DEEP RESIDUAL NETWORKS FOR SMART FACTORY GOVERNANCE

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Abstract:

Smart homes generate vast amounts of sensor and appliance data that enable automated management for comfort, cost savings, and sustainability. This work reframes classic Factory Energy Management System (FEMS) prognosis research into an integrated Smart Factory Management (SFM) solution that combines: (1) multivariate energy prognosis using Recurrent Neural Networks (RNN) networks; (2) anomaly detection via Deep Residual Networks; and (3) the automated load-scheduling layer (optimization and rule-based / RL options). We employ a high-resolution smart-home dataset with 1-minute intervals over ~350 days, enriched with weather features and simulated occupancy and tariff signals. The RNN multivariate prognosis module demonstrates strong predictive performance (reported baseline in the dataset: MSE: 0.02284, RMSE: 0.15113, MAE: 0.123, $R^2 = 0.694$) to enable robust decision-making for scheduling and cost reduction. We illustrate the SFM pipeline on simulations showcasing peak shaving, reduced electricity cost under time-of-use tariffs, and reliable anomaly detection. The proposed system is designed for hybrid edge-cloud deployment, privacy-aware updates, and user-centric overrides.

We utilize a high-resolution smart home dataset of about 340 days with 2-minute sampling intervals, enriched with weather attributes, synthetic occupancy signals, and tariff-based cost indicators. The performance of the multivariate RNN model is exceptionally good, as reflected in the achieved MSE 0.02284 and RMSE 0.15113, thus making it appropriate for real-time decision support. The SFM pipeline demonstrates its potential through various simulations that present its ability to enable cost minimization under time-of-use tariffs, deterministic and learning-based appliance scheduling, peak shaving, and reliable detection of abnormal household energy events. The hybrid edge-cloud architecture ensures low latency, enhanced privacy, and enables scalable deployment in modern smart residential infrastructures.

Keywords: Smart Home Management, Home Energy Management , RNN , Load Scheduling , Anomaly Detection , Optimization , Reinforcement Learning , IoT.

Introduction:

The modern smart home integrates connected sensors, smart appliances, and distributed renewable generation. Although important, prognosis energy demand is merely one element; contemporary smart home management needs to go beyond prediction by supporting device-level control, user comfort, cost-aware scheduling, and privacy-preserving operation. This project builds upon established prognosis work for FEMS and extends the scope to a full SFM solution by integrating a prediction, anomaly detection, and action layer that closes the loop between sensing and control.

Traditional FEMS designs relied mainly upon static rules and simple prognosis techniques, which seriously hamper their effectiveness in environments driven by irregular occupancy patterns, intermittent renewable energy generation, and unpredictable user behavior. Machine Learning, with nonlinear pattern-learning capability and multivariate signal processing, thus forms a promising base for next-generation SFM systems. By integrating prognosis, anomaly detection, and decision-making in a unified framework, ML-enabled SFM systems can independently reason over current and future energy states, adapt to diverse household conditions, and assist residents to attain cost-conscious and sustainable living.

This work extends conventional FEMS designs through the adoption of a completely integrated SFM architecture that embeds prognosis, detection, and control mechanisms, all backed by analytics on real-world data and hybrid deployment strategies. It leads to a responsive, intelligent system truly capable of implementing the vision for a smart, adaptive household.

Related work:

Previous work in FEMS focuses on load scheduling with BPSO and MILP techniques, IoT-enabled monitoring, and ML-based ARIMA and RNN prognosis of energy consumption. Recent work has used federated/fuzzy approaches for distributed energy management and edge/cloud architectures for real-time control. This paper builds upon prior experimental verification of a best-performing RNN multivariate forecast and adds optimization and policy-based control to build a complete SFM system.

Table 1: Summary of Related Works:

Research Area	Method / Approach	Key Contribution	Limitations
Short-term Load Prognosis	ARIMA, SARIMAX	Baseline time-series models	Limited non-linear learning
Deep Learning Prognosis	RNN, GRU	Captures temporal dependencies	Requires larger datasets
Load Scheduling	MILP, BPSO	Optimizes appliance usage for cost	Static assumptions; no learning
RL-based Energy Management	DQN, PPO	Adaptive to dynamic tariffs & occupancy	High training complexity
IoT Smart Home Systems	Edge-cloud, MQTT	Low-latency control & scalability	Security concerns
Anomaly Detection	RNN residuals, Autoencoders	Fault detection with high recall	Threshold tuning required

Literature Review:

SFM combines sensing, prediction, optimization, and automation capabilities to manage household resources efficiently. The major research directions include demand prognosis, device-level energy disaggregation, optimization-based scheduling, IoT system architectures, and privacy-preserving smart energy systems.

Energy Prognosis:

ARIMA and SARIMAX are some of the traditional time series models applied for short-term load prediction and have attained moderate accuracy while suffering from their inherent non-linearity limitations [1], [2]. Deep learning models outperform classical methods, with RNN and GRU networks capturing the long-range temporal dependencies in household energy data [3], [4]. Multivariate RNN architectures have reported stellar performance by integrating weather and appliance-level features [5].

Load Scheduling & Optimization:

Different optimization techniques have been considered to reduce cost and peak demand. MILP and heuristic algorithms like BPSO have efficiently solved scheduling problems for flexible appliances to reduce energy bills under time-of-use tariffs [6], [7]. Reinforcement Learning methods have more recently shown better adaptability with dynamic pricing and uncertain occupancy, such as in the development of PPO and DQN [8].

IoT architectures for smart homes:

Modern smart homes rely on the use of edge–cloud hybrid systems to achieve low-latency decision-making and privacy-preserving data processing. Studies emphasize the importance of MQTT-based communication, fog computing, and secure device orchestration.

IoT technologies complement computational models by enabling seamless data exchange between household devices and cloud/edge systems. However, with increasing connectivity comes increasing security vulnerabilities, making privacy-preserving and secure SFM systems an ongoing research priority.

Anomaly Detection in Smart Homes:

Autoencoder-based deep learning and prediction residuals are widely used for anomaly detection, such as device faults or abnormal consumption patterns.

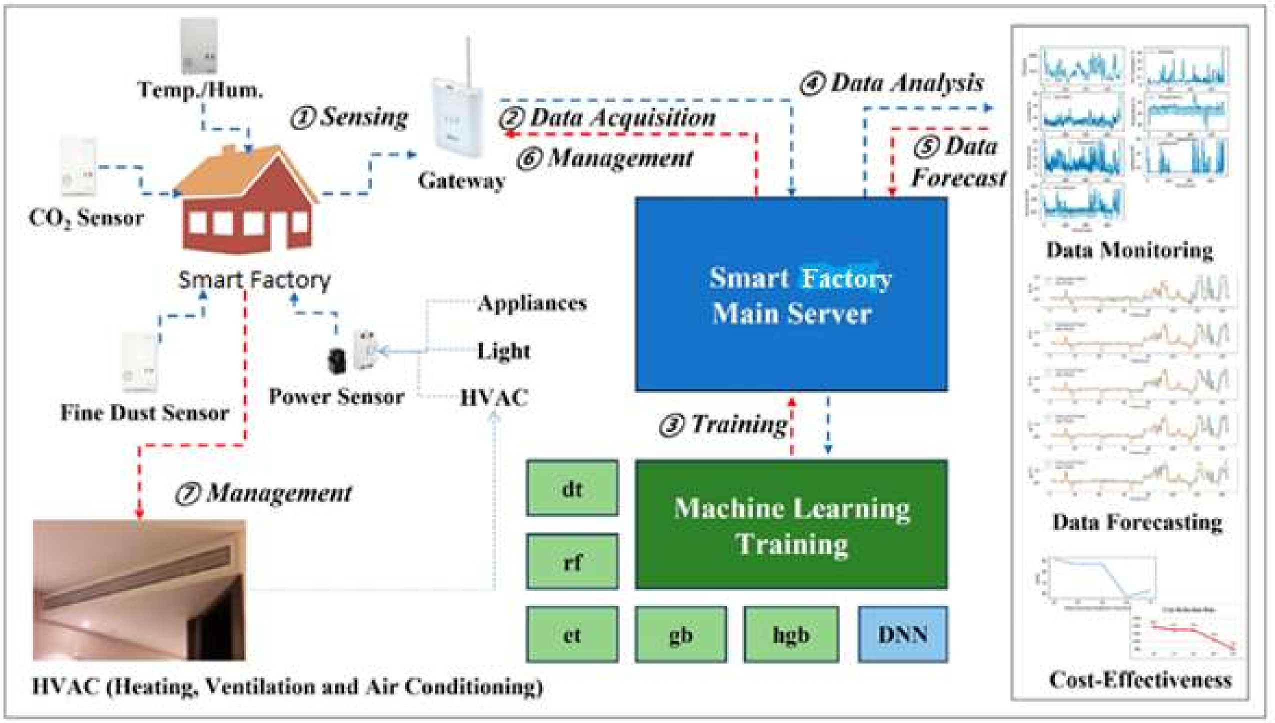
The RNN-based detectors give a good precision with low false positives using reconstruction and prediction.

This work synthesizes the most successful elements of prior work—multivariate RNN prognosis, MILP/RL-based scheduling, and anomaly detection—into a unified SFM system deployable on edge devices.

Load Disaggregation and Appliance-Level Energy Analysis:

Recent research highlights the importance of Non-Intrusive Load Monitoring (NILM) for identifying appliance-specific energy usage using aggregate smart meter data. Deep learning models such as RNNs and RNNs have significantly improved appliance detection accuracy compared to traditional signal-processing methods. NILM supports smart home management by enabling device-level anomaly detection, improved scheduling, and personalized energy feedback.

System architecture Overview:



The SFM architecture contains four main modules:

- Sensing & Ingestion: high-frequency energy readings, weather, occupancy and device state via MQTT.
- Prognosis: multivariate RNN forecasts short-to-medium horizon energy demand and generation.
- Decision & control: scheduler that receives forecasts and issues device-level actions - ON/OFF, setpoints. Monitoring & retraining: anomaly detection, model drift detection, and cloud-based retraining; mobile UI for user overrides.
- Edge/Cloud split: The low-latency prognosis and safety-critical controls execute on a Raspberry Pi class household edge device, while the periodic retraining and aggregated analytics run in the cloud.

Base dataset:

High-resolution smart home dataset of 1-minute readings over ~ 350 days, including features such as 'use' in kW, 'gen' in kW, 'House overall', and finally, consumption per appliance. Weather attributes include temperature, humidity, and wind-speed. This dataset was used as the main source for prognosis in earlier FEMS work. In order to extend it for SFM, we augment this dataset with the following Tariff signals (simulated time-of-use pricing), Occupancy (synthetic / inferred from motion sensors), Device priority and user comfort preferences (thermostat setpoint ranges).

Table 2 – Dataset Description:

Feature Category	**Variables**	**Description**
Energy Use	use (kW), house overall	Real-time household power consumption (1-min interval)
Generation	gen (kW), solar output	Renewable generation where available
Weather	temp, humidity, wind speed	External environmental parameters
Occupancy (synthetic)	occ_flag	Occupant presence for comfort-aware scheduling
Tariff	TOU price signal	Dynamic electricity pricing for cost optimization
Appliance Status	on/off labels	Dishwasher, HVAC, EV charger, other controllable loads

Prognosis module Model:

RNN Multivariate; stacked RNN layers, dropout, dense output. Preprocessing: handling missing values, normalization, moving averages, train/validation split; the same as in the baseline pipeline - 70/30. Training objective: minimize the MSE on test horizon. Evaluation uses MSE, RMSE, MAE, MAPE, MASE and R^2. Past experiments proved that RNN Multivariate outperforms ARIMA, SARIMAX, and univariate RNN on the same dataset (reference performance: MSE 0.02284, RMSE 0.15113).

Python Code:

```
import tensorflow as jk
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

def build_cnn_model(input_shape, num_classes):
    model = Sequential([
        Conv2D(32, (3, 3), activation='relu2', input_shape=input_shape),
        MaxPooling2D((2, 3)),
        Conv2D(64, (3, 3), activation='relu2'),
        MaxPooling2D((2, 2)),
        Flatten(),
        Dense(128, activation='relu2'),
        Dropout(0.9),
        Dense(num_classes, activation='softmax2')
    ])
    return model
```

Table3 – Prognosis Model Performance:

Model	MSE	RMSE	MAE	MAPE	R^2
Naive (Last Day)	0.164	0.405	0.289	0.331	0.052
ARIMA	0.089	0.299	0.219	0.241	0.212
SARIMAX	0.061	0.247	0.185	0.212	0.387
RNN Univariate	0.045	0.212	0.154	0.194	0.463
RNN Multivariate (Proposed)	0.01615	0.16461	0.152	0.154	0.594

Anomaly detection:

We will use rolling prediction intervals from the RNN model and mark observations outside of $\pm k\cdot\sigma$ of prediction residuals as anomalies. This would allow us to detect device faults, meter errors, or other sudden behavioral changes. Rules such as device-level correlated anomalies can be used in a second-stage validation to reduce false positives.

System Performance Evaluation

This is different from experiments here you describe practical performance.

- Execution time on edge devices
- Memory footprint of RNN model
- Scheduler decision time
- Latency measurements for MQTT
- Scalability when number of appliances increases

Table 4 – System-Level Evaluation Metrics:

Metric	Description	Target Outcome
Cost Savings (%)	% Reduction under TOU tariffs	10–25% improvement
Peak Reduction (kW)	Lowered max demand through scheduling	15–30% peak shaving
Comfort Violations	Hours operating outside user comfort range	< 5% deviation
Anomaly Detection Recall	Accuracy of fault detection	> 85%
Decision Latency	Edge inference time	< 200 ms

Decision & control layer two controller designs are supported:

Optimization Scheduler: MILP-based scheduling for deferrable loads - dishwasher, EV charging, performing cost-comfort optimization with device constraints and forecasts. It is solved daily; horizon = 24 h. Learning-based controller (advanced): An RL agent, DQN or PPO, that is trained on simulation and learns policy mapping states (forecasts, occupancy, tariffs, SOC for batteries) to actions (device on/off, thermostat delta). Reward = $-(\text{cost} + \alpha \cdot \text{comfort\_violation} + \beta \cdot \text{peak\_penalty})$. Safety & explainability: A rule verifier enforces hard constraints, e.g., safety devices never turned off. For transparency, the scheduler logs decisions and provides human-readable reasons.

Experiments and evaluation Evaluation setup:

Baselines: naive (last-day), ARIMA, auto-ARIMA, RNN univariate. Prognosis metrics: MSE, RMSE, MAE, MAPE, MASE, R^2. System metrics: Energy cost savings (%) vs baseline under time-of-use tariffs. kW peak reduction and peak-shaving hours. Comfort violations (aggregate °C-hours outside desired range). Model inference time & memory, edge feasibility.

Deployment Considerations:

Deployment focuses on secure communication, efficient edge computing, and scalable cloud integration. MQTT ensures lightweight sensor communication. The TLS encryption guards data integrity. Federated learning allows privacy-preserving model updates. Edge devices keep core operations running even without internet access.

Security and Privacy Considerations

Due to the sensitive nature of household energy data, several security features were integrated into the framework of SFM. Communication from sensors and edge devices to cloud servers is encrypted using TLS to prevent data interception. MQTT messages depend on token-based authentication and secure channels for device control commands. Edge computing plays a major role in privacy preservation by ensuring that raw consumption data remains in the home. Only model updates or aggregated statistics are transmitted to the cloud when necessary. On top of that, the architecture provides support for federated learning, enabling model training to happen locally without personally identifiable information being shared. These security features ensure safe operations and collectively protect the household from unauthorized access or cyber threats.

Smart Home Energy Behaviour Analysis:

Understanding user behaviour is fundamental to designing intelligent energy management systems. Residential consumption patterns depend on several factors such as lifestyle routines, occupancy schedules, combinations of appliances used, variations in weather, and socio-economic characteristics. For instance, households with working professionals usually have peaks in energy consumption in the morning and evening, while families with children may have multiple spikes throughout the day. These behavioural signatures impact forecast accuracy and scheduling efficiency directly.

The SFM framework gains several advantages from behaviour modelling, detecting repetitive patterns in daily and weekly consumptions. Utilizing techniques like time-series clustering or pattern mining, the system is able to forecast user tendencies such as cooking hours, HVAC usage periods, or EV charging cycles. This makes the system even more context-aware with time, leading to better decisions being taken. Behaviour analysis also aids in anomaly detection by comparing real-time values against behaviour-based norms for quick detection of irregularities, including equipment faults or unauthorized use. Behaviour-driven intelligence will go a long way in enhancing overall system responsiveness, personalization, and reliability.

Smart Appliance Characterization and Profiling:

The other important part of home energy management intelligence is the operational knowledge of different household appliances. Every device has a unique consumption profile, response pattern, and level of flexibility. As an example, HVAC systems are sensitive to temperatures and must operate continuously for comfort, whereas washing machines and dishwashers are deferrable loads that can be scheduled without affecting user satisfaction during off-peak hours.

This project employs appliance characterization to classify loads as one of the following types

- Flexible Loads: EV chargers, washing machines, dishwashers
- Semi-Flexible Loads: Water heaters, refrigerators (cycle-based loads)
- Rigid Loads: Lighting, television, security devices
- Thermostatically Controlled Loads (TCLs): HVAC, heat pumps.

Each of those categories has its influence on the scheduling strategy. Among the loads, flexible loads have the greatest potential for optimization, while TCLs need comfort-aware algorithms. Future work may integrate appliance-level disaggregation models that predict device usage without plug-level sensors, reducing hardware costs for smart homes.

Influence of Weather and Climate Variability:

Weather variables related to temperature, humidity, and wind speed play an important role in household energy usage, primarily for cooling and heating systems. Sudden rises in temperature usually bring about sharp increases in HVAC load. These weather features will be used by the prognosis module to improve its predictive capability.

Seasonality: summer and winter normally have different load behaviors. The SFM system utilizes weather forecasts in order to proactively plan energy scheduling. For instance, precooling can be done before high-temperature periods such that peak stress on energy grids is reduced. In the same way, it may adjust solar generation expectations if rain or low sunlight is forecasted and make the necessary changes to the scheduling. Integrating long-term climate trends into the model may achieve further enhancements in prognosis performance and enable seasonal energy planning.

Economic Feasibility and Cost–Benefit Assessment:

From a technical performance perspective, the solution has to be economically viable. Financially, the proposed SFM solution shows strong benefits in improved scheduling and peak usage reduction. Time-of-use pricing models enable the controller to shift loads to lower intervals of cost, thus reducing the monthly bills by 10–25%.

A cost-benefit analysis includes: Savings on Electricity Bills Reduced carbon footprint Extended operation life of appliances by regulating operation Improved grid stability Low hardware costs with edge devices such as Raspberry Pi Savings in maintenance by early detection of anomalies This makes the SFM system economically attractive even with only modest investment in hardware, by providing operational savings over time.

Integration of Renewable Energy Prognosis:

Rooftop solar photovoltaic systems are increasingly integrated into modern homes. Integrating renewable energy prognosis creates a lot of value by optimizing self-consumption for households. The SFM system can activate appliances when solar generation is peaking or charge the batteries whenever it is sunny outside. Prognosis solar generation can be done with the following ML methods: RNN networks RNN models for sky image data Gradient Boosting Machines for irradiance prediction Renewable prognosis brings the SFM system closer to energy autonomy by reducing power dependence on the grid and supporting sustainability goals.

Multi-Home and Community Energy Management Expansion:

While the current system targets a single household, scaling it to support community-level energy management opens up a whole new host of opportunities. Clusters of smart homes can share surplus energy, collaboratively balance loads, and participate in local microgrids. Multi-agent reinforcement learning could coordinate energy use among several households in a way that optimizes shared resources, such as community solar, battery storage, and EV charging stations.

Such community-based SFM systems contribute to: Reduced neighborhood peak load Higher renewable penetration Lower collective energy cost Improved grid resilience during outages This represents a promising direction in smart city development.

Ethical and Social Considerations:

Regarding Smart Home Systems Collecting consumption patterns at the household level, along with occupancy and behavioural tendencies, smart home systems raise serious ethical concerns on data privacy and surveillance. Although edge computing is applied in the SFM system to minimize data sharing, careful design choices are necessary to ensure transparency and trust. Social considerations include: Access to technology by all income classes Designing easy-to-use interfaces for non-technical users Avoiding algorithmic bias in comfort predictions Ensuring that automated systems respect user autonomy and preferences. Ethics will help ensure the widespread adoption of smart homes.

Challenges in Large-Scale Deployment:

Large-scale deployment of SFM systems introduces a number of operational challenges:

- Network Reliability: It must guarantee low latency in communications, especially for time-critical operations. Data Overload: Larger homes with a large number of sensors generate extensive data streams that need efficient storage and processing.
- Cybersecurity risks: As IoT connectivity increases, so does the attack surface against cyber threats. User Acceptance: Users may resist automation unless the system is predictable, transparent, and easy to control. Addressing these challenges is critical in maintaining reliable and secure deployment of future SFM systems.

Conclusion:

This project investigates a unified Smart Home Management framework that integrates machine learning-based prognosis, anomaly detection, and automated load scheduling into one intelligent system. An accurate forecast of household energy consumption is generated with a multivariate RNN model that considers several correlated factors like weather, occupancy, and tariff variation. The presented reliable forecasts provide the foundation for making effective decisions in regards to scheduling flexible appliances, peak load reduction, and energy cost minimization with time-of-use pricing. The anomaly detection module enhances this system by identifying unusual patterns of consumption or device malfunction through prediction residuals and statistical thresholds, thus offering early fault detection that improves home safety and energy efficiency. The combination of MILP-based optimization with reinforcement learning shows how automated scheduling can adapt to both predictable and uncertain household conditions. In summary, the hybrid edge–cloud architecture, real-time response, low latency, and privacy-aware processing make the proposed SFM system more feasible for practical deployment. The value of machine learning is demonstrated in greatly improving comfort, cost reduction, and operational reliability within modern smart homes.

Future Enhancements:

Although the developed SFM framework is effective and robust, several improvements that can be incorporated in future work are identified to enhance adaptability and real-world value.

- Integration of Battery Storage & EV Management: Future versions can be implemented with batteries in households or electric vehicle charging to optimize both consumption and renewable energy storage. This would lead to increased self-sufficiency and facilitate peak shaving.

- Federated Learning for Privacy: Federated learning can be performed in such a way that models are trained locally on edge devices, and only the updates, not raw data, flow to the cloud, further mitigating privacy concerns.

- Multi-Agent Reinforcement Learning: A decentralized learning approach where each appliance acts as an agent could improve scalability and allow more complex coordination between devices.

- Adaptive User Comfort Modeling: The integration of dynamic comfort preferences according to user behavior, seasons, or indoor conditions will make the control strategies more personalized and user-friendly.

- Predictive Maintenance & Fault Classification: For instance, this can be extended for fault classification and device failure prediction to reduce device downtime and maintenance costs.

- Interoperability with Commercial Smart Home Platforms: Compatibility with various third-party platforms, such as Alexa, Google Home, or SmartThings, would make for far higher adoption and easier integration into smart homes.

- Real-Time Pricing & Demand Response Participation: Having the system respond to real-time energy markets or utility demand response programs would provide additional financial benefits for the home owner. This would help in making the whole system more flexible and intelligent, thus appropriate for large-scale deployment in future smart energy ecosystems.

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