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A Taxonomy of Smart-Meter Forecasting Models for Grid Flexibility, Microgrid Energy Management, and Distribution-Level Congestion Control

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Abstract

Smart meters generate high-resolution data that can feed forecasting models for a range of distribution network applications. However, the literature remains fragmented across forecasting methods, data structures, and operational use cases. No comprehensive taxonomy links forecasting model characteristics to the distinct requirements of grid flexibility, microgrid management, and congestion control. This limits the ability of researchers and system operators to choose models according to data availability, forecast horizon, and grid function. This article develops a taxonomy of smart-meter forecasting models for distribution-level operation. The taxonomy maps model categories, data inputs, forecast horizons, and application domains into a structured classification framework. A systematic literature review of 27 peer-reviewed journal articles published from 2017 to 2024 was conducted. Models were classified by mathematical structure, data requirements, forecast horizon, and relevance to grid flexibility, microgrid energy management, and congestion control. The taxonomy organises forecasting approaches into classical time series, conventional machine learning, deep learning, hybrid and ensemble, and probabilistic forecasting categories. Six tables support the review method, model classification, smart-meter data mapping, application suitability analysis, full taxonomy, and research gap assessment. The taxonomy provides a structured decision-support tool for selecting and designing forecasting models for specific distribution grid tasks. It highlights gaps in cross-domain transferability, real-time deployment, benchmarking, data integration, and operational validation.

Keywords Smart-meter forecasting, Taxonomy, Grid flexibility, Microgrid energy management, Congestion control, Distribution network

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Introduction

Smart-meter data has become a central resource for distribution grid intelligence because it captures granular consumption behaviour, temporal variability, and customer-level demand patterns that were previously unavailable to system operators. Wang, Chen, Hong, and Kang describe smart-meter analytics as a foundation for applications ranging from forecasting to anomaly detection and customer segmentation [1]. Yildiz, Bilbao, Dore, and Sproul similarly show that residential smart-meter data enables detailed analysis of electricity consumption behaviour, but they also emphasise challenges related to variability, household heterogeneity, and data interpretation [2]. Within this context, forecasting models provide the analytical bridge between raw metering streams and operational decisions in active distribution networks.

The literature includes forecasting models that support three increasingly important distribution-level functions: grid flexibility, microgrid energy management, and congestion control. Short-term residential load forecasting using long short-term memory networks demonstrates how smart-meter sequences can support demand anticipation at customer or feeder level [3]. Distributed and privacy-preserving forecasting studies extend this logic toward multi-site coordination, where forecasts can inform flexibility services without necessarily centralising raw customer data [4, 5]. Congestion-oriented work further shows that probabilistic forecasting and power-flow-informed learning can help anticipate overload or voltage-related constraints before corrective action is required [6].

This article contributes a taxonomy review that classifies smart-meter forecasting models by model family, data requirement, forecast horizon, and application suitability. Existing studies provide important technical advances, including adaptive recurrent learning [7], deep probabilistic forecasting [8], and transformer-based forecasting [9], but these contributions are often evaluated within separate methodological or application silos. A taxonomy is therefore needed to make explicit which model categories are most compatible with different smart-meter data types and distribution grid tasks. The review develops this classification without conducting new forecasting experiments, focusing instead on analytical organisation of the 2017–2024 literature.

Figure 1 illustrates how smart-meter forecasting connects granular metering data, forecasting model families, and distribution-level operational functions across grid flexibility, microgrid management, and congestion control.

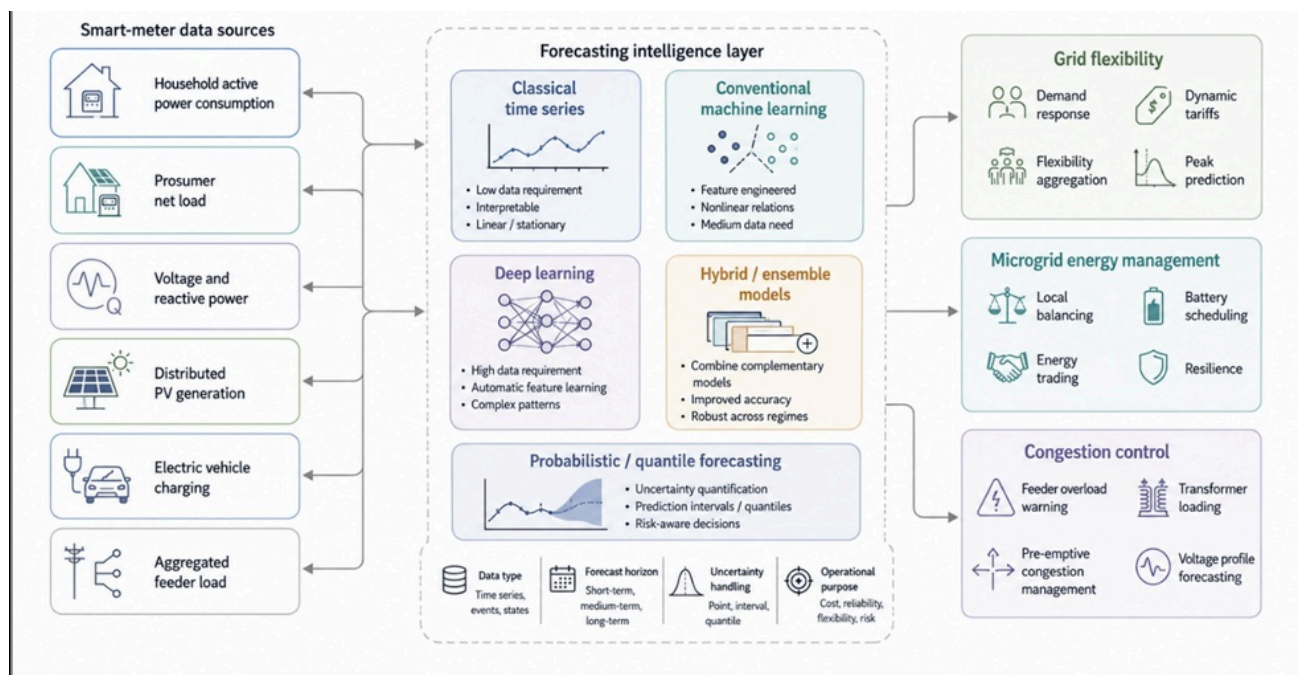


Figure 1. Conceptual Scope of Smart-Meter Forecasting for Distribution-Level Grid Intelligence

Need for Taxonomy

Existing reviews and methodological studies provide valuable coverage of smart-meter analytics, residential load forecasting, and smart-grid applications, but they do not fully integrate model structure, data type, and operational use case into a single classification system. Wang, Chen, Hong, and Kang review broad smart-meter analytics applications, while Kuster, Rezgui, and Mourshed critically assess electrical load forecasting models across building and energy contexts [1, 10]. Dewangan, Abdelaziz, and Biswal focus specifically on smart-grid load forecasting using smart-meter information, yet the classification is not primarily organised around flexibility, microgrid management, and congestion-control suitability [11]. As a result, model choice can remain method-driven rather than task-driven.

A structured taxonomy is necessary because smart-meter forecasting requirements differ substantially across applications, even when similar algorithms are used. Forecasts for demand response may prioritise customer-level peak timing, while microgrid scheduling may require net-load and local-generation forecasts, and congestion control may require feeder, transformer, or voltage-sensitive predictions [4, 6]. Deep learning and ensemble models may be attractive for complex temporal patterns, but their operational value depends on data resolution, missing-data handling, interpretability, and deployment constraints [7, 12]. This taxonomy therefore provides a decision-oriented classification that links forecasting method selection to the operational function it is expected to support.

Figure 2 shows why a taxonomy is needed by contrasting method-centred forecasting studies with task-aligned model selection based on data type, forecast horizon, uncertainty needs, and distribution-grid application.

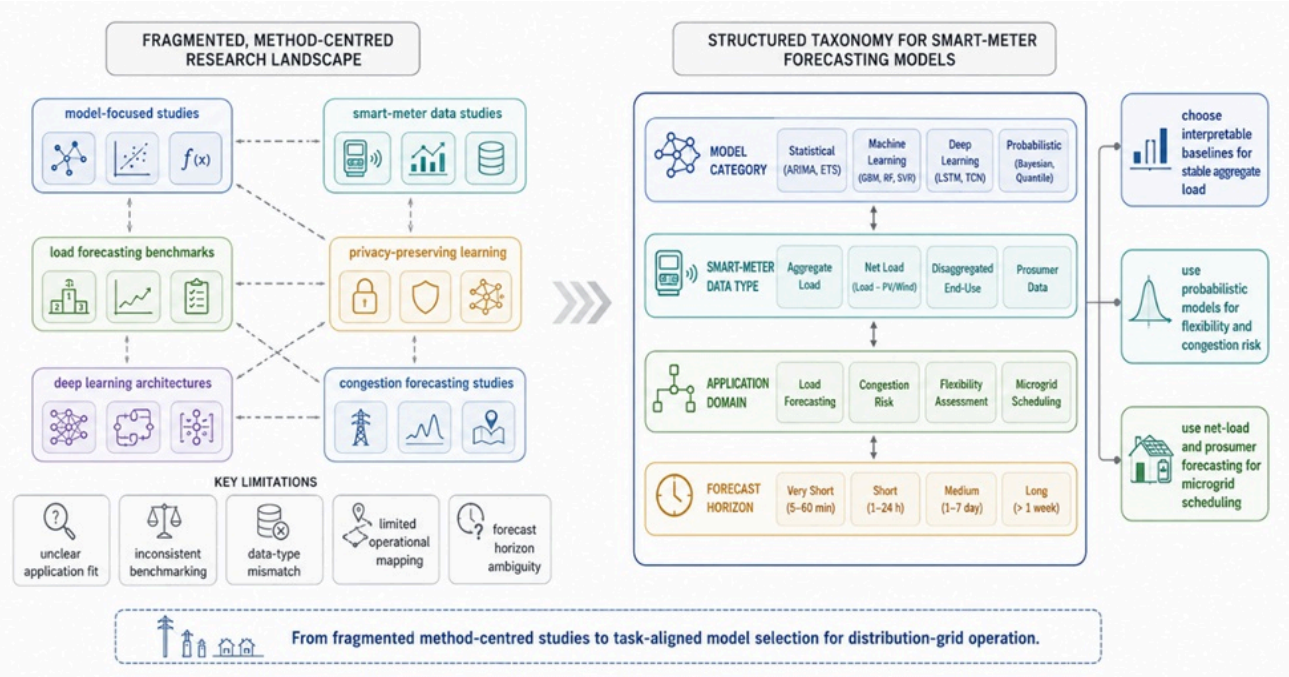


Figure 2. Rationale for a Taxonomy: From Fragmented Forecasting Studies to Task-Aligned Model Selection

Review Method

Search strategy and databases

The review used a targeted literature search covering smart-meter forecasting, short-term load forecasting, microgrid energy management, grid flexibility, and distribution-level congestion control from 2017 to 2024. The search prioritised peer-reviewed journal articles from IEEE Transactions on Smart Grid, Applied Energy, Energy, International Journal of Electrical Power & Energy Systems, Renewable and Sustainable Energy Reviews, Energy and AI, and related Q1 energy informatics journals. Search strings combined terms such as “smart meter,” “forecasting,” “load forecasting,” “microgrid,” “demand response,” “distribution congestion,” “deep learning,” and “taxonomy,” reflecting the scope of prior smart-meter analytics and forecasting reviews [1, 11]. The resulting corpus was screened to retain studies that directly informed forecasting model classification or distribution-grid application mapping.

Inclusion/exclusion criteria

Articles were included when they used, reviewed, or classified forecasting models relevant to smart-meter data, residential or distribution-level load prediction, privacy-preserving forecasting, flexibility applications, microgrid energy management, or congestion-oriented distribution operation. Studies such as Kong, Dong, Jia, Hill, Xu, and Zhang were included because they demonstrate smart-meter-based residential forecasting with recurrent neural networks [3], while Fekri, Grolinger, and Mir were included because federated recurrent forecasting addresses distributed smart-meter settings [4]. Articles were excluded if they were conference papers, policy documents, standards, non-peer-reviewed sources, or studies outside the 2017–2024 window. Studies that focused on power systems but did not provide forecasting relevance to smart-meter analytics or distribution-level operation were not retained unless they contributed to taxonomy dimensions such as data type, model class, or operational suitability.

Classification framework

The classification framework organised the 27 included studies along four axes: forecasting model category, smart-meter data type, application domain, and forecast horizon. Model categories were derived from repeated methodological patterns in the literature, including classical time series, conventional machine learning, deep learning, hybrid and ensemble approaches, and probabilistic forecasting [8, 13]. Data categories reflected smart-meter and distribution-grid observability, including active power consumption, net load, voltage-related measurements, reactive power, and prosumer generation traces [2, 6]. **Table 1** summarises the literature search and screening process leading to the final set of 27 included studies.

Table 1. Literature Search and Screening Summary

Stage	Description	Count
Records identified through database searches	Records retrieved using targeted searches across smart-meter forecasting, load forecasting, grid flexibility, microgrid management, and congestion-control terms	214
Additional records identified through citation tracking	Additional peer-reviewed journal articles found through backward and forward citation checking of major review and forecasting papers	36
Total records identified	Combined database and citation-tracking records before deduplication	250
Duplicates removed	Duplicate records removed across databases and citation sources	48
Records screened by title and abstract	Records screened for relevance to smart-meter forecasting, distribution-grid operation, model taxonomy, or application suitability	202
Records excluded after title and abstract screening	Records excluded for weak relevance, non-journal format, non-forecasting focus, or lack of smart-meter/distribution-grid connection	119
Full-text articles assessed	Articles assessed for methodological relevance, date range, peer-reviewed status, and application-domain fit	83
Full-text articles excluded	Articles excluded because they were outside 2017–2024, lacked DOI information, were conference papers, or did not support taxonomy construction	56
Studies included in taxonomy review	Final peer-reviewed journal articles used for taxonomy construction	27

Forecasting Model Categories

Classical time series models

Classical time series models, including ARIMA, SARIMA, exponential smoothing, and related statistical methods, remain important baselines in smart-meter forecasting because they provide interpretable temporal structures and relatively low computational cost. Jagait, Fekri, Grolinger, and Mir explicitly use ARIMA within an online ensemble framework, showing how classical models can remain relevant under changing load patterns when combined with adaptive learning [12]. Kuster, Rezgui, and Mourshed also identify traditional statistical models as essential reference points for evaluating newer forecasting approaches [10]. In this taxonomy, classical models are classified as low-complexity, baseline-oriented methods best suited for stable aggregate loads, limited feature spaces, and settings where interpretability is more important than nonlinear representation capacity.

Conventional machine learning

Conventional machine learning models include random forests, support vector regression, gradient boosting, shallow neural networks, and other supervised learning methods that can incorporate weather variables, calendar features, lagged consumption, and customer-level descriptors. Tavassoli-Hojati, Ghaderi, Iranmanesh, Hilber, and Shayesteh demonstrate how neuro-fuzzy modelling can support smart-grid short-term load forecasting while preserving some interpretive structure [14]. Mehdipour Pirbazari, Farmanbar, Chakravorty, and Rong further show that smart-meter forecasting models must be evaluated for generalisation across households and data conditions rather than only local accuracy [15]. In this taxonomy, conventional machine learning occupies an intermediate category between transparent statistical baselines and high-capacity deep learning models.

Deep learning models

Deep learning models are prominent in smart-meter forecasting because they can capture nonlinear temporal dependencies, customer heterogeneity, and complex sequential patterns in high-resolution load data. Kong, Dong, Jia, Hill, Xu, and Zhang use LSTM recurrent neural networks for short-term residential load forecasting, while Shi, Xu, and Li develop a pooling deep recurrent architecture for household load forecasting [3, 16]. Fekri, Patel, Grolinger, and Sharma extend this direction through online adaptive recurrent learning, highlighting the need to update models as consumption behaviour changes [7]. Transformer-based and attention-based approaches further expand this category by improving long-range temporal representation and contextual feature weighting [9, 17].

Hybrid and ensemble models

Hybrid and ensemble models combine complementary methods to improve robustness, adaptivity, or feature representation under non-stationary smart-meter conditions. Zhang, Tian, Ma, Li, Lu, and Niu combine variational mode decomposition with stacking ensemble learning, illustrating how signal decomposition and ensemble aggregation can be used to handle complex load patterns [18]. Mujeeb and Javaid propose predictive analytics schemes for electricity load and price, demonstrating the value of combining optimisation-inspired learning and data-driven estimation in smart-grid contexts [19]. In this taxonomy, hybrid and ensemble models are treated as structurally composite methods whose value lies not only in accuracy but also in their ability to combine temporal decomposition, nonlinear learning, and application-specific decision support.

Table 2 summarises the main categories of load forecasting models, highlighting their typical data requirements, key methodological strengths, and inherent limitations, and providing a comparative overview to support appropriate model selection for different operational and data conditions.

Table 2. Overview of Forecasting Model Categories

Category	Key Algorithms	Typical Data Requirements	Strengths	Limitations

Classical time series	ARIMA, SARIMA, exponential smoothing, autoregressive models	Regular historical consumption series, stable sampling interval, limited missing values	Transparent, computationally efficient, useful as baselines, suitable for aggregate stable demand	Weak nonlinear representation, limited ability to handle heterogeneous households, sensitive to non-stationarity
Conventional machine learning	Random forest, support vector regression, gradient boosting, neuro-fuzzy models, shallow neural networks	Historical load, calendar variables, weather features, customer descriptors, lagged values	Handles nonlinear covariates, flexible feature integration, often easier to train than deep models	Requires feature engineering, may generalise poorly across feeders or customer groups, limited sequence representation
Deep learning	LSTM, GRU, CNN, sequence-to-sequence RNN, attention networks, transformers	High-resolution sequential data, larger training sets, weather/calendar covariates, sufficient computing resources	Strong temporal pattern learning, suitable for high-dimensional and non-stationary data, adaptable to complex load profiles	Data-hungry, less interpretable, sensitive to drift, requires careful validation and deployment monitoring
Hybrid and ensemble models	Decomposition plus learning, stacking ensembles, ARIMA-RNN hybrids, adaptive ensembles	Multiple historical series, decomposed signals, engineered features, sometimes external variables	Improves robustness, combines complementary model strengths, useful for non-stationary load behaviour	Can be complex to reproduce, may increase computational burden, difficult to interpret operationally
Probabilistic and quantile models	Quantile regression, probabilistic neural networks, conditional density models, scenario forecasting	Historical load distributions, uncertainty drivers, sufficient observations across operating conditions	Represents forecast uncertainty, supports risk-aware scheduling and congestion prevention, useful for flexibility markets	Requires probabilistic calibration, harder to communicate to operators, benchmarking is less standardised

Smart-Meter Data Types

Active power consumption data

Active power consumption is the most widely used smart-meter data type in short-term load forecasting because it directly represents customer, building, feeder, or aggregation-level demand. Residential consumption studies show that active power traces contain strong daily, weekly, and behavioural patterns, but these patterns can vary substantially across households and seasons [2]. Deep recurrent forecasting studies rely heavily on active power sequences because they provide the temporal signal needed for LSTM, RNN, and attention-based learning [3, 17]. In this taxonomy, active power consumption is classified as the foundational data type for demand response, peak forecasting, aggregate flexibility estimation, and baseline load prediction.

Voltage and reactive power data

Voltage and reactive power measurements are less commonly foregrounded than active consumption, but they are critical for distribution-level operational applications such as voltage management, congestion detection, and feeder constraint forecasting. Hernandez-Matheus, Berg, Gadelha, Aragués-Peñalba, Bullich-Massagué, and Galceran-Arellano develop a congestion forecast framework that connects probabilistic power flow and machine learning, indicating that operational forecasting must account for network-state variables rather than consumption alone [6]. Voltage-related forecasting is particularly relevant when distributed energy resources, unbalanced loading, or local congestion risks affect service quality. In this taxonomy, voltage and reactive power data are treated as grid-state data types that support congestion-control and voltage-profile applications more directly than customer-facing flexibility applications.

Net load and prosumer data

Net load and prosumer data combine consumption, distributed generation, storage behaviour, and sometimes electric vehicle charging, making them especially important for microgrid management and flexibility provision. Xu, Dai, Li, Wu, and Chen develop an interpretable transformer-based model for probabilistic residential net load forecasting, showing how prosumer-oriented forecasting requires both temporal learning and uncertainty representation [20]. Federated and distributed forecasting studies also show that prosumer and household-level data may be privacy-sensitive, requiring methods that learn from local data without fully centralising it [4, 5]. **Table 3** classifies smart-meter data types according to resolution, model compatibility, and preprocessing requirements.

Table 3. Smart-Meter Data Types and Forecasting Model Compatibility

Data Type	Typical Resolution	Suitable Model Categories	Preprocessing Needs
Active power consumption	1-minute to hourly readings, often aggregated to 15-minute or hourly intervals	Classical time series, conventional machine learning, deep learning, hybrid models	Missing-value imputation, calendar alignment, outlier handling, lag construction, seasonal decomposition
Reactive power	1-minute to hourly readings when available through advanced meters or grid sensors	Conventional machine learning, hybrid models, probabilistic forecasting	Synchronisation with active power, scaling, noise filtering, treatment of low-load intervals
Voltage magnitude	Feeder, transformer, or customer-level voltage readings at sub-hourly or hourly intervals	Conventional machine learning, probabilistic models, hybrid congestion-oriented models	Phase alignment, topology mapping, detection of abnormal voltage events, removal of sensor artefacts
Net load	Consumption minus local generation, usually sub-hourly or hourly	Deep learning, probabilistic forecasting, transformers, hybrid models	PV-consumption separation, weather alignment, negative-load treatment, uncertainty calibration
Distributed PV generation	Sub-hourly or hourly generation traces, often linked to weather and irradiance	Machine learning, deep learning, hybrid weather-informed models	Weather feature integration, daylight filtering, cloud-event handling, normalisation by system size
Electric vehicle charging load	Irregular event-based or interval-metered charging profiles	Deep learning, hybrid models, probabilistic forecasting	Session detection, event aggregation, missing session reconstruction, behavioural clustering

Aggregated feeder load	Feeder-level or transformer-level demand, typically 5-minute to hourly	Classical time series, machine learning, probabilistic forecasting, hybrid models	Customer aggregation, topology validation, peak-event labelling, alignment with operational constraints
Privacy-preserving distributed data	Locally retained household or site-level smart-meter data	Federated recurrent models, distributed deep learning, adaptive models	Local standardisation, secure aggregation design, drift monitoring, site-level quality checks

Grid Flexibility Applications

Demand response and load shifting

Demand response applications require forecasts that identify when demand is likely to peak, how flexible loads may be shifted, and which customer segments can provide operationally useful reductions. Smart-meter analytics literature shows that granular consumption traces can support customer-level and aggregate demand insight, but the forecasting model must be matched to the temporal granularity of the demand response action [1]. Deep recurrent models are suitable when the objective is to capture nonlinear daily and weekly consumption patterns, as shown in residential short-term load forecasting studies using LSTM and pooled recurrent architectures [3, 16]. In this taxonomy, demand response forecasting is therefore classified as a short-horizon, behaviour-sensitive application requiring active power consumption data, calendar variables, and models capable of representing temporal variability.

Dynamic tariff design

Dynamic tariff design depends on forecasts that estimate expected demand under time-varying price conditions, peak periods, and possible customer response. Predictive analytics models for electricity load and price show that tariff-oriented forecasting requires both consumption prediction and price-sensitive contextual information [19]. Smart-meter data can reveal household-level behavioural diversity, but Yildiz, Bilbao, Dore, and Sproul show that this diversity also makes tariff forecasting sensitive to customer segmentation and aggregation level [2]. Within the taxonomy, dynamic tariff forecasting is positioned between load prediction and flexibility estimation because the model must anticipate both baseline demand and the likely timing of consumption adjustment.

Flexibility service provision

Flexibility service provision requires forecasts that quantify available upward or downward flexibility at household, feeder, aggregator, or microgrid level. Federated load forecasting studies show that distributed forecasting can support multi-site or customer-level prediction while reducing the need to centralise sensitive smart-meter data [4, 5]. Adaptive federated forecasting further indicates that flexibility-oriented models must handle changes in local consumption patterns across time and participants [21]. In this taxonomy, flexibility service forecasting is treated as an uncertainty-sensitive application where probabilistic, distributed, and adaptive models are more suitable than static point-forecasting approaches.

Peak load prediction

Peak load prediction is one of the most direct uses of smart-meter forecasting for grid flexibility because it identifies intervals where load shifting, demand response, or local flexibility activation may be needed. Probabilistic residential load forecasting is especially relevant because peak periods are uncertain and often operationally more important than average demand [8]. Enhanced deep networks for short-term and medium-term load forecasting demonstrate how high-capacity models can be used for multiple planning horizons, although the operational interpretation of peak forecasts remains a challenge [22]. Table 4 maps forecasting model categories to grid flexibility use cases and identifies the main modelling challenges for each application.

Table 4. Forecasting Models to Grid Flexibility Applications Mapping

Flexibility Application	Suitable Model Categories	Forecast Horizon	Key Challenges
Demand response event planning	Deep learning, conventional machine learning, hybrid models	15 minutes to day-ahead	Customer heterogeneity, behavioural uncertainty, baseline estimation, event fatigue
Load shifting optimisation	Classical time series, machine learning, deep learning	Intra-day to day-ahead	Identifying shiftable demand, separating flexible and inflexible loads, rebound effects
Dynamic tariff design	Machine learning, hybrid models, probabilistic forecasting	Day-ahead to week-ahead	Price-response uncertainty, segmentation bias, interaction with weather and occupancy
Flexibility service aggregation	Federated learning, probabilistic forecasting, adaptive recurrent models	Real-time to day-ahead	Privacy constraints, local model drift, aggregation across heterogeneous customers
Peak load prediction	Deep learning, probabilistic models, hybrid ensembles	15 minutes to day-ahead	Extreme-event calibration, rare peaks, high penalty for missed overload intervals
Flexibility reserve estimation	Probabilistic forecasting, quantile models, scenario-based learning	Hour-ahead to day-ahead	Uncertainty communication, reserve confidence levels, coordination with market rules

Proposed Taxonomy

Taxonomy dimensions and structure

The proposed taxonomy is organised around four core dimensions: model category, smart-meter data type, application domain, and forecast horizon. This structure extends broad smart-meter analytics classifications by making the operational purpose of the forecast explicit rather than treating forecasting as a standalone technical task [1]. It also builds on electrical load forecasting reviews that compare model families but do not fully map them to grid flexibility, microgrid management, and congestion-control applications [10]. The taxonomy therefore functions as a decision framework for matching forecasting design to distribution-level operational needs.

Figure 3 presents the proposed taxonomy architecture, showing how model category, smart-meter data type, forecast horizon, and operational application jointly determine suitable forecasting designs.

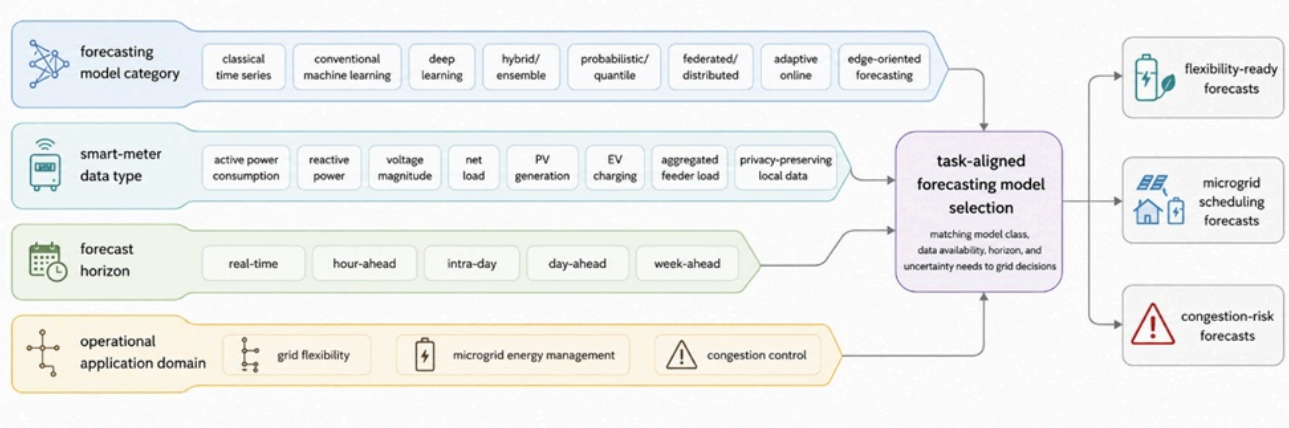


Figure 3. Integrated Taxonomy Architecture for Smart-Meter Forecasting Model Selection

Integration of data, model, and application

The taxonomy reveals that model suitability depends on the interaction between data type, modelling structure, and intended application. Active power consumption is sufficient for many demand response and peak prediction tasks, but microgrid management often requires net load and local generation data, while congestion control requires feeder, transformer, voltage, or reactive power information [20, 23]. Deep learning methods are most useful where high-resolution sequential data and nonlinear behaviour dominate, whereas probabilistic and hybrid models become more relevant where uncertainty affects operational risk [8, 18]. This integrated view prevents the misleading assumption that one high-performing model category is universally suitable across all distribution-grid forecasting tasks.

Operationalization: how to use the taxonomy

The taxonomy can be used by first identifying the operational decision, then selecting the required data type, forecast horizon, and model family. For example, demand response planning may begin with active power consumption and customer-level features, while congestion control may require feeder aggregation, voltage measurements, and probabilistic outputs [6, 13]. Reviews of smart-meter load forecasting show that model evaluation should account for data quality, missing values, sampling resolution, and application relevance rather than relying only on generic forecast-error measures [11, 24]. Operational use of the taxonomy therefore requires aligning model selection with decision timing, data observability, uncertainty tolerance, and implementation constraints.

Illustrative examples of taxonomy use

A utility seeking short-term residential peak forecasts for demand response could use deep recurrent or hybrid models trained on active power, calendar, and weather data, following the methodological logic of LSTM and adaptive recurrent forecasting studies [3, 7]. A microgrid operator seeking battery scheduling support would require net-load forecasting and may benefit from transformer-based probabilistic models or decomposition-based ensembles because local generation and consumption jointly shape storage decisions [18, 20]. A distribution operator seeking feeder congestion warnings would prioritise probabilistic or machine-learning models that incorporate network-state information and power-flow constraints [6]. Table 5 presents the complete taxonomy by linking model category, data type, application domain, forecast horizon, and performance indicators.

Table 5. Complete Taxonomy of Smart-Meter Forecasting Models

Model Category	Data Type	Application Domain	Forecast Horizon	Typical Performance Indicators

Classical time series	Active power consumption	Baseline load forecasting, aggregate peak prediction	Hour-ahead to day-ahead	Mean absolute error, root mean square error, mean absolute percentage error, peak timing error
Classical time series	Aggregated feeder load	Feeder demand monitoring	Day-ahead	Forecast bias, peak error, seasonal residual structure
Conventional machine learning	Active power plus weather and calendar variables	Demand response planning, tariff design	15 minutes to day-ahead	Error by time block, peak-period error, feature importance stability
Conventional machine learning	Voltage and reactive power	Voltage management, transformer monitoring	Real-time to hour-ahead	Voltage deviation error, constraint violation detection, classification accuracy for risk intervals
Deep learning	High-resolution household consumption	Residential load forecasting, peak load prediction	5 minutes to day-ahead	Sequence error, peak capture rate, temporal stability, generalisation across households
Deep learning	Net load and prosumer data	Microgrid balancing, PV-consumption coordination	15 minutes to day-ahead	Net-load error, ramp forecasting error, probabilistic interval coverage when available
Transformer and attention models	Long smart-meter sequences with contextual variables	Net-load forecasting, complex prosumer forecasting	Hour-ahead to day-ahead	Forecast accuracy, attention interpretability, uncertainty calibration, peak-event detection
Hybrid and ensemble models	Decomposed load series, weather features, calendar variables	Battery scheduling, flexible load management	Hour-ahead to week-ahead	Component-wise error, ensemble robustness, scheduling sensitivity
Hybrid and ensemble models	Feeder load and asset-level aggregation	Congestion warning and transformer loading	Real-time to day-ahead	Overload warning precision, false-alarm rate, missed-event rate
Probabilistic and quantile models	Active power consumption and uncertainty drivers	Flexibility reserve estimation, peak-risk forecasting	Hour-ahead to day-ahead	Prediction interval coverage, pinball loss, calibration error, sharpness
Probabilistic and quantile models	Net load, PV generation, storage state proxies	Microgrid scheduling and local energy trading	15 minutes to day-ahead	Scenario reliability, quantile loss, risk-aware scheduling usefulness
Federated and distributed models	Locally retained household or site-level smart-meter data	Flexibility aggregation, privacy-preserving microgrid coordination	Hour-ahead to day-ahead	Local model error, cross-site generalisation, communication cost, privacy-preserving utility
Adaptive online models	Streaming active power and contextual features	Real-time flexibility and drift-sensitive forecasting	Real-time to hour-ahead	Drift response time, online error, model update stability

Edge-oriented models	Smart-meter and edge sensor measurements	Pre-emptive congestion management, local control	Real-time to hour-ahead	Latency, local forecast error, event detection speed, computational efficiency
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Gaps

Cross-domain generalization

A major gap is the limited evidence that smart-meter forecasting models generalise across households, feeders, microgrids, and congestion-control contexts. Generalisation analysis of short-term load forecasting shows that models trained under one data condition may not transfer reliably to another without recalibration or adaptation [15]. Federated and adaptive forecasting studies address part of this issue, but they also reveal that local data heterogeneity and drift remain persistent barriers to reusable model deployment [4, 21]. Future research should therefore test model transferability across customer groups, network assets, climate zones, and application domains rather than reporting performance in isolated datasets.

Real-time and edge implementation

Real-time and edge implementation remain underdeveloped relative to the number of studies proposing high-capacity forecasting architectures. Edge sensing data-imaging approaches suggest one path toward local processing, but the literature still provides limited evidence on latency, communication cost, model updating, and operator integration under real grid conditions [25]. Online adaptive recurrent forecasting shows that models can be updated as new smart-meter data arrives, yet practical deployment requires governance over drift detection, retraining frequency, and failure handling [7]. This gap is especially important for congestion control and microgrid resilience, where delayed or unstable forecasts may reduce operational usefulness.

Benchmarking and reproducibility

Benchmarking and reproducibility are persistent weaknesses because smart-meter forecasting studies often differ in datasets, aggregation levels, train-test splits, error metrics, and forecast horizons. Reviews of load forecasting techniques in smart grids emphasise that inconsistent evaluation practices make it difficult to compare models fairly across studies [24, 26]. Probabilistic forecasting adds further complexity because calibration, sharpness, and risk-oriented metrics must be considered alongside conventional point-forecast errors [8, 13]. Table 6 maps the main research gaps to future research directions and expected impacts for smart-meter forecasting taxonomy development.

Table 6. Research Gaps and Future Directions

Gap	Description	Potential Research Direction	Expected Impact	Priority
Cross-domain generalisation	Models are often tested on narrow datasets and may not transfer across households, feeders, or microgrids	Multi-site benchmarking across customer groups, climates, aggregation levels, and grid assets	More reliable model selection for utilities and aggregators	High
Real-time deployment	Many models are evaluated offline without latency, streaming, or operational-control constraints	Edge-ready forecasting pipelines with latency reporting and online model monitoring	Improved suitability for congestion control and fast flexibility activation	High

Privacy-preserving forecasting	Customer-level smart-meter data is sensitive, limiting centralised model training	Federated, split-learning, and privacy-preserving forecasting architectures	Wider data access without exposing raw customer profiles	High
Probabilistic calibration	Uncertainty forecasts are not always calibrated for operational risk decisions	Standard calibration tests, prediction interval evaluation, and risk-aware metrics	Better flexibility reserve estimation and congestion-risk management	High
Data-quality handling	Missing values, irregular sampling, and meter faults are handled inconsistently	Shared preprocessing protocols and transparent data-quality reporting	More reproducible and robust forecasting workflows	Medium
Application-specific benchmarking	Generic forecast errors do not always reflect demand response, microgrid, or congestion-control value	Task-specific metrics such as peak capture, overload warning accuracy, and scheduling sensitivity	Better alignment between model performance and operational usefulness	High
Interpretability	Deep and hybrid models can be difficult for operators to understand	Interpretable forecasting models, feature-attribution methods, and operator-facing explanations	Increased trust and improved operational adoption	Medium
Integration with grid models	Many smart-meter forecasts are not connected to topology, power flow, or asset constraints	Coupled forecasting and distribution-network simulation frameworks	Stronger support for voltage management and congestion prevention	High
Lifecycle management	Few studies address model maintenance, drift, retraining, and degradation after deployment	Forecasting model lifecycle protocols for monitoring, retraining, and governance	More sustainable use of forecasting systems in operational settings	Medium

Conclusion

This taxonomy review classified smart-meter forecasting models according to model category, data type, application domain, and forecast horizon. The resulting framework shows that forecasting model selection should be driven by the operational decision being supported, not by algorithmic novelty alone. Classical, machine learning, deep learning, hybrid, probabilistic, federated, adaptive, and edge-oriented models each occupy distinct positions in the distribution-grid forecasting landscape. The taxonomy provides a structured way to connect smart-meter data with grid flexibility, microgrid energy management, and congestion-control applications.

The review also highlights important gaps in cross-domain generalisation, real-time deployment, privacy-preserving learning, benchmarking, interpretability, and integration with grid models. Future research should move beyond isolated accuracy reporting toward application-specific evaluation and operational validation. Smart-meter forecasting will become more useful for distribution networks when model development is aligned with data quality, uncertainty, forecast horizon, and decision context. A structured taxonomy can support this transition by guiding both researchers and practitioners toward more transparent and operationally relevant forecasting design.

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