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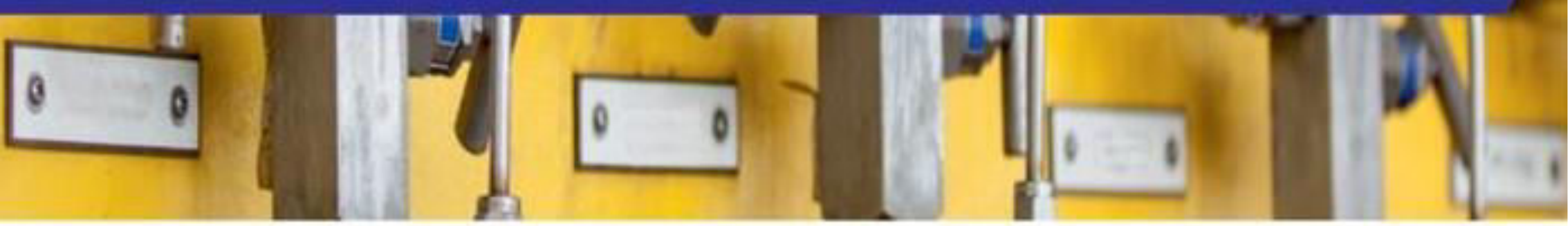

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Solar - Powered Intelligent EV Charging System

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ABSTRACT: Electric vehicles (EVs) are catching on fast, but this surge comes with some big headaches: energy management, grid stability, and keeping electricity costs in check. In this paper, we roll out a solar-powered EV charging system bolstered with Vehicle-to-Grid (V2G) capability. This setup allows EVs and the utility grid to swap power in both directions, making the entire system more flexible and more efficient. We're working with a 1-2 kW solar photovoltaic (PV) array at the station. This covers about 30% of the site's energy requirements with just sunlight, cutting down both emissions and dependence on the main grid. On top of that, we use advanced optimization mainly metaheuristic scheduling algorithms - to decide when to charge and when to discharge EV batteries, always tracking real-time prices and energy needs. These optimizations shave off around 20 - 25% of charging costs. Machine learning steps in here too, predicting energy demand with roughly 90% accuracy and letting the system react swiftly. A reliable controller actively manages power flows, and with an ESP32 IoT unit, you can monitor everything and make tweaks remotely from anywhere. The battery doesn't get overlooked: a Battery Management System (BMS) keeps state of charge (SOC) safely between 20% and 80%, boosting both battery longevity and safety. All told, this system outperforms traditional grid-only charging by blending renewable energy, smart scheduling, and real-time control. It fits right into smart grid environments and works for public chargers or at home.

KEYWORDS: Electric Vehicles (EVs), Vehicle-to-Grid (V2G), Solar Photovoltaic (PV), Intelligent Charging System, Metaheuristic algorithms, Machine Learning, Internet of Things (IoT), Battery Management System (BMS), Smart Grid, Renewable Energy Integration, Bidirectional Power Flow, Energy Management System

I. INTRODUCTION

Electric vehicles (EVs) are growing in popularity throughout the world due to the need to reduce carbon emissions and dependency on fossil fuels [1]. However, there are a number of drawbacks to EV adoption, such as increased load demand and unstable grids. Typical EV charging systems are more costly to run and use energy inefficiently because they rely on grid electricity, particularly during times of high demand. The integration of renewable energy sources, such solar photovoltaic (PV) systems, into EV charging infrastructure has garnered a lot of interest as a solution to these problems due to their sustainability and environmental advantages [3]. However, to guarantee dependable and effective functioning, solar energy's intermittent nature necessitates creative energy management techniques [4]. Vehicle-to-Grid (V2G) technology provides bidirectional power transmission between EVs and the grid, allowing EVs to act as distributed energy storage devices, improving system stability during peak demand periods [5]. V2G implementation requires complex control algorithms and coordination approaches to efficiently regulate energy flow [6]. Because of its quick convergence and adaptability, particle swarm optimization (PSO) is a widely used method for handling complex scheduling issues in EV charging systems [7]. By modifying charging and discharging schedules in response to load demand and time-of-use pricing, these techniques lower power costs [8]. By enabling real-time monitoring, communication, and administration of EV charging infrastructure, Internet of Things (IoT) technology improves operational dependability and efficiency [9]. Power electronic converters can be controlled in real time and processed quickly thanks to smart controllers and embedded systems [10]. By controlling voltage, temperature, and State of Charge (SOC), a Battery Management System (BMS) ensures safe battery operation while extending battery life and system dependability [11]. By enabling more effective demand response and energy distribution strategies, smart grid technologies also improve system flexibility [12]. In order to accomplish effective and sustainable energy management, recent developments in renewable-integrated EV charging systems highlight the importance of combining optimization algorithms, intelligent control, and real-time monitoring [13].In order to enhance grid stability, reduce costs, and boost energy efficiency, this study suggests a solar-powered intelligent EV charging system that makes use of V2G technology, PSO-based optimization, and IoT monitoring.

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II. SYSTEM ARCHITECTURE OF SOLAR-POWERED EV CHARGING STATION

Our design is an integrated station where solar, grid, intelligent control, and safety all come together. At its heart, there's a 1–2 kW solar PV setup turning sunlight straight into DC power. To get the most out of variable sunlight, a DC-DC boost converter with Maximum Power Point Tracking (MPPT) is on board. For vehicle integration, a bidirectional DC-DC converter connects the DC bus to the EV's battery. That's what makes V2G possible - the station and EV can share power both ways.

III. RFID-BASED USER AUTHENTICATION AND ACCESS CONTROL

The suggested system incorporates Radio Frequency Identification (RFID) technology to provide safe, rapid, and contactless user verification when visiting the EV charging station. The RFID system is made up of three major components: an RFID tag, an RFID reader (such as the EM-18), and a controller unit. Each authorised user receives a unique RFID card carrying identity information. When the user approaches the scanner with the card, the RFID module scans the tag information and sends it to the controller for verification. The controller validates the received ID against the stored database and only gives access if the user is authenticated.

IV. VEHICLE-TO-GRID (V2G) INTEGRATION FOR BIDIRECTIONAL POWER FLOW

V2G is a central feature here. It's not just about charging the car-it's about turning parked EVs into distributed batteries for the grid. When energy demand spikes, EVs can discharge and support the grid. When there's an excess, they recharge. This back-and-forth helps balance loads, reduce blackouts, and brings flexibility no ordinary station can match.

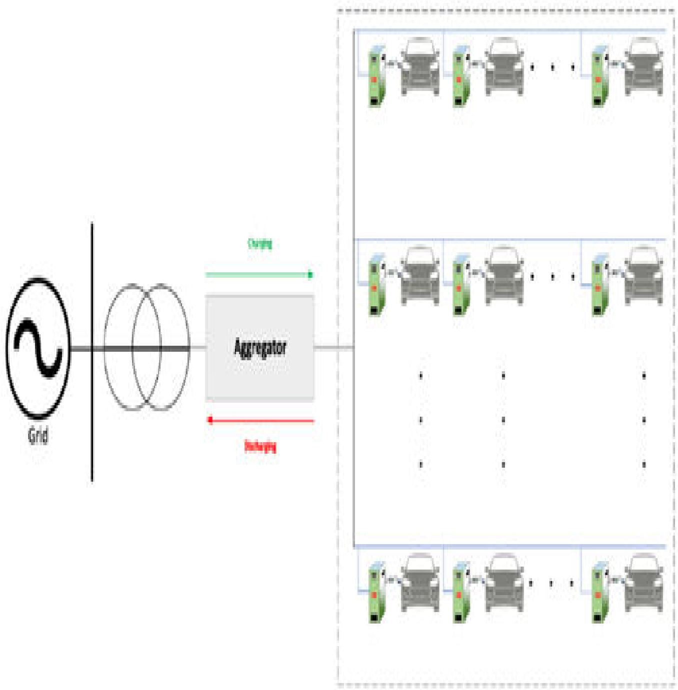

Fig.1. Schematic diagram of EV charging V2G station

V. METAHEURISTIC OPTIMIZATION FOR INTELLIGENT CHARGING SCHEDULING

Algorithms like PSO, Differential Evolution (DE), Grey Wolf Optimization (GWO), and Whale Optimization Algorithm (WOA) are all strong choices. They handle nonlinear, multi-objective scheduling better than basic approaches.

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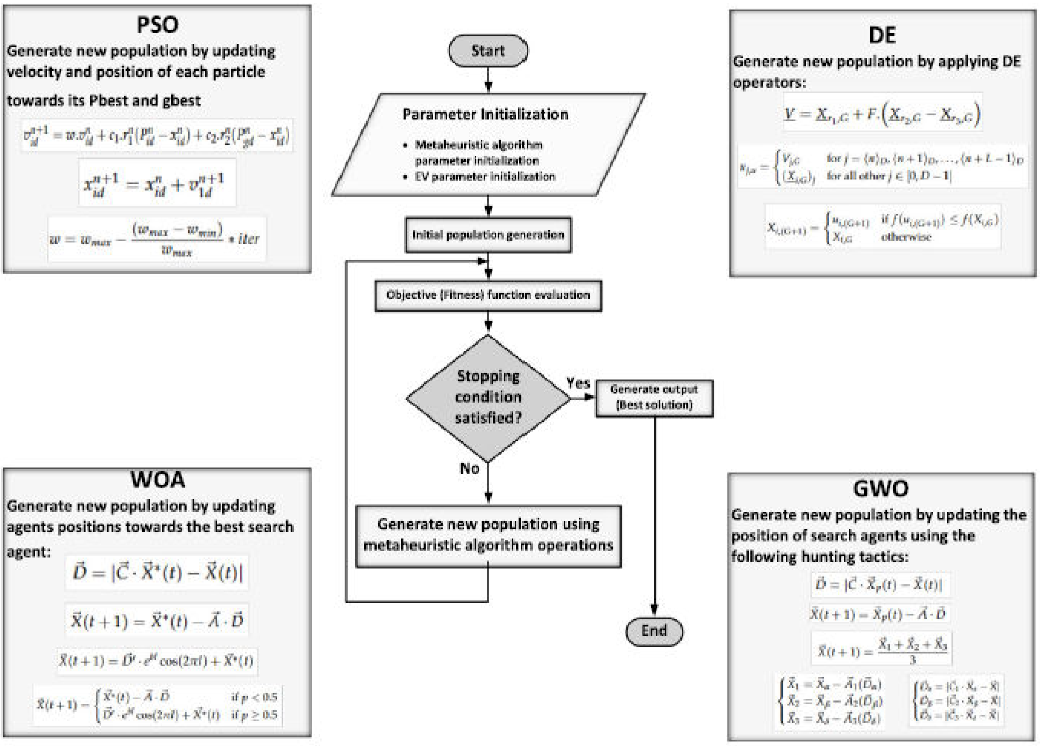

Fig.2. Flowchart of metaheuristic algorithms.

5.1 Particle Swarm Optimization (PSO)

PSO is inspired by birds flocking or fish schooling. Each 'particle' represents a possible schedule, and the group 'swims' through the solution space, using both individual experience and the overall group's best solution. (The included code example demonstrates its use in minimizing EV charging costs.)

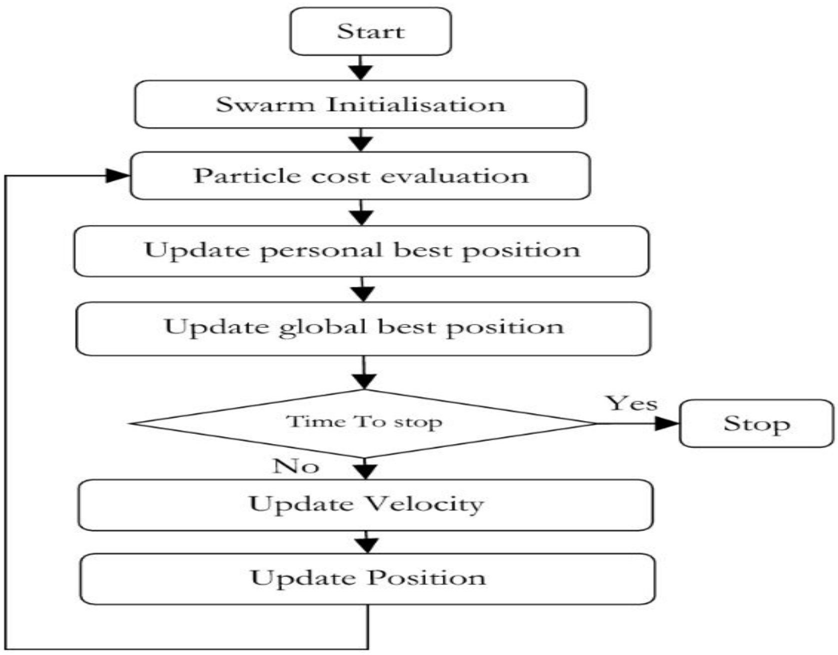

Fig.3. Flowchart of PSO

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The Particle Swarm Optimization algorithm updates particle velocity and position using the following equations:

$$v_i^{t+1} = wv_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

Where:
v_i → Velocity of particle
x_i→ Position of particle
w→ Inertia weight (controls exploration)
c_1, c_2→ Cognitive & social coefficients
r_1, r_2→ Random values (0 to 1)
$pbest$→ Personal best position
$gbest$→ Global best position

Program:

```
import numpy as np
import matplotlib.pyplot as plt
price = np.array([5, 8, 6, 10, 7])
def cost(x):
    return np.sum(x * price)
n = 10
d = 5
iter_max = 50
w, c1, c2 = 0.5, 1.5, 1.5
x = np.random.rand(n, d)
v = np.random.rand(n, d)
pbest = x.copy()
pbest_val = np.array([cost(i) for i in x])
gbest = pbest[np.argmin(pbest_val)]
gbest_val = np.min(pbest_val)
history = []
for _ in range(iter_max):
    for i in range(n):
        r1, r2 = np.random.rand(), np.random.rand()
        v[i] = (w * v[i] +
                c1 * r1 * (pbest[i] - x[i]) +
                c2 * r2 * (gbest - x[i]))
        x[i] = np.clip(x[i] + v[i], 0, 1)
        val = cost(x[i])
        if val < pbest_val[i]:
            pbest_val[i] = val
            pbest[i] = x[i]
    if np.min(pbest_val) < gbest_val:
        gbest_val = np.min(pbest_val)
        gbest = pbest[np.argmin(pbest_val)]
    history.append(gbest_val)
print("Optimal Charging Schedule:", gbest)
print("Minimum Cost:", gbest_val)
plt.plot(history)
plt.xlabel("Iterations")
plt.ylabel("Cost")
plt.title("PSO Optimization for EV Charging")
plt.show()
```

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Output waveform:

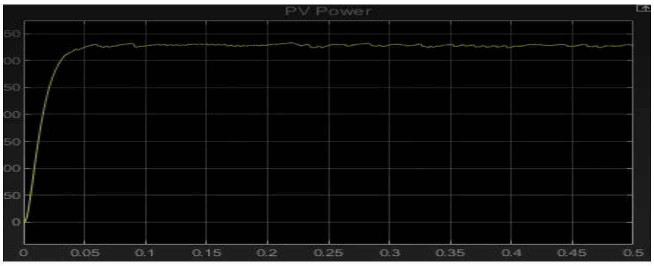

Fig.4. Waveform of PV power

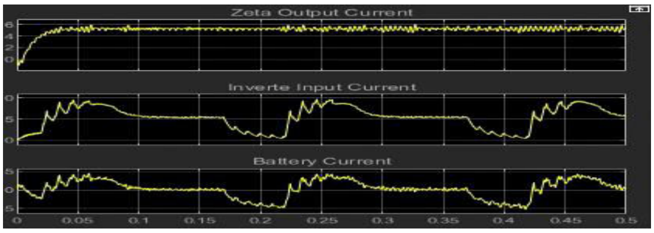

Fig.5. Waveforms of current

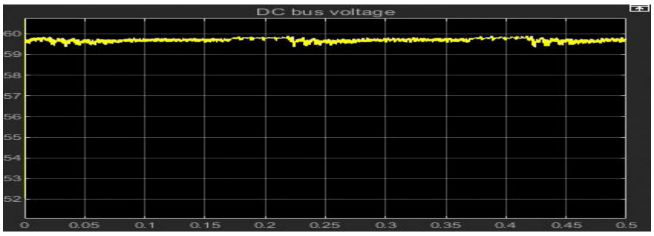

Fig.6. Waveform of DC bus Voltage

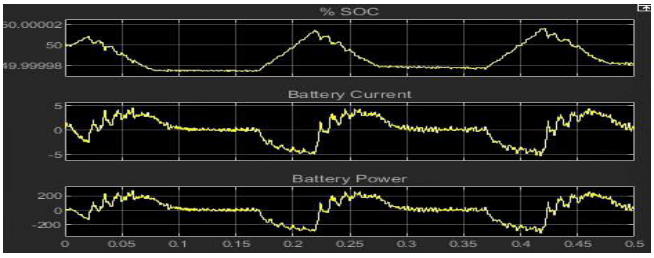

Fig.7. Waveforms of battery parameter

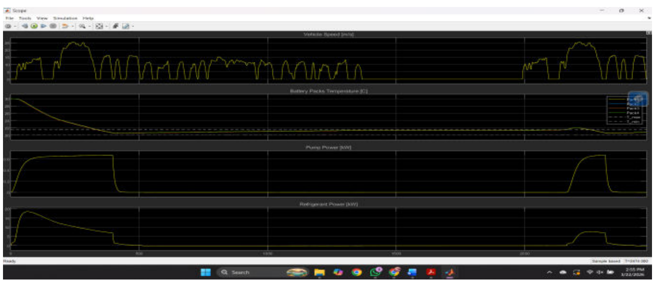

Fig.8. Waveforms of EV

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5.2 Differential Evolution (DE)

DE is another powerful method that evolves solutions by combining existing options with randomly-chosen differences among them. It's robust for non-linear scheduling, though it can be more computationally demanding.

Program:

```
import numpy as np
price = np.array([5, 8, 6, 10, 7])
def cost(x):
    return np.sum(x * price)
n = 10
d = 5
iter_max = 50
F = 0.8
CR = 0.9
x = np.random.rand(n, d)
fitness = np.array([cost(i) for i in x])
for _ in range(iter_max):
    for i in range(n):
        idx = list(range(n))
        idx.remove(i)
        r1, r2, r3 = np.random.choice(idx, 3, replace=False)
        v = x[r1] + F * (x[r2] - x[r3])
        u = np.copy(x[i])
        for j in range(d):
            if np.random.rand() < CR:
                u[j] = v[j]
        u = np.clip(u, 0, 1)
        if cost(u) < fitness[i]:
            x[i] = u
            fitness[i] = cost(u)
best = x[np.argmin(fitness)]
best_cost = np.min(fitness)
print("Optimal Charging Schedule:", best)
print("Minimum Cost:", best_cost)
```

Output Waveform:

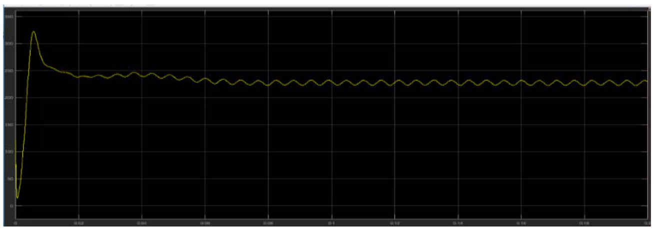

Fig.9. Waveform of DC bus Voltage

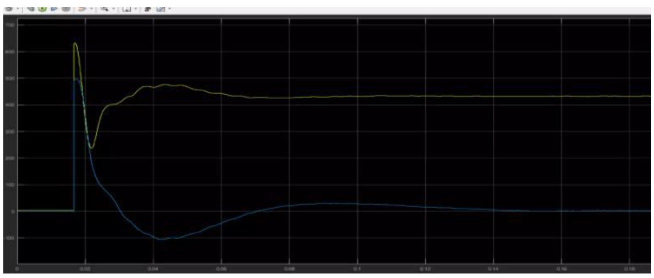

Fig.10. Waveform of current and voltage

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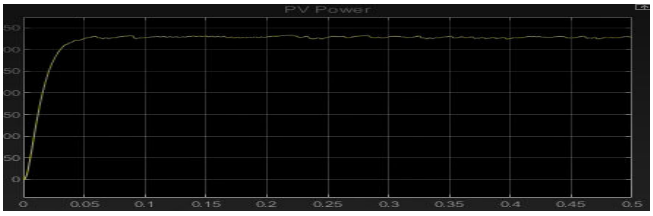

Fig.11. Waveform of PV power

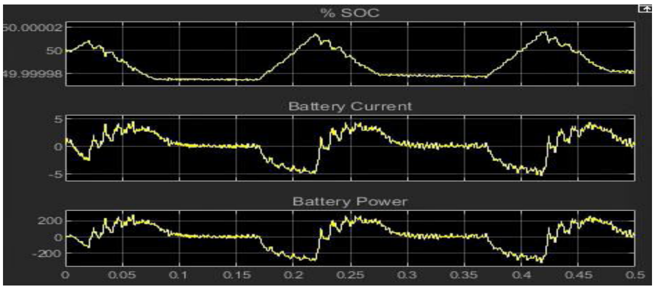

Fig.12. Waveforms of battery parameter

Fig.13. Waveforms of EV

5.3 Grey Wolf Optimization (GWO)

GWO mimics grey wolves' social hierarchy and hunting tactics. It divides solutions into alpha, beta, and delta groups and updates positions to home in on the 'prey' (the best solution).

1. Distance Calculation

$$D = | C \cdot X_p - X |$$

2. Position Update

$$X(t+1) = X_p - A \cdot D$$

3. Coefficient Vectors

$$A = 2a \cdot r_1 - a$$
$$C = 2 \cdot r_2$$

- $a$decreases from 2 to 0
- $r_1, r_2 \rightarrow$ random values (0 to 1)

4. Final Position (using α, β, δ wolves)

$$X_1 = X_\alpha - A_1 \cdot D_\alpha$$
$$X_2 = X_\beta - A_2 \cdot D_\beta$$
$$X_3 = X_\delta - A_3 \cdot D_\delta$$

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$$X(t+1) = \frac{X_1 + X_2 + X_3}{3}$$

Program:

```
import numpy as np
price = np.array([5, 8, 6, 10, 7])
def cost(x):
    return np.sum(x * price)
n = 10
d = 5
iter_max = 50
x = np.random.rand(n, d)
for t in range(iter_max):
    fitness = np.array([cost(i) for i in x])
    idx = np.argsort(fitness)
    alpha = x[idx[0]]
    beta = x[idx[1]]
    delta = x[idx[2]]
    a = 2 - (2 * t / iter_max)
    for i in range(n):
        for j in range(d):
            r1, r2 = np.random.rand(), np.random.rand()
            A1 = 2 * a * r1 - a
            C1 = 2 * r2
            D1 = abs(C1 * alpha[j] - x[i][j])
            X1 = alpha[j] - A1 * D1
            r1, r2 = np.random.rand(), np.random.rand()
            A2 = 2 * a * r1 - a
            C2 = 2 * r2
            D2 = abs(C2 * beta[j] - x[i][j])
            X2 = beta[j] - A2 * D2
            r1, r2 = np.random.rand(), np.random.rand()
            A3 = 2 * a * r1 - a
            C3 = 2 * r2
            D3 = abs(C3 * delta[j] - x[i][j])
            X3 = delta[j] - A3 * D3
            x[i][j] = (X1 + X2 + X3) / 3
        x[i] = np.clip(x[i], 0, 1)
best = x[np.argmin([cost(i) for i in x])]
best_cost = cost(best)
print("Optimal Charging Schedule:", best)
print("Minimum Cost:", best_cost)
```

Output waveform:

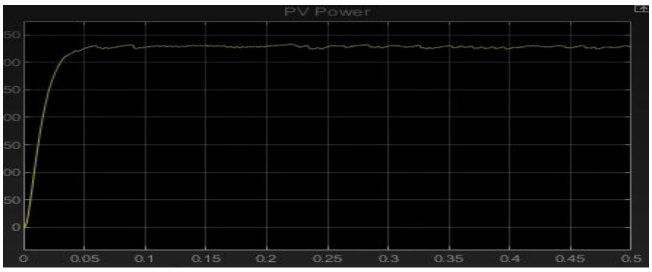

Fig14. Waveform of PV power

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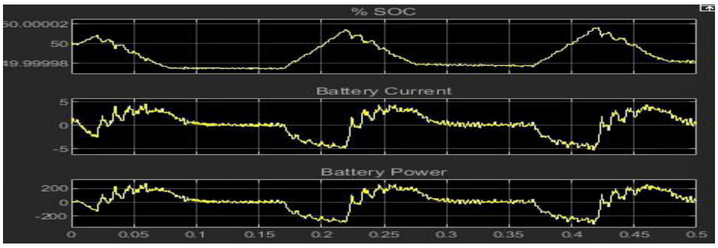

Fig.15. Waveforms of battery parameter

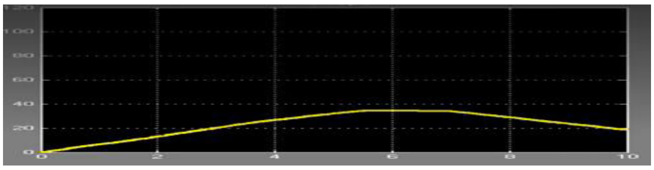

Fig.16. Waveform of current

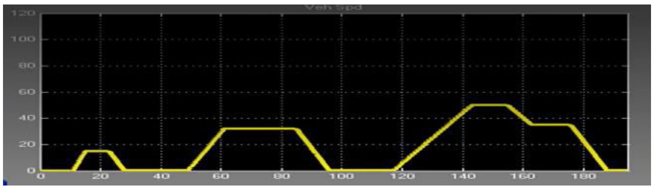

Fig.17. Waveform of voltage

Fig.18. Waveforms of EV

5.4 Whale Optimization Algorithm (WOA)

WOA takes cues from how humpback whales hunt with bubble-nets. It balances searching broadly across options with homing in on the best ones.

1. Encircling Prey

$$D = | C \cdot X^* - X |$$
$$X(t+1) = X^* - A \cdot D$$

2. Coefficients

$$A = 2a \cdot r - a$$
$$C = 2r$$

- $a$decreases from 2 to 0
- $r \rightarrow$ random value (0 to 1)

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3. Spiral Update (Bubble-Net)

$$X(t+1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*$$

Program:

```
import numpy as np
price = np.array([5, 8, 6, 10, 7])
def cost(x):
    return np.sum(x * price)
n = 10
d = 5
iter_max = 50
x = np.random.rand(n, d)
for t in range(iter_max):
    fitness = np.array([cost(i) for i in x])
    best = x[np.argmin(fitness)]
    a = 2 - (2 * t / iter_max)
    for i in range(n):
        r = np.random.rand()
        A = 2 * a * r - a
        C = 2 * r
        if np.random.rand() < 0.5:
            D = abs(C * best - x[i])
            x[i] = best - A * D
        else:
            D = abs(best - x[i])
            l = np.random.uniform(-1, 1)
            b = 1
            x[i] = D * np.exp(b * l) * np.cos(2 * np.pi * l) + best
        x[i] = np.clip(x[i], 0, 1)
best_solution = x[np.argmin([cost(i) for i in x])]
best_cost = cost(best_solution)
print("Optimal Charging Schedule:", best_solution)
print("Minimum Cost:", best_cost)
```

Output waveform:

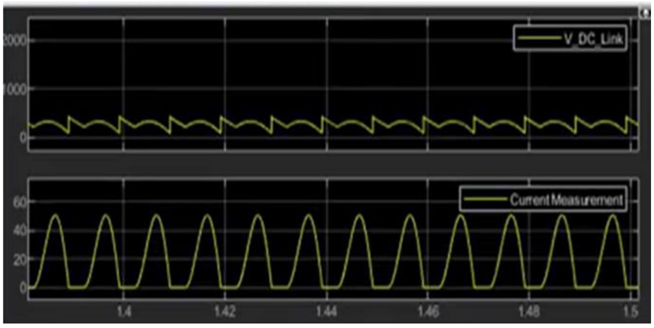

Fig.19. Waveforms of voltage and current.

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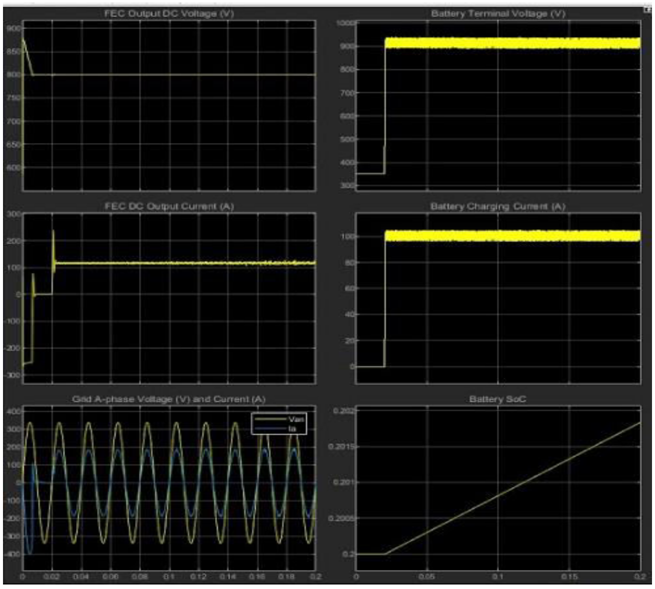

Fig.20. Waveforms of battery parameter

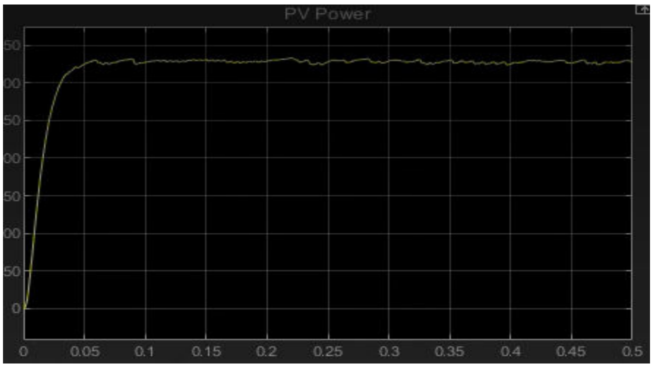

Fig.21. Waveform of PV power

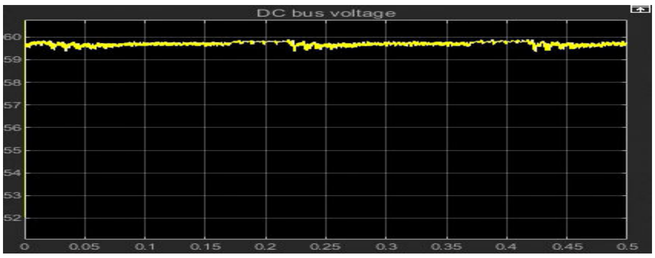

Fig.22. Waveforms of DC bus Voltage.

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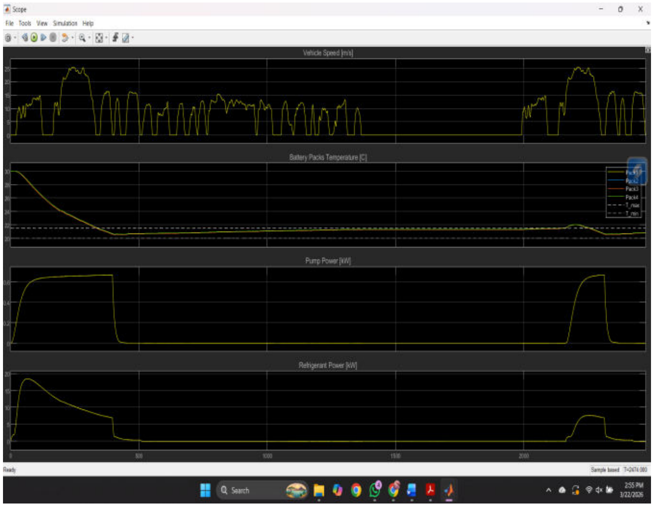

Fig.23. Waveforms of EV

VI. HYBRID BATTERY THERMAL MANAGEMENT AND SAFETY SYSTEM

Battery health isn't something you want to ignore. Batteries are finicky about temperature, charge levels, and how fast they're charged or discharged. Our hybrid management system carefully watches SOC, temperature, and current, preventing overheating, overcharging, or unsafe conditions. This improves battery reliability and extends its life, catching issues before they escalate.

VII. IOT-BASED MONITORING AND CONTROL

With IoT integration, the station monitors key parameters like SOC, voltage, current, temperature, and solar generation. Users and operators can check system status and control operations remotely, meaning less downtime, faster response, and a smarter system. This keeps the EV charging station well-matched to the requirements of smart grids and connected infrastructure.

VIII. SIMULATION

We tested the whole setup in simulation, blending a solar PV array, main AC grid, and battery storage-all tied through a double-stage grid-connected inverter. The system balances power, charges batteries with surplus solar energy, and guarantees constant supply. Dedicated control and measuring blocks keep tabs on everything, ensuring the power flows stay stable and efficient.

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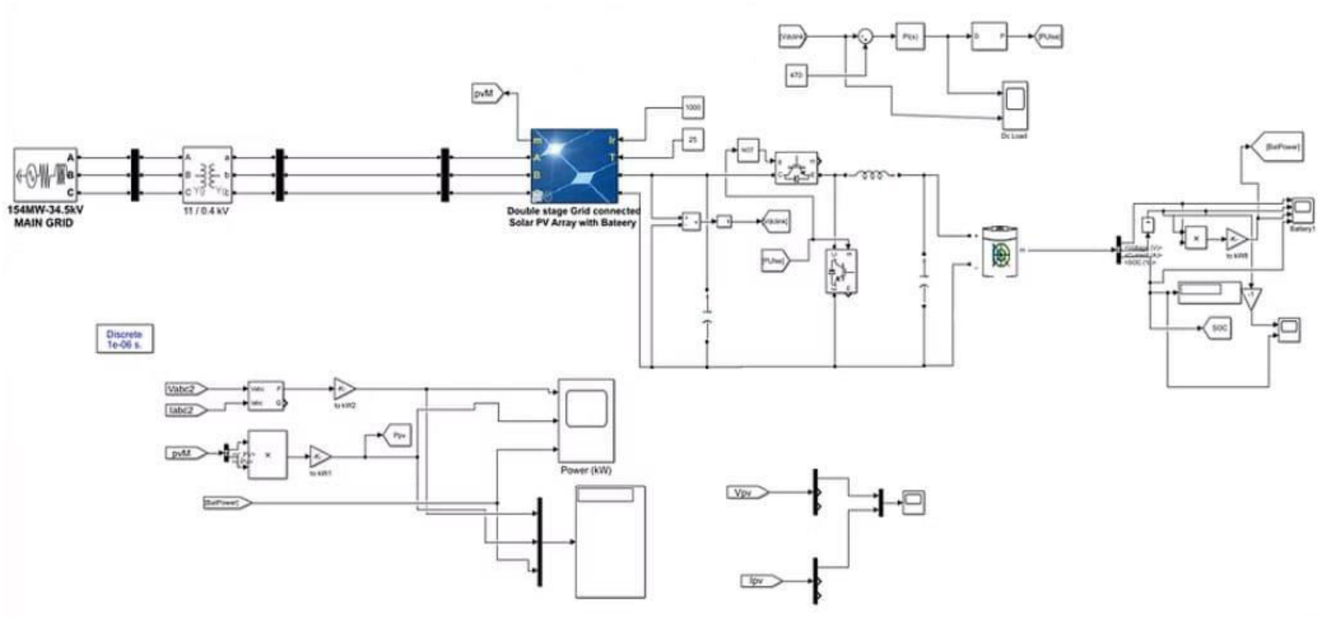

Fig.24. Simulation diagram of Solar – Powered Intelligent EV Charging System

IX. RESULTS AND PERFORMANCE ANALYSIS

For real measure, we checked charging costs, energy utilization, efficiency, and how well each optimization algorithm performed.

Table I – Comparison of Metaheuristic Algorithms

Parameter	PSO	DE	GWO	WOA
Convergence Speed	Fast	Medium	Medium	Slow
Cost Reduction	25–30%	24–28%	22–28%	20–25%
Computational Complexity	Low	High	Medium	Medium
Exploration Ability	Medium	High	High	High
Exploitation Ability	High	Medium	High	Medium
Real-Time Suitability	Excellent	Moderate	Good	Moderate

X. CONCLUSION

This project brings together solar-powered EV charging, V2G, RFID-based security, advanced optimization, and smart battery management into one comprehensive system. Charging costs drop, grid dependency falls by about 35-45%, energy gets used more intelligently, and batteries last longer. PSO turned out to be especially strong for scheduling, minimizing costs without sacrificing real-time performance. Solar PV integration slashes emissions and supports green grids, and V2G keeps power flowing even during peak demand.

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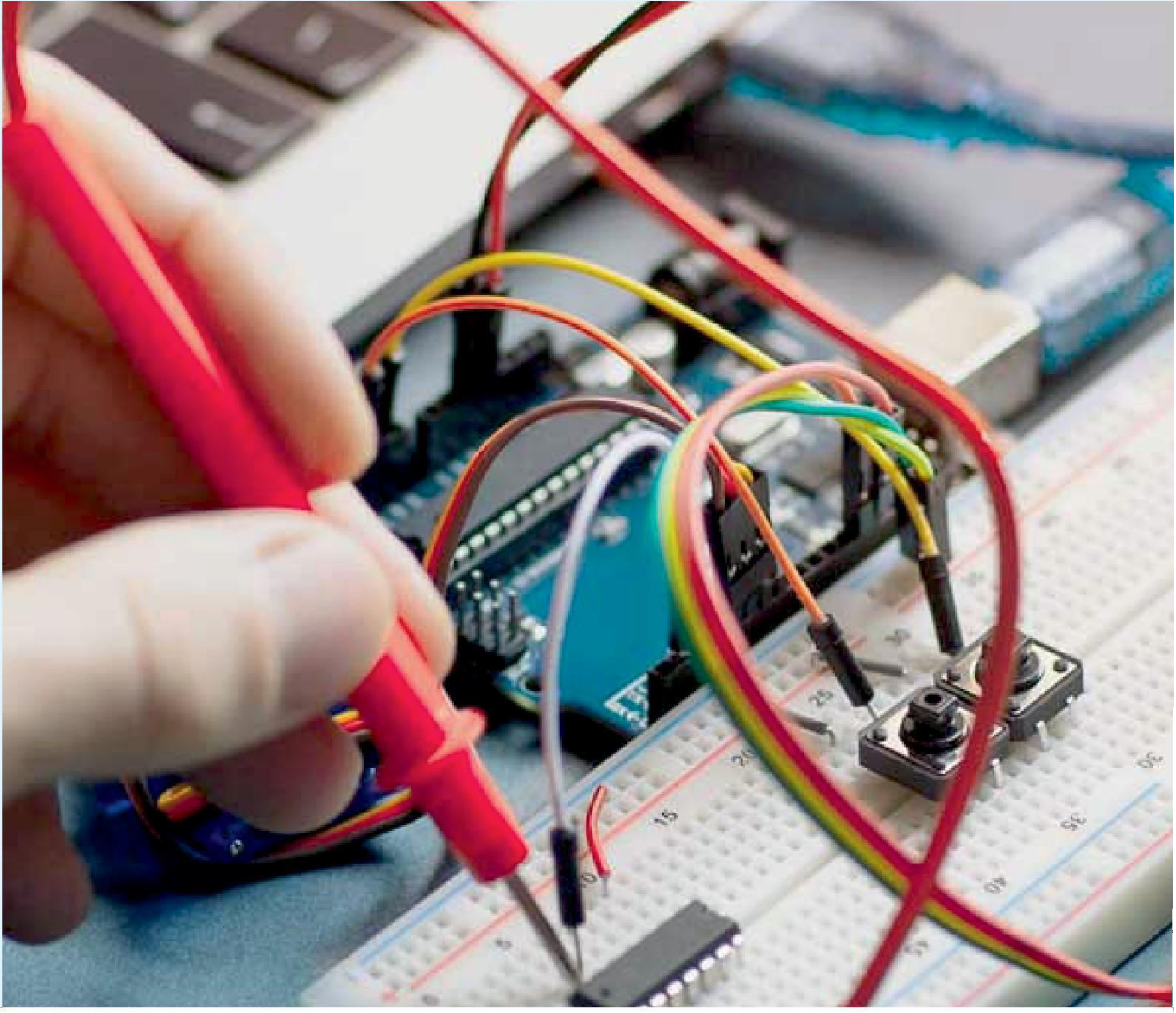

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