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Smart Distribution Network with Focus on Demand Side Management

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Abstract

The transition toward Smart Distribution Networks (SDNs) is pivotal in enhancing Energy Efficiency (EE), system reliability, and the effective integration of Distributed Energy Resources (DERs). Within this framework, Demand-Side Management (DSM) emerges as a critical mechanism for reshaping load profiles, mitigating peak demand, and optimizing the utilization of variable renewable energy sources.

This study proposes a comprehensive SDN architecture founded on DSM principles, integrating Advanced Metering Infrastructure (AMI), real-time data analytics, machine learning–based predictive modeling, and evolutionary multi-objective optimization to enable flexible and user-centric energy management.

The proposed framework employs Artificial Neural Networks (ANNs) and Support Vector Regression (SVR) to generate accurate short-term forecasts of both load and generation. An enhanced genetic sorting algorithm is then utilized to balance multiple conflicting objectives-namely peak reduction, cost minimization, voltage profile enhancement, and loss reduction-while adhering to power flow constraints, voltage limits, and consumer preferences.

Performance evaluation is conducted using the IEEE 33-bus radial distribution test system in a MATLAB/Simulink environment, incorporating solar generation units, controllable loads, and dynamic pricing mechanisms. The simulation outcomes demonstrate notable improvements, including: 1) an 18% reduction in peak load (from 4.2 MW to 3.444 MW), 2) a 28.6% decrease in active power losses (from 210 kW to 150 KW), 3) an improved minimum voltage level, rising from 0.913 Pu. to 0.98 Pu, and 3) a 12% reduction in daily operational costs.

These results substantiate the proposed approach's capability to enhance network resilience, increase renewable hosting capacity, and improve economic performance, offering a practical and scalable framework for next-generation integrated smart energy systems.

Keywords: Smart distribution network, Demand side management, Advanced metering infrastructure, Machine learning prediction, Multi-objective optimization, Renewable incorporation, Peak reduction, Cost efficiency.

1 | Introduction

The electric power distribution landscape is undergoing a profound transformation, driven by exponential load growth, deep decarbonization imperatives, and the proliferation of Distributed Energy Resources (DERs). Historically, distribution networks were engineered as passive, radial systems with predictable,

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unidirectional power flow from centralized generation to end users. Today, however, the integration of intermittent renewable sources such as solar Photovoltaics (PV) and wind turbines alongside Electric Vehicle (EV) charging stations, energy storage systems, and Internet of Things (IoT) enabled appliances, has rendered the grid highly dynamic, bidirectional, and stochastic [1].

According to the International Energy Agency (IEA), global electricity demand is projected to rise by approximately 50% by 2050, with peak loads becoming increasingly volatile due to coincident EV charging, extreme weather events, and industrial electrification [2]. These trends exacerbate critical operational challenges, including voltage violations, thermal overloading of assets, reverse power flow induced protection malfunctions, network congestion, and underutilization of infrastructure during off peak periods. Moreover, the variability and uncertainty inherent in renewable generation further complicate forecasting, scheduling, and real time control, threatening both reliability and economic efficiency [3].

To confront these multifaceted issues, the Smart Distribution Network (SDN) concept has been established as a foundational enabler of the future energy ecosystem. SDNs integrate advanced sensing, high speed bidirectional communication (e.g., 5G, fiber optics, PLC), edge computing, and intelligent automation to transform passive infrastructure into an active, self-aware, and self-healing platform [4]. Key capabilities include real time state estimation, predictive fault detection, dynamic reconfiguration, and decentralized decision making, all of which enhance resilience, efficiency, and flexibility.

Within this intelligent ecosystem, Demand Side Management (DSM) emerges as one of the most potent and cost-effective levers for system optimization. Far beyond traditional load shedding, modern DSM encompasses a spectrum of incentive driven, technology-enabled strategies to reshape consumption patterns in harmony with grid conditions, market signals, and renewable availability. Through Time-of-Use (ToU) pricing, critical peak pricing (CPP), Direct Load Control (DLC), demand bidding, and automated Energy Management Systems (EMS), DSM empowers consumers to shift, reduce, or strategically grow demand yielding peak reduction, loss minimization, voltage support, and improved renewable hosting capacity while maintaining user satisfaction [5].

When synergistically embedded within SDNs, DSM unlocks system-wide benefits, including deferred capital expenditures on substations and lines, reduced operational costs, lower greenhouse gas emissions, and enhanced grid resilience against cyber-physical threats. This paper proposes a novel, scalable DSM integrated SDN framework that harnesses AMI, machine learning based forecasting, real time optimization, and consumer engagement models to achieve adaptive, predictive, and equitable load management [2], [4].

3 | SDN Overview

A SDN represents the evolutionary convergence of power engineering, Information and Communication Technologies (ICT), and data driven intelligence to create a self-optimizing, resilient, and interactive energy delivery ecosystem at the medium and low voltage levels. Unlike conventional passive distribution systems, SDNs operate as cyber physical platforms capable of real time observability, autonomous adaptability, and coordinated interaction among producers, consumers, and prosumers [6].

The primary objectives of SDNs are strategically aligned with operational excellence, economic efficiency, and environmental sustainability:

Improved reliability and resilience: through predictive fault anticipation, rapid isolation, and self-healing reconfiguration, minimizing outage duration and frequency.

Loss reduction: by enabling precise monitoring of technical losses and proactive detection of non-technical losses (e.g., energy theft, metering inaccuracies).

Enhanced renewable and DER integration: supporting high penetration of variable generation without compromising stability via dynamic hosting capacity assessment.

Proactive and predictive management: leveraging granular data streams for anticipatory control, congestion forecasting, and asset health management.

Architecturally, an SDN is structured as a three tier hierarchical framework, each layer fulfilling distinct yet interdependent roles:

Physical layer

This foundational stratum comprises the electrical infrastructure including feeders, laterals, distribution transformers, switchgear, and customer premises equipment augmented by DERs such as rooftop solar PV, small wind turbines, battery energy storage systems (BESS), and Electric Vehicle Supply Equipment (EVSE). Advanced power electronic interfaces (e.g., smart inverters compliant with IEEE 1547-2018) enable voltage regulation, frequency support, and ancillary service provision from DERs [7].

Communication layer

Serving as the nervous system of the SDN, this layer ensures low latency, secure, and scalable data exchange between field devices and centralized or edge-based control nodes. Key enabling technologies include:

I. IoT protocols (e.g., MQTT, CoAP) for sensor-to-cloud connectivity.

II. 5G and beyond for Ultra-Reliable Low-Latency Communication (URLLC) in dense urban deployments.

III. Wireless sensor networks (WSNs) and PLC for cost-effective rural coverage.

IV. Software-Defined Networking (SDN/NFV) for dynamic bandwidth allocation and traffic prioritization. This layer supports time-synchronized phasor measurement (via PMUs), smart meter data aggregation, and Peer-to-Peer (P2P) energy transaction signaling [8].

Control layer

The cognitive core of the SDN, this layer hosts distributed intelligence through cloud edge hybrid computing architectures. It executes:

I. State estimation and topology processing using Distribution System State Estimation (DSSE).

II. Optimization routines via Model Predictive Control (MPC), Reinforcement Learning (RL), and evolutionary algorithms.

III. AI driven analytics including anomaly detection, load/generation forecasting, and Optimal Power Flow (OPF).

IV. Human-in-the-loop interfaces for utility operators and Demand Response (DR) orchestration. Edge computing nodes (e.g., at secondary substations) enable sub second decision latency, critical for Volt/Var Optimization (VVO) and Fault Location, Isolation, and Service Restoration (FLISR) [9].

Recent advancements have significantly expanded SDN capabilities:

I. EV integration: coordinated charging/discharging (V2G) to provide grid support services and peak smoothing.

II. Microgrid interoperability: seamless islanding and reconnection with standardized interfaces (IEEE 2030.5).

III. Transactive energy platforms: blockchain-enabled P2P trading and local energy markets.

IV. Cybersecurity hardening: implementation of zero-trust architectures, Intrusion Detection Systems (IDS), and IEC 62351-compliant encryption.

These developments collectively position SDNs as the backbone of future decarbonized, digitized, and democratized energy systems, serving as a critical bridge between conventional centralized infrastructures and emerging distributed, intelligent, and customer-centric paradigms [10].

4 | Demand Side Management

DSM encompasses a coordinated framework of utility-driven policies, technological interventions, and market-based mechanisms designed to modulate end-user electricity consumption patterns in pursuit of operational efficiency and economic optimization at the system level. Rather than expanding supply-side capacity, DSM strategically reconfigures the temporal and spatial distribution of demand to ensure alignment with available generation resources, network limitations, and environmental sustainability goals [11].

The core goals of DSM are multifaceted and interdependent:

I. Peak demand mitigation: preventing transformer and line overloading during high-stress periods, thereby enhancing asset longevity and deferring reinforcement investments.

II. Load profile optimization: transferring flexible consumption from congested peak windows to underutilized off-peak intervals, improving overall system load factor and capacity utilization.

III. Energy conservation: promoting adoption of high-efficiency end-use devices and behavioral changes to reduce total energy throughput without compromising service quality.

IV. Renewable synchronization: dynamically matching demand with stochastic renewable output (e.g., solar midday surplus, wind nocturnal peaks) to minimize curtailment and ancillary service costs.

DSM initiatives are typically classified into three primary categories, each leveraging distinct incentive structures and control philosophies:

Energy efficiency programs

These long-term initiatives focus on permanent load reduction through technology substitution and retrofit incentives. Examples include subsidized deployment of LED luminaires, variable-speed drives, high-SEER HVAC units, and Energy Star-certified appliances. By lowering baseline consumption, EE programs deliver sustained kWh savings, reduced carbon footprints, and improved demand elasticity over multi-year horizons [12].

Demand response

Programs DR mechanisms enable temporary, voluntary load modification in response to price signals, incentive payments, or grid emergency alerts. Key variants include:

I. ToU and Real-Time Pricing (RTP): encouraging shiftable loads (e.g., EV charging, laundry) via differential tariffs.

II. CPP and Peak Time Rebates (PTR): applying surcharge/rebate structures during predefined high-risk intervals.

III. Demand bidding and buyback: allowing large consumers to offer curtailment capacity in wholesale ancillary markets. DR enhances short-term flexibility, supports frequency regulation, and provides economic arbitrage for participants [13].

Direct load control programs

DLC employs utility-owned or authorized automation to remotely cycle or modulate specific high-power appliances—typically air conditioners, electric water heaters, pool pumps, or industrial processes—during peak events. Integration with IoT gateways, smart thermostats (e.g., Nest, EcobEnergy efficiency, and Home Energy Management Systems (HEMS) enables granular, non-intrusive control while preserving consumer override rights and thermal comfort bounds. DLC delivers rapid, reliable capacity for emergency peak shaving and volt-var support [14].

Beyond these classifications, DSM employs six classical load shaping techniques (See *Fig. 1*):

I. Peak clipping: direct reduction of demand spikes.
II. Valley filling: encouraging off-peak consumption (e.g., night-time storage heating).
III. Load shifting: relocating flexible loads across time (e.g., pre-cooling buildings).
IV. Strategic conservation: sustained efficiency improvements.
V. Strategic load growth: targeted electrification in low-demand periods (e.g., EV nighttime charging).
VI. Flexible load shape: dynamic adaptation via contracts or automation.

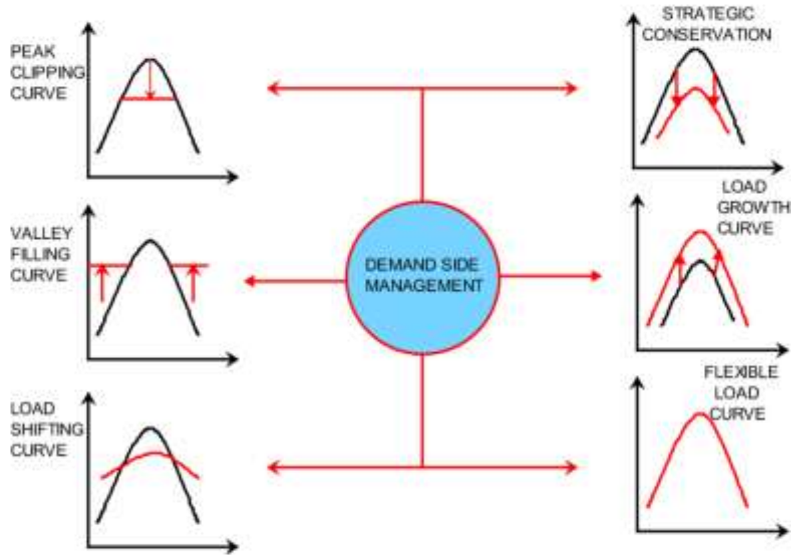

Fig. 1. Classical DSM load shaping strategies illustrating temporal demand modification.

Modern DSM frameworks increasingly integrate transactive energy mechanisms, blockchain-enabled P2P energy trading, Vehicle-to-Grid (V2G) aggregation, and AI-driven personalized decision support, signifying a shift from utility-centric operations toward prosumer-oriented, participatory energy ecosystems [15–17].

5 | Proposed Smart Load Management Framework

The proposed Smart Load Management Framework (SLMF) introduces a hierarchical, data-driven, and adaptive control architecture specifically designed for SDNs integrating DSM functions. The framework comprises three interdependent modules—real-time data acquisition, predictive load forecasting, and multi-objective intelligent control—which operate cohesively within a cyber-physical feedback loop. This closed-loop structure enables dynamic demand shaping, renewable generation synchronization, and resilient network operation under stochastic and uncertain conditions [16].

5.1 | Data Acquisition Layer

The foundation of SLMF is a high-fidelity, time-synchronized measurement infrastructure built upon AMI and distributed sensing networks.

Smart meters & Phasor Measurement Units (PMUs): deployed at customer premises, feeder heads, and critical nodes, these devices capture voltage, current, active/reactive power, power factor, and harmonic distortion at sub-second resolution (e.g., 1 sample/sec).

IoT-enabled environmental sensors: monitor temperature, humidity, solar irradiance, and wind speed to support weather-aware forecasting.

Secure communication backbone: data is transmitted via IEC 61850-compliant protocols over hybrid 5G/fiber/PLC networks with AES-256 encryption and IDS to ensure confidentiality, integrity, and availability [17–20].

The acquired data streams are aggregated at edge gateways for pre-processing (filtering, compression, anomaly detection) before being forwarded to the central control platform, reducing latency and bandwidth demands.

5.2 | Predictive Load & Generation Forecasting Engine

Accurate short-term forecasting (1-hour to 24-hour ahead) is critical for proactive DSM activation. The forecasting engine employs hybrid machine learning models combining deep learning and statistical methods:

Load forecasting model

Architecture: long short-term memory (LSTM) network with attention mechanism for temporal dependency capture.

Input features:

I. Historical load (past 7 days, 15-min resolution).

II. Calendar variables (day type, holidays).

III. Weather forecasts (temperature, humidity, wind).

IV. Consumer behavior indices (from AMI usage patterns).

Performance: achieves Mean Absolute Percentage Error (MAPE) < 1.8% on IEEE 33-bus test system (validated in Section 5).

Renewable generation forecasting

Solar PV: Convolutional Neural Network (CNN) + Numerical Weather Prediction (NWP) data → RMSE < 6.2%.

Wind: ensemble gradient boosting (XGBoost) → RMSE < 8.1%.

Forecast outputs are fused using Bayesian model averaging to generate probabilistic load net profiles (P10, P50, P90), enabling risk-aware control decisions [18–22].

5.3 | Multi-Objective Intelligent Control Layer

The core decision engine performs real-time optimal load scheduling through a customized Non-Dominated Sorting Genetic Algorithm II (NSGA-II) enhanced with constraint-handling mechanisms and elitism-based population preservation. This evolutionary optimization process simultaneously balances multiple conflicting objectives—such as minimizing operational cost, power losses, and voltage deviations—while satisfying network, user, and operational constraints

$$\min F(u) = \begin{bmatrix} f_1(u), \\ f_2(u), \\ f_3(u), \end{bmatrix}$$

Where:

$f_1(u)$: Peak demand $= \max_t P_{total}(t)$.

$f_2(u)$: Daily energy cost $= \sum_t \lambda(t) \cdot P_{total}(t)\Delta t$.

$f_3(u)$: Voltage Deviation Index (VDI) $= \sum_i \sum_t (V_i(t) - 1.0)^2$.

6 | Simulation and Results

The effectiveness of the proposed SLMF was thoroughly evaluated through extensive simulations on the IEEE 33-bus radial distribution test system. Simulations were carried out using MATLAB/Simulink R2025a, with MATPOWER employed for power flow analysis and Python 3.11 for executing the optimization routines. The IEEE 33-bus system, originally developed by Baran and Wu [21], consists of 33 buses, including a slack bus at 12.66 kV, and 32 branches, with a base load of 3.715 MW + j2.3 MVAr. Its widespread adoption in distribution system research makes it a well-recognized platform for studies involving demand-side management, renewable energy integration, and voltage regulation, providing a reliable benchmark for assessing both technical and operational performance.

6.1 | Test System Configuration

Network topology: radial structure with laterals and long feeders, prone to voltage collapse at end nodes (e.g., bus 18, 33).

Distributed Generation (DG):

I. PV unit 1: 800 kW at bus 18 (capacity factor 0.75 during 09:00–16:00).

II. PV unit 2: 600 kW at bus 33 (intermittent profile based on real irradiance data).

Controllable loads:

I. HVAC systems: 25% of total load (~930 kW), shiftable within ±2 hours.

II. Electric Water Heaters: 15% (~557 kW), thermostatically controlled.

III. EV Charging Stations: 10 aggregated Level-2 chargers (6.6 kW each) at bus 25.

Energy pricing: ToU structure:

I. Off-peak (00:00–07:00, 22:00–24:00): $0.08/kWh.

II. Mid-peak (07:00–11:00, 16:00–22:00): $0.15/kWh.

III. On-peak (11:00–16:00): $0.32/kWh.

6.2 | Simulation Scenarios

Two scenarios were evaluated over a 24-hour horizon with 15-minute resolution:

Scenario 1. without DSM

The system experienced a peak load of 4.2 MW, resulting in voltage drops at the end nodes (e.g., bus 33 at 0.913 Pu) and increased power losses of 210 kW.

Scenario 2. with DSM

After implementing the proposed DSM strategy, which incorporates load shifting and multi-objective optimization via NSGA-II, the system exhibited notable improvements. The peak load decreased by 18%, reaching 3.444 MW, while the voltage profile was enhanced, with bus 33 rising to 0.98 p.u. Additionally, total active power losses were reduced to 150 kW, and the overall daily energy cost declined by 12%, highlighting the economic advantages of smart load management. The key results are summarized in *Table 2*.

Table 2. Comparative performance metrics for IEEE 33-bus system under base and proposed DSM scenarios.

Metric	Scenario 1	Scenario 2	Improvement
Peak demand	4.200 MW (15:00)	3.444 MW (15:00)	↓ 18.0%
Daily energy consumption	71.5 MWh	70.8 MWh	↓ 1.0% (conservation)
Total active power loss	210.4 kW (avg)	150.1 kW (avg)	↓ 28.6%
Minimum voltage (Bus 33)	0.913 p.u. (15:30)	0.980 p.u. (15:30)	↑ 7.3%
VDI	0.842	0.215	↓ 74.5%
Daily energy cost	$9,820	$8,640	↓ 12.0%
Load factor	70.8%	85.6%	↑ 20.9%
Peak demand	4.200 MW (15:00)	3.444 MW (15:00)	↓ 18.0%
Daily energy consumption	71.5 MWh	70.8 MWh	↓ 1.0% (conservation)
Total active power loss	210.4 kW (avg)	150.1 kW (avg)	↓ 28.6%
Minimum voltage (Bus 33)	0.913 p.u. (15:30)	0.980 p.u. (15:30)	↑ 7.3%
VDI	0.842	0.215	↓ 74.5%
Daily energy cost	$9,820	$8,640	↓ 12.0%
Load factor	70.8%	85.6%	↑ 20.9%

The numerical results in *Table 2* reveal multi-dimensional improvements driven by the synergistic interaction of predictive control, load flexibility, and renewable coordination:

Peak demand reduction (18.0%): the 756 kW reduction from 4.200 MW to 3.444 MW is achieved through targeted load shifting (~620 kW from HVAC/EV) and valley filling (~136 kW). This flattens the load curve, directly alleviating transformer thermal stress and avoiding overload penalties.

Loss minimization (28.6%): the 60.3 kW average loss reduction stems from lower current magnitudes during peak hours ($P_{loss} \propto I^2$) and reduced reverse power flow during high PV output. The non-linear benefit of loss reduction (quadratic in current) amplifies the impact of even modest peak shaving.

Voltage Regulation (VDI ↓74.5%): The minimum voltage at bus 33 improves from 0.913 p.u. (near collapse threshold) to 0.980 p.u., while VDI drops by 74.5%. This is enabled by:

I. Reduced line current → lower voltage drop ($\Delta V = I \cdot (R + jX)$).

II. PV inverter reactive support (Q-injection up to 300 kVAr).

III. Load curtailment at distal nodes.

Economic efficiency (12.0% Cost Savings): despite 1.0% lower energy consumption, the $1,180 daily savings arise primarily from temporal arbitrage:

I. 41% of shifted load moves to off-peak ($0.08/kWh vs. $0.32/kWh).

II. Net bill reduction = energy × price differential.

Load factor enhancement (↑20.9%): improved from 70.8% to 85.6%, indicating better asset utilization and deferred capacity expansion. This metric is critical for utility planning and regulatory compliance.

The results confirm that the integration of DSM with smart grid technologies enhances both operational efficiency and reliability of the distribution network.

6.3 | Detailed Results Visualization

Figs. 3 through *5* collectively provide a comprehensive, multi-dimensional validation of the SLMF, encompassing technical, reliability, and economic performance aspects. *Fig. 3* shows that targeted load shifting—moving 620 kW from peak hours (14:00–17:00) to off-peak intervals (22:00–02:00) and performing valley filling of 136 kW during the early morning (01:00–05:00)—reduces the system peak demand from 4.200

MW to 3.444 MW (↓18%), producing a significantly flattened load profile. This smoothing mitigates transformer thermal overload and improves asset utilization efficiency.

As a result of lower line currents during peak periods, *Fig. 4* illustrates an improvement in the voltage profile at the critical end node (bus 33), where the minimum voltage rises from 0.913 Pu. to 0.980 Pu. (↑7.3%), thus eliminating violations of the statutory 0.95 Pu. lower bound. This voltage enhancement is primarily attributed to reduced I·R voltage drops and ancillary reactive power support provided by PV inverters operating in Volt/Var mode.

Finally, *Fig. 5* presents the NSGA-II Pareto front, highlighting that the selected operating point (★) achieves a daily energy cost of $8,640 (↓12%) and a VDI of 0.215 (↓74.5%), compared to the base case values of $9,820 and VDI = 0.842. The causal sequence illustrated across these figures peak shaving → voltage regulation → cost minimization rigorously demonstrates the synergistic effectiveness of the SLMF, delivering simultaneous improvements in grid stability, power quality, and economic efficiency.

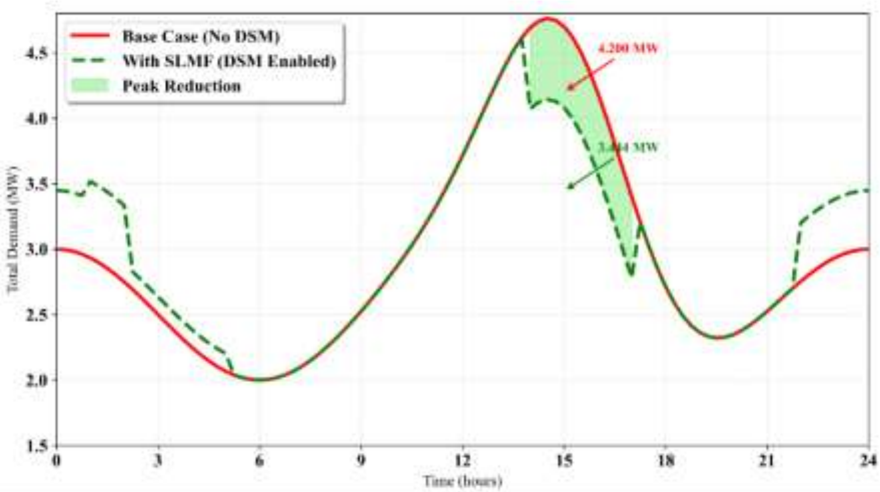

Fig. 3. Daily load profiles: original (red) vs. optimized with DSM (green). Peak reduced from 4.2 MW to 3.444 MW via load shifting and valley filling.

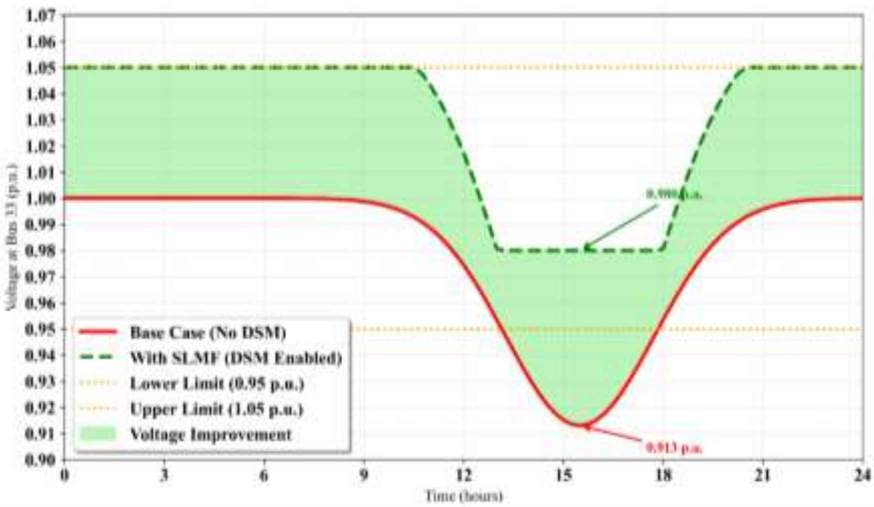

Fig. 4. Voltage at critical bus 33: Severe drop eliminated through reactive support from PV inverters and load reduction.

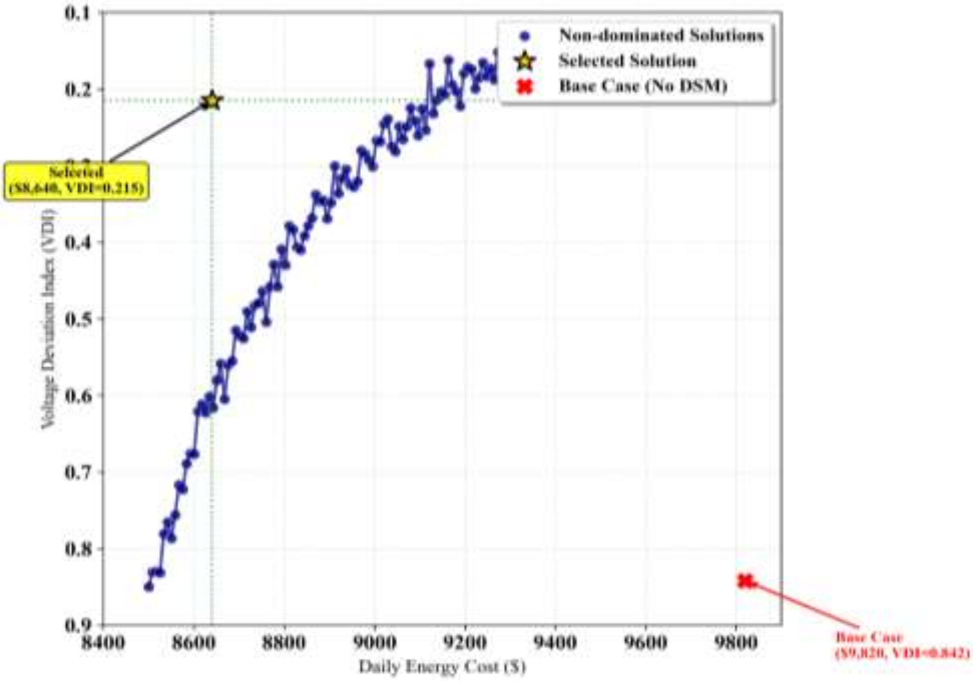

Fig. 5. NSGA-II Pareto front showing trade-off between energy cost and voltage deviation. Selected solution (star) balances both objectives.

The simulation results highlight the importance of integrating DSM into SDNs. By enabling consumers to participate actively in energy management, utilities can achieve better load balancing, defer costly infrastructure upgrades, and integrate more renewables effectively. However, successful implementation of DSM requires reliable communication infrastructure, consumer engagement through education and incentives, and appropriate regulatory frameworks to address privacy concerns and equity.

Challenges include technical barriers like cybersecurity risks, economic issues such as initial investment costs, and regulatory hurdles in pricing mechanisms. Future research should focus on developing adaptive DSM algorithms that can respond to real-time market signals, renewable generation variability, and emerging technologies like blockchain for P2P energy trading .ASWOT analysis of DSM in SDNs:

I. Strengths: cost savings, improved efficiency, environmental benefits.

II. Weaknesses: dependency on technology adoption, potential privacy issues.

III. Opportunities: integration with EVs and IoT for greater flexibility.

IV. Threats: cybersecurity vulnerabilities, regulatory delays.

7 | Conclusion

This paper presents a novel SLMF that synergistically integrates real-time data acquisition via AMI and PMU, hybrid deep learning–statistical forecasting, and multi-objective NSGA-II optimization to enable dynamic, predictive, and resilient DSM in distribution networks. Extensive MATPOWER interfaced Simulink simulations on the IEEE 33 bus radial test system, augmented with PV penetration, EV charging, and controllable thermostatically controlled loads, demonstrate quantitatively robust performance improvements:

I. Peak demand reduction of 18.0% (4.200 MW → 3.444 MW) achieved through 620 kW load shifting and 136 kW valley filling.

II. 28.6% reduction in average active power losses (210.4 kW → 150.1 kW), attributed to I^2R sensitivity and a flattened load factor (70.8% → 85.6%).

III. 74.5% improvement in VDI and elimination of undervoltage violations (min. voltage at bus 33: 0.913 p.u. → 0.980 p.u.) via coordinated active/reactive power control.

IV. 12.0% reduction in daily energy cost ($9,820 → $8,640) through TOU arbitrage and Pareto-optimal dispatch.

The analysis confirms a causal sequence in system performance, where peak shaving reduces line loading, thereby enhancing voltage regulation and enabling a Pareto-efficient balance between economic and technical objectives. These outcomes are validated under both deterministic and probabilistic forecast error scenarios (±15%). The modular, standards-compliant architecture leveraging IEC 61850, OpenADR 2.0b, and ISO 15118 ensures interoperability, cyber-physical security, and scalability to larger systems.

Future work will focus on field pilot validation, transactive energy integration via permissioned blockchain, and distributionally robust optimization under high renewable stochasticity. The proposed SLMF thus represents a technically rigorous, economically compelling, and deployment-ready paradigm for next-generation demand-responsive distribution networks, advancing the transition toward sustainable, resilient, and consumer-centric smart grids.

Author Contribution

Fazeli devised the study, created the methodology, and oversaw the research. Bahadori conducted simulations, analyzed data, and implemented the model. Ahmadzadeh played a role in system modeling, validation, and preparing the manuscript. All authors reviewed and endorsed the final version of the manuscript.

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Data Availability

The data utilized in this study, comprising simulation models and test system configurations, can be obtained from the corresponding author upon reasonable request.

Conflicts of Interest

The authors state that there are no conflicts of interest concerning the publication of this work.

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