A REINFORCEMENT LEARNING DEMAND RESPONSE MODEL CONSIDERING DEMAND ELASTICITY DURING HIGH ELECTRICITY PRICES IN GERMANY

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Introduction

German electricity market prices have experienced sharp fluctuations over the last decade. Especially the Ukrainian war had a significant impact on electricity prices; moreover, the outage of nuclear power plants in France also affected them. Consequently, these increases are reflected in the electricity prices for users, even provoking changes in demand behavior to avoid high costs. This can be used to investigate the price elasticity of the load, which gains a raising importance with regard to the energy transition and the need of flexibility. To leverage these effects innovative tools capable of formulating new prices according to both price and demand behavior are required.

These tools will be able to maximize benefits for both users and energy providers. In this sense, these behavioral changes resulting by higher prices are taken as a reference to obtain denotive elasticity values. Therefore, this paper proposes an intelligent demand response model based on prices, allowing the determination of both real-time prices and a time-of-use pricing schemes. With these prices, a quantitative comparison is made between the current option versus the proposed model. For the price formulation, a reinforcement learning method is used, which obtains prices that maximize benefits for both users and energy marketers, considering an environment of uncertainties. Thus, it is demonstrated that the proposed pricing based on artificial intelligence is suitable for price formulation compared to other options.

Objective

To incentivize demand response, an improved price formulation is proposed, which is applied to German residential electricity data. For this, an intelligent model based on real-time prices is designed, considering elasticity and maximizing benefits for both users and electricity providers. For the formulation of optimal prices, this work uses a novel adaptive artificial intelligence tool, under reinforcement learning, in an environment of uncertainty both in energy consumption and in electricity supply prices.

Methodology

In this work, a group of residential users from the openMeter project, located in Germany as well as average German customer prices are taken as the basis. In addition, the user elasticity obtained from an elasticity analysis for the year 2021-2022 is used. The users' demand has been considered shiftable, i.e., it can be modified in response to price variations over a given period. Therefore, the demand can be modified within the set maximum and minimum limits. The energy provider can increase or decrease the price of energy to influence users' consumption. The reinforcement learning approach is used for price formulation, focusing on object-oriented learning from the interaction between an agent (aggregator or service provider) and its environment (users' consumption). This allows extracting more information about users compared to other approaches within machine learning. Specifically, for a learning agent, actions to be taken are not established; instead, actions that produce the greatest reward are determined through trial and error [1], [2], [3]. This is essential as the agent's goal is to maximize the reward. For this, it is necessary to define the agent's actions and the variables that make up the

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environment. Thus, the reward comprises mutual benefits between users and service providers. On the one hand, the model seeks to maximize the electricity provider's earnings, i.e., the utility resulting from the buying and selling of energy within the wholesale market [4], [5]. However, on the other hand, the user should benefit from the variation in consumption. Finally, a comparison is made between the resulting price from the proposed methodology and the selling price to users.

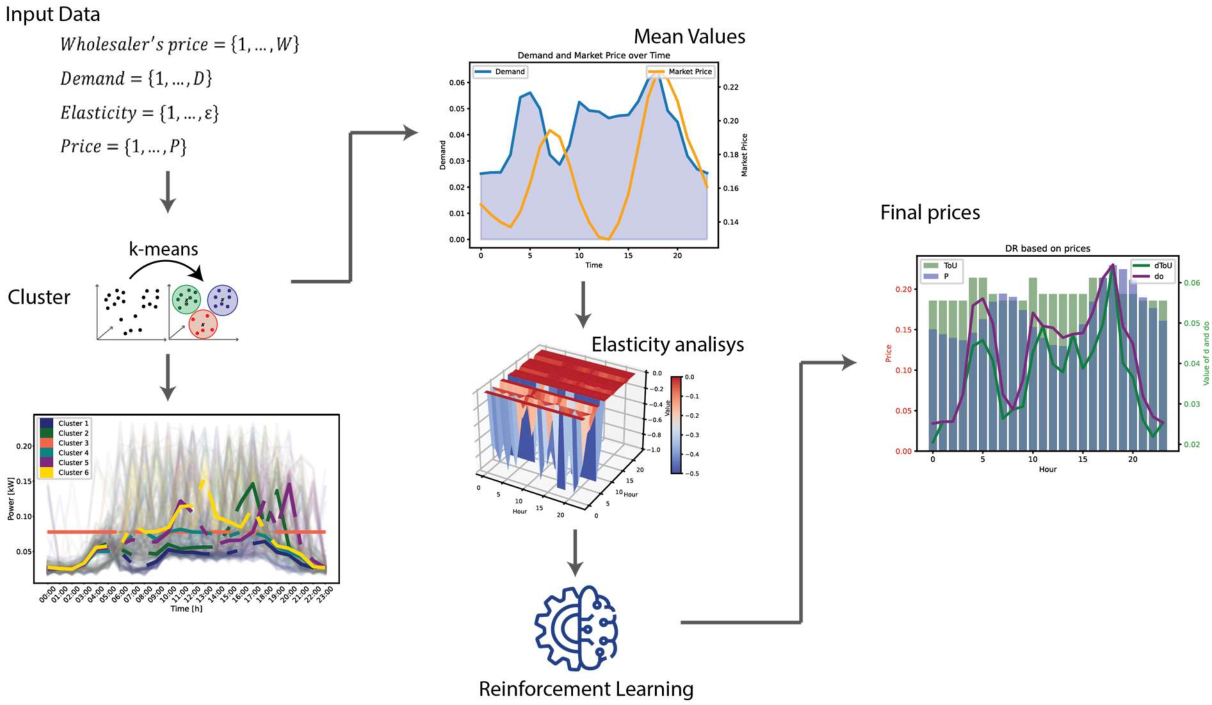

Figure 1: Methodological Framework.

Results and Conclusions

This article introduces a new demand response model based on price (*Figure 1*), approached through the lens of reinforcement learning. In this case, the proposed methodology, leveraging elasticity analysis and reinforcement learning, is adept at identifying optimal times (hours of the day) when users are inclined to alter their demand. This leads to a dual benefit: a reduction in peak loads and a decrease in energy bills for consumers. Furthermore, considering that the reinforcement learning algorithm aims to maximize the benefits for both users and service providers, a time-of-use pricing system is derived. This system adapts to the fluctuating prices in the wholesale market as well as the elasticity of demand. Hence, it is intriguing to compare the obtained values against the prices currently offered to users. It is demonstrated that by having a price that accounts for user behavior, drastic price increases for consumers can be avoided. This enables users to actively participate in modifying their demand while simultaneously preventing profit losses for electricity service providers. In a nutshell, a powerful tool for price formulation is presented, taking into account uncertainties in both prices and demand.

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