

**ADVANCED OPTIMIZATION TECHNIQUES FOR  
ELECTRIC VEHICLE CHARGING IN SMART GRID**

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**DEPARTMENT OF ELECTRICAL ENGINEERING  
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FOR ELECTRIC VEHICLE CHARGING IN  
SMART GRID**

*by*

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*Submitted*

**in fulfillment of requirements of degree of Doctor of Philosophy**

*to the*



**INDIAN INSTITUTE OF TECHNOLOGY DELHI**

**JULY, 2025**

# CERTIFICATE

This is to certify that the thesis entitled '**ADVANCED OPTIMIZATION TECHNIQUES FOR ELECTRIC VEHICLE CHARGING IN SMART GRID**', being submitted by **Ubaid Bashir Qureshi** to **Indian Institute of Technology, Delhi** is a record of bonafide research work carried out under my supervision. I consider it worthy for consideration of the award of the degree **Doctor of Philosophy** in Electrical Engineering. The results obtained here have not been submitted to any other University or Institute for the award of any degree or diploma.

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# Abstract

This thesis presents advanced optimization techniques to enhance electric vehicle (EV) charging within smart grids, addressing challenges in cost efficiency, operational flexibility, and renewable energy integration. With growing EV adoption and renewable energy use, traditional power systems must adapt to dynamic demands and generation variability. The work begins with a stochastic optimization model for commercial EV charging stations with renewable energy sources and battery storage. This model minimizes operational costs, reduces charging disruptions, and extends battery life by balancing energy from the grid, renewables, and EV batteries. Using convex optimization ensures efficient real-time scheduling, improving station profitability and renewable utilization.

The study further examines EV integration into Virtual Power Plants (VPPs) through a stochastic optimization framework enhanced by Mixture Density Neural Networks (MDNNs). The framework optimises energy storage and dispatch by modelling uncertainties in EV demand and renewable energy supply, supporting grid stability and profitability. Empirical results show the model effectively increases renewable utilization and outperforms traditional methods under variable conditions. The research also addresses the routing and scheduling of mobile EV charging stations, employing a modified savings algorithm to optimize travel routes and service times, reducing overall travel time while meeting charging needs flexibly and efficiently.

A novel menu-based pricing strategy using a Stackelberg game framework is introduced, balancing profitability for operators with user affordability to encourage sustainable charging behaviours. This adaptive pricing model benefits both social welfare and economic viability. Finally, a deep reinforcement learning framework optimizes mobile charging van routing based on real-time demand and conditions, minimizing service time and operational costs while dynamically adapting to demand and geography. This thesis provides a robust suite of optimization techniques for EV charging within the smart grid. It demonstrates substantial improvements in cost efficiency, reliability, and renewable integration, underscoring their potential to advance sustainable transportation in future power systems.

## थीसिस सारांश (हिंदी में)

यह शोध स्मार्ट ग्रिड के भीतर इलेक्ट्रिक वाहन (EV) चार्जिंग को बेहतर बनाने के लिए उन्नत अनुकूलन तकनीकों को प्रस्तुत करता है, जो लागत दक्षता, परिचालन लचीलापन और नवीकरणीय ऊर्जा एकीकरण से संबंधित चुनौतियों का समाधान करता है। जैसे-जैसे EV का उपयोग और नवीकरणीय ऊर्जा का प्रचलन बढ़ रहा है, पारंपरिक विद्युत प्रणालियों को गतिशील मांगों और उत्पादन की अनिश्चितता के अनुसार अनुकूलित होना आवश्यक है।

शोध की शुरुआत एक स्टोकास्टिक अनुकूलन मॉडल से होती है, जो व्यावसायिक EV चार्जिंग स्टेशनों के लिए प्रस्तावित है और जिसमें नवीकरणीय ऊर्जा स्रोतों तथा बैटरी भंडारण का उपयोग किया गया है। यह मॉडल ग्रिड, नवीकरणीय स्रोतों और EV बैटरियों से ऊर्जा संतुलित करके परिचालन लागत को न्यूनतम करता है, चार्जिंग में व्यवधान को घटाता है और बैटरी जीवन को बढ़ाता है। उत्तल अनुकूलन (Convex Optimization) का प्रयोग करके वास्तविक समय में दक्ष शेड्यूलिंग प्राप्त की गई है, जिससे स्टेशन की लाभप्रदता और नवीकरणीय ऊर्जा उपयोग में वृद्धि होती है।

इसके पश्चात शोध वर्चुअल पावर प्लांट्स (VPPs) में EV एकीकरण की जांच करता है, जिसमें स्टोकास्टिक अनिश्चितताओं को मॉडल करने के लिए Mixture Density Neural Networks (MDNNs) द्वारा संवर्धित अनुकूलन ढांचा प्रस्तावित है। यह ढांचा EV मांग और नवीकरणीय ऊर्जा आपूर्ति में अनिश्चितता को ध्यान में रखते हुए ऊर्जा भंडारण और वितरण का अनुकूलन करता है, जिससे ग्रिड स्थिरता और लाभप्रदता को बढ़ावा मिलता है। अनुभवजन्य परिणाम दर्शाते हैं कि यह मॉडल पारंपरिक विधियों की तुलना में अधिक प्रभावी है, विशेषतः परिवर्तनीय परिस्थितियों में।

शोध में मोबाइल EV चार्जिंग स्टेशनों के मार्ग निर्धारण और शेड्यूलिंग को भी संबोधित किया गया है, जहाँ संशोधित सेविंग्स एल्गोरिद्म का उपयोग करके यात्रा मार्गों और सेवा समय का अनुकूलन किया गया है, जिससे कुल यात्रा समय कम होता है और चार्जिंग आवश्यकताओं को लचीले और कुशल तरीके से पूरा किया जाता है।

एक नवीन मेनू-आधारित मूल्य निर्धारण रणनीति भी प्रस्तुत की गई है, जो स्टैकेलबर्ग गेम फ्रेमवर्क पर आधारित है। यह रणनीति ऑपरेटरों के लाभ और उपयोगकर्ताओं की वहन क्षमता के बीच संतुलन बनाती है, जिससे सतत चार्जिंग व्यवहार को प्रोत्साहन मिलता है। यह अनुकूली मूल्य निर्धारण मॉडल सामाजिक कल्याण और आर्थिक व्यवहार्यता दोनों को लाभ पहुंचाता है।

अंततः, एक डीप रिइन्फोर्समेंट लर्निंग फ्रेमवर्क मोबाइल चार्जिंग वैन के मार्ग निर्धारण का अनुकूलन करता है, जो वास्तविक समय की मांग और भौगोलिक स्थितियों के अनुसार गतिशील रूप से अनुकूलन प्रदान करता है। यह सेवा समय और परिचालन लागत को न्यूनतम करता है।

यह शोध स्मार्ट ग्रिड के भीतर EV चार्जिंग के लिए एक मजबूत अनुकूलन तकनीकों का संग्रह प्रस्तुत करता है, और लागत दक्षता, विश्वसनीयता तथा नवीकरणीय ऊर्जा एकीकरण में उल्लेखनीय सुधार दर्शाता है, जो भविष्य की सतत परिवहन प्रणालियों के लिए मार्ग प्रशस्त करता है।

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# Nomenclature

## Acronyms/Abbreviations

AGC Automatic Generation Control

ANN Artificial Neural Network

API Application Programming Interface

ARIMA Autoregressive Integrated Moving Average

BMS Battery Management System

CCS Central Charging Station

CNN Convolutional Neural Network

CPR Charging Power Rate

CSO Charging Station Operator

CVRSPTW Capacitated Vehicle Routing and Scheduling Problem with Time Windows

CVX Convex Programming

DA Day-Ahead Market

DCFC Direct Current Fast Charging

DCOPF Direct Current Optimal Power Flow

DER Distributed Energy Resources

DMS Demand Management System

DNN Deep Neural Network

DOD Depth of Discharge

DQN Deep Q-Network

DR Demand Response

DRL Deep Reinforcement Learning

DSO Distribution System Operator

EDF Earliest Deadline First

EMS Energy Management System

ESS Energy Storage System

EV Electric Vehicle

EVCS Electric Vehicle Charging Station

FCS Fixed Charging Station

FNN Feedforward Neural Network

G2V Grid-to-Vehicle

GA Genetic Algorithm

GMM Gaussian Mixture Model

HVAC Heating, Ventilation, and Air Conditioning

ILP Integer Linear Programming

LMP Locational Marginal Price

LP Linear Programming

LSTM Long Short-Term Memory

MAE Mean Absolute Error

MAPE Mean Absolute Percentage Error

MCS Mobile Charging Station

MCV Mobile Charging Vehicle

MDNN Mixture Density Neural Network

MILP Mixed Integer Linear Programming

MIQP Mixed Integer Quadratic Programming

MOOP Multi-objective Optimization Problem

MPC Model Predictive Control

MSE Mean Squared Error

NJN Nearest-Job-Next

NLP Nonlinear Programming

NP Non-deterministic Polynomial time

PEV Plug-in Electric Vehicle

PHEV Plug-in Hybrid Electric Vehicle

PSO Particle Swarm Optimization

PV Photovoltaic

RE Renewable Energy

RES Renewable Energy Source

RHC Receding Horizon Control

RL Reinforcement Learning

RMCDRL Routing of Mobile Charging Vans using Distributed Deep Reinforcement Learning

RMSE Root Mean Squared Error

RTP Real-Time Pricing

SDG Sustainable Development Goal

SoC State of Charge

STP Short-Term Prediction

TOU Time-of-Use

TSO Transmission System Operator

TSP Traveling Salesman Problem

V2B Vehicle-to-Building

V2G Vehicle-to-Grid

VPP Virtual Power Plant

VRP Vehicle Routing Problem