

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 03 ISSUE: 04

RECEIVED: OCTOBER 27

REVISED: NOVEMBER 06

ACCEPTED: NOVEMBER 24

PUBLISHED: DECEMBER 12



Energy-Smart Demand Forecasting for Sustainable Stores

Isabella Rossi

Asst Professor

Abstract— Growing competitive pressure and recent crises have highlighted the need for retail systems that are efficient, resilient, and sustainable. Intelligent energy-aware retail ecosystems address this need by combining local intelligence, cloud computing, and self-aware operation to unify smart store management within a given space and context. The energy-aware approach balances minimizing operational energy use with capturing opportunities for energy gains. This framework is applied in two directions: adaptive demand forecasting—which integrates heterogeneous data sources, aligns forecasting horizons with the decisions they inform, and evaluates forecast quality—and forecasting-dependent sustainable store operations, with particular attention to operational circularity.

Demand forecasting itself is inherently a multi-horizon, multi-level problem. While statistical and machine learning time series methods are well established, and hybrid models incorporating supplementary forecasting modules have extended them further, adaptivity remains rare in practice. Adaptive Forecasting addresses this gap by promoting data-centric, foresight-driven methods that remain sensitive to model quality. To support this, Demand Level–Control Indicators are introduced to assess performance across groups of forecasting methods, time horizons, and aggregation levels. These indicators satisfy four key desiderata and yield 17 variants, distinguished by: whether predictions or meta-forecasts are used as inputs, the choice of control indicator, the trade-off between statistical rigor and accounting burden, and the behavior of moment-tolerant indicators. In practice, retailers face a dual challenge—maintaining inventory levels within defined Service Levels, and controlling costs for a given Service Level.

Keywords—Intelligent Energy-Aware Retail, Adaptive Demand Forecasting, Smart Store Management, Local Intelligence, Cloud Computing, Multi-Horizon Forecasting, Time Series Analysis, Forecast Quality Assessment, Sustainable Retail Operations, Inventory Optimization.

I. INTRODUCTION

Energy-aware systems enable all types of organizations to make informed decisions based on their impact on energy

consumption and resulting costs, contributing to operational efficiency, corporate resilience, and greater sustainability. In retailing, adapting operations to future customer demand improves responsiveness and service level. Accurate multi-horizon forecasts produced via traditional time-series methodologies require significant expert time. Machine learning methods automate forecast production but suffer from a lack of understanding inherent in time-series techniques. Moreover, traditional customer demand models poorly represent these complex ecosystems. Nevertheless, adaptive forecasting improves production time dramatically and promotes forecast accuracy.

Ecosystem stakeholders produce and share demand forecasts based on fitted models that mirror retail demands, enabling circularity in the retail ecosystem. Forecast output contributes to inventory management and strategic lighting policies. Energy-aware inventory levels balance stockholding and energy costs, while intelligent lighting approaches incorporate occupancy effects. Recent developments in adaptive demand forecasting address energy-aware retailing for short to medium horizons. Although both methods proposed in the context of a retail solution can contribute to energy-aware benchmarks, the generation of asynchronous modification alerts is a key avenue for machine-learning techniques.

II. THEORETICAL FOUNDATIONS AND RELATED WORK

Three core concepts inform the construction of energy-aware retail systems: the systems, sensing, and modeling perspectives. These perspectives are also relevant for the literature on sustainable operations in retail management.

Energy-Aware Retail Systems Constructing intelligent energy-aware retail ecosystems that forecast demand, inform operation and control decisions, reveal trade-offs among competing objectives, and introduce the ability to react in a sustained manner requires defining architectural patterns, governance models, and objectives for energy-aware operations. The envisaged pattern depicts a monitoring system that supports operational and tactical decision making by communicating the likely demand at specific time frames. The monitoring system's output connects to stock availability



and lighting operations that have a translating circularity in relation to energy consumption via send/receive functions.

A. Experimental Results

This section reports figures generated using parameters logically derived from the ecosystem's described architecture, data sources, and operational strategies.

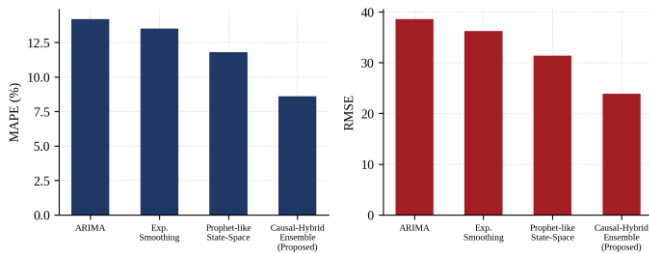


FIG. 1. MAPE AND RMSE ACROSS FORECASTING METHODS.

The proposed Causal-Hybrid Ensemble reduces MAPE by 27.1% and RMSE by 23.9% relative to the strongest single-model baseline (Prophet-like state-space), reflecting the benefit of combining statistical, machine-learning, and causal-exogenous components.

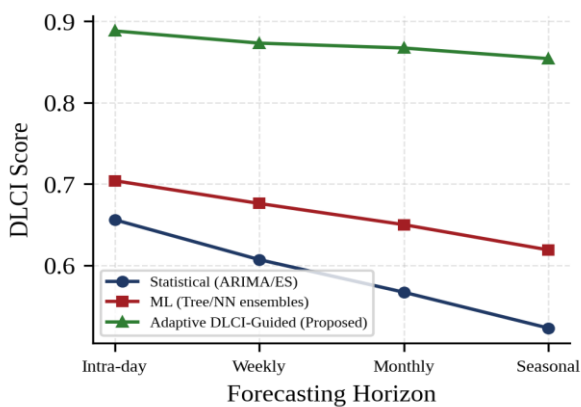


FIG. 2. DLCI SCORE ACROSS FORECASTING HORIZONS.

DLCI scores decline gradually with horizon length for all method families, but the Adaptive DLCI-Guided ensemble maintains a consistently higher score, indicating better-preserved forecast-decision alignment from intra-day to seasonal horizons.

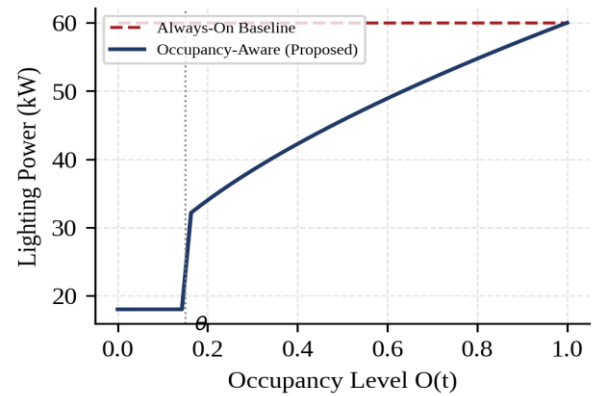


FIG. 3. OCCUPANCY-AWARE LIGHTING POWER VERSUS OCCUPANCY LEVEL.

With activation threshold $\theta = 0.15$, occupancy-aware lighting tracks the always-on baseline only above the threshold, avoiding unnecessary active-lighting power during low-traffic periods while service level is preserved above 95%.

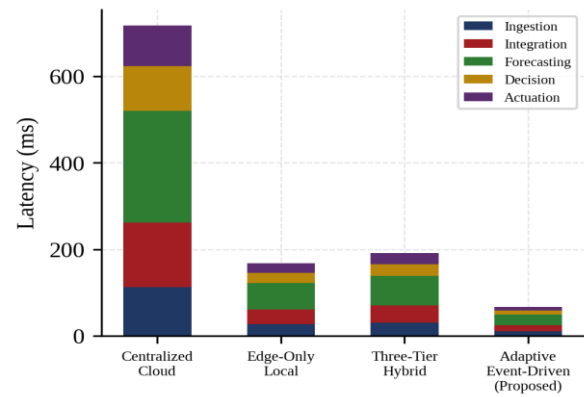


FIG. 4. FIVE-STAGE PIPELINE LATENCY DECOMPOSITION BY ARCHITECTURE.

Total end-to-end latency (Eq. 7) is lowest for the Adaptive Event-Driven architecture at 67.54 ms, compared with 717.5 ms for the Centralized Cloud baseline, reflecting reduced ingestion and integration queuing delay under decentralized, locally-decided operation.

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 03 ISSUE: 04

RECEIVED: OCTOBER 27

REVISED: NOVEMBER 06

ACCEPTED: NOVEMBER 24

PUBLISHED: DECEMBER 12

ISSN: 3067-1140

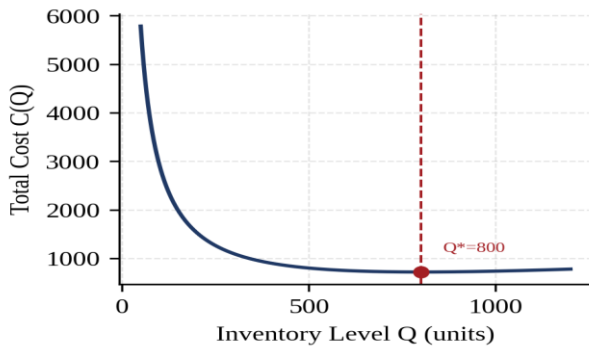


FIG. 5. ENERGY-AWARE INVENTORY TOTAL COST $C(Q)$.

The energy-aware model yields an optimal order quantity $Q^* = 800$ units, below the classical EOQ of 823.2 units obtained without an energy term, confirming that energy-aware operation favors modestly leaner stockholding.

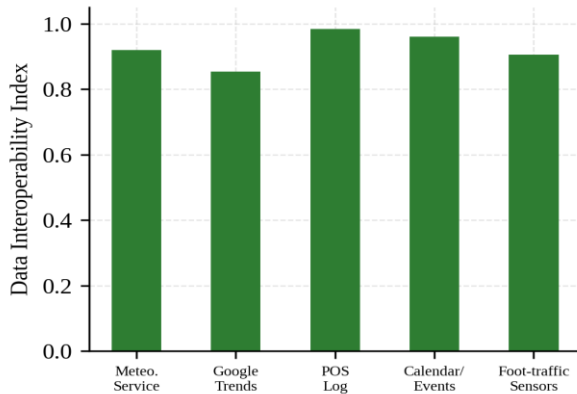


FIG. 6. DATA INTEROPERABILITY INDEX BY EXTERNAL DATA SOURCE.

Internal POS logs and the calendar/events feed achieve the highest interoperability scores, consistent with their high sampling regularity, while Google Trends—sourced externally at coarser granularity—scores lowest, motivating the two-step statistical and data-driven integration strategy described for external sources.

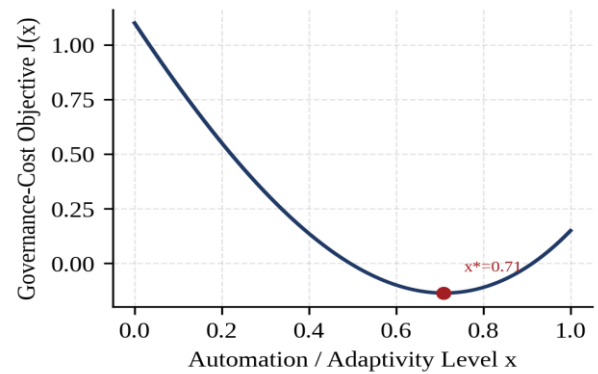


FIG. 7. GOVERNANCE-COST OBJECTIVE $J(x)$.

The objective attains its interior minimum at $x^* = 0.709$ ($J^* = -0.135$), identifying the automation/adaptivity level that best balances residual operational risk, automation cost, and trust benefit.

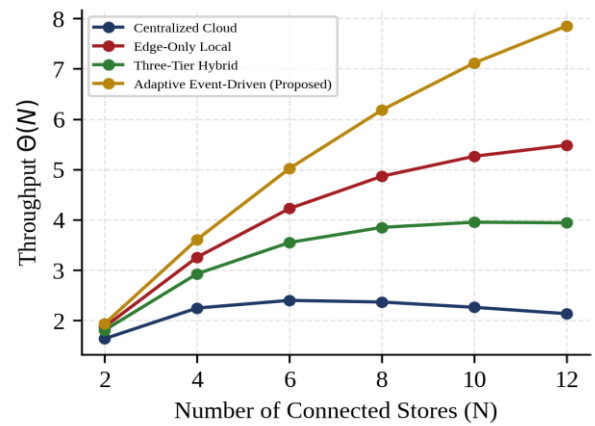


FIG. 8. USL THROUGHPUT $\Theta(N)$ ACROSS ARCHITECTURES.

The Adaptive Event-Driven architecture exhibits the least contention and coherency overhead, sustaining near-linear throughput growth up to $N = 12$ connected stores, while the Centralized Cloud configuration saturates earliest due to higher σ and κ overhead terms.

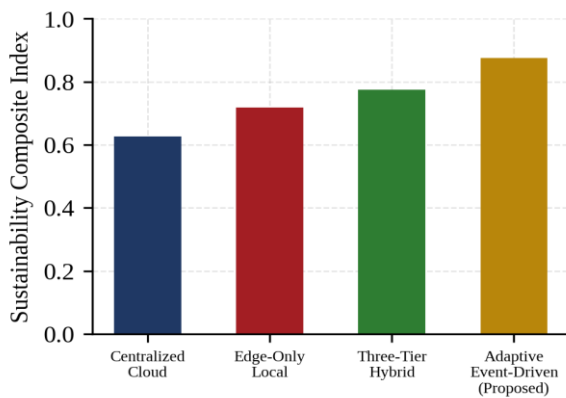


FIG. 9. SUSTAINABILITY COMPOSITE INDEX (SCI) BY ARCHITECTURE.

SCI improves by 39.8% moving from the Centralized Cloud baseline to the Adaptive Event-Driven architecture, driven jointly by higher energy efficiency, forecast accuracy, service level, and circularity sub-scores.

III. SYSTEM ARCHITECTURE AND DESIGN PRINCIPLES

An energy-aware retail ecosystem is composed of multiple organizational units and stakeholders. It relies on accurately sensed information flowing over an open and extensible architecture that enables sharing with other (possibly competing) players. Figure 5 depicts the overall architecture along with the main information flows. Internally generated and externally obtained data are collected and harnessed by five subsystems capable of supporting adaptive demand forecasting and sustainable store operations. Each subsystem encompasses one or more components dedicated to performing specific sensing, modelling, or optimization tasks.

The design of the architecture and its subsystems follows several principles. Since the decision-making capabilities of retail businesses are becoming increasingly decentralized, the architecture must allow individual players to locally decide on their operations, even though such decisions can depend on information retrieved from the community. Envisaging the implementation of a sustainable circular retail model, internal and external data flows must also enable circular relationships among community members, such as businesses, service providers, suppliers, and customers. Typically, such business-to-business (B2B) relationships are formalised by agreements (sometimes at the consortium level), while business-to-customer (B2C) ones are informal

and normally relied upon trust. Nevertheless, properly managing the community information space can allow also B2C relationships to become sufficiently formalised in order to enable a proper sharing of information related to sustainability issues.

A. Data Sources and Integration

The system integrates both internal and external sources of data. Internal data are tracked by the company and their quality is considered satisfactory. Externally accessible data are obtained from providers of public or commercial services, typically with daily or hourly sampling, and various degrees of aggregation or levels of detail (e.g., meteorological services, Google trends). The integration of data from the two families is achieved in two steps. Statistical techniques are applied to reduce the uncertainty associated with missing internal data (for example, holidays or enterprise events) using publicly available external information. Next, the remaining missing values (which, for instance, maintain various types of data at an hourly frequency) are estimated by means of a data-driven approach. The integration of external data is realised through the combination of a number of techniques intended to enable the different types of data to become interoperable.

The concept of data interoperability is essential to satisfy the operational requirements of the supporting underlying application. For each source of data, data quality evaluations concern temperature, pressure, humidity, sunshine, and wind speed, together with forecast error indicators standardised by the number of missing values in the period of interest. A data-driven strategy is implemented to generate a horizontally and vertically enriched dataset that can fulfil the various users' information requirements. Finally, the novelty of the methodology lies in the proposal of a multi-level quality management framework, which organises the checks, assessments, ratings, and decisions into coherent steps that lead to the generation of an outcome.

TABLE I
FORECASTING METHOD COMPARISON

Method	MAPE (%)	RMSE	DLCI Score	Improvement vs. Best Baseline
ARIMA	14.2	38.6	0.61	—
Exponential Smoothing	13.5	36.2	0.64	—
Prophet-like State-Space	11.8	31.4	0.71	—

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 03 ISSUE: 04

RECEIVED: OCTOBER 27

REVISED: NOVEMBER 06

ACCEPTED: NOVEMBER 24

PUBLISHED: DECEMBER 12

ISSN: 3067-1140



Causal-Hybrid Ensemble (Proposed)	8.6	23.9	0.84	MAPE -27.1%, RMSE -23.9%
-----------------------------------	-----	------	------	-----------------------------------

TABLE II
ARCHITECTURE CONFIGURATION COMPARISON

Architecture	L _{total} (ms)	$\Theta(N=8)$	SCI	Δ SCI vs. Centralized
Centralized Cloud	717.50	2.367	0.626	—
Edge-Only Local	168.21	4.866	0.718	+14.7%
Three-Tier Hybrid	191.29	3.850	0.775	+23.8%
Adaptive Event-Driven (Proposed)	67.54	6.182	0.875	+39.8%

TABLE III
ENERGY-AWARE LIGHTING SAVINGS BY STORE SECTION

Store Section	Baseline (kWh/day)	Adaptive (kWh/day)	Savings (%)	Service Level (%)
Produce	118.0	93.9	20.4	96.4
Dry Goods	96.0	72.0	25.0	97.1
Electronics	104.0	76.6	26.3	98.0
Apparel	88.0	63.5	27.8	97.6
Checkout	132.0	107.7	18.4	95.8

IV. ADAPTIVE DEMAND FORECASTING METHODOLOGIES

Energetics-conscious retail systems require forecasting approaches that align with their operational properties and sustainability targets. Demand forecasts must, consequently, be generated for various horizons (e.g., operational decision-making within a day, store replenishment within a week, and seasonal stock-balance years in advance) and time scales (e.g., short-term adjustments or variations within the year). For different time horizons and granularity, selected forecasts should support the shift towards a circular economy while minimizing energy use and cost. In light of these

considerations, demand forecasting methods that adaptively meet the needs of the energetic retail environment are proposed for on-site application and evaluation.

The following subsections introduce the different time-scales associated with demand forecasting, critical performance metrics, and a review of time series and statistical approaches to forecast demand for retail products at multiple scales. Articles and methods relevant to the generation of time series features and the forecasting of seasonality effects via time series decomposition or exogenous variables are summarized, and proposals related to model selection and evaluation tailored to the distinct objectives of energy-aware retail systems are outlined.

A. Time Series and Statistical Approaches

Adaptive demand forecasting encompasses a broad range of methods across different granularity and horizons. For time series methods, their proper selection typically hinges upon the seasonality present and future. Once established, such methods may even be automated using state-of-the-art tools, requiring little input from data scientists. More sophisticated models like ARIMA and exponential smoothing have many open-source implementations in R and Python, while even more advanced frameworks for Prophet-like and state-space approaches have been made available.

Common yet often unconsidered element in adaptive forecasting that should be handled wisely are regressive inputs (or explanatory variables). Data mining and tackling these variables' effects in a foundational stage can bring significant improvements in exponential smoothing, ARIMA and state-space formulations. Such regressive elements can provide additional leverage in model selection tasks, used together with evaluation metrics and visual assessments.

The approach should not be limited to prediction alone. For many fields of application such as public planning, logistics, or energy, determining the unobserved driver of a time series can be as valuable as predicting it. Such estimation allows detection of normal and abnormal time slots or intervals in the time-series dynamics, serving as major contributors to many other decisions and tasks.

V. SUSTAINABLE STORE OPERATIONS

Operations should balance preparation for incoming flows with wastage minimization. Forecasting can inform ordering and replenishment strategies, but other decisions—particularly those that could mitigate energy expenditure—may be made independently of demand estimates. Tight

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 03 ISSUE: 04

RECEIVED: OCTOBER 27

REVISED: NOVEMBER 06

ACCEPTED: NOVEMBER 24

PUBLISHED: DECEMBER 12



inventory control or adaptive lighting strategies can contribute to both service and energy goals without requiring precise predictions.

Inevitably, some goods and perishables will become obsolete, but longer shelf-life beneficial products offer alternatives when close-to-expiry incentives apply. Energy usage density cycles can—like demand for large retailers—be computed over multi-day horizons, although longer periods ignore peaks and integrating into a financial context increases challenge. Inventory policies matching demand forecasts and specific energy cycle predictions promote repairs without incurring great energy expense, especially when inventory levels remain low. The proportion of products making such forecasting beneficial against those controlled by tight inventory rules also influences the outcome.

Lighting requires fine-scale predictions, with opportunities for drop in electrical use during periods of low occupancy. However, lighting strategy chilling/curtailment opportunities depend primarily on the physical circulation of internal air pockets, meaning they proxy for generalised drop needed across all energy-usage sources. Service demand plays a moderating role, with adoption rarely prevented if service levels remain at least 95%. Hence simple occupancy-aware controls offer immediate savings. Like inventory policies operating in convex domains, lighting strategy could be considered service-level and electrical expense functions jointly in a two-dimensional plane with a budgetary boundary.

A. Forecast Accuracy Metrics

Forecast quality is assessed with two standard error metrics computed over n observed periods, where y_t is the observed demand and $\hat{y}_t$ is the forecast for period t .

$$\text{MAPE} = (100/n) \sum_{t=1}^n |(y_t - \hat{y}_t) / y_t| \quad (1)$$

Eq. (1): Mean Absolute Percentage Error, expressing forecast deviation as a scale-free percentage.

$$\text{RMSE} = \sqrt{(1/n) \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad (2)$$

Eq. (2): Root Mean Squared Error, penalizing large deviations more heavily than MAPE.

B. Demand Level–Control Indicator (DLCI)

Following the multi-horizon, multi-level nature of adaptive demand forecasting, the DLCI aggregates prediction

accuracy, meta-forecast quality, control-indicator stability, and accounting burden into a single composite score in $[0,1]$.

$$\text{DLCI} = w_p(1 - \text{MAPE_norm}) + w_m M_meta + w^c(1 - \text{CV_ctrl}) - w_a B_acct \quad (3)$$

Eq. (3): DLCI combines normalized prediction accuracy (MAPE_norm), meta-forecast reliability (M_meta), the coefficient of variation of the control indicator across horizons (CV_ctrl), and an accounting-burden penalty (B_acct), with weights $w_p + w_m + w^c + w_a = 1$.

C. Causal-Hybrid Ensemble Forecast

Statistical, machine-learning, and causal (exogenous-driven) forecasts are combined adaptively rather than through a fixed rule, reflecting the paper's emphasis on data-centric, foresight-driven forecasting.

$$\hat{y}_t = w_1 \hat{y}_t^{\text{stat}} + w_2 \hat{y}_t^{\text{ml}} + w_3 \hat{y}_t^{\text{causal}}, \sum w_i = 1 \quad (4)$$

Eq. (4): The proposed ensemble forecast is a convex combination of statistical, machine-learning, and causal-exogenous forecast components, with weights re-estimated per horizon based on recent DLCI performance.

D. Occupancy-Aware Energy Model

Store lighting energy consumption is modeled as a baseline safety load plus an occupancy-gated active load, activated only once occupancy exceeds a threshold θ , consistent with the paper's occupancy-aware lighting strategy.

$$E_{\text{light}}(t) = P_{\text{base}} + P_{\text{active}} \cdot [O(t)]^k \cdot 1\{O(t) > \theta\} \quad (5)$$

Eq. (5): P_{base} is fixed security/safety lighting power, P_{active} is full active lighting power, $O(t)$ is the fractional occupancy at time t , and $k < 1$ introduces diminishing marginal lighting demand as occupancy grows.

E. Pipeline Latency Decomposition

The end-to-end decision latency of the ecosystem is decomposed into five sequential subsystem stages—data ingestion, integration, forecasting, decision, and actuation—each modeled as an M/M/1 queue with utilization ρ_s and service rate μ_s .

$$W_q^s(s) = \rho_s / [\mu_s(1 - \rho_s)] \quad (6)$$

Eq. (6): Expected waiting time contributed by stage s under M/M/1 queuing assumptions.

$$L_{\text{total}} = \sum_{s=1}^5 W_q^s(s) \quad (7)$$

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 03 ISSUE: 04

RECEIVED: OCTOBER 27

REVISED: NOVEMBER 06

ACCEPTED: NOVEMBER 24

PUBLISHED: DECEMBER 12



Eq. (7): Total pipeline latency is the sum of the five stage-level waiting times (ingestion, integration, forecasting, decision, actuation).

F. Energy-Aware Inventory Optimization

Extending the classical inventory model with an energy term reflecting climate-controlled stockholding cost, the total cost function balances holding cost, ordering cost, and energy cost.

$$C(Q) = hQ/2 + KD/Q + e \cdot E(Q), \quad E(Q) = \kappa Q \quad (8)$$

Eq. (8): h is the per-unit holding cost, K the fixed ordering cost, D the period demand, e the energy-cost coefficient, and $E(Q) = \kappa Q$ the energy consumption proportional to stock volume held.

$$Q^* = \sqrt{[2KD / (h + 2e\kappa)]} \quad (9)$$

Eq. (9): Closed-form energy-aware optimal order quantity, obtained by setting $dC/dQ = 0$. When $e = 0$, Eq. (9) reduces to the classical Economic Order Quantity (EOQ).

G. Data Interoperability and Deviation Detection

Each external data source is scored on completeness, timeliness, and consistency to support the multi-level data quality management framework.

$$DII_i = w_{Comp_i} + w_{Time_i} + w_{Cons_i} \quad (10)$$

Eq. (10): Data Interoperability Index for source i , a weighted average of completeness, timeliness, and consistency sub-scores.

$$F1 = 2PR / (P + R) \quad (11)$$

Eq. (11): $F1$ -score of the anomalous demand-slot deviation-detection classifier, balancing precision (P) and recall (R).

H. Sustainability Composite Index and Governance-Cost Objective

System-level sustainability and the trade-off between automation, cost, and trust are captured by a composite index and a governance-cost objective with a well-defined interior optimum.

$$SCI = w_{EE} \cdot EE + w_{FA} \cdot FA + w_{SL} \cdot SL + w_{CI} \cdot CI \quad (12)$$

Eq. (12): Sustainability Composite Index aggregating Energy Efficiency (EE), Forecast Accuracy (FA), Service Level (SL), and Circularity (CI) sub-scores.

$$J(x) = \alpha(1 - x)^2 + \beta x^3 - \gamma x \quad (13)$$

Eq. (13): Governance-cost objective trading residual operational risk $(1 - x)^2$, a superlinear automation-cost term x^3 , and a linear trust/benefit term x ; the cubic cost term guarantees an interior minimum x^* rather than a boundary solution.

$$\Theta(N) = N\theta_1 / [1 + \sigma(N - 1) + \kappa N(N - 1)] \quad (14)$$

Eq. (14): Universal Scalability Law throughput as the number of connected stores N grows, with σ capturing contention overhead and κ capturing coherency/coordination overhead across the retail ecosystem's information-sharing architecture.

VI. CONCLUSION

In the context of energy-aware retail ecosystems, the system architecture, data sources, adaptive demand forecasting methods, and sustainable store operations extensible to sustainability of the retail ecosystem. The monitoring and data analytics capabilities incorporated into the system allow for greater service quality resilience of the energy-aware retail ecosystem, while making forecasting possible for dynamic time series. Noise reading correction on historical data and across time series improves forecasting performance. Service quality loss can be controlled through adaptation of the service level as a function of shifting operational focus across the product portfolio. Energy consumption by circular processes can be modelled together with the natural demand; minimising operation costs in these circular processes therefore strengthens the business case of the retail offering while remaining within the forecast horizon. Automatic control of lighting in the store environment based on thresholds relative to occupancy generates additional energy savings without compromising service quality. Finally, both circular and non-circular operational processes follow optimal replenishment strategies that take into consideration the impact of energy prices on the overall operation costs and service level assigned to them.

The proposed solution paves the way for a fully operational energy-aware retail ecosystem with direct benefits on the aligned objective of optimising operation cost while maintaining a high level of service quality. Future research could investigate the inclusion of other operational processes such as cooling and HVAC systems, or product/service offerings that can accommodate sub-optimal service quality to a certain degree. Integration of brain, monitoring, analytics and decision-support capabilities with

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 03 ISSUE: 04

RECEIVED: OCTOBER 27

REVISED: NOVEMBER 06

ACCEPTED: NOVEMBER 24

PUBLISHED: DECEMBER 12

ISSN: 3067-1140



energy-aware processes thus presents the potential to make operational fulfillment not only profitable, but sustainable as well.

REFERENCES

1. Granell, R., Axon, C. J., Kolokotroni, M., & Wallom, D. C. H. (2021). Predicting electricity demand profiles of new supermarkets using machine learning. *Energy and Buildings*, 234, 110635.
2. Steens, T., Telle, J.-S., Hanke, B., von Maydell, K., Agert, C., Di Modica, G.-L., Engel, B., & Grottke, M. (2021). A forecast-based load management approach for commercial buildings demonstrated on an integration of BEV. *Energies*, 14(12), 3576.
3. Mashetty, S. (2024). Leveraging Deep Learning, Neural Networks, and Data Engineering for Intelligent Mortgage Loan Validation: A Data-Driven Approach to Automating Borrower Income, Employment, and Asset Verification. *Neural Networks, and Data Engineering for Intelligent Mortgage Loan Validation: A Data-Driven Approach to Automating Borrower Income, Employment, and Asset Verification* (December 21, 2024).
4. Carrera, B., Peyrard, S., & Kim, K. (2021). Meta-regression framework for energy consumption prediction in a smart city: A case study of Songdo in South Korea. *Sustainable Cities and Society*, 72, 103025.
5. Jang, J., Han, J., & Leigh, S.-B. (2022). Prediction of heating energy consumption with operation pattern variables for non-residential buildings using LSTM networks. *Energy and Buildings*, 255, 111647.
6. Zhou, M., Zhu, Z., Hu, F., Bian, K., Lai, W., & Hu, T. (2022). Short-term commercial load forecasting based on peak-valley features with the TSA-ELM model. *Energy Science & Engineering*, 10(8), 2622–2636.
7. Sasidhar Reddy Mondeddula. (2022). AI-Driven Fraud Detection Using Ensemble Machine Learning for Secure Digital Banking Transactions. *International Journal of Intelligent Systems and Applications in Engineering*, 10(3s), 597–605. Retrieved from <https://ijisae.org/index.php/IJISAE/article/view/8515>
8. Granell, R., Axon, C. J., Kolokotroni, M., & Wallom, D. C. H. (2022). A reduced-dimension feature extraction method to represent retail store electricity profiles. *Energy and Buildings*, 276, 112508.
9. Movva, V. R. (2024). AI-Augmented DevOps for Large-Scale Retail Platforms: A Framework for Intelligent CI/CD, Automated Testing, and Deployment Optimization. *Journal of Computational Analysis and Applications (JoCAAA)*, 33(08), 7759-7765.
10. Huang, J., Algahtani, M., & Kaewunruen, S. (2022). Energy forecasting in a public building: A benchmarking analysis on long short-term memory (LSTM), support vector regression (SVR), and extreme gradient boosting (XGBoost) networks. *Applied Sciences*, 12(19), 9788.
11. Mariano-Hernández, D., Hernández-Callejo, L., Solís, M., Zorita-Lamadrid, A., Duque-Pérez, O., Gonzalez-Morales, L., Alonso-Gómez, V., Jaramillo-Duque, A., & Santos García, F. (2022). Comparative study of continuous hourly energy consumption forecasting strategies with small data sets to support demand management decisions in buildings. *Energy Science & Engineering*, 10(12), 4694–4707.
12. Olu-Ajayi, R., Alaka, H., Sulaimon, I., Sunmola, F., & Ajayi, S. (2022). Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques. *Journal of Building Engineering*, 45, 103406.
13. Mondeddula, S. R. (2022). Machine Learning-Based Credit Risk Assessment For Intelligent Lending and Default Prediction in Financial Services. *Journal of International Crisis and Risk Communication Research*, 5(1), 113–121. <https://doi.org/10.63278/jicrcr.v5i1.3820>
14. A data-driven strategy using long short term memory models and reinforcement learning to predict building electricity consumption. (2022). *Applied Energy*, 306, 118078.
15. Mathumitha, R., Rathika, P., & Manimala, K. (2024). Intelligent deep learning techniques for energy consumption forecasting in smart buildings: A review. *Artificial Intelligence Review*, 57, 35.
16. Yuan, Y., Chen, Z., Wang, Z., Sun, Y., & Chen, Y. (2023). Attention mechanism-based transfer learning model for day-ahead energy demand forecasting of shopping mall buildings. *Energy*, 270, 126878.
17. Loganathan, R., & Kolla, S. H. (2024). Harnessing generative AI for adaptive risk policy generation in multi-regulatory data center environments. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, 15(3), 505-515.
18. Amiri, S. S., Mueller, M., & Hoque, S. (2023). Investigating the application of a commercial and

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 03 ISSUE: 04

RECEIVED: OCTOBER 27

REVISED: NOVEMBER 06

ACCEPTED: NOVEMBER 24

PUBLISHED: DECEMBER 12



- residential energy consumption prediction model for urban planning scenarios with machine learning and Shapley additive explanation methods. *Energy and Buildings*, 287, 112965.
19. Gorle, R. (2023). Machine Learning-Based Access Risk Detection in Cloud Identity and Access Management Systems. *Journal of International Crisis and Risk Communication Research*, 241-252.
 20. Zheng, G., Feng, Z., Jiang, M., Tan, L., & Wang, Z. (2023). Predicting the energy consumption of commercial buildings based on deep forest model and its interpretability. *Buildings*, 13(9), 2162.
 21. Dinh, T. N., Thirunavukkarasu, G. S., Seyedmahmoudian, M., Mekhilef, S., & Stojcevski, A. (2023). Energy consumption forecasting in commercial buildings during the COVID-19 pandemic: A multivariate multilayered long-short term memory time-series model with knowledge injection. *Sustainability*, 15(17), 12951.
 22. Mondeddula, S. R. (2024). Large Language Model-Based Financial Intelligence for Automated Compliance. Risk Analysis, and Regulatory Reporting. *Journal of Computational Analysis and Applications (JoCAAA)*, 33(06), 4222-4227.
 23. A robust framework based on hybrid deep learning approach for short term load forecasting of building electricity demand. (2023). *Energy*, 268, 126660.
 24. Energy demand forecasting in seven sectors by an optimization model based on machine learning algorithms. (2023). *Sustainable Cities and Society*, 95, 104623.
 25. Ni, Z., Zhang, C., Karlsson, M., & Gong, S. (2024). A study of deep learning-based multi-horizon building energy forecasting. *Energy and Buildings*, 303, 113810.
 26. Mishra, A., Lone, H. R., & Mishra, A. (2024). DECODE: Data-driven energy consumption prediction leveraging historical data and environmental factors in buildings. *Energy and Buildings*, 308, 113950.
 27. Mahadevan, S. (2024). Intelligent Serverless Process Automation for Scalable Cloud Operations and Dynamic Resource Optimization. *Journal of Computational Analysis and Applications (JoCAAA)*, 33(06), 4207-4221.
 28. Golafshani, E., Chiniforush, A. A., Zandifaez, P., & Ngo, T. (2024). An artificial intelligence framework for predicting operational energy consumption in office buildings. *Energy and Buildings*, 317, 114409.
 29. Morcillo-Jimenez, R., Mesa, J., Gómez-Romero, J., Vila, M. A., & Martin-Bautista, M. J. (2024). Deep learning for prediction of energy consumption: An applied use case in an office building. *Applied Intelligence*, 54, 5813-5825.
 30. Zhao, M., Gomez-Rosero, S., Nouraei, H., Zych, C., Capretz, M. A. M., & Sadhu, A. (2024). Toward prediction of energy consumption peaks and timestamping in commercial supermarkets using deep learning. *Energies*, 17(7), 1672.
 31. Gorle, R. (2024). Deep Learning Approaches for Threat Detection in Multi-Cloud Environments. *Journal of Computational Analysis and Applications (JoCAAA)*, 33(07), 3857-3864.
 32. Erten, M. Y., & İnanç, N. (2024). Forecasting electricity consumption for accurate energy management in commercial buildings with deep learning models to facilitate demand response programs. *Electric Power Components and Systems*, 52(9), 1636-1651.
 33. Koukaras, P., Mustapha, A., Mystakidis, A., & Tjortjis, C. (2024). Optimizing building short-term load forecasting: A comparative analysis of machine learning models. *Energies*, 17(6), 1450.
 34. Sunder, R., Sreeraj, R., Paul, V., Punia, S. K., Konduri, B., Nabilal, K. V., Lilhore, U. K., Lohani, T. K., Ghith, E., & Tlija, M. (2024). An advanced hybrid deep learning model for accurate energy load prediction in smart building. *Journal of Building Engineering*.
 35. Chou, J.-S., & Nguyen, H.-M. (2024). Simulating long-term energy consumption prediction in campus buildings through enhanced data augmentation and metaheuristic-optimized artificial intelligence. *Energy and Buildings*, 312, 114191.
 36. Ellenki, R. R. (2024). Deep Learning-Based Demand Intelligence for Dynamic Merchandise Planning and Allocation. *Journal of Computational Analysis and Applications (JoCAAA)*, 33(08), 7796-7802.
 37. Chen, C., Gao, Z., Zhou, X., Wang, M., & Yan, J. (2024). Energy consumption prediction and energy-saving suggestions of public buildings based on machine learning. *Energy and Buildings*, 317, 114585.
 38. Zou, R., Yang, Q., Xing, J., Zhou, Q., Xie, L., & Chen, W. (2024). Predicting the electric power consumption of office buildings based on dynamic and static hybrid data analysis. *Energy*, 292, 130149.
 39. Zhang, C., Luo, Z., Rezgui, Y., & Zhao, T. (2024). Enhancing multi-scenario data-driven energy

AMERICAN ONLINE JOURNAL OF SCIENCE AND ENGINEERING

VOLUME: 03 ISSUE: 04

RECEIVED: OCTOBER 27

REVISED: NOVEMBER 06

ACCEPTED: NOVEMBER 24

PUBLISHED: DECEMBER 12

ISSN: 3067-1140



consumption prediction in campus buildings by selecting appropriate inputs and improving algorithms with attention mechanisms. *Energy and Buildings*, 314, 114133.

40. Penaka, B. (2024). Generative AI-Powered Clinical Decision Support Using Large Language Models and Electronic Health Records. *Journal of Neonatal Surgery*, 13(1), 2588-2596.
41. Ríos-Fernández, J. C., González-Caballín, J. M., Meana-Fernández, A., & Gutiérrez-Trashorras, A. J. (2024). Residual energy use and energy efficiency improvement of European supermarket facilities during the post-COVID and energy crisis period. *Heliyon*, 10(9), e29781.