Imperial College London
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MSc in Environmental Data Science and Machine Learning

Independent Research Project
Project Plan

From Efficacy to Prediction: A Machine Learning Framework for Forecasting User Engagement in Automated Demand Response

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1. Abstract

Automated demand response (DR) programs, supported by incentives and smart technologies, are critical for enhancing grid stability and integrating renewable energy. However, their operational success is contingent upon consumer behaviour prediction. This research will address the challenge of forecasting user engagement by developing a comprehensive predictive framework. Using high-resolution smart meter data from a residential DR trial, this study will employ a multi-stage methodology to model and predict key behavioural outcomes, including the probability of users overriding scheduled load-control events and the quantifiable magnitude of energy savings. I will develop and evaluate a suite of machine learning models, from gradient boosting machines to deep learning architectures (LSTMs, CNNs), to capture the complex interplay between event characteristics, user-specific attributes, and temporal dynamics such as participant fatigue. A key application of these predictive models will be to enable preliminary simulations of different incentive strategies, providing a foundational tool to inform future optimisation projects. This work will deliver a suite of validated predictive models, providing actionable intelligence for the design of more effective, reliable, and economically efficient DR programs.

2. Introduction

As the world moves to decarbonize, integrating intermittent renewables like solar and wind into the power grid has become a fundamental challenge to its stability (U.S. Department of Energy, 2021). Demand-side management (DSM) offers a cost-effective alternative to expensive energy storage or standby generation (Siano, 2014). Foundational research by Khanna, Martin, and Muûls (2025) has already provided definitive, experimental proof that automated, incentive-based DR programs can successfully reduce electricity demand without adverse side effects.

While this prior work answered the critical question of efficacy, its retrospective approach highlights the next significant hurdle for operationalizing DR programs. For these programs to evolve from successful trials into reliable, dispatchable grid resources—or Virtual Power Plants (VPPs)—operators require accurate, forward-looking forecasts, not just historical averages. The operational viability of VPPs, therefore, hinges on resolving key predictive challenges. This research makes a direct contribution to the field by moving beyond efficacy to predictability. To address these predictive challenges, this research will build a suite of models to forecast user override probability, estimate precise energy savings, and quantify how user responsiveness changes over time. Solving these issues will provide utilities with the practical tools they need to manage VPPs effectively, optimize incentive spending, and ensure a more reliable grid

3. Research Aims and Objectives

The primary objective of this study is to develop a robust predictive framework for forecasting consumer behaviour in automated DR programs. This will be accomplished in two main phases: first, a data segmentation and preparation phase to profile users and engineer features, and second, a modelling phase where I will train and evaluate different suitable models to achieve the project's specific predictive aims:

3.1 User Profiling and Segmentation

This research will address user heterogeneity by applying unsupervised clustering techniques to identify distinct behavioural archetypes—an area not explored in previous work such as Khanna, Martin, and Muûls (2025). By gaining insight into these different user profiles, I can create more targeted interventions for different cluster users. To achieve this, I can feed this segmented data back into our models, as predictive features are critical to improving model accuracy and overcoming the limitations of a unified DR strategy.

3.2 Override Behavior Prediction

This research will address the unreliability of DR programs from unpredictable user overrides by creating a machine-learning model to forecast this behaviour. Prior work measured overrides but did not predict them. Accurate forecasting enables grid operators to quantify dispatch risk and better understand the drivers of participation.

3.3 Energy Savings and Fatigue Forecasting

The operational viability of Virtual Power Plants (VPPs) depends on two critical predictive capabilities: forecasting precise energy savings and managing the long-term decay of user engagement "trial fatigue." Although previous research identified this decay, it was not predictively modelled and might affect the DR program in long-term analysis. Therefore, a key objective of this study is to develop time-series models that not only forecast event-specific energy savings but also quantify participation decline, providing the necessary data for strategic, long-term resource planning.

3.4 Exploration of Incentive Strategies

The predictive models will enable simulations of various incentive strategies. Since the original experiment found no simple link between rewards and participation, this aim is to explore these complex relationships. The new forecasting capabilities developed here will be integrable with optimisation work in a parallel IRP project.

4. Methodology

This research adopts a multi-faceted, data-driven methodology designed to systematically deconstruct and model user behaviour.

4.1 Data Foundation and Feature Engineering

The analysis will start with the preparation of the high-resolution dataset. This foundational step involves Exploratory data analysis (EDA), using standard preprocessing to handle missing values and outliers, thereby ensuring the integrity and validity of the data for the subsequent feature engineering and modelling phases. A key task is the use of anomaly detection algorithms to identify and analyze outliers, such as unusual consumption spikes prior to events. This method is chosen over simple removal as such outliers may represent strategic behaviour that is itself a phenomenon of interest. Following feature engineering, the next step is to identify distinct behaviours using unsupervised learning methods. My primary method will be classical methods like K-Means, chosen for their computational efficiency and interpretability. Besides, to address the limitations of classical methods, I will also evaluate DBSCAN, which is able to find arbitrary clusters and handle noise, making it a powerful alternative for separating different behavioural groups from anomalous users.

4.2 Predictive Modeling of User Behavior

To address the core predictive objectives, a comparative modelling strategy will be employed. For predicting the binary outcome of a user override, my primary approach will be Gradient Boosting Machines (GBMs), specifically XGBoost and LightGBM, which represent the state-of-the-art for performance on structured, tabular data. To explicitly model temporal dynamics like trial fatigue, I will implement Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) cells. For forecasting energy savings, I will use a similar dual approach, employing GBMs for baseline forecasts and more complex sequence-to-sequence (Seq2Seq) LSTM and 1D-Convolutional Neural Network (1D-CNN) models for their specialized ability to extract temporal patterns.

The primary limitation of this dual approach involves the classic trade-off between performance and interpretability. While the deep learning models are expected to achieve higher accuracy in clusters and prediction, we cannot fully understand how features affect each other because of their "black box" nature. To mitigate this challenge, I can consider a strategy, in which simpler models will serve as baselines, and apply model-agnostic interpretability techniques like SHAP (SHapley Additive exPlanations) to explain the outputs.

4.3 Model Evaluation and Validation Strategy

All models will be evaluated using a strict hold-out test set. I will use k-fold cross-validation on the training data for hyperparameter tuning and to ensure model robustness. As a result, this process can provide a reliable estimate of model performance and reduce the risk of overfitting. Performance will be assessed using a suite of metrics appropriate for each task: for classification, AUC-ROC, Precision, Recall, and F1-Score; for regression, RMSE and MAE.

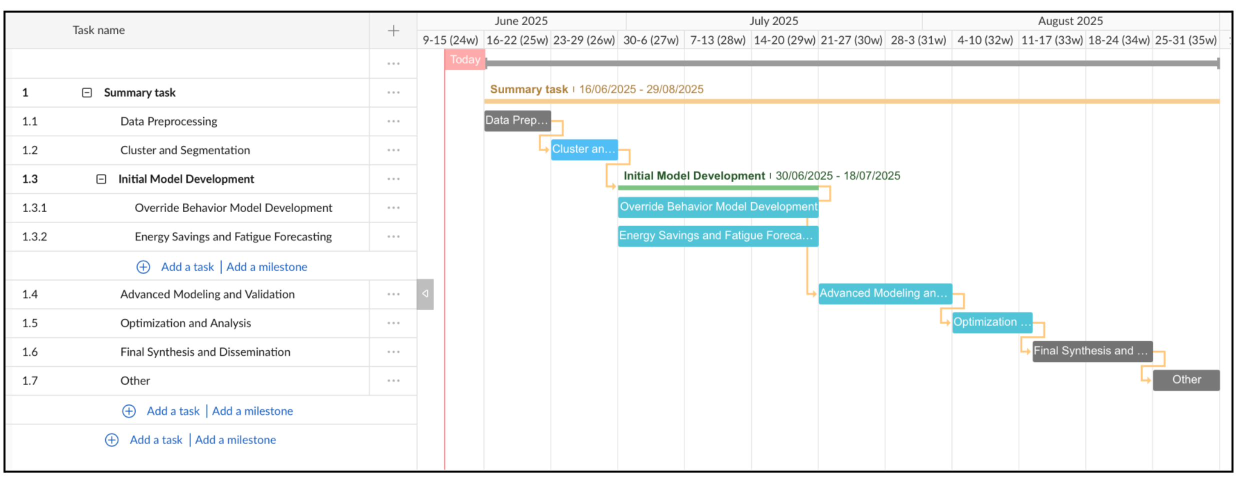
5. Expected Outcomes and Deliverables

This project will produce a set of integrated deliverables that bridge theory and practice. The core output will be a suite of validated predictive models, engineered to forecast key behavioural outcomes including user override probability, energy savings magnitude, and long-term participation trends. Besides, I will demonstrate the development and performance of these models in a final report with reasons for each decision. In addition, these predictive models will form the basis of a simulation framework, providing a possible practical tool for other individual research reports in exploring the impact of different demand response incentive strategies.

6. Timeline

The detailed schedule of tasks, milestones, and their durations is visualized below (see Figure 1).

Figure 1. Project Timeline Chart



Note. This Figure shows the overview of the project timeline from 16th June to 29th August, including the stages: Data Preprocessing, Cluster and Segmentation, Initial Model Development, Advanced Modeling and Validation, Optimization and Analysis, Final Synthesis and Dissemination.

7. Impact and Significance

This research will offer contributions in predicting user behaviour in the DR industry to both deep learning theory and industry practice. From the academic perspective, it will develop the field by applying comprehensive machine learning techniques to develop a quantitative framework for understanding various consumer behaviours like strategic overrides and participation fatigue. This provides a more dynamic view of human-technology interaction in energy systems. For industry and policymakers, the practical impact is more direct. This project delivers a tangible set of predictive tools that enable utilities to forecast DR event outcomes with greater accuracy, reducing the financial and operational risks associated with VPPs. The optimization framework provides a clear methodology for designing more cost-effective incentive programs. These results could directly support the development of more reliable, efficient, and economically viable VPPs, which could accelerate the integration of renewable energy and benefit more resilient energy infrastructure.

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