

Optimization-Based EV Charging Coordination in Urban Village Distribution Networks Considering Energy Arbitrage and Transformer Thermal Ageing

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Abstract

The rapid penetration of electric vehicles (EVs) in residential distribution systems introduces significant operational challenges such as transformer overloading, feeder congestion, voltage instability, increased feeder power losses, and accelerated transformer thermal ageing. These issues become more critical in urban village distribution networks due to limited transformer ratings and dense residential loading characteristics. This paper presents an optimization-based EV charging coordination framework considering energy arbitrage and distribution operational cost minimization. The proposed methodology integrates transformer thermal ageing analysis, feeder operational constraints, voltage regulation limits, battery state-of-charge constraints, and vehicle-to-grid (V2G) operation into a unified optimization framework. Comparative optimization analysis using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) is performed to evaluate convergence characteristics, thermal management capability, and computational complexity. Mathematical modelling of EV charging dynamics, distribution power flow, transformer hotspot temperature, ageing acceleration factor, and operational cost functions is developed. The proposed system is implemented in MATLAB/Simulink under uncontrolled charging, time-of-use charging, GA-optimized charging, and PSO-optimized charging scenarios. Simulation results demonstrate that the proposed GA-based optimization significantly reduces transformer hotspot temperature, peak demand, operational cost, and feeder loading while improving voltage regulation and charging coordination performance. Comparative analysis indicates that PSO provides faster convergence and lower computational complexity, whereas GA achieves superior optimization quality and thermal performance under highly nonlinear operating conditions.

Keywords— Electric vehicle charging, transformer thermal ageing, energy arbitrage, Genetic Algorithm, Particle Swarm Optimization, vehicle-to-grid, smart distribution systems.

I. INTRODUCTION

The increasing global demand for sustainable transportation systems has accelerated the deployment of electric vehicles (EVs) across modern power systems. EVs provide environmental benefits through reduction of greenhouse gas emissions and improved energy efficiency compared to conventional internal combustion engine vehicles [1]. However, large-scale EV integration introduces significant operational challenges in electrical distribution systems including transformer overloading, voltage instability, feeder congestion, increased feeder losses, and accelerated transformer thermal ageing [2].

Residential distribution networks are highly vulnerable to these impacts because EV charging demand is generally concentrated during evening peak load periods. Simultaneous charging of multiple EVs significantly increases transformer loading and feeder current, resulting in excessive winding hotspot temperature and insulation degradation [3]. Uncontrolled charging conditions may also produce voltage profile deterioration and increased operational cost.

Smart charging and vehicle-to-grid (V2G) technologies have emerged as effective approaches for mitigating EV-induced operational challenges [4]. Optimization-based charging coordination allows intelligent scheduling of charging and discharging operations considering electricity tariff variation, transformer thermal limits, feeder constraints, and EV owner requirements. Several optimization techniques including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), fuzzy logic, and linear programming have been investigated for EV charging coordination applications [5].

Although previous studies focused mainly on charging cost minimization, limited attention has been given to simultaneous optimization of transformer thermal ageing, feeder operational cost, energy arbitrage benefit, and voltage regulation constraints under urban village distribution conditions. Moreover, comparative analysis between GA and PSO for transformer thermal management applications remains limited.

Large-scale EV integration has become an important research topic in modern smart grid applications. Several studies investigated the impact of EV charging on distribution system performance including transformer loading, voltage regulation, feeder losses, and thermal ageing [6].

Clement-Nyans et al. [7] analyzed the impact of plug-in hybrid electric vehicle charging on residential distribution systems and reported severe transformer loading under uncontrolled charging conditions. Deilami et al. [8] proposed real-time coordinated charging methods for reducing power losses and improving voltage profile. Sundström and Binding [9] investigated flexible EV charging optimization considering distribution network operational constraints.

Transformer thermal ageing under EV charging conditions has been widely studied using IEEE thermal ageing standards. Turker et al. [10] demonstrated that uncontrolled EV charging significantly accelerates transformer insulation degradation because of excessive hotspot

temperature rise. Gong et al. [11] investigated transformer lifetime reduction under varying EV penetration levels.

Time-of-use (TOU) charging methods shift charging demand toward low electricity tariff periods; however, secondary peak loading may occur due to simultaneous charging concentration [12]. Smart coordinated charging methods improve operational efficiency by considering transformer loading limits, feeder constraints, and voltage regulation requirements.

Vehicle-to-grid (V2G) technology enables bidirectional power exchange between EV batteries and utility grids [13]. During peak demand periods, EV batteries can support the grid through controlled discharging operation. However, improper V2G coordination may create reverse power flow and voltage rise problems.

Genetic Algorithm is widely used for nonlinear optimization problems because of strong global search capability and effective avoidance of local minima trapping [14]. However, GA generally exhibits higher computational complexity and slower convergence. Particle Swarm Optimization provides faster convergence and lower computational burden through simplified velocity and position update mechanisms [15]. Nevertheless, PSO may experience premature convergence under highly constrained nonlinear search conditions [16].

Existing studies mainly focus on charging cost minimization without detailed transformer thermal ageing analysis. Several optimization approaches neglect simultaneous consideration of feeder operational cost, voltage constraints, and energy arbitrage benefits. Comparative analysis between GA and PSO for urban residential EV charging coordination remains limited[17]-[19]. Practical transformer thermal constraints under varying EV penetration conditions also require further investigation[20]-[21]. This paper presents a comparative optimization framework for EV charging scheduling considering energy arbitrage and transformer operational cost minimization. The proposed methodology integrates transformer thermal ageing modelling, feeder operational analysis, voltage regulation constraints, and V2G coordination into a unified optimization framework implemented using MATLAB/Simulink.

The major contributions of this work are summarized as follows:

- Development of an optimization-based EV charging coordination framework considering transformer thermal ageing and operational cost.
- Integration of energy arbitrage and V2G operation into distribution system optimization.
- Mathematical modelling of EV charging dynamics and transformer thermal behaviour.
- Comparative implementation of Genetic Algorithm and Particle Swarm Optimization techniques.
- MATLAB/Simulink validation under various EV charging scenarios.
- Comparative evaluation of convergence speed, computational complexity, and thermal performance.

Section II presents the literature review and research gap analysis. Section III describes the proposed system and mathematical modelling. Section IV discusses the control strategy and implementation methodology. Section V presents simulation results and comparative analysis. Section VI concludes the paper and presents future research directions.

II. PROPOSED SYSTEM AND MATHEMATICAL MODELLING

A. Proposed System Architecture

The proposed urban village distribution system consists of residential feeders, distribution transformers, EV charging stations, EV aggregators, and an optimization controller. The controller coordinates charging and discharging schedules considering transformer thermal limits, electricity tariff variation, feeder loading conditions, and EV battery constraints.

The system operates under both grid-to-vehicle (G2V) and vehicle-to-grid (V2G) operating modes.

B. EV Charging Power Modelling

The total active power demand of the distribution system is expressed as:

$$P_{total}(t) = P_{base}(t) + P_{EV}(t) + P_{loss}(t) \quad (1)$$

where P_{base} represents residential load demand, P_{EV} denotes EV charging/discharging power, and P_{loss} indicates feeder power loss.

The apparent power demand is given by:

$$S(t) = \sqrt{P_{total}^2(t) + Q_{total}^2(t)} \quad (2)$$

C. Battery State-of-Charge Modelling

The EV battery state-of-charge (SoC) dynamics are represented as:

$$SOC(t + 1) = SOC(t) + \frac{\eta_c P_{\{EV\}}(t) \Delta t}{C_{bat}} \quad (3)$$

where η_c is charging efficiency, C_{bat} is battery capacity, and Δt is the charging interval.

The battery operating constraint is defined as:

$$SOC_{max} \leq SOC(t) \leq SOC_{min} \quad (4)$$

Positive charging power represents G2V operation, whereas negative charging power indicates V2G operation.

D. Energy Arbitrage Modelling

The energy arbitrage benefit is formulated as:

$$SOC_{max} \leq SOC(t) \leq SOC_{min} \quad (5)$$

$$C_{arb} = \sum_t \lambda(t)(P_{dis}(t) - P_{chg}(t)) \quad (6)$$

where $\lambda(t)$ denotes electricity tariff variation.

E. Distribution Power Flow Modelling

The feeder active power loss is expressed as:

$$P_{loss} = I_{br}^2 R_{br} \quad (7)$$

The bus voltage deviation is given by:

$$\Delta V_i = V_i - V_{ref} \quad (8)$$

Voltage magnitude is maintained within permissible operating limits:

$$0.95 \leq V_i \leq 1.05 \quad (9)$$

F. Transformer Thermal Ageing Modelling

Transformer hotspot temperature is expressed as:

$$\theta_H = \theta_A + \Delta\theta_{TO} + \Delta\theta_H \quad (10)$$

where θ_A represents ambient temperature, $\Delta\theta_{TO}$ is top-oil temperature rise, and $\Delta\theta_H$ denotes winding hotspot rise.

The ageing acceleration factor is formulated as:

$$F_{AA}^t = e^{\left(\frac{15000}{383}\right) - \left(\frac{15000}{\theta_H^t + 273}\right)} \quad (11)$$

The transformer loss-of-life is determined using IEEE thermal ageing standards.

G. Objective Function Formulation

The optimization objective combines arbitrage penalty cost, feeder loss cost, peak demand cost, and transformer ageing cost:

$$J = C_{arb} + C_{peak} + C_{loss} + C_{age} \quad (12)$$

The optimization minimizes operational cost while satisfying transformer thermal and feeder operational constraints.

H. Genetic Algorithm Modelling

The GA optimization process uses selection, crossover, mutation, and replacement operations.

The fitness function is expressed as:

$$Fitness = f(C_{ABpen}, C_{peak}, C_{loss}, C_{TxLoL}) \quad (13)$$

The selection probability equation is:

$$P_i = \frac{f_i}{\sum_{j=1}^N f_j} \quad (14)$$

GA provides strong exploration capability for nonlinear EV charging optimization problems.

I. Particle Swarm Optimization Modelling

The PSO velocity update equation is expressed as:

The particle velocity update equation is:

$$v_i^{k+1} = wv_i^k + c_1r_1(p_i^k - x_i^k) + c_2r_2(g^k - x_i^k) \quad (15)$$

where:

- v_i = Particle velocity
- x_i = Particle position
- w = Inertia weight
- c_1, c_2 = Acceleration coefficients
- r_1, r_2 = Random variables
- p_i = Personal best position
- g = Global best position

The particle position update equation is:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (16)$$

The inertia weight equation is:

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{iter_{max iter}} \right) \quad (17)$$

PSO optimization provides faster convergence and lower computational complexity compared to conventional optimization techniques.

III. CONTROL STRATEGY AND IMPLEMENTATION

The proposed control strategy continuously monitors transformer loading, feeder current, voltage profile, electricity tariff variation, and EV charging demand. The optimization controller dynamically modifies EV charging schedules to minimize transformer thermal stress and operational cost. During low tariff periods, EVs operate in G2V mode to charge batteries. During peak demand intervals, selected EVs participate in V2G operation to support grid operation and reduce transformer loading.

The controller incorporates:

- Battery SoC monitoring
- Voltage regulation control

- Feeder current monitoring
- Transformer thermal management
- Energy arbitrage coordination
- Optimization-based charging scheduling

The GA implementation generates random charging schedules and evaluates each individual using the developed fitness function. Crossover and mutation operations improve global search capability and prevent premature convergence.

In PSO implementation, each particle represents a charging schedule solution. Particle velocity and position are updated iteratively based on personal best and global best solutions.

The proposed framework is implemented in MATLAB/Simulink using residential load models, transformer thermal ageing models, EV charging subsystems, and optimization controllers.

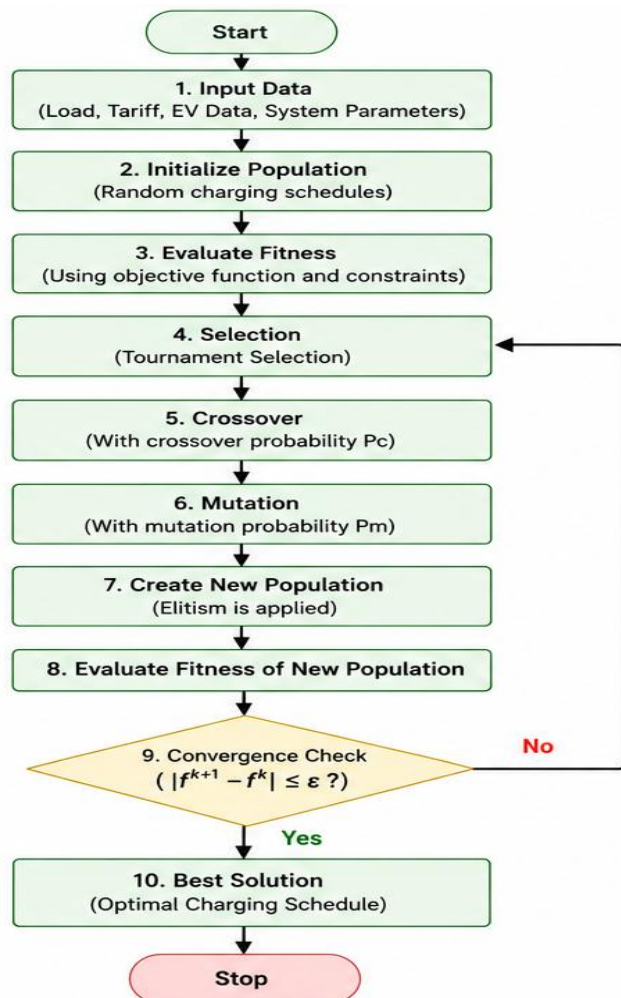


Fig 1 : Flowchart of Genetic Algorithm Based EV Charging Optimization

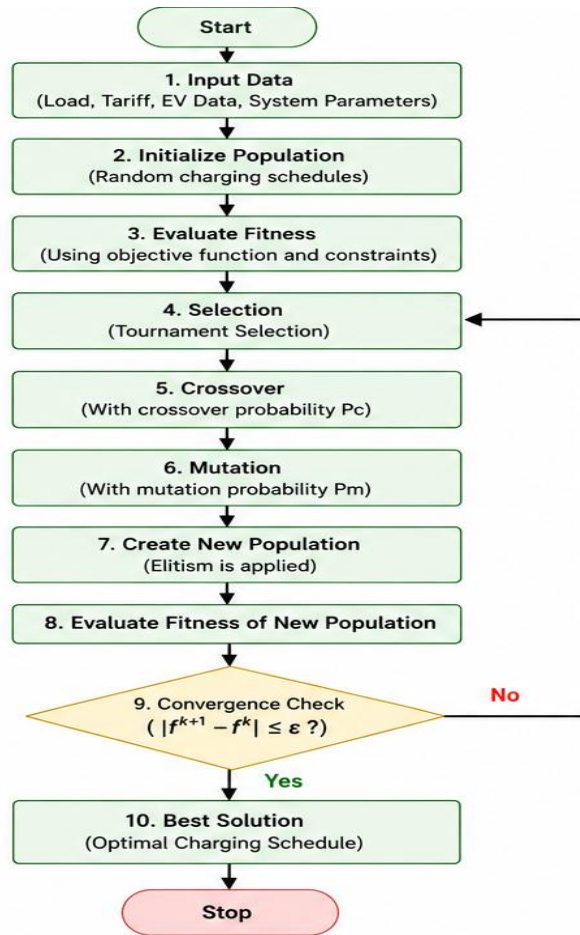


Fig 2 : Flowchart of PSO Algorithm Based EV Charging Optimization

IV. RESULTS AND DISCUSSION

Simulation studies were carried out in MATLAB/Simulink under uncontrolled charging, TOU charging, GA optimization, and PSO optimization scenarios.

A. Load Profile Analysis

The uncontrolled charging method produced severe charging concentration during residential peak demand periods, resulting in excessive transformer loading and feeder current increase. TOU charging shifted charging demand toward low tariff periods; however, secondary peak demand conditions were observed.

The proposed optimization-based charging strategy distributed charging demand uniformly throughout the operating cycle, thereby reducing peak loading and improving load balancing performance.

B. Transformer Thermal Performance

The proposed optimization framework significantly reduced transformer hotspot temperature compared to uncontrolled charging conditions. It was observed that coordinated charging effectively minimized transformer thermal stress and insulation degradation.

The maximum hotspot temperatures obtained were:

- GA Optimization: 49.54 °C
- PSO Optimization: 76.42 °C

The obtained results confirm that GA optimization provides superior transformer thermal management capability.

C. Operational Cost Analysis

The final objective function values obtained were:

- GA Optimization: 573.4435
- PSO Optimization: 10430.2566

The comparative analysis indicates that GA achieved significantly lower operational cost because of improved global search capability and effective charging coordination.

D. Peak Load Reduction

The peak demand obtained using GA optimization was 39.07 kW, whereas PSO optimization resulted in 92.84 kW peak demand. The proposed GA framework effectively reduced charging concentration and transformer loading.

E. Convergence Characteristics

PSO demonstrated faster convergence and lower computational complexity because of simplified particle update mechanisms. However, premature convergence toward local optimum solutions was observed under highly constrained operating conditions. GA exhibited slower but more stable convergence characteristics because of crossover and mutation operations.

F. Comparative Performance Analysis

Table 1. Shows the performance analysis comparison.

Table 1. Performance analysis comparison

Parameter	GA Optimization	PSO Optimization
Objective Cost	573.4435	10430.2566
Peak Load	39.07 kW	92.84 kW
Hotspot Temperature	49.54 °C	76.42 °C
Execution Time	76.7291 s	11.0200 s
Convergence Speed	Moderate	Fast
Thermal Performance	Excellent	Moderate

The obtained results demonstrate that GA provides superior optimization quality and thermal management performance, whereas PSO offers reduced computational burden and faster execution suitable for real-time applications.

V. CONCLUSION

This paper presented an optimization-based EV charging coordination framework considering energy arbitrage and transformer thermal ageing in urban village distribution systems. Mathematical modelling of EV charging dynamics, transformer thermal behaviour, feeder operational constraints, and optimization control equations was developed. Comparative optimization analysis using Genetic Algorithm and Particle Swarm Optimization was performed using MATLAB/Simulink implementation. Simulation results demonstrated that optimization-based charging coordination significantly reduces transformer hotspot temperature, feeder loading, peak demand, and operational cost. GA optimization achieved superior global optimization capability and thermal performance under highly nonlinear constrained operating conditions. PSO demonstrated faster convergence and lower computational complexity suitable for real-time implementation. The proposed framework provides an effective solution for intelligent EV charging coordination in future smart distribution networks with high EV penetration.

Future work may include renewable energy integration, deep learning-based charging coordination, stochastic EV modelling, and hardware-in-the-loop implementation.

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