chaotic Trigonometric Search Algorithm). The effectiveness of the proposed approach is validated on the Indian Utility 62-bus test system. Simulation results show a reduction in overall operating cost across all considered scenarios, demonstrating the efficacy of the proposed method in reactive power management and highlighting the superior performance and versatility of CTSA in addressing diverse operational challenges.*

**Key words:** *Reactive power planning, Domestic Load Modelling, optimal power flow, overall operational expenditure*

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## 1. INTRODUCTION

Due to increased electrification at end-use sectors, automation and the use of energy-demanding Information and Communication Technology (ICT), the electricity demand is increasing day by day. The main challenge here is to ensure a reliable power supply without affecting the network stability, which is taken care of by the grid operators. Their key responsibility is to effectively manage the reactive power resources and factors affecting them. One such important factor is the system voltage. Unstable system voltage not only poses threats to the system's stability but also affects the power system economy. Grid operators make sure that there is operational surplus of reactive power not only for voltage control but also to enhance system resilience against power disturbances. Thus, reactive power planning (RPP) is a technically demanding problem due to its complex nature and significantly influences the power system performance and economy.

RPP considers both investment in VAr resources and grid operation planning [1]. First, the type of VAr resources is identified, followed by their location and capacity. This investment decision guides for the proper control settings of the voltage regulating devices [2]. Also, numerous probabilistic factors such as end-user demand, plant availability and power output limits of units and power transmission constraints that affect the network variables must be incorporated into RPP. The network variables affecting the RPP include the real-time generation of online units, transmission line loading, OLTC setting, and deployment of VAr support units.

The operational performance of the power system is highly influenced by the characteristics of connected loads. The growth in non-linear load; demands modelling the loads, and it is emerging as a key area of interest in both academia and the power sector. The major blackout in southern Sweden in 1987 highlighted the importance of load modelling, as poorly modelled system loads result in inconsistent system simulations, which can compromise reliability and trigger severe consequences. The behaviour of the power system network varies with time and location, requiring consideration of both spatial and temporal load variability, making load modelling a complex task.

Researchers are now focusing more on managing both power generation and consumption so as to make the network more efficient and stable. In [3], Plug-in Hybrid Electric Vehicles (PHEVs) were integrated into a microgrid. Optimal operation was achieved by adjusting the changes in the load pattern, resulting in lower peak demand and more stable voltage profile. Following this, authors in [4] introduced a demand-side management (DSM) framework combining the effect of both load shifting and curtailment. In addition to minimizing system costs and emissions, the proposed work effectively reduced network stress making micro grid operation more reliable. Further, advancements have been made on the generation side. In [5], the optimal integration of Solar Photovoltaic (SPV) into the transmission network enhanced voltage profiles, minimized losses, and eased congestion, strengthening grid reliability. Additionally, in [6], application of the chaotic chimp sine cosine (C-CHOA-SC) algorithm optimised hydrothermal scheduling with achieving cost reductions, emission mitigation, and better voltage control.

RPP is a non-linear problem and is difficult to solve since it depends on many parameters and unpredictable conditions. Effective RPP helps to stabilise system voltage, minimise transmission losses, thus ensuring efficient operation. Over the last few years, many optimisation techniques have been developed to solve this non-linear and convex problem. Conventional methods such as Linear (LP) [7], Non-linear (NLP) [8] and mixed

integer (MINLP) [9] non-linear programming suffered from pre-mature convergence. To address this local convergence problem, algorithms such as Particle Swarm Optimisation (PSO) [10], Genetic Algorithm (GA) [11], Differential Evolution (DE) [12], and Tabu Search [13] were implemented. An improved PSO (IPSO) was proposed in [14] wherein the improved initial particles suppressed the particle oscillation across its boundary. Grey Wolf Optimisation (GWO) [15] was employed to minimise operating costs and reduce power losses without being converged locally. In [16], authors combined a decomposition technique with PSO, addressing system economics and contingency. A combined RPP with transmission expansion planning (TSE) using Real Genetic Algorithm (RGA) and Interior point method (IPM) was used in [17], outperforming traditional methods.

Authors in [18] developed a metaheuristic-based RPP to minimise active power losses and retain optimal voltage level. Similarly, in [19], the authors achieved the optimal cost using advanced optimisation techniques when compared with the traditional algorithms. Incorporating series and shunt compensation in the existing transmission network has proven effective both in terms of cost and system stability. The authors in [20] proposed an approach using series-shunt compensators to reduce operational costs and improve voltage stability. The same objective was addressed in [21] by deploying compensation devices via a contingency-based planning framework. Additionally, in [22] a RPP framework using fuzzy theory was introduced to improve node voltages and the step size of voltage controllers. The proposed method was tested in an 82-bus Indian test system.

In [23], the authors used least squares optimisation to reduce the I-squared indices for weak bus and implemented it on the Indian utility 24-bus system. Likewise, in [24], a hybrid intelligence-based solution was presented to optimise the control parameters. A mathematical framework for bidding in the day-ahead electricity market was proposed in [25], ensuring efficient reactive power dispatch while optimizing both costs and system security. In [26], a bio-inspired Gorilla Troops Optimizer (GTO) was applied to minimize the system operating cost with reduced transmission losses.

Considering demand variations at the end users side, in [27] a techno-economic model was proposed combining series and shunt compensation under changing load conditions to achieve both cost savings and efficient system performance. Besides, in [28] reactive power was managed considering variations in both active and reactive loads to minimize operational cost and enhance system stability. These studies illustrate the evolution of reactive power management strategies, from conventional optimization and fuzzy control to advanced metaheuristic and hybrid approaches.

Load modeling significantly influences optimal reactive power management. In the existing literature, RPP has been done using conventional static load models wherein either impedance, current or power is kept as a fixed entity. In [29], the impact of demand response was considered in load modeling to improve reactive power control and avoid voltage instability in real-world systems. Owing to the growing integration of power electronic loads, the role of load modelling plays a key role in the transient response of the generating units [30]. Modelling the load properly accurately estimates control strategies and voltage stability thresholds vital to both power system planning and operational decisions [31]. Load modelling for power system simulation was presented in [32], with models implemented in Virtual Test Bed (VTB).

For decades, load models that reflect grid demands from all consumer types have been extensively studied. Traditionally, domestic electricity demand has been assumed to vary minimally regardless of housing type and occupancy. This assumption allows utilities to

employ a standard load profile (SLP) to predict household demand on a 15-minute interval [33]. A MATLAB-based model to predict the domestic power demand, incorporating domestic usage habits and environmental factors, was proposed in [34]. Further, [35] emphasized the role of steady-state load modeling in optimizing reactive power distribution, enabling better voltage regulation and cost reduction. In [36], a probabilistic domestic load modelling approach was developed to capture the impact of load variation on the profile accuracy.

The goal of India's energy policy is to expand the power sector, making sure energy stays affordable and helps the economy grow. A flat reactive power rate of 5 paise/kVArh was proposed by the Electricity Grid Code (IEGC) for  $\pm 3\%$  voltage deviation at the EHV level, offering limited incentives for dynamic reactive power (DVAR) investment. In contrast, the USA, Australia, and Great Britain use structured mechanisms—like cost-based compensation and indexed payments—to better support reactive power investment and system stability [37]. Unlike developed countries, Indian power networks are more susceptible to voltage instability; despite this, most research does not include the system operating cost in RPP studies. In the literature, the performance of power systems considering both active and reactive loads using load flow techniques remains underexplored.

To capture the load composition under voltage variations in steady-state conditions in the article [38] authors have used machine learning to estimate the ZIP coefficients. A big data-based load modeling framework was developed in [39] for the Central China Power Grid to address the seasonal patterns and improved model accuracy. To the best of the authors' understanding, the combined effect of active and reactive loads on the overall operational expenditure (OOE) using power flow analysis has not been previously analysed. The proposed work presents innovative RPP strategy using the proposed Chaotic Trigonometric Search Algorithm (CTSA) for the Indian power sector targeting enhanced economic efficiency. In the proposed work, the authors aim to analyze potential changes, if any, in the overall operational expenditure after integrating load models into the system.

The key contributions of proposed work can be summarized as follows:

- Weak Bus identification using Voltage Stability Index (VSI).
- The proper choice of load model and its class with consideration for temporal fluctuations, based on data constraints, and economic management under these load scenarios.
- Analysis of network performance enhancement for both base case and combined active-reactive loading using power flow analysis for the Indian Utility test bus system.
- Optimal parameter values using the proposed CTSA optimization technique.
- An analysis comparing the best compromise solutions of OOE after and before RPP with load modelling.

Sections II and III present the problem formulation and the proposed methodology, respectively. Section IV discusses the simulation results on standard test bus networks, followed by conclusions in Section V.

## 2. PROBLEM FORMULATION

The proposed work focuses on minimizing OOE for the static exponential load models. It is essential to ensure an optimal flow of VAR as this helps to achieve reduced real power losses and enhanced voltage stability. To achieve this, the objective function is formulated by incorporating five distinct cost elements, which are  $E_{RPL}$ ,  $E_{GQ}$ ,  $E_{Lch}$ ,  $E_{CS_w}$ , and  $E_{DT}$ . Mathematically, the objective function can be expressed as

$$OOE = E_{RPL} + E_{GQ} + E_{Lch} + E_{CS_w} + E_{DT} \quad (1)$$

### 2.1. Components of Objective Function

The first component of equation (1) is a function of active power loss and is represented by equation (2).

$$\begin{aligned} E_{RPL} &= RP_L \times \text{energy usage rate} \\ &= RP_L \times (0.06 \times 24 \times 365 \times 10^5) \\ &= \sum_{p=(F_b, T_b)}^n g_p \left[ V_{F_b}^2 + V_{T_b}^2 - 2V_{F_b}V_{T_b} \cos(\delta_{F_b} - \delta_{T_b}) \right] \times (0.06 \times 24 \times 365 \times 10^5) \end{aligned} \quad (2)$$

The second and third components of equation (1) are computed in relation to the magnitude of VAR contribution and are mathematically represented in equations (3) and (4).

$$\begin{aligned} E_{GQ} &= \text{price of VAR generation} \times Q_{gen} \\ &= (0.0068 \times 24 \times 365) \times Q_{gen} \\ &= (0.0068 \times 24 \times 365) \times \sum_{p=1}^{N_{gen}} \left[ \alpha_{gen} Q_i^2(p) + \beta_{gen} Q_i(p) + \gamma_{gen} \right] \end{aligned} \quad (3)$$

The cost coefficients  $\alpha_{gen}$ ,  $\beta_{gen}$  and  $\gamma_{gen}$  are obtained from the modified triangle method [40].

$$\begin{aligned} E_{Lch} &= Q_{Lch} \times \text{unit price of VARs due to line} \\ &= Q_{Lch} \times 11.6068 \\ &= \sum_{Lch=1}^{N_{Lch}} \left[ V_{F_b}^2 \frac{Y_{Lch}}{2} + V_{T_b}^2 \frac{Y_{Lch}}{2} \right] \end{aligned} \quad (4)$$

The cost component related to line charging is considered as an additional VAR source as highlighted in [41].

The fourth cost component is related to the cost associated with the installation of shunt capacitors and is mathematically represented in equation (5).

$$\begin{aligned} E_{CS_w} &= \frac{E_{cap} \times C_{MVAR}}{C_{sw} \times AF \times WL} \\ &= \frac{C_{MVAR} \times \$11600}{2 \times 365 \times 0.98 \times 40} \\ &= \$ 0.4053 \times E_{cap} \end{aligned} \quad (5)$$

Authors have assumed the value for  $E_{Cap}$ ,  $C_{sw}$ ,  $AF$  and  $WL$  and to be \$11600/MVAR, 98%, and 40 years, respectively.

The last cost component of equation (1) is related to transformer tappings formulated as in equation (6).

$$\begin{aligned} E_{DT} &= \frac{E_T \times C_T}{T_{sw} \times AF \times WL \times TR_{ch}} & (6) \\ &= \frac{\$20000 \times C_T}{11 \times 365 \times 0.98 \times 40 \times TR_{ch}} \\ &= \frac{0.127 \times C_T}{TR_{ch}} \end{aligned}$$

The values for are assumed to be  $E_T$ ,  $T_{sw}$ ,  $AF$  and  $WL$  are assumed to be \$20000/MVA, 11x365, 98%, and 40 years, respectively. The numerical values employed in the formulation of the above equations are obtained from references [42] and [43]. It is to be noted that the proposed work is based on a single objective function.

## 2.2. Constraints on Network Variables

The proposed objective function ensures that all equality and inequality constraints are consistently maintained.

**Power balance equations:**

$$\left. \begin{aligned} P_{gm} - P_{dm} &= |V_m| \sum_{n=1}^{N_b} |V_n| \left[ |G_{mn}| \cos(\delta_m - \delta_n) + |B_{mn}| \sin(\delta_m - \delta_n) \right] \\ Q_{gm} - Q_{dm} &= |V_m| \sum_{n=1}^{N_b} |V_n| \left[ |G_{mn}| \sin(\delta_m - \delta_n) - |B_{mn}| \cos(\delta_m - \delta_n) \right] \end{aligned} \right\} \quad (7)$$

**Active and reactive power generation limits:**

$$\left. \begin{aligned} P_{gm}^{\min} &\leq P_{gm} \leq P_{gm}^{\max} & \forall m \in N_g \\ Q_{gm}^{\min} &\leq Q_{gm} \leq Q_{gm}^{\max} & \forall m \in N_g \end{aligned} \right\} \quad (8)$$

**Limits on bus voltage and line currents:**

$$\left. \begin{aligned} V_g^{\min} &\leq |V_g| \leq V_g^{\max} & \forall g \in N_{bus} \\ I_{m-n} &\leq I_{(m-n)g}^{\max} & \forall g \in N_{TL} \end{aligned} \right\} \quad (9)$$

**Reactive source generation limits:**

$$Q_c^{\min} \leq Q_c \leq Q_c^{\max} \quad \forall c \in N_{ShC} \quad (10)$$

**Power transfer limits on transmission lines:**

$$|V_m| |V_n| |Y_{mn}| \cos(\delta_m + \delta_n - \delta_m) - |V_i|^2 |Y_{mn}| \cos(\delta_{mn}) \leq P_{mn}^{\max} \quad (11)$$

**Transformer tap limits:**

$$tap_m^{\min} \leq |tap_m| \leq tap_m^{\max} \quad \forall m \in N_T \quad (12)$$

**3. PROPOSED METHODOLOGY**

RPP is a complex and non-linear problem that cannot be solved directly by the Newton-Raphson (NR) method, and thus involves a step-by-step approach as described in the subsequent sub-section in detail. Figure 1 shows the proposed workflow for the CTSA optimization technique.

**3.1. Identification of critical nodes**

To address voltage instability, weak nodes are identified where additional reactive power support is provided as part of a proactive planning measure. The weak nodes identification is achieved by evaluating the Voltage Stability Index (VSI), as given in equation (13).

$$VSI_{\delta V_{sh}} = \frac{4Q_n(R_{mn} + X_{mn})^2}{X_{mn}(V_m^2 + 8R_{mn}Q_n)} \quad (13)$$

It is assumed that the line shunt admittance is of negligible significance [44].

**3.2. Integration of Load Model**

Load modelling involves expressing the load's voltage dependency using algebraic equations. These equations allow for the modeling of loads that exhibit a power change with a change in frequency or voltage. The choice of load models influences the voltage stability, but their consideration in RPP remains limited in the literature. Various studies addressed the RPP problem for normal and stressed loading scenarios. Integration of active and reactive load model on RPP using power flow analysis has not been previously analyzed. So, in the proposed work, the authors aim to analyse potential changes, if any, in the OOE after integrating exponential static load models into the system. The exponential model prevails due to its accurate characterization of the interdependence between active and reactive power flows.

Over the last ten years, from 2013 to 2023, the compound annual growth rate of domestic energy consumption increased to 6.824%. About 25.794% of India's 1403.4 TWh energy consumption in 2023 came from households [45]. As a result of rising household incomes and technological advancements, this figure is anticipated to grow further. The proposed methodology also considers the impact of seasonal and time variations in domestic load models. Seasonal load fluctuations are most prominent during winter and summer, primarily due to heating and lighting demands in winter and cooling loads in summer. Keeping this in mind, variations in domestic load models across both summer and winter seasons, including day and night, are taken into account. The mathematical equation (14) and (15) represents the proposed model.

$$P_m = P_m^{sp} V_m^\alpha \quad (14)$$

$$Q_m = Q_m^{sp} V_m^\beta \quad (15)$$

Where  $V_m$  is the  $m^{\text{th}}$  bus voltage,  $\alpha$ ,  $\beta$  are the active and reactive power exponents, respectively, and  $P_m^{sp}$ ,  $Q_m^{sp}$  are the specified active and reactive power, respectively. The changes in the proposed objective function are explored for the Indian Utility 62 Bus System. It is assumed that the line's shunt admittance is of negligible significance.

The static model loads in the case of exponential load modelling can be represented as shown in equation (16) and (17).

$$\frac{P}{P_0} = \left( \frac{V}{V_0} \right)^\alpha \quad (16)$$

$$\frac{Q}{Q_0} = \left( \frac{V}{V_0} \right)^\beta \quad (17)$$

where the active and reactive components can be calculated using equations (18) and (19).

$$\alpha = \frac{(P - P_0)/P_0}{(V - V_0)/V_0} \quad (18)$$

$$\beta = \frac{(Q - Q_0)/Q_0}{(V - V_0)/V_0} \quad (19)$$

Equations (20) and (21) represent the modified conventional power flow equations after incorporating the exponential load modelling.

$$P_i = \sum_{n=1}^N |V_i|^{\alpha+1} |V_n| |Y_{in}| \cos(\theta_{in} + \delta_n - \delta_i) \quad (20)$$

$$Q_i = - \sum_{n=1}^N |V_i|^{\beta+1} |V_n| |Y_{in}| \sin(\theta_{in} + \delta_n - \delta_i) \quad (21)$$

### 3.3. Application of proposed CTSA

The authors proposed an optimization technique to solve the highly convex, non-linear RPP, incorporating the exponential static load model on the Indian test bus system. The CTSA optimization technique uses chaos theory to enhance exploration and exploitation, balancing trade-offs with randomized variations and non-linear dynamics. The optimal value of the parameters was also determined using other metaheuristic algorithms.

The proposed work introduces the following position-updating equations for both exploration and exploitation phases:

$$P_i^{l_{c+1}} = \begin{cases} P_i^{l_c} + (M_D \times \sin(D_M) \times |(D_C \times DP_i^{l_c})| - P_i^{l_c}), & S_T < 0.3 \\ P_i^{l_c} + (M_D \times \cos(D_M) \times |(D_C \times DP_i^{l_c})| - P_i^{l_c}), & 0.3 < S_T < 0.66 \\ DP_i^{l_c} + (DP_i^{l_c} - P_i^{l_c}) \times \tan(\theta), & \text{otherwise} \end{cases} \quad (22)$$

Equation (22) simulates three mechanisms. The algorithm selects the sine mechanism when  $S_T < 0.3$ , the cosine mechanism when  $0.3 < S_T < 0.66$ , and the tangent mechanism otherwise. Each mechanism contributes significantly to the capabilities of the CTSA algorithm.

The parameter,  $D_M$  is a random number within the specified range  $[0 \ 2\pi]$ . It determines the degree of movement in the direction of or away from the target.

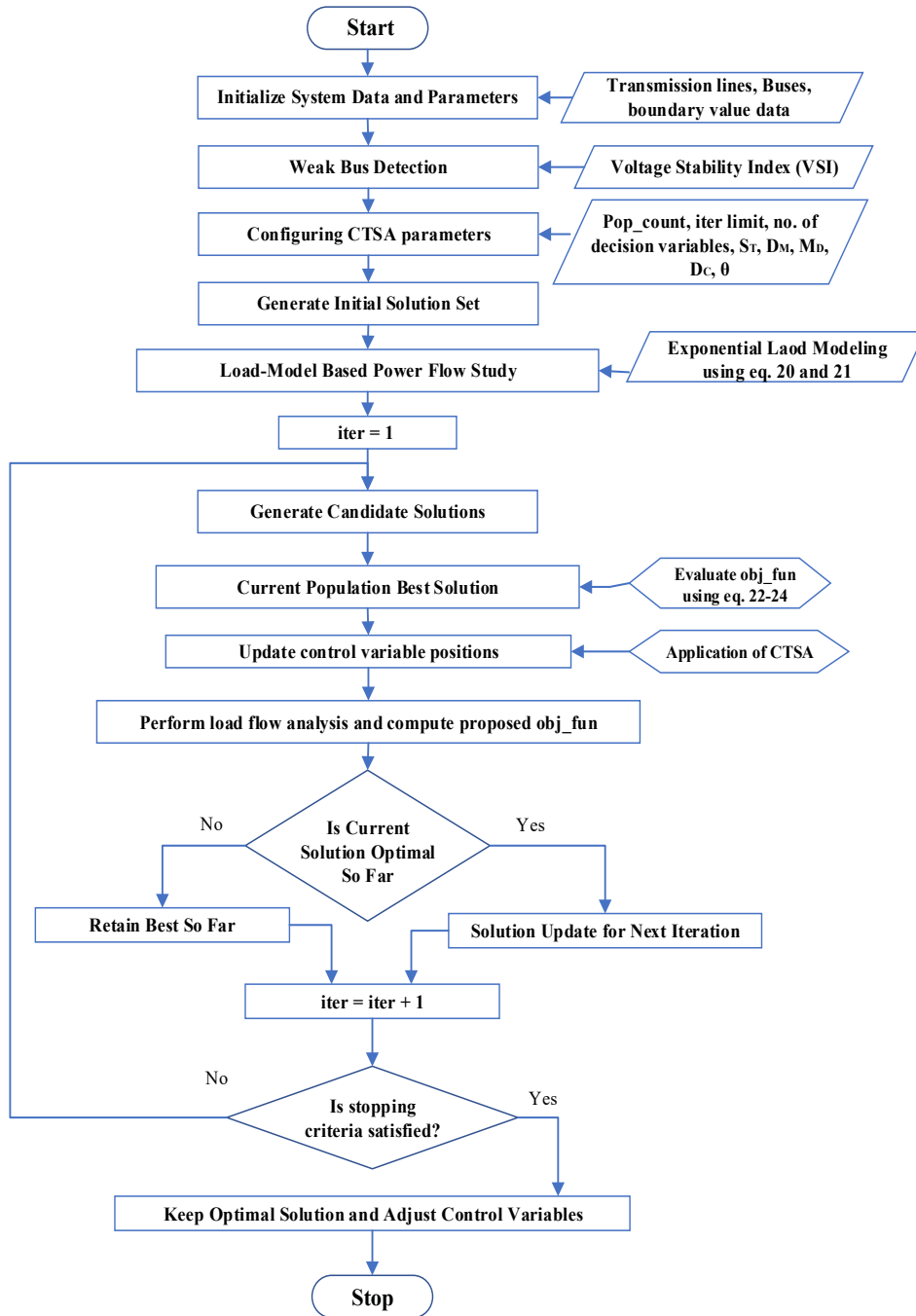


Fig. 1 Flowchart of proposed work

The updated position is adaptively adjusted using equation (23):

$$M_D = \frac{I_c \times const}{I_m} - const \quad (23)$$

where  $I_c$ ,  $I_m$  and  $const$  represent the count for the ongoing iteration, the total iterations performed, and a fixed value. The parameter  $M_D$  determines the movement direction toward or away from the target. There is a linear decline in its value from  $const$  to 0.

The Parameter  $D_C$  decides the influence of the destination, highlighting or minimizing its effect on distance calculation. The Parameter  $S_T$  alternates between sine, cosine, and tangent components, allowing the algorithm to explore various approaches and refine the optimization process. Its value falls within the range of [0, 1].

Finally, the angle  $\theta$  is randomly changed to minimize the possibility of sticking in a local solution and is calculated using equation (24).

$$\theta = \begin{cases} m \times rand, & I_c > D_C \\ m \times n, & otherwise \end{cases} \quad (24)$$

where

$$\begin{aligned} m &= (m \times a) - m \\ n &= 1 - \left[ \left( \frac{9}{10} \right) \times \sqrt{\left( \frac{I_c}{I_m} \right)} \right] \\ a &= \pi - \left[ (\pi) \times \left( \frac{I_c}{I_m} \right)^2 \right] \end{aligned}$$

#### 4. RESULT AND DISCUSSION

The proposed algorithm was implemented in MATLAB 2023b, and all simulations were executed on an Intel Core i5 processor and 8 GB of RAM. To evaluate the effectiveness of the proposed work, the Indian Utility 62-bus test network was considered. This bus system consists of 62 buses, 89 transmission lines, 19 generators, and 11 OLTCs. The Indian 62-bus system data were taken from [46]. The effectiveness of the proposed CTSA algorithm was tested using a sample size of 40, and its results were analysed after 30 individual runs each with 100 iterations. The numerical values for  $\alpha$  and  $\beta$  is taken from [47]. The weak buses identified for placement of shunt capacitors are bus no. 16, 13, 21, and 46. Authors have calculated all the cost parameters in Indian rupees and have assumed \$1 to be equivalent to ₹83.08. The OOE for the base case (without RPP) was ₹3.0622 x 10<sup>9</sup>. Four different cases considering temporal variations under domestic load modelling is considered. A detailed analysis of the proposed work for different seasons and time of the day for domestic load modelling is given below.

*Case 1:* Daytime in the summer season

*Case 2:* Night-time in the summer season

*Case 3:* Daytime in the winter season

*Case 4:* Night-time in the winter season

The numerical values of the OOE obtained using CTSA and other metaheuristic algorithms are shown in Tables 1 – 4. It is observed from the table that the combination of CTSA and VSI yields the minimum active power loss and OOE. Also, all the bus voltages were found to be in the pre-specified range.

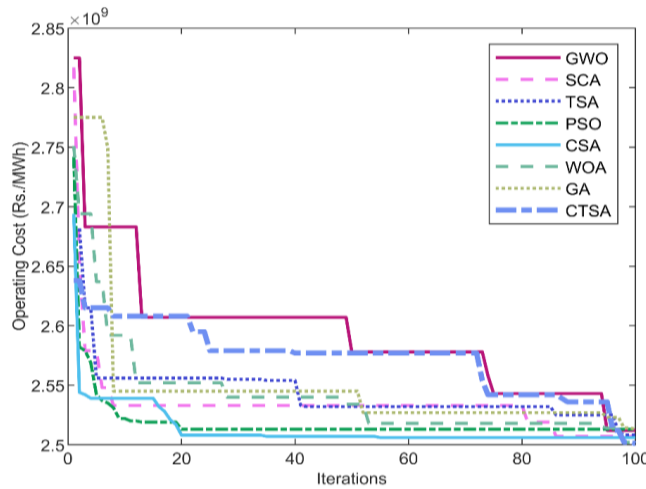
Figure 2 – 5 shows the convergence of OOE with respect to the number of iterations for all four cases from different optimisation techniques. A gradual reduction in OOE is observed with each iteration, indicating a smooth convergence.

When the temporal variation along with the exponential load modelling is considered in the conventional power flow, a remarkable reduction is seen in the overall system operational expenditure.

During the summer season, Case 1 exhibits a reduction in operational cost and real power loss by 18.32% and 18.45%, respectively, indicating significant improvement in daytime performance. In Case 2, the improvements are even more pronounced, with reductions of 24.63% in operational cost and 19.88% in real power loss.

**Table 1** Simulation result of the proposed method for case 1 in the domestic load sector

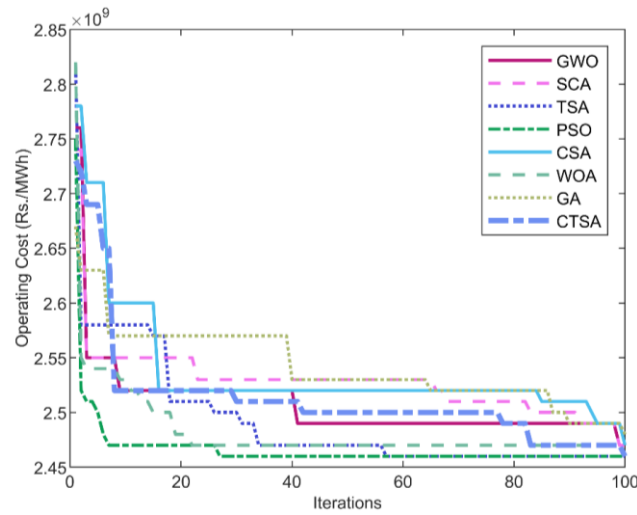
	PSO	GA	GWO	WOA	SCA	CSA	TSA	CTSA
<i>ERPL</i>	2.502x10 <sup>9</sup>	2.502x10 <sup>9</sup>	2.501x10 <sup>9</sup>	2.493x10 <sup>9</sup>	2.496x10 <sup>9</sup>	2.496x10 <sup>9</sup>	2.497x10 <sup>9</sup>	2.490x10 <sup>9</sup>
<i>EGQ</i>	5.460x10 <sup>6</sup>	5.452x10 <sup>6</sup>	5.456x10 <sup>6</sup>	5.448x10 <sup>6</sup>	5.448x10 <sup>6</sup>	5.448x10 <sup>6</sup>	5.457x10 <sup>6</sup>	5.451x10 <sup>6</sup>
<i>ELch</i>	5.426x10 <sup>6</sup>	5.435x10 <sup>6</sup>	5.436x10 <sup>6</sup>	5.430x10 <sup>6</sup>	5.437x10 <sup>6</sup>	5.437x10 <sup>6</sup>	5.436x10 <sup>6</sup>	5.438x10 <sup>6</sup>
<i>EDT</i>	5.321x10 <sup>2</sup>	5.445x10 <sup>2</sup>	5.354x10 <sup>2</sup>	5.401x10 <sup>2</sup>	5.368x10 <sup>2</sup>	5.368x10 <sup>2</sup>	5.318x10 <sup>2</sup>	5.404x10 <sup>2</sup>
<i>ECSw</i>	2.340x10 <sup>1</sup>	2.389x10 <sup>1</sup>	1.187x10 <sup>1</sup>	1.160x10 <sup>1</sup>	1.743x10 <sup>1</sup>	1.743x10 <sup>1</sup>	2.040x10 <sup>1</sup>	2.969x10 <sup>1</sup>
<i>OOE</i>	2.513x10 <sup>9</sup>	2.513x10 <sup>9</sup>	2.512x10 <sup>9</sup>	2.502x10 <sup>9</sup>	2.507x10 <sup>9</sup>	2.507x10 <sup>9</sup>	2.508x10 <sup>9</sup>	2.501x10 <sup>9</sup>
<i>RPL</i>	0.573	0.573	0.573	0.571	0.572	0.572	0.572	0.570



**Fig. 2** Convergence of OOE from various algorithms for case 1 in the domestic sector

**Table 2** Simulation result of the proposed method for case 2 in the domestic load sector

	PSO	GA	GWO	WOA	SCA	CSA	TSA	CTSA
<i>ERPL</i>	2.453x10 <sup>9</sup>	2.472x10 <sup>9</sup>	2.460x10 <sup>9</sup>	2.458x10 <sup>9</sup>	2.456x10 <sup>9</sup>	2.454x10 <sup>9</sup>	2.449x10 <sup>9</sup>	2.446x10 <sup>9</sup>
<i>EGQ</i>	5.460x10 <sup>6</sup>	5.448x10 <sup>6</sup>	5.451x10 <sup>6</sup>	5.456x10 <sup>6</sup>	5.451x10 <sup>6</sup>	5.455x10 <sup>6</sup>	5.460x10 <sup>6</sup>	5.457x10 <sup>6</sup>
<i>ELch</i>	5.451x10 <sup>6</sup>	5.448x10 <sup>6</sup>	5.470x10 <sup>6</sup>	5.452x10 <sup>6</sup>	5.452x10 <sup>6</sup>	5.472x10 <sup>6</sup>	5.456x10 <sup>6</sup>	5.465x10 <sup>6</sup>
<i>EDT</i>	5.278x10 <sup>2</sup>	5.397x10 <sup>2</sup>	5.369x10 <sup>2</sup>	5.278x10 <sup>2</sup>	5.516x10 <sup>2</sup>	5.360x10 <sup>2</sup>	5.278x10 <sup>2</sup>	5.380x10 <sup>2</sup>
<i>ECSw</i>	4.041x10 <sup>1</sup>	2.46x10 <sup>1</sup>	2.690x10 <sup>1</sup>	2.550x10 <sup>1</sup>	2.222x10 <sup>1</sup>	2.237x10 <sup>1</sup>	4.041x10 <sup>1</sup>	2.388x10 <sup>1</sup>
<i>OOE</i>	2.464x10 <sup>9</sup>	2.483x10 <sup>9</sup>	2.471x10 <sup>9</sup>	2.469x10 <sup>9</sup>	2.467x10 <sup>9</sup>	2.465x10 <sup>9</sup>	2.460x10 <sup>9</sup>	2.457x10 <sup>9</sup>
<i>RPL</i>	0.562	0.566	0.563	0.563	0.562	0.562	0.561	0.560



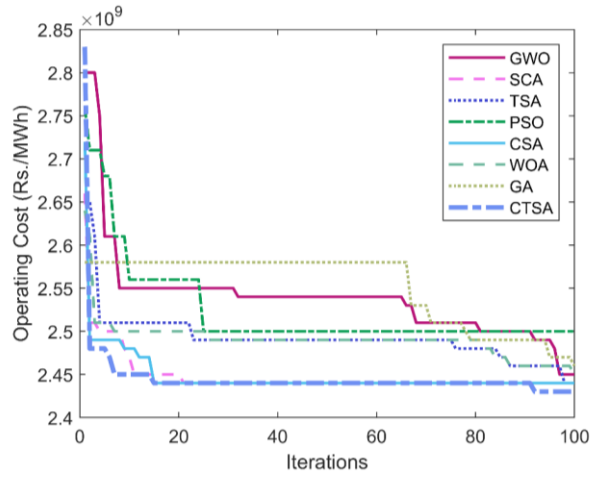
**Fig. 3** Convergence of OOE from various algorithms for case 2 in the domestic sector

Case 3 demonstrates a decrease of 20.48% in operational cost and 20.6% in active power loss. Case 4 continues this trend, achieving respective reductions of 21.1% and 21.11% in the same parameters. Among all the cases considered, the proposed work performed the best and stayed reliable even during low-demand conditions.

The proposed work performed better in terms of cost minimization and power loss reduction across all four seasonal and time-based scenarios when compared to the base case. When compared with other conventional metaheuristic techniques such as PSO, GA, GWO, Whale optimization Algorithm (WOA), Sine-Cosine Algorithm (SCA), Circle Search Algorithm (CSA) and Trigonometric Search Algorithm (TSA), CTSA consistently delivers more optimal and stable solutions, highlighting its efficacy in solving complex power system optimization problems under dynamic environmental scenarios.

**Table 3** Simulation result of the proposed method for case 3 in the domestic load sector

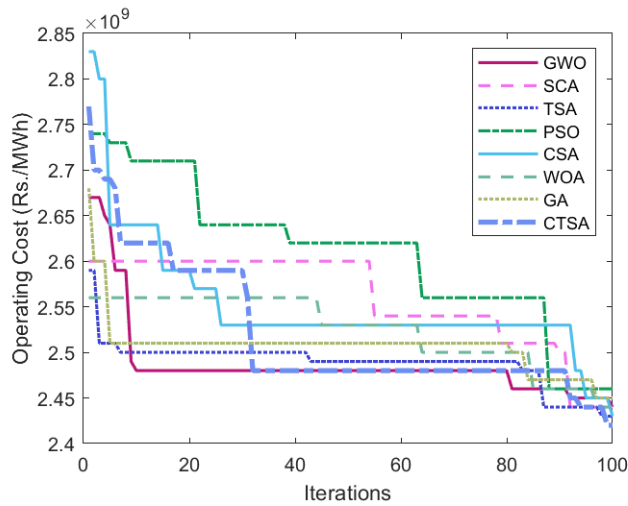
	PSO	GA	GWO	WOA	SCA	CSA	TSA	CTSA
$ER_{PL}$	$2.490 \times 10^9$	$2.451 \times 10^9$	$2.436 \times 10^9$	$2.434 \times 10^9$	$2.430 \times 10^9$	$2.428 \times 10^9$	$2.426 \times 10^9$	$2.424 \times 10^9$
$EGQ$	$5.448 \times 10^6$	$5.453 \times 10^6$	$5.454 \times 10^6$	$5.448 \times 10^6$	$5.457 \times 10^6$	$5.460 \times 10^6$	$5.456 \times 10^6$	$5.458 \times 10^6$
$EL_{ch}$	$5.435 \times 10^6$	$5.451 \times 10^6$	$5.463 \times 10^6$	$5.461 \times 10^6$	$5.463 \times 10^6$	$5.470 \times 10^6$	$5.475 \times 10^6$	$5.464 \times 10^6$
$EDT$	$5.278 \times 10^2$	$5.278 \times 10^2$	$5.351 \times 10^2$	$5.386 \times 10^2$	$5.372 \times 10^2$	$5.428 \times 10^2$	$5.442 \times 10^2$	$5.375 \times 10^2$
$ECS_w$	$4.815 \times 10^1$	$3.610 \times 10^1$	$2.598 \times 10^1$	$2.406 \times 10^1$	$3.529 \times 10^1$	$3.753 \times 10^1$	$2.130 \times 10^1$	$3.600 \times 10^1$
$OOE$	$2.501 \times 10^9$	$2.462 \times 10^9$	$2.447 \times 10^9$	$2.445 \times 10^9$	$2.441 \times 10^9$	$2.439 \times 10^9$	$2.437 \times 10^9$	$2.435 \times 10^9$
$RPL$	0.570	0.561	0.558	0.557	0.557	0.556	0.556	0.555



**Fig. 4** Convergence of OOE from various algorithms for case 3 in the domestic sector

**Table 4** Simulation result of the proposed method for case 4 in the domestic load sector

	PSO	GA	GWO	WOA	SCA	CSA	TSA	CTSA
$E_{RPL}$	$2.450 \times 10^9$	$2.440 \times 10^9$	$2.431 \times 10^9$	$2.429 \times 10^9$	$2.425 \times 10^9$	$2.416 \times 10^9$	$2.419 \times 10^9$	$2.405 \times 10^9$
$E_{GQ}$	$5.450 \times 10^6$	$5.451 \times 10^6$	$5.449 \times 10^6$	$5.454 \times 10^6$	$5.458 \times 10^6$	$5.451 \times 10^6$	$5.451 \times 10^6$	$5.449 \times 10^6$
$E_{Lch}$	$5.437 \times 10^6$	$5.475 \times 10^6$	$5.484 \times 10^6$	$5.461 \times 10^6$	$5.454 \times 10^6$	$5.473 \times 10^6$	$5.474 \times 10^6$	$5.469 \times 10^6$
$E_{DT}$	$1.032 \times 10^1$	$1.357 \times 10^1$	$1.913 \times 10^1$	$2.769 \times 10^1$	$3.011 \times 10^1$	$1.620 \times 10^1$	$3.023 \times 10^1$	$2.110 \times 10^1$
$E_{CSw}$	$5.417 \times 10^2$	$5.286 \times 10^2$	$5.482 \times 10^2$	$5.460 \times 10^2$	$5.278 \times 10^2$	$5.415 \times 10^2$	$5.480 \times 10^2$	$5.331 \times 10^2$
$OOE$	$2.460 \times 10^9$	$2.451 \times 10^9$	$2.442 \times 10^9$	$2.440 \times 10^9$	$2.436 \times 10^9$	$2.427 \times 10^9$	$2.430 \times 10^9$	$2.416 \times 10^9$
$RPL$	0.561	0.559	0.557	0.556	0.555	0.553	0.554	0.551



**Fig. 5** Convergence of OOE from various algorithms for case 4 in the domestic sector

## 5. CONCLUSION AND FUTURE SCOPE

Authors have presented an innovative RPP strategy employing steady-state load models. The proposed work focuses on exponential load modelling with domestic load class considering temporal variation in the conventional power flow. The proposed objective function was framed by integrating multiple cost components associated with VAr support and was able to accurately estimate the total operational cost for different cases of domestic load class in an economic manner.

The key contributions and distinct findings of the study are summarised as follows:

- A notable reduction in total operating cost and real power loss was achieved by incorporating active and reactive power load models in optimisation-based RPP.
- The proposed RPP approach achieved the lowest OOE and RPL, thereby significantly reducing the reactive power costs compared to the base case.
- CTSA effectively identified optimal control parameters after incorporating exponential steady-state load models. This validates the use of CTSA for solving large-scale, complex reactive power planning problems.

The results demonstrate the ability of CTSA to achieve fast and reliable convergence to find the optimal solution. The present work focuses on the domestic load sector using exponential load modelling for RPP. This approach can be extended to other load sectors, to evaluate sector-wise impacts more comprehensively. Additionally, the proposed methodology can be tested on larger test bus systems to further validate its robustness, and effectiveness in real-world power system scenarios.

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