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The Impact of Electricity Tariffs on Optimal Production Scheduling

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Abstract: Energy costs can represent a large portion of the total production costs, and therefore, any changes in electricity tariffs can have a significant impact on profitability. This paper analyses how different types of electricity tariffs can affect the scheduling of a case study model, in particular, how time-of-use tariffs and real-time-pricing tariffs affect the single-machine scheduling problem of a production process with the introduction of the energy vector in the optimization cost. The influence of tariffs is examined, and their impact on optimal production scheduling is evaluated from an approach in demand response price-based programs, for ensuring cost-effectiveness while looking at the carbon footprint of the industrial process. The results indicate that the cost improvement of one tariff over the other is not consistent across all time periods. Meanwhile, the carbon footprint is reduced with a real-time-pricing tariff, since the real-time-pricing mechanism and the generation mix of fossil fuel technologies are positively correlated.

Keywords: energy-aware scheduling; single-machine scheduling; TOU electricity tariff; RTP electricity tariff; CO_2 emissions

1 Introduction

Demand response (DR) is a control strategy in which customers are incentivized to reduce their electricity usage when the reliability of the grid is at risk, normally during peak hours, in order to achieve grid balancing. DR offers several benefits

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including an increase of grid stability, reduction of electricity costs by reducing peak demands and economic benefits for those customers who participate in DR programs. Utilities also reduce costs avoiding the need for more generation capacity (Siano, 2014).

The main classification of DR programs are price-based programs and incentive-based programs (Albadi and El-Saadany, 2007). Price-based programs implement electricity price tariffs in order to motivate customers to improve their load consumption patterns, while in incentive-based programs the customer is offered to reduce the load consumption over a given period of time for a payment. This paper focuses on two of the main strategies from the price-based programs: time-of-use (TOU) pricing and real-time-pricing (RTP) (Jordehi, 2019).

Industries often plan production ahead based on the expected energy consumption cost throughout time-varying rates (Nandy et al., 2022). In TOU pricing the cost of electricity is based on the time of the day and day of the week. Under TOU pricing, the cost of electricity is typically higher during peak demand periods and lower during off-peak periods. This type of pricing mechanism is often used to encourage customers to shift their electricity usage to off-peak periods, in order to reduce strain on the grid during peak periods (Torriti, 2012).

RTP, on the other hand, is a pricing mechanism where the cost of electricity varies in real-time based on the supply and demand of electricity in the wholesale electricity market (Paschalidis et al., 2012). This means that the price of electricity can be very high during periods of high demand or when there are shortages in supply, and very low during periods of low demand or when there is excess supply.

Some industries may be unable to shift their consumption to off-peak periods, such as those with continuous production and steady power drawn from the grid, as well as facilities operating near the full processing capacity (Nandy et al., 2022). This can result in higher costs for these customers who are forced to operate in peak periods, and may make TOU pricing less appealing for them. In these cases, RTP tariffs can be presented as an alternative, with the added risk that the price of electricity can change frequently and unpredictably. This can make it challenging for customers to predict their electricity bills accurately and may result in unexpected costs. For large industries it can be financially burdensome.

This paper analyses how different types of electricity tariffs can affect the optimal scheduling of a case study model from the cost and CO_2 emissions perspective.

2 Case study

The case study is based on the Standard Profil Spain (SPS) company, focused only on sealing systems for the automobile market. The production process of the case study consists in 4 continuous rubber extrusion lines without any intermediate buffers, where each line produces different rubber profiles used in sealing systems.

The aim of the production scheduling is to sequence the different profiles, according to the lines' capacity, to meet the desired demand. A line is modelled as a single machine and its different state transitions are depicted in Fig. 1. Only one job can be processed by a machine at a time, and jobs cannot be interrupted.

Each machine has four different states, with different associated energy consumptions, where one state can represent multiple jobs (Fig. 1): The "Start line" state represents the start of the line from scratch; the "Production" state encompasses the set of steady production operations; the "Change profile" state represents the change of a profile to another in the same line; and the "Stop" state represents a zero-consumption state of the line.

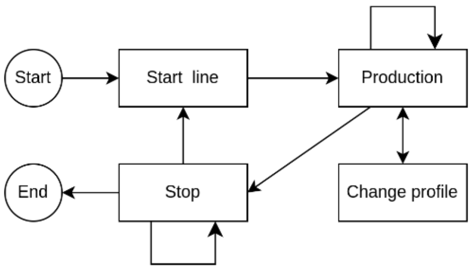

Fig. 1 State-based model diagram of a single machine's transitions

The production horizon is divided into a set number of periods, with each job's processing time expressed in terms of these periods. Additionally, the number of periods required to complete a single-machine transition between states may vary.

3 Method

A mixed-integer linear programming (MILP) algorithm has been developed to optimize the scheduling plan of the SPS case study, to sequence the production order of the different rubber profiles in each line. The objective function minimizes the energy costs of the scheduling plan, taking into account the electricity and gas consumption and the price associated with each type of consumption. The gas price is constant throughout the time horizon, in contrast to the electricity price, being the last one a major factor in the optimal scheduling plan. The optimal scheduling takes into account constraints from the single-machine problem, as well as workers, shared resources and demand constraints.

The algorithm takes the hourly price of the electricity tariff as an input, as well as the hourly consumption associated to the different states of each line, from the estimation provided by the SPS data in Table 1.

Table 1 Electricity and gas consumption of the different machine states (Fig. 1)

	Start Line	Production	Change profile	Stop
Electricity (kWh)	100	135	75	0
Gas (kWh)	300	280	280	0

The total consumptions, costs and emissions are then analysed from the optimal scheduling sequence for both TOU and RTP tariffs. Currently, the case study planning is involved in a TOU program, which has a consistent price distribution throughout the year, including equivalent peak and valley periods. This encourages having the same optimal planning throughout the year. In contrast, the RTP operates with distinct hourly price distributions each day. To choose an appropriate day for calculating the optimal scheduling, hierarchical clustering techniques were employed to classify days from the dataset into similar price distributions to explain the differences in measurements obtained for each tariff.

In this paper the electricity price in Spain is taken as an input variable. For each day, the RTP hourly prices were normalized and then concatenated. To group hourly profiles by similar price distributions of the different days the clustering process has been performed on 24-dimension vectors. Each day represents an observation with 24 features corresponding to the different hourly prices for that day. The Ward algorithm was used to define the clusters and the second derivative of the merge distance was used to identify the number of clusters, using the elbow method, following a similar approach from (Yeardley et al., 2020). The study is done during a 24-hour period of two different scenarios: the most common and the most atypical hourly prices distributions. The nearest day from the centroid of the biggest cluster is used as a statistically significant representation of a common hourly price distribution, while the farthest day from the centroid of the smallest cluster is used as a statistically significant representation of an atypical hourly price distribution.

4 Results

The 2nd of March of 2020 is found to be representative as the most common price distribution, while the 16th of May of 2019 is representative as the most atypical price distribution. In Table 2 there are the different measures used to compare the optimal scheduling from RTP and TOU pricing tariffs: the total electricity consumption (kWh), the cost associated with the electricity consumption multiplied by the normalized price curve, and the kg of CO_2eq emissions associated with the electricity consumption. The hourly coefficient of energy in kgCO_2eq is variable according to the generation mix of the grid. In Fig. 2 there are the hourly measures from each pricing tariff for each price distribution.

The RTP tariff results in lower consumption, for both price distributions, despite the difference not being significant compared to the TOU tariff. The case study meets its demand by shifting production in a way that makes the RTP tariff advantageous. The emissions are always lower with the RTP tariff because production is shifted to off-peak hours, which correspond to periods of lower generation from fossil fuel technologies (Leal et al., 2023). With the TOU tariff, even though there is a shift in production to off-peak zones, the price curve and generation curve are not correlated, and off-peak hours may coincide with peak generation periods, which negatively impact the carbon emissions of the production process.

Table 2 Measurement results for the optimal scheduling of RTP and TOU pricing tariffs for the total 24-hour production plan

Distribution	Measure	RTP	TOU
Common	Consumption (kWh)	7385.00	7435.00
	Cost (€)	2498.77	3052.93
	Emissions (kgCO_2eq)	6999.35	7073.19
Atypical	Consumption (kWh)	7385.00	7435.00
	Cost (€)	3936.08	2222.64
	Emissions (kgCO_2eq)	11025.43	16626.71

Finally, with the most common price distribution, the RTP tariff allows for cost reduction, where the TOU tariff is penalized due to the difficulty of shifting all production outside peak periods. However, in the atypical distribution the problem of unpredictable high prices does negatively affect energy costs.

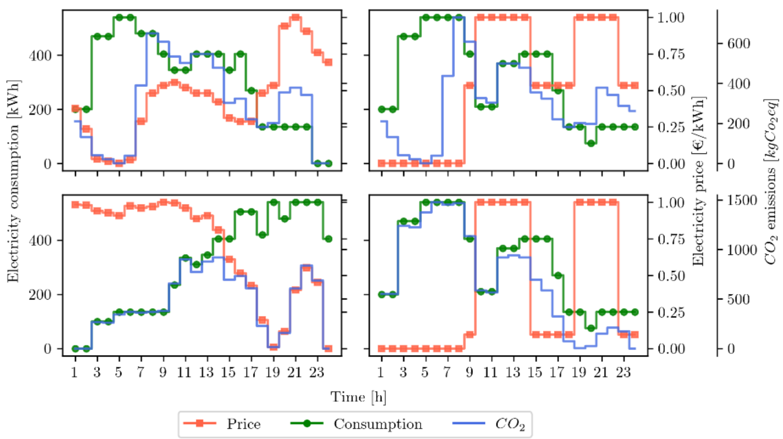

Fig. 2 Hourly measures of RTP (left) and TOU (right) tariffs, for the common price distribution (top) and the atypical price distribution (bottom)

5 Conclusion

This paper analyses how different electricity tariffs affect the optimal scheduling plan of a single-machine production process. The results suggest that different pricing strategies from the price-based DR programs, such as TOU pricing and RTP can have a significant impact on electricity costs and emissions, while little effect on total optimal consumption. Hierarchical clustering techniques were used to identify similar price distributions throughout the RTP curves. In the atypical distribution, the TOU tariff is more cost-effective due to a low price in the unpredictable high price period of the RTP tariff. However, the results show better cost during most of the price distributions under the RTP strategy, as represented by the common distribution, and lower emissions regardless of the price distribution. Choosing the appropriate electricity tariff can lead to better production planning and significant savings in energy costs from one tariff to another.

In the future, it is intended to penalize emissions and they will represent a cost to be taken into account for future production processes (World Bank, 2021). If TOU strategies are used during favourable time periods, it would be recommended to include the emissions in the total cost, to be minimized in the production plan.

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