P-ISSN: 3050-9572
E-ISSN: 3050-9580
EUROPEAN DATA SCIENCE JOURNAL
Volume: 03 Issue: 03
RECEIVED: JULY 23 REVISED: AUGUST 04 ACCEPTED: AUGUST 28 PUBLISHED: SEPTEMBER 05

Predictive Intelligence for Sustainable Urban Energy Management

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Abstract

The challenge of satisfying ever-growing energy demand while respecting environmental constraints is critical for both human history and present circumstances. Indeed, energy systems have gradually transformed, becoming remarkably complex over the last century, in order to meet the developments of the associated end-use sectors and continue to provide energy services. In this context, the management and operation of the energy systems at different timescales represent increasingly difficult tasks — especially for large geographical areas — but are fundamental to ensuring that daily lives are not unduly affected by energy shortages.

Demand-side management and demand response have appeared on the energy scene and become increasingly relevant over the years in the quest for sustainable development. Indeed, energy efficiency improvements and the optimization of the energy use at the demand level have great potential for operating and managing service supply in a sustainable way. Although demand-side management, demand response, and energy efficiency have very different goals, characteristics, and symbolism, they share many common traits that have led to their convergence and the merging together of demand-side activities. For this reason, such activities can be managed from a common framework in order to provide effective artificial intelligence–enabled predictive analytics in support of sustainable energy consumption also for smart (or intelligent) cities.

Keywords: Sustainable Energy Systems, Demand-Side Management (DSM), Demand Response (DR), Energy Efficiency Optimization, AI-Enabled Energy Analytics, Smart Grid Technologies, Intelligent Energy Management Systems, Predictive Load Forecasting, Sustainable Energy Consumption Models, Smart City Energy Platforms, Distributed Energy Resource Integration, Real-Time Energy Monitoring, Multi-Timescale Energy Operations, Renewable Energy Integration, Energy System Complexity Modeling, Artificial Intelligence in Power Systems, Urban Energy Optimization Frameworks, Grid Resilience and Stability, Data-Driven Energy Policy Support, Intelligent Demand-Side Analytics.

1. Introduction

P-ISSN: 3050-9572
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EUROPEAN DATA SCIENCE JOURNAL
Volume: 03 Issue: 03
RECEIVED: JULY 23 REVISED: AUGUST 04 ACCEPTED: AUGUST 28 PUBLISHED: SEPTEMBER 05

The economic growth and social welfare of developed and developing countries depend on accessible energy at an acceptable price. Reducing energy consumption and related greenhouse gases is vital if European Union national objectives and the 2020 climate change goals are to be met. For this reason, all levels of energy systems must analyze, predict, and optimize energy using AI-powered predictive analytics. Energy systems are a collection of interconnected energy-generating plants, ports, transmission and distribution networks, management centers, and energy-consuming consumers.

An energy system's function and performance depend on physical, economic, and social facts and various operational and maintenance constraints. Emerging digital technologies support even better demand-side management decisions in buildings, neighborhoods, and cities. These enabled predictive analytics such as time-series forecasting of energy consumption for better prediction performance, enhanced predictive accuracy, coherence, long-short-term dependencies, and energy efficiency, and support demand-side management by predicting energy demand. Enriching building-level data by non-meteo data/factors allows for high-level predictive DR solution analysis. Exploiting the digital-twin approach helps identify energy reduction and response potentials in the neighborhood. Furthermore, the contingent relationship between users and their renewable distributed energy resources is approximated through intelligent classification to support resilience and cost optimization.

1.1. Overview of Energy Systems and Their Significance

Smart cities represent a multilayered, large-scale engineering and science ecosystem with the development of city-level cognitive calculations as a main orientation. The smart city development direction of energy efficiency, low carbon, and sustainability is difficult to achieve without AI-enabled predictive analytics of energy consumption for sustainable consumption reduction-control schemes and demand-side management measures based on city-level energy response elasticity. AI-enabled iterative-size predictive analytics calls for the support of various internal and external real-time, multi-source heterogeneous big data, integrating cloud-edge-end intelligence, Internet of Things (IoT) sensors monitoring, and AI modeling.

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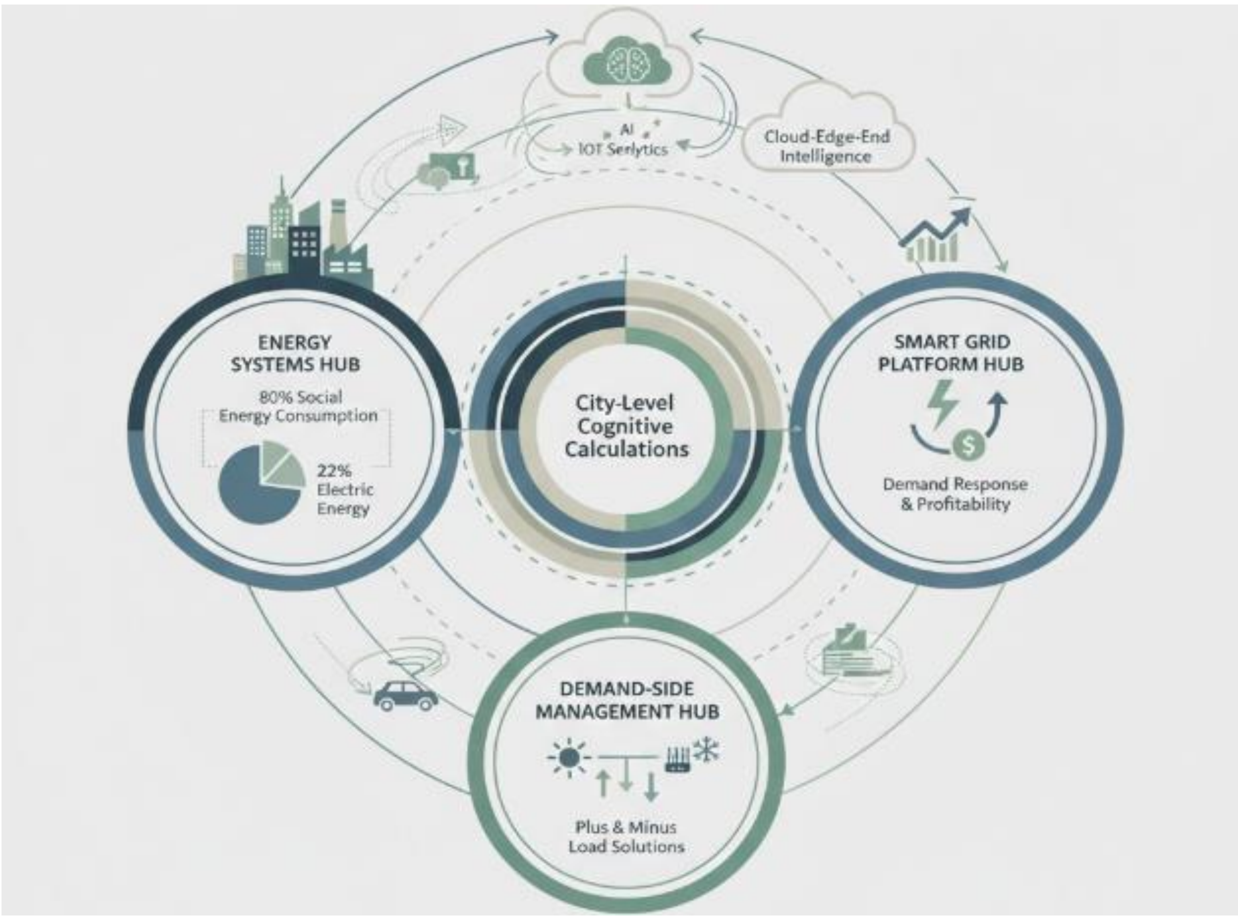

Fig 1: Multilayered Cognitive Computing for Smart City Energy Systems: AI-Enabled Predictive Analytics and Cloud-Edge-End Intelligence in Demand-Side Management

Energy systems of various levels — cities, districts, neighborhoods, buildings — are the main hubs for residents' living, production, and travelling. Energy consumption of these systems accounts for over 80% of total social energy consumption. Electric energy consumption accounts for 22% in the first-level energy system with coal, oil, gas, and electric energy as the main components. Based on the extreme scarcity of grid resources in summer and the harmonious coexistence of supply and demand in winter, harmonious smart plus- and minus-load solutions should be proposed for hot city areas in summer and cold city areas in winter respectively in the

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second-level electricity system development. Demand-side energy elasticity depicts the smtysigma level and plays a key role in guiding urban-level demand-response adaptability analysis for city profitability and price-saving strategies in the third-level smart grid-energy platform system.

2. Conceptual Framework

The conceptual foundations of sustainable energy consumption systems for smart cities originate from the areas of Energy Systems and Demand-Side Management. Energy consumption systems for cities, communities, groups, and individuals have the potential to be optimized to a certain extent with traditional approaches and methodologies. However, the wider application of artificial intelligence and machine learning models to smart- and micro-grid energy systems in combination with other relevant distributed energy resource portfolios is relatively untested practice. The application of AI- and ML-based predictive analytics models to buildings, neighborhoods, and districts—to the demand side of the energy system—has not received much public attention and is critically analyzed herein.

The literature on energy demand forecasting is vast, yet the literature on data-driven AI/ML models applied to the control and optimization of commercial and residential buildings and demand response is still maturing. Although multiple AI-based electric energy consumption prediction models for specific buildings have been developed in recent years with high performance, building occupants and external factors are non-stationary and human behaviors, such as heating and cooling, exhibit seasonal and even temporal time dependency.

Equation 1) Data + feature engineering

1.1 Target series and resampling

Let raw meter readings be $y(\tau)$ at irregular timestamps τ. For hourly modeling, resample to uniform time steps $t \in \{1, \dots, T\}$:

$$y_t = \frac{1}{|\mathcal{W}_t|} \sum_{\tau \in \mathcal{W}_t} y(\tau)$$

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where $\mathcal{W}_t$ is the set of raw observations inside hour t. (If using sum-energy per hour, replace average with sum.)

Missing-data imputation (one common baseline):

$$y_t \leftarrow \begin{cases} y_t, & \text{if observed} \\ y_{t-24}, & \text{if missing (seasonal carry-forward)} \end{cases}$$

1.2 Time-of-day / season cyclical encodings

For hour-of-day $h_t \in \{0, \dots, 23\}$, encode cyclicity via:

$$\text{hour\_sin}_t = \sin\left(\frac{2\pi h_t}{24}\right), \qquad \text{hour\_cos}_t = \cos\left(\frac{2\pi h_t}{24}\right)$$

Similarly for day-of-week $d_t \in \{0, \dots, 6\}$:

$$\text{dow\_sin}_t = \sin\left(\frac{2\pi d_t}{7}\right), \qquad \text{dow\_cos}_t = \cos\left(\frac{2\pi d_t}{7}\right)$$

1.3 Exogenous feature vector (weather, holidays, events)

Create a feature vector:

$$\mathbf{x}_t = [\text{temp}_t \quad \text{holiday}_t \quad \text{hour\_sin}_t \quad \text{hour\_cos}_t \quad \cdots]^\top$$

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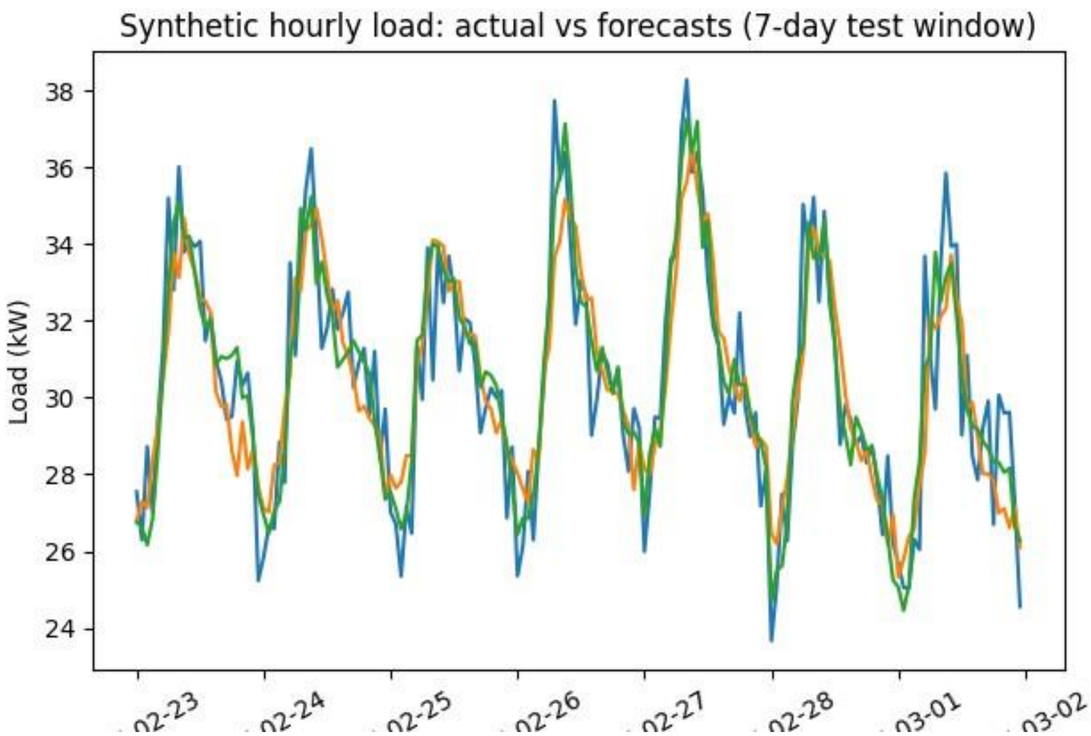

2.1. Theoretical Foundations and Principles of Energy Systems

Energy consumption prediction is a fundamental part of energy management. Energy consumption forecasting helps energy providers anticipate demand changes and manage supply accordingly. Predicting how much electricity loads will consume in the immediate future can also be useful for Demand Response programs. At the household level, providing the user with forecasts can foster energy savings, allowing the user to shift consumption from higher- to lower-cost hours. At the neighborhood level, optimizing demand through DR can help balance the grid during peak hours. Additionally, energy consumption forecasts can be used to increase the efficiency of heating and cooling systems.

Energy efficiency and Demand-Side Management strategies are typically focused on large buildings, commercial or industrial areas. For these buildings, detailed Building Energy Simulation models can be developed to estimate future energy consumption. These models

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represent the thermal behavior of the building and can be coupled with weather forecasts to provide predictions for the next few hours/day. To compute future energy consumption for a neighborhood or a district consisting of a large number of buildings, the effort that is usually needed in generating the detailed models can be exceedingly high. For smaller residential neighborhoods, McEnery et al. used statistical models on historical consumption data of similar houses to generate predictions, while Ng et al. used building characteristics and weather forecasts to predict future home consumption.

3. Data Architecture and Feature Engineering

Energy consumption data originating from a quite heterogeneous set of sources require a structured strategy to be proofed with. The following subsections address the steps required around data preprocessing and feature engineering of the actual predictive model.

Regardless of the forecasting approach or method, the prepared data should contain predictive factors for energy consumption that take the individual building context into account. The feature set hence varies for every location and among differing neighborhoods. Meanwhile, providing a sufficiently rich and precise feature description across the whole dataset is not only highly important, but indeed indispensable for the prediction accuracy and the prospects for reliable energy demand response initiatives. The full feature set employed within the time series approach and the factor-augmented demand response initiative consists of the above-mentioned weather forecasts, holiday, time-of-day, and season indicators combined with unobserved factors that are approximated by Idiosyncratic Factors of a Principal Component Analysis (PCA) on the time of day-adjusted time series of energy consumption squared.

3.1. Data Preprocessing and Model Preparation

The performance of predictive models relies heavily on the quality of the underlying data. Feature engineering refers to the process of transforming the initial dataset into a collection of derived variables suitable for model training. The first step consists of applying standard preprocessing techniques for missing data imputation, outlier removal, and temporal resampling to ensure that the dataset is complete and uniformly sampled at the desired temporal frequency. Time-based descriptors are then added to reflect the cyclical nature of both electric loads and renewable energy generation. The final transformation captures domain knowledge through the mapping of particular weather descriptors and the values of relevant national or regional holidays.

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The dataset is then split into training and testing sets based on chronological order. Time series and ML-based models demand different treatments in this regard. For time series models, including additive ARIMA and state-space models, the training set serves as the training period, while the testing set represents future time steps for which predictions will be produced. For ML-based models, such as those based on RF or GBM, a temporal hold-out validation approach is used, where the most recent samples are used for validation. The training samples will not explicitly contain overlap with the testing set but will include similar feature values when classified through a sliding window strategy. Further consideration is given to the presence of leaks, where information about the target variable has been used during training. In usual ML model setups, a potential leak occurs whenever a sample included in the training period has contained future values of the target variable at the moment of prediction.

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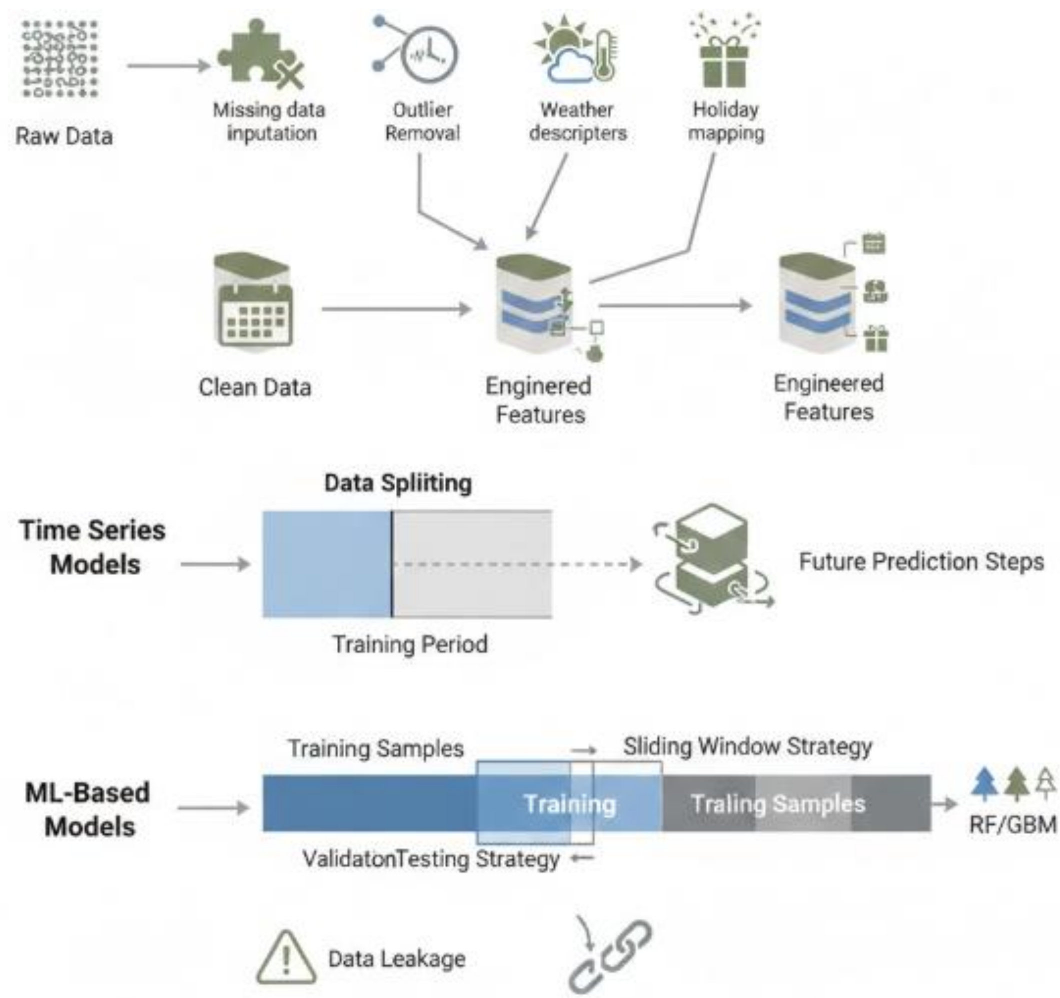

Fig 2: Temporal Feature Engineering and Validation Strategies for Load and Renewable Forecasting: A Comparative Framework for Time-Series and Machine Learning Models

4. Predictive Modeling Approaches

Predictive analytics creates intelligence that foresees future behavior of physical dynamical systems. Actionable knowledge created by predictive analytics is used in energy systems for different purposes such as energy efficiency and demand response. Predictive

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analytics operates at different scales: time series forecasting, demand response via machine learning, and model predictive control of distribution grids. Time series forecasting aims at forecasting future energy consumption on the basis of past data only. A simple univariate ARMA forecast is enriched by exogenous variables such as weather information, holidays, special events, and the usage of electric vehicles. A simplified version of the forecast is also made available as a benchmark for more complex approaches. Demand response creates predictive models that combine different kinds of data and are applied for different purposes such as building cooling and heating, and electric vehicles.

Electric vehicles are an emerging consumer category that is expected to considerably grow in the near future and become an important driver of electricity consumption patterns. A machine learning demand response predictive model is developed at the fleet scale and it aims at forecasting future charging patterns of a fleet of electric vehicles based on trip data, historical charging activity, and the time of day. The generated predictions are suitable to optimize the participation of the fleet in a demand response program as well as to improve the energy efficiency in a neighborhood by sending convincing guidance to the e-car drivers.

Equation 2) Time-series forecasting equations (ARMA / ARIMA / ARIMAX)

2.1 ARMA(p, q) from "past + shock" components

1. **Autoregression (AR) part** says current load depends on past load:

$$y_t = c + \sum_{i=1}^{p} \phi_i \, y_{t-i} + \varepsilon_t$$

2. **Moving average (MA) part** says current load depends on past forecast errors:

$$y_t = c + \varepsilon_t + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j}$$

3. Combine them (ARMA):

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$$\boxed{y_t = c + \sum_{i=1}^{p} \phi_i \, y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j}}$$

Step-by-step forecast (1-step ahead):

- Define information set $\mathcal{F}_{t-1}$ = all observations up to $t-1$.
- Then the optimal linear forecast is:

$$\hat{y}_{t|t-1} = \mathbb{E}[y_t \mid \mathcal{F}_{t-1}] = c + \sum_{i=1}^{p} \phi_i \, y_{t-i} + \sum_{j=1}^{q} \theta_j \, \hat{\varepsilon}_{t-j}$$

with residual:

$$\hat{\varepsilon}_t = y_t - \hat{y}_{t|t-1}$$

2.2 ARIMA(p, d, q) (adding differencing for non-stationarity)

If the series has trend / changing level, difference it d times.

First difference:

$$\nabla y_t = y_t - y_{t-1}$$

Second difference:

$$\nabla^2 y_t = \nabla(\nabla y_t) = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2})$$

ARIMA is simply "ARMA applied to the differenced series":

$$\nabla^d y_t = c + \sum_{i=1}^{p} \phi_i \, \nabla^d y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j}$$

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2.3 ARIMAX / ARMAX (adding exogenous features like weather/holidays)

Add $\mathbf{x}_t$ into the mean model:

$$\boxed{y_t = c + \boldsymbol{\beta}^\top \mathbf{x}_t + \sum_{i=1}^{p} \phi_i \, y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j}}$$

4.1. Time Series Forecasting

Energy consumption time series often exhibit seasonal patterns that are also affected by external factors such as calendar events and weather. When time series for multiple geographically dispersed buildings are available, advanced methods like Long Short-Term Memory networks and Convolutional Neural Networks can be considered. Alternatively, states and clusters with similar energy consumption patterns can be defined. In addition to time-series methods, a broader modelling approach can be pursued in which buildings' predictions are conditioned on the demand of other buildings within the community. In this case, the appliance level disaggregation must be addressed, which can be done with Non-Intrusive Load Monitoring techniques.

Incentives for demand response programs can be predicted by relaxing the time-of-use pricing schema according to temperature ranges. For residential buildings equipped with smart thermostats a rule-based approach can be employed, while data-driven models have to be applied to non-thermostat appliances. Also, NEST players can be identified. Building level predictive models for consumption, thermal comfort, NEST and demand response incentives can all be represented as Markov-jump Linear systems. Their application can be extended beyond the building scale, targeting neighborhoods and small districts equipped with distributed energy resources.

4.2. Machine Learning for Demand Response

Nevertheless, its operational effectiveness can be enhanced by making predictions of electricity consumption. This is because DR events, when initiated or moderated by the grid or energy providers, require sufficient situational awareness. For example, in the case of widespread DR events, DR curtailment usually requires more than just an individual household or business acting to respond to the event. Therefore, it is appropriate to predict not just the

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consumption of ordinates within an area but additionally at the neighbourhood and building levels. A Machine Learning-based model for predicting the hourly load of a neighbourhood or a building, as opposed to regional or national load, is developed to assist in effective DR implementation and provide useful situational awareness by consolidating the demand response of individual electricity consumers. In addition, synthetic data that captures unique neighbourhood features can be generated via the Generative Adversarial Network technique, improving prediction performance even when training data is scarce. The model is applied to a case study in the city of Toronto which resembles neighbourhood characteristics common in any metropolitan area worldwide.

Moreover, with the development of smart grids, more flexibility has been introduced in the energy system. As a result, several independent research projects, such as the Demand Response Project and the OpenADR Initiative, have been launched to enhance smart grid responsiveness. These projects aim to utilize Demand Response (DR) as a grid management tool to bring together electricity producers and consumers. Capacity management is then an open problem because it deals with the loss manageable resources in the system.

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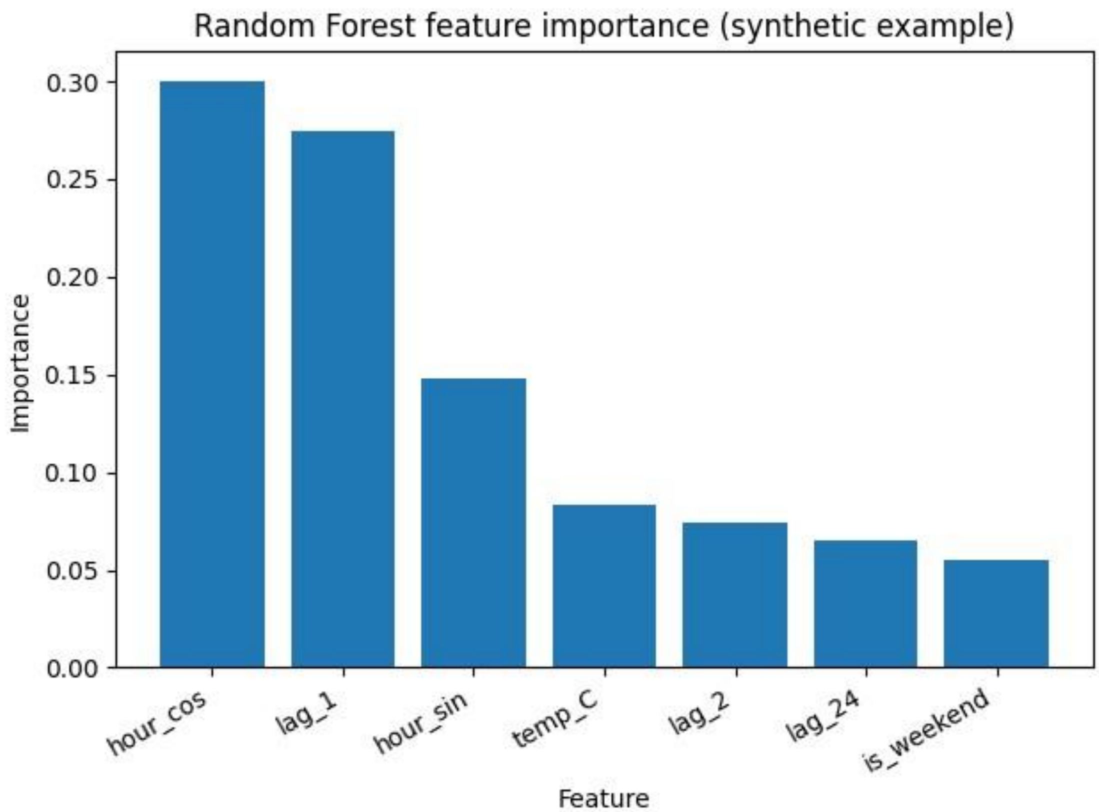

Equation 3) PCA "idiosyncratic factors"

Let y_t be load and let h_t be hour-of-day.

3.1 Time-of-day adjustment

Compute hour-wise mean:

$$\mu_h = \frac{1}{|\{t: h_t = h\}|} \sum_{t:h_t=h} y_t$$

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Adjusted series:

$$\tilde{y}_t = y_t - \mu_{h_t}$$

3.2 Squaring (as the paper states)

$$z_t = \tilde{y}_t^2$$

3.3 Form the data matrix for PCA

Suppose you have N buildings (or meters) so each time t has a vector $\mathbf{z}_t \in \mathbb{R}^N$.
Stack them into $Z \in \mathbb{R}^{T \times N}$.

Center columns:

$$\bar{\mathbf{z}} = \frac{1}{T} \sum_{t=1}^{T} \mathbf{z}_t, \qquad Z_c = Z - \mathbf{1}\bar{\mathbf{z}}^\top$$

3.4 Covariance and eigen-decomposition

$$\Sigma = \frac{1}{T-1} Z_c^\top Z_c$$

Find eigenpairs:

$$\Sigma \mathbf{v}_k = \lambda_k \mathbf{v}_k$$

Sort $\lambda_1 \geq \lambda_2 \geq \cdots$. Take first K eigenvectors:

$$V_K = [\mathbf{v}_1, \dots, \mathbf{v}_K]$$

3.5 Principal component scores (latent factors)

$$F = Z_c V_K$$

Here $F \in \mathbb{R}^{T \times K}$ are the common factors.

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3.6 Reconstruction and "idiosyncratic factors" (residual part)

Reconstruction:

$$\hat{Z}_c = FV_K^\top$$

Idiosyncratic component:

$$\boxed{U = Z_c - \hat{Z}_c}$$

5. Energy Efficiency and Demand-Side Management

Cities account for around 75% of global energy consumption and 80% of greenhouse gas emissions. Improving energy efficiency in cities is therefore a crucial piece in achieving global climate targets. While this makes sense from both an economic and environmental perspective, deploying energy-efficient measures at scale is challenging due to insufficient financial incentives that enable the fruition of investments. A promising avenue for fostering energy efficiency is on the demand side, where people and businesses reduce the amount of energy they use, such as taking simple actions to reduce their energy consumption and thereby save money on their energy costs.

In this context, leveraging technology, intelligent energy use and flexibility have gained attention in recent years, enabling the development of new business models, such as Demand-Response (DR) schemes, where users get rewarded for reducing their electricity consumption at critical times. Buildings constitute the main proportion of energy use in cities, and building energy simulation tools quantify how the building might perform under different design alternatives, helping stakeholders make better decisions. Decomposition of urban energy consumption on a building level allows the prediction and identification of building energy conservation measures, supporting urban planners and local governments in their efforts to reduce the overall energy consumption in a city. Building Level Consumption Profiles provide detailed information on when to provide DR events, and they forecast future energy consumption to aid automated DR deployment.

5.1. Building-Level Analytics

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Recent research suggests that, in terms of intelligent buildings, energy consumption, environmental indicators, and indoor comfort can be jointly optimized. For an evaluation: keywords are tuned according to user behaviour, occupancy patterns are extracted with different time spans, consequentially distinct models are trained.

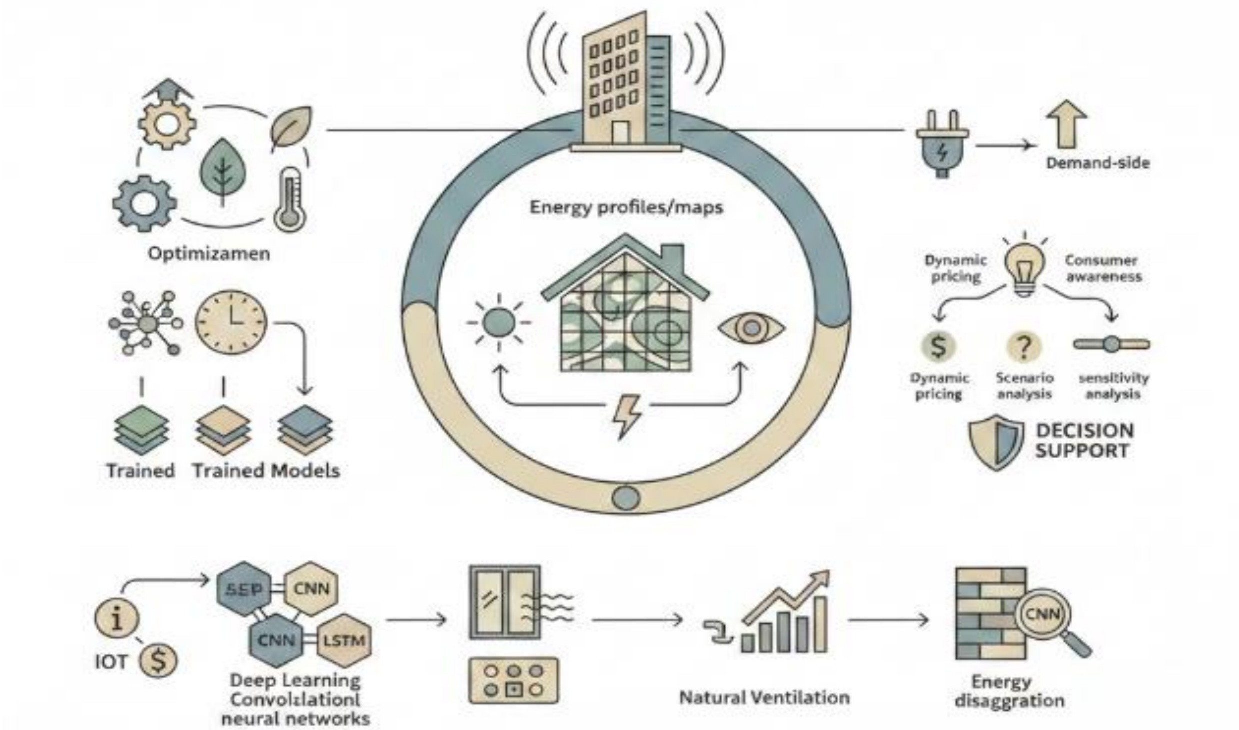

Fig 3: Deep-Mapping Smart Environments: A Multimodal Neural Framework for Predictive Energy Optimization and Demand-Response Deciphering

The data can be linked with a home image, defining energy profiles as energy maps, therefore the prediction can provide a visual guide for optimal operation, control and design. Building energy disaggregation and prediction with Internet of Things (IoT) and Time-of-Use (TOU) pricing is also investigated, through neural-based deep learning convolutional neural networks. Specifically catering for natural ventilation buildings, a predictive model can provide active control information to make the building operating systems more effective and efficient. For building component classification, advanced deep learning methods of CNNs and LSTMs

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can be adapted. Since building-level energy usages currently remain untracked and unreported, deep learning systems can be adopted. For individual smart buildings, a novel approach is proposed for the prediction of operating energy in order to perform active control of active systems, thereby facilitating demand-side management and consumer awareness. The predicted result combined with dynamic electric price strategy, scenario analysis and sensitivity analysis can provide decision support for key parameters in designing and indicating system-operating activity in the new demand–response supply chain.

5.2. Neighborhood and District-Level Strategies

At a neighborhood level, energy consumption is influenced by social, cultural, and lifestyle habits. Simulations demonstrate that even with similar climatic years, energy demand can vary by over 30% based on settlers' daily schedules and habits. Hence, demand-side management strategies should consider the scheduling profile of a neighborhood to minimize peak consumption more effectively. Furthermore, such strategies may incrementally reduce demand in several regions, even if some settlements set less or no energy reduction during demand peaks. At the district level, commercial buildings, particularly supermarkets that operate 24/7, account for the highest absolute energy consumption. However, when normalized by floor area, hotels become the largest energy consumer, followed by supermarkets. District building energy consumption is influenced by the structure of the building typologies, their scheduling profiles, and the microclimate conditions. These characteristics should all be considered in demand-side management strategies for greater overall efficiency. Building energy management systems that support predictive and ΔTE-based demand response control are tested using real data, incorporating weather-driven electric vehicle charging. Accurate prediction of building energy consumption, together with ΔTE-based control, reduces energy cost through participation in demand response programs, while the minimized peak load lessens stress on the power grid. Prediction and ΔTE-based control models are integrated into a cloud-based infrastructure to support public building energy management. Predictive data from a large commercial building are obtained from the existing energy monitoring and control systems, combined with an artificial neural network trained on the monitored data. The empirical results show that ΔTE-driven energy control yields site energy cost savings in excess of six percent, enabling active participation in demand response programs. Moreover, the minimized peak load alleviates stress on the local power grid and reduces the overall environmental footprint. Further cost reductions are anticipated through the implementation of dynamic electricity tariff structures.

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Model	MAE	RMSE	MAPE_%
Linear ARX	1.265964854556231	1.5838514909383161	4.181009232354888
Random Forest	0.9617274284395612	1.2259750477800175	3.180374602926566

6. Integration with Smart Grids and Distributed Energy Resources

All energy-related scenarios have to cope with mismatched supply and demand. Adverse impacts of extreme weather lead to demand patterns that can deviate from their expected behaviours and make it difficult for the energy supply sector to cope. Future energy supply must include renewable energy sources with fluctuating generation patterns, which have to match the demand. A smart grid can act as a complementary solution to help stabilize the grid. Demand response solves part of the mismatch problem by making demand more flexible and improving the demand–supply matching over short time horizons. Nevertheless, renewables such as wind and solar power are not predictable over long time horizons.

Different solutions exist. A neighbourhood storage solution aims to enable building owners to share a pool of batteries installed in selected buildings within neighbourhoods. Due to the limited predictability of demand, a model to quantify the economic viability of neighbourhood storage solutions is developed. Incremental role of district heating in facilitating renewable transition; support from policy incentives and heating support contribution to higher uptake of deep geothermal initiatives beyond the analysed years. Flexible electric demand for a district participating in a university campus virtual power plant. The changes in grid coefficient and thermal inertia of the buildings in the district can support the effective cycling and selection of HVAC by the aggregated capacities.

Equation 4) Machine learning demand-response

4.1 Supervised learning setup

Let features be $\mathbf{x}_t$ and target be y_t. The ML model is:

$$\hat{y}_t = f(\mathbf{x}_t)$$

Training (empirical risk minimization):

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$$\boxed{\min_{f \in \mathcal{F}} \frac{1}{|\mathcal{T}_{train}|} \sum_{t \in \mathcal{T}_{train}} \ell\left(y_t, f(\mathbf{x}_t)\right)}$$

Common loss for point forecast: $\ell = (y - \hat{y})^2$ (MSE).

4.2 Temporal hold-out (no leakage)

If split time-ordered at $t = t_0$:

- Train: $t \leq t_0$
- Test/validation: $t > t_0$

6.1. Synergies Between Smart Grids and Distributed Energy Solutions

A smart grid is envisioned as an intelligent infrastructure that allows for real-time monitoring, control, and communication across all energy flows in the interconnected system. Smart grids rely on pervasive sensor deployment, advanced monitoring and control capabilities, and increased communication capabilities across the power network through the integration of smart meters, smart appliances, and automated demand response capabilities. Complementary advances in distributed energy resource (DER) technologies enable the development of flexible technologies that can be deployed locally. These non-dispatchable DER include plug-in electric vehicles, photovoltaic panels, heat pumps with thermal energy storage, and local small-scale wind generation. Batteries with a high cycle life will also be deployed in the grid as a growing sector of the market. Distributed energy technologies can play an important role in enhancing energy efficiency and reducing greenhouse gas emissions at all scales: the individual building, community neighborhood, or city district.

The operational efficiencies and environmental benefits of distributed energy technologies can only be realized if comprehensive planning and control approaches with the capability to optimally and dynamically coordinate all energy resources in the distribution domain are developed. Such optimization must consider the constraints imposed by the local grid. The planning and control of individualized energy systems can align the building with the rest of the electrical grid while also maintaining comfort constraints. Managed plug-in hybrid

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and electric vehicles are enabled to charge during off-peak hours and participate in vehicle-to-grid services toward enhancing the stability and reliability of the overall electrical grid.

7. Conclusion

In summary, the contributions and implications of the proposed approach have been discussed. The integration of predictive analytical techniques with data sources from various domains holds the potential to address the prediction of near-term energy consumption at various aggregation levels. Demand-response programs are vital in managing the day-to-day energy consumption of users. A hybrid ML-DL prediction model framework is proposed to improve both prediction accuracy and computational time. The three layers at different levels of aggregation provide insights into energy consumption and generation patterns, and can increase the sustainability and resilience of a smart city's energy sector.

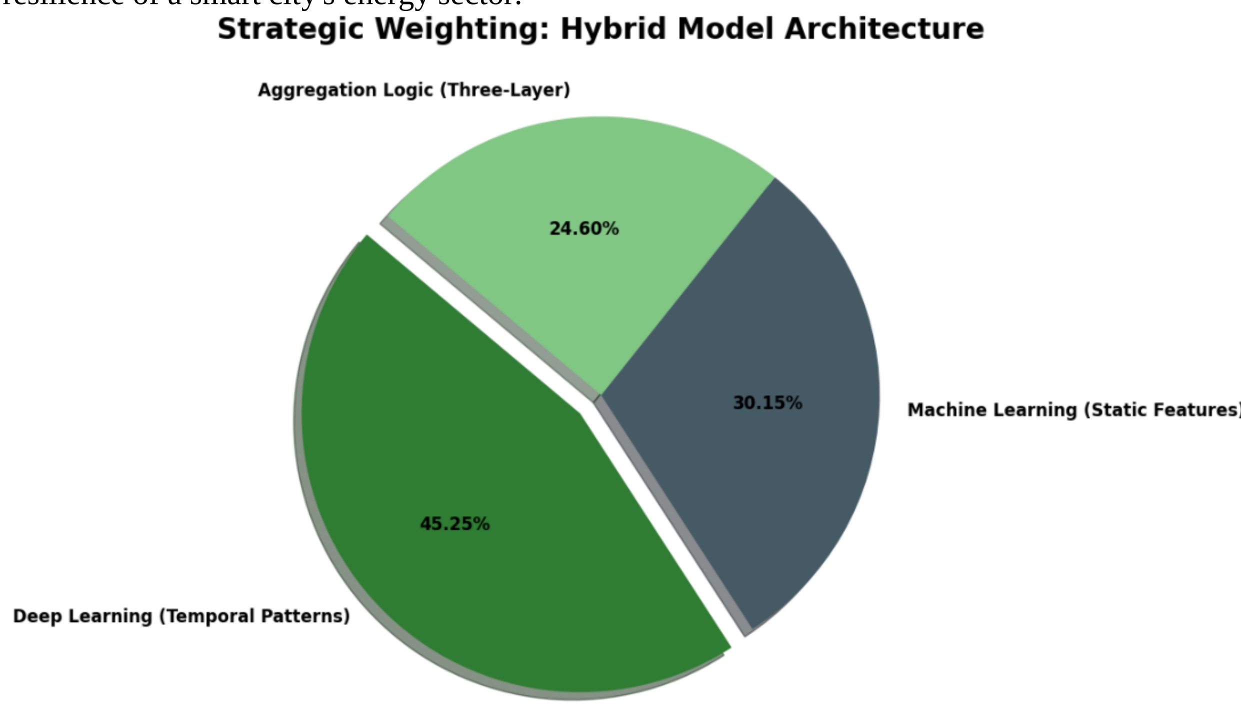

Fig 4: Strategic Weighting: Hybrid Model Architecture

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Future research directions will explore the integration of quality-of-supply factors such as voltage, frequency, and harmonic distortion with energy-prediction models. Advanced machine-learning algorithms, including ensemble methods such as gradient-boosting trees, random forests, and xgboost, will also be examined and tested. In addition, other distributed-energy-resource size-and-location-optimization techniques will be developed, tested, and validated in a simulated smart grid and distributed-energy-resources environment.

7.1. Future Directions and Research Opportunities

The development of AI-enabled predictive-analytic solutions to inform energy-system operations, management, and planning in smart cities remains an evolving field of research. Future work will focus on new techniques and advancements across several relevant domains. The time-series forecasting toolbox presented above will be extended. Options to explore include additional algorithms, a Bayesian forecasting approach, boosting ensemble-multimodel forecasting, and a probabilistic forecasting framework that incorporates pinball loss as an evaluation criterion for the algorithm's relative quality.

The optimization of models that use machine learning to "predict" consumer uptake of demand-response offerings is another area for further investigation. Work will also explore building-level energy consumption under-layer analytics—analysis of energy use in individual buildings to identify phase-shift potential, thermal-storage feasibility, and energy-efficiency-upgrade priorities—as well as district- and neighborhood-level strategies that synergize multiple individual assets. A predictive-analytic toolbox that integrates demand-side resources with smart grid infrastructure and supports the optimal investment strategies of suppliers in distributed energy resources will also be developed.

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P-ISSN: 3050-9572 E-ISSN: 3050-9580
EUROPEAN DATA SCIENCE JOURNAL
Volume: 03 Issue: 03
RECEIVED: JULY 23 REVISED: AUGUST 04 ACCEPTED: AUGUST 28 PUBLISHED: SEPTEMBER 05

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