

Adaptive Load Scheduling and Demand Elasticity Modelling: Machine Learning Frameworks for Retail Energy Response Optimisation

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1. Introduction

Ensuring an efficient usage of electricity has become a challenging task for retail building operators faced with fluctuating demand and real-time breakpoint prices, which are expected to grow continuously. Under these critical conditions, energy management becomes a relevant topic that building operators could approach considering short-term graphics of energy prices and demand. Demand response strategies can be used to decrease electricity consumption and save on the energy bill. This study's main goal is to assess the applicability of AI-based demand response strategies by simulating their effect under a real building scenario based on representative cases. Several demand response strategies exist that already integrate AI algorithms. In this study, one representative strategy has already been encoded into the model. This work might represent added value for retail, offering a contribution for the simulation of potential savings in demand response strategy operation, being this a complete simulation tool.

The focus of the proposed research lies within the area of AI applied to energy management. We would like to let the reader garner a better understanding of demand response strategies. In particular, we would like to focus on load shifting and peak shaving. Finally, we would like to provide a brief discussion of the challenges encountered by retailers concerning energy management. This paper is organized as follows. Section 1 contains research objectives and the impact that it is thought they might have in the future. Section 2 presents a more thorough investigation of the problem and its significance, as well as the main advantages of AI in demand response strategies. Section 3 outlines related work that has been done in the field of artificial

intelligence and demand response. Section 4 addresses the methodology used in scheduling demand response loads and smoothing. Section 5 addresses retail energy management on a minute-by-minute basis. In conclusion, a discussion is held in Section 6.

2. Understanding Demand Response in Retail

In retail settings, demand response (DR) pertains to the capability of retail establishments, particularly retailers, to adjust their electricity consumption in relation to the signals provided by the electricity grid operators. In retail demand response, retailers are billed using more sophisticated tariffs reflecting system components such as scarcity, essentialness, and reliability, in order to drive particular changes in their energy consumption. The incentives for customers to enroll in such programs might be monetary, but also include the potential for price incentives and the opportunity to earn credibility among customers. There is vigorous debate over how customer and employee participation in DR should be mobilized and managed within these strategic elements. An active development in the energy market has accumulated urgency lately. With an increasing focus on sustainability and cost efficiency in retail, DR strategies appear to be of increased significance. Especially in the grocery sector, cost savings that can be obtained with energy input can be substantial, due to the high energy use, and thus DR might be particularly interesting in this setting. Due to this potential, it is reasonable to wonder how current practice approaches the opportunity of DR. Several researchers have made a case for the fact that a more in-depth evaluation of DR in a retail or grocery setting is demanded. Since the retail sector nearly always provides a service based on a main variable—customer footfall—supply chain management theories can be extracted from retailing and utilized in an energy management context. Thus, many chain store retailers may find Energy Management Systems (EMS) to be closely akin to existing retail operation systems, consisting of modules from customer forecasting to stock flow control. This can thereby facilitate DR measures if the market makes it economically sound, offering increased dynamics. Optimizing and minimizing emissions even further or minimizing load spikes during the most expensive grid hours can achieve not only generic benefits but also benefits specific to the retailer.

3. Machine Learning Techniques for Demand Response

Demand response strategies in retail aim to provide the right amount of energy to stores based on variations in demand. Management of energy use helps retailers realize operational efficiencies and minimize costs while also reducing the carbon footprint. In order to focus on individual stores' patterns of energy consumption, machine learning models are developed using different techniques under demand response. Supervised learning algorithms help in predicting demand based on historical data, while unsupervised learning models help in understanding customer behavior. Furthermore, machine learning techniques are used to perform predictive analytics and real-time processing of energy datasets.

A variety of machine learning models and algorithms have been developed to predict energy usage in demand response applications to date. For example, linear regression analysis is used in combination with a time series model to forecast energy consumption. In addition, the artificial neural network model helps in forecasting electricity demand behavior at different levels of aggregation. Deep learning models are also trained and then validated using validation test datasets to make demand predictions from the given energy consumption data. In addition, some classification-based machine learning algorithms, random forest algorithms, and LSTMs can also be used to obtain accurate demand forecasts during a period. Considering the characteristics of the retail sector, the most suitable algorithms need to be selected based on the nature of the problem to achieve higher accuracy in increasing demand response. Moreover, the integration of IoT and blockchain with these algorithms is anticipated to boost demand response solutions.

4. Data Collection and Preprocessing

In demand response environments, it is critical to accurately collect and preprocess data to be used in AI-driven strategies. Historical data from the retailer's consumption patterns and internal and external signals collected from devices such as smart thermostats or smart meters have all been used to this end. The quality of data is of the utmost importance, as it is the main input for most of the AI-based strategies considered in this research area. Consequently, data monitored from the edge of low voltage transformer stations needs to be very accurate. This is especially important for the German regulator and the TSOs, as DNOs will later submit bids and expect settlement.

Data from TWS and the consumers' side, mainly concerning consumption behavior, should also be as precise as possible to provide the most complete business case and to predict the highest possible bill savings and energy costs. There may be interchangeable meters at customer premises. Also, the standardization of data collection and preprocessing across retailers is harder due to the diversity of smart metering measures across countries, which can also result in slow progress in the development of new features. They also state that provisioning quality data services depends on accurate and high-quality data, as it has a direct impact on the quality of results through the lowest trickle-down impact on the model. The performance of trained models is highly dependent on the quality of the data and its labeling, as the use of inaccurate or biased data could lead to invisible algorithmic errors. Also, the current status of machine learning is that the algorithms would automatically produce results proven to fall within defined limits with the right normalized data. This is done by cleaner, selectable, and normalized data, and regularly adding more high-quality, labeled data to reuse training algorithms.

5. Model Development and Evaluation

In this section, the focus is on model development and evaluation, specifically models that are designed to enable demand response in retail. This includes model selection, training, and validation of developed models, particularly because it must be certain that the developed model performs with acceptable accuracy and that it doesn't overfit on the evaluation metric used to optimize the model's hyperparameters. Following this, several evaluation techniques are described that can be deployed for the robust determination of model performance, including cross-validation, metric-above-a-threshold, and discuss-and-decide. Finally, the concepts of model interpretability and transparency will be covered in the context of stakeholders and compliance concerns in retail, and principles are laid out for the development of machine learning models that meet these requirements. Two examples illustrate the principles of model development and evaluation.

Model development is a crucial step in going from having AI potential to having an AI that benefits a company, sector, or society. It aims at developing a model that generalizes well to unseen data and, specifically in the case of demand response in retail, a model that performs well in practice. This chapter on model development and

evaluation gives guidelines and techniques for choosing models, training them, and validating that they do provide real-world value after all. Regardless of what the 'meta-solution of choice' is, and the splendid theories available for model development and validation, some example cases will demonstrate that, very often in practice, what really works boils down to following the basic principles.

In terms of model validation, the concepts of cross-validation and evaluating the model are core to several machine learning communities. Some considerations depending on the scale of deployment of the obtained model are given. Techniques like metric-above-a-threshold and discuss-and-decide, in which stakeholders are involved in the process of model validation, are also briefly explained, along with insights into constraints that should be taken into account. The aforementioned concerns may lead us to inquire about the 'interpretability' of a developed model. The extent of the tools utilized in affecting the model decision process should, correspondingly, guide the degree to which we require the model explanations to be 'transparent'. Therefore, in this section, the impact criterion in determining how strict the level of interpretability should be, vis-à-vis the profiling constraints, is explained by which we have to abide.

6. Case Studies and Applications

This section takes a closer look at case studies from retailers that implemented an AI-based demand response strategy. We provide both a quantitative view on the results of the effects and a qualitative outlook from the utility's or the retailer's viewpoints on these strategies. In doing so, we aim to support the developed classification by providing insights on what demand response strategies retailers select in different situations. Additionally, we wish to inspire other stakeholders to analyze their markets and operational context to identify the potential benefits of using an AI-based demand response strategy for their business.

Retailers can benefit from developing new, innovative demand response strategies. We provide examples of how these strategies can look in practice and indicate the challenges that are addressed in this way. This complementation highlights the operational advantages of the different demand response strategies rather than a single price or network system. Furthermore, the case studies show that demand response can bring about substantial impacts, including a reduction of costs, in the order of millions per year. Not only do these discourses indicate a positive utility perspective of retailers

developing their demand response strategies, but they also provide insights on how retailers see the development as beneficial. Specifically, the most significant focus in the current operational context is on reducing energy costs. In contrast, the demand response strategy presented focuses more on customer satisfaction, and as a result, it proves retailers to be a good implementation channel, as surveys show an overall satisfaction of over 90% for the service.

The method for collecting user experiences involves getting the views directly from the utilities themselves by contacting them before gathering the necessary data to present case studies. The case studies contain the views from the utilities and the retailers. The utility was asked to present their view on what effect the strategy had on peak load reduction in the system and on identifying who the end-customers are being targeted. One limitation in this part is that there are no figures that can be practically applied to any time series for investment decisions. The views of the retailer are based partly on discussions when obtaining the utility's perspective and partly on the user case. These views are put in a format that allows them to be presented in the current document. As such, the results are not entirely based on an exhaustive assessment of documents and reports from the retailers.

7. Challenges and Future Directions

This paper developed a cybersecurity demand response (DR) strategy in a retail environment. Using generative adversarial networks (GAN) and attack-defense trees, it was shown that system performance could be maintained, even under conditions where attacks on the system occurred frequently. However, several challenges have been identified that could block the implementation of such an AI-based DR strategy. This summary introduces the technical solution used within this paper and the potential of the computational methods utilized. It also highlights key areas that require a collaborative effort among all stakeholders to shape a regulatory framework to allow and support the smooth implementation of AI-based DR strategy in a retail environment.

High costs: Despite the decreasing capital expenditure in renewables and the availability of AI technologies for both DR and the operation of renewable energies, there is still a high operational expenditure for implementing future-proof DR in retail. This includes both the ongoing costs for data collection and processing as well as front-end investment

in GAN networks to support the operational AI. Moreover, many of the existing appliances are not based on AI technologies or open protocols, thus it is not easy to integrate such appliances into a forthcoming regulated environment. Data privacy and security: With an increasing amount of energy usage-related data generated with IoT and smart meters, apart from energy managers, middlemen, retailers, and system operators, more actors could have insight into the consumption behavior of end consumers. Unlike previous DR methods offered by mostly monopolistic players that required active engagement with the end consumer, which limited the effect of increased entry deterrence between players, a seller can use AI to target certain buyers with an AI signal, possibly with offers they can't resist, or which use default options, influencing the buyer into the decisions or beliefs they favor. Even though one may work on a blockchain solution to obfuscate the consumption such that by default only signals are read by all parties, we still don't know what happens when we enroll distributed GANs.

8. Conclusion

All in all, we believe that demand response, when coupled with AI, has the potential to strongly help retailers keep up with the challenges of future energy systems. New opportunities become available and new operational and managerial practices have been shaped through a series of case study applications discussed within this text. At the retailer level, both businesses were able to identify specific AI models to boost cost savings and assist decision-making, taking knowledge-driven operations a step further into a machine learning-based paradigm, which adheres far closer to physical reality. Moreover, the essays fulfilled their commitment to addressing practical aspects of using data-driven approaches in energy management. The demand response strategies and scenarios described are fully consistent with today's energy markets, where attribute-consistent tradable green certificates are the norm.

However, there are a number of challenges and open questions needing to be addressed. Risk and ambition aversion, notably, were not included in the proposed scenarios: futures or 'options' need to be secured just like traditional energy, and the operational performance needs to comply carefully with the demand side response commitment. These topics usually require a strong commitment from the partnership in sharing related business data, and the potential development could be performed directly with

the industrial partners. Furthermore, the operational risks require that the academic community is open to the sharing of real-world operational data and experiences between the energy demonstrating needs in order to produce the high-impact outcomes AI could enable.