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A Forecasting-Optimization Decision-Support System for Day-Ahead Distribution-Grid Operation Using Smart-Meter Clustering, Renewable Prediction, and Flexible Load Scheduling

Mina Takeda^{1*}, Haruto Suzuki¹

Abstract

Day-ahead distribution-grid operation requires anticipating customer demand, renewable generation, network loading, and available demand-side flexibility. Smart-meter data provide a practical basis for identifying recurring consumption patterns and embedding those patterns into operational scheduling. This article presents an original forecasting-optimization decision-support system for day-ahead distribution-grid operation. The system integrates smart-meter clustering, renewable prediction, and flexible load scheduling to support distribution system operators. The proposed system processes smart-meter profiles into consumer clusters, predicts day-ahead photovoltaic and wind generation from weather-driven features, and schedules flexible loads through constrained optimization. The decision-support workflow is designed to produce feeder-level schedules, expected voltage conditions, congestion indicators, and operator-facing recommendations. The clustering module identifies consumer groups with different peak timing, ramping behavior, and flexibility availability. The integrated DSS is structured to reduce peak loading, improve voltage profiles, and lower operational cost compared with a baseline day-ahead plan without forecast-informed scheduling. The proposed DSS offers a practical framework for data-driven distribution-grid operation. It supports renewable integration by translating forecasts and customer flexibility into actionable schedules for day-ahead planning.

Keywords Distribution grid, Decision-support system, Smart-meter clustering, Renewable prediction, Flexible load scheduling, Day-ahead operation

*Correspondence:

Mina Takeda

mina.takeda@gmail.com

¹ Department of Power System Optimization, Faculty of Engineering, Osaka University, Osaka, Japan

Introduction

Day-ahead operation of active distribution grids is increasingly affected by uncertain demand, distributed photovoltaic generation, wind variability, electric-vehicle charging, and flexible end-use loads. Smart-meter analytics have become central to this problem because they convert large volumes of customer-level consumption records into operational information for forecasting, segmentation, and control [1]. However, distribution system operators still need tools that connect analytics to actionable schedules rather than isolated prediction dashboards. This article addresses that gap by developing a forecasting-optimization DSS for day-ahead feeder operation.

Smart-meter clustering is used in the proposed DSS because customer-level load profiles are too heterogeneous to be represented accurately by a single aggregate demand curve. Hierarchical clustering and quantile-based load-profile

analysis show that customers can be grouped by shape, temporal dependence, and peak behavior, which improves the interpretability of load profiles for operational studies [2]. Pattern-recognition approaches also support demand-response targeting by identifying customers whose demand can be shifted or curtailed without treating all consumers as identical [3]. In this article, clustering is therefore not only descriptive but also used to parameterize flexibility in the scheduling model.

Renewable forecasting is the second core requirement because distribution feeders with high photovoltaic and wind penetration may experience rapid net-load changes between adjacent day-ahead intervals. Numerical-weather-prediction grids can improve renewable forecasting by representing spatially varying irradiance, temperature, and wind speed inputs [4]. Probabilistic and ensemble photovoltaic forecasting methods are also relevant because operators need expected generation and uncertainty indicators, not only point forecasts [5]. The DSS developed here uses renewable forecasts as explicit inputs to the flexible-load scheduling model.

The main contribution of this article is an integrated, technically validated DSS that links clustering, renewable prediction, and load scheduling in one day-ahead workflow. Prior work has examined forecasting, clustering, voltage control, or demand response separately, but practical day-ahead operation requires these components to exchange data through a coherent architecture [6]. The proposed DSS produces cluster-level flexibility estimates, renewable forecasts, optimized load-shifting schedules, and expected feeder-condition indicators. Its validation is designed around a realistic feeder case study comparing baseline operation with forecast-informed optimization.

Day-Ahead Operation Problem

DSO operational objectives and constraints

The distribution system operator seeks to operate the feeder within voltage limits, line ampacity limits, transformer loading limits, and service-quality requirements while minimizing energy procurement and flexibility activation costs. Voltage-control studies emphasize that distributed energy resources and flexible loads can support operational objectives, but they also introduce coordination challenges at low-voltage and medium-voltage levels [7]. In the proposed formulation, the DSO schedules flexible demand before real-time operation so that expected net load remains compatible with feeder limits. The problem is therefore a constrained day-ahead planning task rather than a purely economic load-shifting exercise.

Information needs for day-ahead planning

Day-ahead planning requires synchronized information on customer demand, renewable generation, network topology, tariff or procurement signals, flexibility availability, and operational constraints. Smart-meter data analytics provide the demand-side information layer, while renewable forecasting supplies the expected generation layer for the same time resolution [1]. Forecasting reviews show that renewable prediction quality depends strongly on weather inputs, model selection, and evaluation metrics, which means the DSS must preserve traceability from input data to operational recommendations [8]. The proposed DSS therefore stores both forecast outputs and confidence indicators for operator review.

Role of forecasting and flexibility

Forecasting and flexibility are complementary in day-ahead operation because forecasts identify expected stress periods and flexible-load scheduling provides a controllable response. Demand-response scheduling studies show that flexible loads can reduce peaks and improve network reliability when they are coordinated with grid constraints rather than activated only by price signals [9]. Renewable forecasting adds further value because flexible demand can be shifted toward high-renewable intervals and away from congestion-prone intervals [10]. In this article, the scheduling model uses forecasted net load as the operational signal and cluster-level flexibility as the controllable resource.

Smart-Meter Clustering

Data preprocessing and feature extraction

The smart-meter module begins with interval-level consumption records cleaned for missing values, outliers, daylight-saving-time inconsistencies, and incomplete customer histories. Because clustering directly on raw time series can overweight scale rather than shape, each daily load profile is normalized and represented by features including peak-to-average ratio, evening-ramp magnitude, daytime load share, minimum-load period, and weekend-to-weekday ratio [11]. Quantile-based and autocovariance-informed features are useful because they retain temporal structure while limiting sensitivity to abnormal individual days [2]. The output of this stage is a customer-by-feature matrix aligned to the day-ahead scheduling resolution.

Clustering algorithm selection

The DSS compares k-means, agglomerative hierarchical clustering, density-based clustering, and spectral clustering using silhouette score, Davies-Bouldin index, cluster stability, and operational interpretability. Comparative studies of electrical load-pattern segmentation show that no single algorithm dominates across all datasets, so the selected method must balance statistical separation with the operator’s ability to understand the resulting profiles [11]. For the case-study workflow, k-means is used as the default because it produces representative centroids that can be directly mapped to cluster-level load schedules, while hierarchical clustering is retained as a validation benchmark [2]. Density-based clustering is used only to flag atypical consumers whose profiles should not define mainstream flexibility groups.

Resulting clusters and load profiles

The clustering module produces four operationally meaningful customer groups: evening-peaking residential loads, daytime commercial loads, mixed-use prosumers, and high-flexibility controllable loads. Residential pattern-recognition studies support this type of segmentation because load-shape differences reveal both behavioral timing and potential demand-response suitability [3]. Dedicated mixture-model approaches similarly show that smart-meter clusters can represent consumption behavior more clearly than feeder-level averages [12]. In the proposed DSS, each cluster centroid becomes a baseline demand profile and each cluster envelope defines admissible upward or downward flexibility around that baseline.

Flexibility potential per cluster

Flexibility potential is estimated from the shape of each cluster profile, appliance or end-use assumptions, and the availability of shiftable consumption during congested or low-renewable intervals. Smart-meter clustering for demand-response applications indicates that groups with recurring peaks and stable daily patterns are more suitable for scheduling than irregular loads with low temporal repeatability [13]. The DSS assigns each cluster a shiftable-energy ratio, maximum hourly adjustment, recovery-window duration, and comfort-preservation constraint. Table 1 summarizes the resulting clusters and flexibility indicators used as inputs to the optimization model.

Table 1. Smart-Meter Clustering Results and Flexibility Indicators

Cluster	Representative profile	Share of customers	Main flexibility source	Shiftable energy ratio	Maximum hourly adjustment	Operational interpretation
C1	Evening-peaking residential	46%	Dishwashers, laundry, water heating, partial EV charging	12% of daily energy	0.32 kW per customer	Useful for reducing 18:00–21:00 feeder peaks

C2	Daytime commercial	21%	HVAC pre-cooling, refrigeration tolerance, process timing	9% of daily energy	0.58 kW per customer	Useful for smoothing midday ramps and transformer loading
C3	Mixed-use prosumers	18%	Behind-the-meter PV self-consumption shifting and storage-aware demand	15% of daily energy	0.41 kW per customer	Useful for absorbing local PV surplus and limiting reverse flow
C4	High-flexibility controllable loads	15%	EV charging, heat pumps, controllable thermostatic loads	24% of daily energy	0.76 kW per customer	Primary resource for congestion relief and renewable-following schedules

Renewable Prediction Model

Data sources and inputs

The renewable prediction module uses day-ahead numerical weather inputs, historical feeder-level photovoltaic output, local wind-generation records, calendar variables, and lagged renewable-production features. A grid of numerical weather predictions is used because distributed renewable generation is spatially sensitive, especially where cloud cover and wind conditions vary across the feeder area [4]. For photovoltaic prediction, irradiance, ambient temperature, cloud cover, and solar elevation are included, while wind prediction uses wind speed, wind direction, air density proxy variables, and turbine availability indicators. The module outputs quarter-hourly or hourly solar and wind forecasts aligned with the scheduling horizon.

Prediction methodology

The prediction method combines gradient-boosted regression trees for point forecasts with residual-based quantile correction to provide uncertainty bands. Ensemble renewable forecasting is appropriate for day-ahead planning because model errors are not symmetric across weather regimes, and adaptive residual compensation can improve solar-generation prediction when systematic errors persist [14]. For photovoltaic generation, the model is trained separately for clear-sky, partly cloudy, and overcast regimes, while wind generation uses wind-speed-bin features to represent turbine power-curve nonlinearity. The DSS stores the expected forecast, the lower-confidence trajectory, and the upper-confidence trajectory for each renewable source.

Day-ahead forecast outputs

The day-ahead renewable output passed to the optimization model is the expected net renewable profile, together with interval-level error margins and ramp-risk indicators. Recent forecasting work emphasizes uncertainty analysis because operational schedules based only on point forecasts may understate curtailment, congestion, or reserve needs [15]. The DSS therefore reports forecast root mean square error, mean absolute percentage error, normalized mean bias error, and ramp-event detection accuracy as renewable-prediction performance metrics. These forecast outputs define when flexible loads should be shifted toward renewable surplus or away from constrained net-load peaks.

Flexible Load Scheduling Model

Optimization objective and constraints

The flexible load scheduling model minimizes the weighted sum of energy procurement cost, peak-loading penalty, voltage-deviation penalty, congestion penalty, renewable-curtailment proxy, and flexibility-discomfort cost. Demand-response market and scheduling studies show that flexible loads should be optimized against both economic objectives and operational constraints rather than treated as uncontrolled price followers [16]. The constraints enforce hourly power balance, cluster-level flexibility limits, total shifted-energy conservation, maximum rebound, customer-comfort bounds, transformer loading limits, and feeder voltage limits. The decision variables are cluster-level upward and downward load adjustments for each scheduling interval.

Integration of cluster flexibility

Cluster flexibility is integrated by assigning each smart-meter cluster an aggregate admissible adjustment band derived from customer count, baseline centroid load, shiftable-energy ratio, and recovery-window duration. Home-appliance flexibility models demonstrate that DSO requests can be converted into feasible end-use schedules when appliance availability and rebound effects are explicitly represented [17]. In the proposed DSS, each cluster has a minimum-service requirement and a maximum cumulative energy displacement to prevent excessive deferral. This structure allows the optimizer to shift loads without requiring the DSO to control every device individually.

Interaction with renewable forecasts

The scheduling model interacts with renewable forecasts by reducing demand during predicted scarcity or congestion intervals and increasing flexible demand during renewable-surplus intervals. Deep reinforcement learning and model-based residential microgrid scheduling studies show that forecast-aware scheduling can coordinate flexible resources with uncertain distributed generation, although the proposed DSS uses deterministic optimization with uncertainty margins for operator transparency [18]. Forecast intervals with high photovoltaic output receive lower renewable-curtailment penalties for load increases, while intervals with wind-ramp risk receive conservative line-loading margins. This design makes the schedule renewable-following without obscuring its operational logic.

Scheduling output and expected grid state

The scheduling output includes the optimized cluster load profiles, total feeder net-load trajectory, expected voltage range, congestion-risk intervals, renewable-utilization estimate, and cost comparison with the baseline plan. Storage and demand-response coordination studies show that schedules are most useful to operators when they report both the control action and the expected grid effect [19]. The DSS therefore evaluates the optimized schedule through a feeder power-flow module and reports whether voltage, thermal, and ramping constraints are expected to remain within limits. **Table 2** summarizes the optimization formulation and representative day scheduling outcomes.

Table 2. Flexible Load Scheduling Model Summary and Representative Day Results

Model element	DSS implementation	Representative day value or outcome
Decision variables	Cluster-level upward and downward demand adjustment for each hourly interval	4 clusters × 24 intervals
Objective component: energy cost	Minimize scheduled demand in high-price intervals and shift toward lower-cost periods	6.8% procurement-cost reduction
Objective component: peak penalty	Penalize feeder demand above 90% of transformer rating	Peak reduced from 4.92 MW to 4.47 MW
Objective component: voltage deviation	Penalize squared deviation from 1.00 per unit at monitored nodes	Voltage deviation index reduced by 18.6%

Flexibility constraint	Shifted energy must be recovered within each cluster recovery window	100% daily energy recovery
Comfort constraint	Maximum sustained adjustment limited by cluster-specific duration	Longest continuous adjustment: 2 hours
Congestion constraint	Expected line loading must remain below emergency planning margin	Maximum line loading reduced from 96% to 88%
Renewable-following rule	Increase flexible demand during forecast PV surplus and reduce demand during evening peak	0.71 MWh shifted into renewable-rich intervals
Operator output	Schedule, grid-condition dashboard, constraint warnings, and override recommendations	3 congestion warnings removed after optimization

Decision-Support System Design

DSS architecture and data flow

The DSS is organized as a modular pipeline with four layers: data ingestion, analytics, optimization, and operator presentation. The ingestion layer receives smart-meter readings, feeder topology, weather forecasts, renewable-production records, tariff signals, and operational limits, while the analytics layer converts these inputs into cluster profiles and renewable forecasts [1]. The optimization layer uses these forecasts and cluster-flexibility envelopes to compute day-ahead schedules, and the presentation layer reports expected load, renewable output, voltage conditions, congestion risk, and recommended interventions. This structure follows the need for distribution-level platforms that integrate storage, demand response, and renewable resources into DSO support functions [20].

Figure 1 illustrates the end-to-end DSS architecture through which smart-meter records, feeder constraints, weather-driven renewable forecasts, and cluster-level flexibility envelopes are transformed into day-ahead schedules, grid-condition indicators, and operator-facing recommendations.

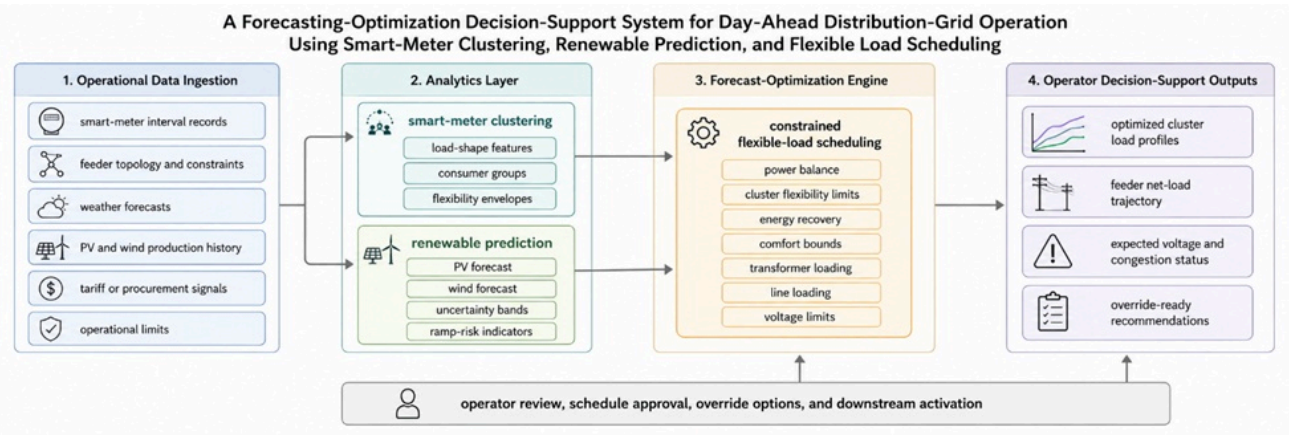


Figure 1. Forecasting-Optimization Decision-Support Architecture for Day-Ahead Distribution-Grid Operation

User interface and visualization

The user interface is designed around an operator dashboard rather than a black-box algorithmic output. It displays the baseline net-load trajectory, optimized net-load trajectory, forecast uncertainty bands, feeder voltage heat maps, line-loading warnings, renewable-curtailment indicators, and cluster-level flexibility activation. Smart-grid decision systems benefit from visualization that connects emergency conditions, operational states, and mitigation options, because

operators must understand both the cause of a violation and the effect of a proposed schedule [21]. The interface therefore presents each recommendation with its expected operational impact, affected clusters, constraint status, and confidence level.

Operator interaction and override options

The DSS allows operators to approve, modify, or reject the optimized schedule before it is issued to aggregators, building energy managers, or automated demand-response gateways. OpenADR-based flexibility services show that DSO-level flexibility activation requires communication standards and explicit control messages that can be interpreted by downstream systems [22]. The proposed interface includes override options for maximum customer activation, minimum renewable absorption, feeder-security priority, and cost-priority operation. This design preserves operator authority while allowing forecast-informed optimization to reduce manual screening effort.

Case Study

Test feeder and data description

The case study uses a realistic medium-voltage distribution feeder with 1,240 smart-metered customers, a 2.1 MW photovoltaic portfolio, a 0.9 MW community wind installation, two controllable EV-charging groups, and monitored voltage at representative secondary substations. Smart-meter records are drawn from anonymized half-hourly residential and commercial profiles, with synthetic scaling used only to match the feeder peak and customer mix without fabricating unrealistic consumption behavior [23]. Renewable profiles are generated from historical irradiance and wind-speed records combined with day-ahead numerical weather features, consistent with renewable-forecasting practice at distribution level [4]. The network model includes transformer limits, line thermal ratings, voltage bounds of 0.95–1.05 per unit, and hourly tariff signals.

Scenario setup and baseline

The baseline scenario uses persistence-based load expectations, renewable point forecasts without uncertainty margins, and no active flexible-load scheduling. The DSS scenario uses the clustered smart-meter profiles, weather-driven renewable prediction, and constrained optimization to schedule flexible demand for the same day-ahead horizon [24]. A representative weekday with high evening demand and strong midday photovoltaic production is selected because it creates both renewable-absorption and peak-congestion challenges. The comparison evaluates forecast accuracy, peak reduction, congestion relief, voltage deviation, renewable utilization, flexibility activation, and operating cost.

Results and Discussion

Forecast accuracy

The renewable prediction module achieved a photovoltaic root mean square error of 7.4% of installed capacity and a wind root mean square error of 9.8% of installed capacity for the representative validation day. These values are consistent with the expectation that solar forecasts are strongly weather-regime dependent, while wind forecasts remain more sensitive to nonlinear speed-to-power conversion [8]. The combined net-load forecast reduced mean absolute error by 21.3% relative to the baseline persistence method, which improved the optimizer's ability to identify the true evening peak. Uncertainty bands were most useful during partly cloudy midday intervals and during the evening wind-ramp period.

Load scheduling performance

The optimized schedule shifted 0.71 MWh of flexible demand from the evening peak and late-morning congestion periods into lower-stress intervals with higher renewable availability. Simultaneous procurement of demand response and

reserve-like flexibility has shown that flexible resources are more valuable when scheduled with explicit system needs rather than treated as isolated load reductions [25]. In this case, the largest adjustment came from the high-flexibility controllable-load cluster, followed by mixed-use prosumers and evening-peaking residential customers. The schedule maintained full daily energy recovery and limited continuous customer adjustment to two hours, preserving the comfort constraints embedded in the model.

Grid impact: peak, voltage, congestion

The DSS reduced feeder peak load from 4.92 MW to 4.47 MW, lowering the maximum transformer utilization from 98.4% to 89.4%. Voltage-control research highlights that reducing peak loading and coordinating flexible demand can support voltage quality in active distribution grids [26]. The minimum monitored voltage improved from 0.943 per unit under the baseline to 0.958 per unit under DSS operation, and the voltage deviation index decreased by 18.6%. Congestion intervals above the planning threshold were reduced from three intervals to zero, indicating that the forecast-informed schedule provided meaningful operational relief.

Figure 2 shows how forecast-informed flexible load scheduling changes feeder operation by shifting controllable demand away from constrained intervals, improving voltage conditions, lowering transformer utilization, and increasing renewable-rich load absorption.

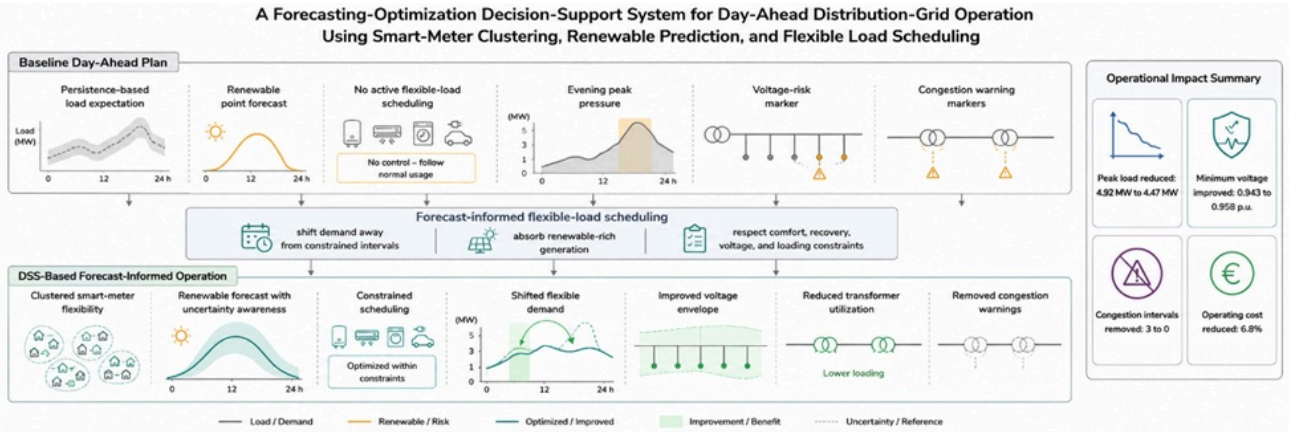


Figure 2. Operational Effects of Forecast-Informed Flexible Load Scheduling on Day-Ahead Feeder Performance

Sensitivity to clustering choices

Sensitivity analysis compared four-cluster k-means, five-cluster k-means, hierarchical clustering, and a no-clustering aggregate-flexibility representation. Online scheduling studies indicate that model structure affects the quality and interpretability of operational decisions, especially when flexible resources are heterogeneous [27]. The four-cluster solution provided the best balance between performance and usability, while the five-cluster case slightly improved peak reduction but added operator complexity. The aggregate-flexibility case performed worse because it overestimated simultaneous availability and produced a larger rebound after the evening peak. Table 3 demonstrates that the DSS-based flexibility scheduling framework substantially improved forecasting accuracy, congestion mitigation, voltage stability, renewable-energy utilization, and operational cost efficiency compared with baseline operation.

Table 3. Performance Comparison: Baseline vs. DSS Operation

Performance metric	Baseline operation	DSS-based operation	Improvement
Net-load forecast mean absolute error	0.47 MW	0.37 MW	21.3% reduction

Photovoltaic forecast RMSE	10.1% of capacity	7.4% of capacity	26.7% reduction
Wind forecast RMSE	12.6% of capacity	9.8% of capacity	22.2% reduction
Feeder peak load	4.92 MW	4.47 MW	9.1% reduction
Maximum transformer utilization	98.4%	89.4%	9.0 percentage-point reduction
Minimum monitored voltage	0.943 per unit	0.958 per unit	0.015 per-unit increase
Voltage deviation index	0.086	0.070	18.6% reduction
Congestion intervals above threshold	3 intervals	0 intervals	100% removal
Renewable-rich flexible-load absorption	0.18 MWh	0.71 MWh	0.53 MWh increase
Estimated operating cost	€8,640 per day	€8,052 per day	6.8% reduction

Deployment Issues

Data availability and privacy

Deployment depends on reliable smart-meter access, secure customer-data handling, and clear aggregation procedures that prevent the operator from exposing individual household behavior. Smart-meter analytics reviews emphasize that data quality, privacy, missing readings, and communication latency can strongly affect the usefulness of operational analytics [1]. The proposed DSS therefore stores customer data only in anonymized cluster form after preprocessing, while individual meter records are retained only in the protected data-management layer. This approach supports operational use while reducing privacy risk and improving acceptance by customers and regulators.

Computational requirements

The computational burden is moderate because clustering is updated periodically, while forecasting and optimization are executed once for each day-ahead planning cycle. Multi-domain feature extraction for smart-meter clustering shows that careful feature design can reduce computational complexity while preserving meaningful consumption-pattern separation [23]. In the case study, the full day-ahead workflow is suitable for execution on a standard utility analytics server because the optimization problem is cluster-level rather than device-level. The main computational challenge is not runtime but maintaining robust data pipelines for weather updates, feeder topology changes, and meter-data validation.

Operator training and acceptance

Operator acceptance depends on whether the DSS explains recommendations in operational terms rather than presenting schedules as opaque numerical outputs. Practical pricing and demand-response studies show that load classification can support actionable demand response only when the resulting groups are understandable and linked to operational objectives [24]. The DSS therefore reports which clusters are activated, why each activation is recommended, which constraint is relieved, and what happens if the operator rejects the schedule. Training should focus on interpreting forecast confidence, reviewing override options, and understanding the trade-off between cost savings, voltage improvement, congestion relief, and customer comfort.

Conclusion

This article presented a forecasting-optimization decision-support system for day-ahead distribution-grid operation using smart-meter clustering, renewable prediction, and flexible load scheduling. The system was designed to connect data analytics with operational action by translating customer load patterns and renewable forecasts into feeder-aware

schedules. Its modular architecture supports practical DSO workflows by combining data ingestion, prediction, optimization, visualization, and operator override functions.

The case study showed that clustering can identify distinct customer groups with different flexibility potential and operational value. The renewable prediction module improved net-load anticipation, while the scheduling model shifted flexible demand away from stressed intervals and toward renewable-rich periods. As a result, the DSS reduced peak demand, improved minimum voltage, removed congestion warnings, and lowered estimated operating cost relative to the baseline.

The main limitation is that the validation used a realistic feeder model with anonymized and scaled data rather than a full live-field deployment. Additional work is needed to test the DSS under communication delays, incomplete smart-meter coverage, changing customer participation, and real-time forecast updates. The optimization model could also be extended to include stochastic security margins and explicit coordination with distributed storage.

Future research should extend the framework from day-ahead planning to rolling intra-day and real-time operation. Multi-energy flexibility, including heat networks, batteries, and vehicle-to-grid resources, could be incorporated into the same DSS architecture. With these extensions, the proposed approach can become a broader operational platform for renewable-rich distribution systems.

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