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Title: Dynamics of energy costs and emissions in operations: analysing energy operational adjustment

Year: 2025

Version: Accepted manuscript

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Please cite the original version:

Helo, P., & Mayanti, B. (2025). Dynamics of energy costs and emissions in operations: analysing energy operational adjustment. In *51st International Conference on Computers & Industrial Engineering (CIE51)*, 1589-1597. <https://www.proceedings.com/79578.html>



DYNAMICS OF ENERGY COSTS AND EMISSIONS IN OPERATIONS: ANALYSING ENERGY OPERATIONAL ADJUSTMENTS

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ABSTRACT

The amount of energy use in operations and the source of that energy influence the greenhouse gas footprint. This paper analyses the dynamics of energy use in manufacturing where energy price and carbon emission from the grid are hourly fluctuating and vary at different times of the days. Three scenarios are analysed (1) pre-/postponement of operations, (2) storage effect and value, (3) system effect of simultaneous operations. Based on the analyses, we show how different strategies may impact the cost of energy consumed and energy-related emissions. These objectives may be conflicting with each other. A simulator software is presented to analyse the scenarios.

Keywords: operations, sustainability, energy, demand respond, decarbonisation

1 INTRODUCTION

Energy plays an important role in several manufacturing operations. Energy is often consumed in process steps, but its storage is often limited. Electrical energy is the most common form of energy, but other forms of energy take place in operations, e.g. heat energy. Depending on process types, different forms of energy may substitute for each other. For example, heating an industrial building may be based on centralised district heating and supported by electricity-based heating solutions. Local energy production, such as using solar panels or using excess heat from manufacturing processes may take place.

The impact of electricity pricing policies, such as peak pricing or carbon taxes on renewable energy investments and carbon emissions have been studied in grid level. The analysis by Kök el al [1] show that optimal decisions may vary based on market and production characteristics of regions. Also field experiments [2] have shown that dynamic pricing influences consumer behaviour, e.g. shifting consumption to dampen peak hours. Variability of energy pricing is causing possibilities for energy traders but stakeholders such as industrial energy consumers should also consider the effects. Hourly-based market for electricity is commonly used in Nordic countries. During the past few years, large variability, peak prices, and a significant amount of negative price hours have changed the environment. Figure 1 shows an example of

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a day in Nordpool market FI area, showing how market price and emissions vary during a single day.

Earlier studies have proposed storage and disposal strategies for stakeholders [3]. Data-driven models for decision-making have been proposed. Alvarez et al [4] developed a model based on ML and optimisation for capacity planning in smart grids, combining forecasting methods and uncertainty. Zhang et al [6] analysed peak price and uniform price policies impacting company-level decisions.

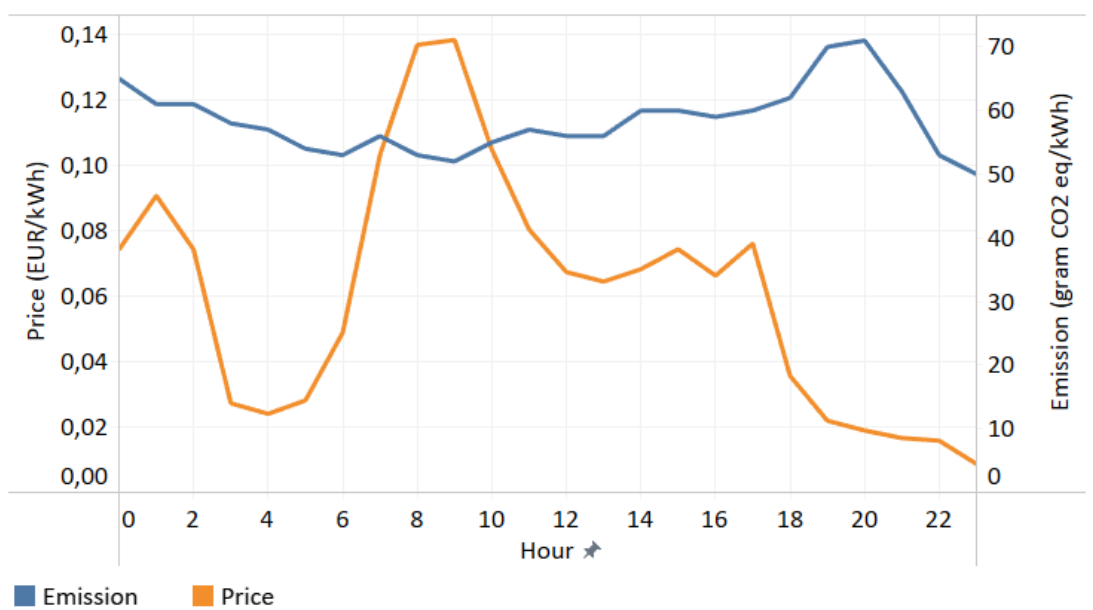


Figure 1: Hourly price vs carbon emission per kWh.

Industrial companies have a need to manage sustainability of their operations. Companies require digital systems to manage product-level up-to-date information about environmental emissions [6]. The data supporting the decision-making in supply chains should be based on commonly agreed databases and processes [7].

The impact of energy in operations is related to the cost of manufacturing and environmental impacts. Both these features are important factors for monitoring the performance of a system. This paper outlines possible adjustment on energy cost and emission dynamics and a calculator for studying various conditions.

2 STRATEGIES

In order to build a decision support system for an industrial company three adjustment mechanisms are considered. In the first example, energy consumption and production take place in the same site. Then, load shifting is added to advance or postponing the consumption. Energy storage is added and then the optimisation model is presented. Finally, the case of synchronization of several sites or system effect of simultaneous operations is added to consideration.

2.1 Energy model for a single site

In order to study the dynamics of energy-related costs and emissions we consider an operation which is connected to a grid and consumes electricity. Figure 2 illustrates the variables:

- $c(t)$ - Local consumption quantity at each hour t [kWh]
- $p(t)$ - Local production quantity at each hour t [kWh]
- $b(t)$ - Buying price for energy from grid [eur/kWh]
- $s(t)$ - Selling price for energy to grid [eur/kWh]
- e_cost - Emission rate for energy purchased from the grid [kg CO₂ eqv/kWh]

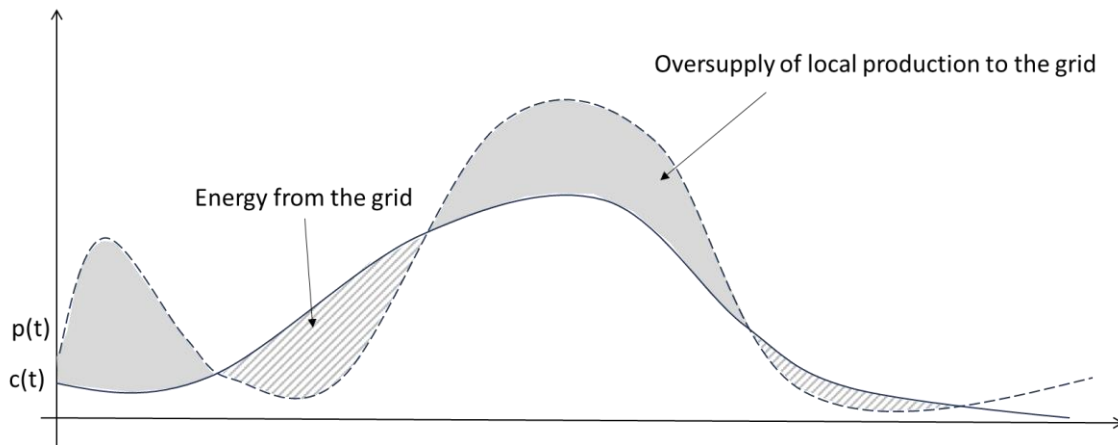


Figure 2: Industrial site energy consumption and local production

From the figure 1 we can yield total consumption

$$C_{total} = \int_0^{24} c(t) dt \quad \text{and total production } P_{total} = \int_0^{24} p(t) dt$$

The Input to grid, which means energy needed from the grid without storage is

$$G_{in}(t) = \max(0, c(t) - p(t))$$

$$G_{in_total} = \int_0^{24} G_{in}(t) dt$$

And respectively output to grid which refers to oversupply of local production to the grid is

$$G_{out}(t) = \max(0, p(t) - c(t))$$

$$G_{out_total} = \int_0^{24} G_{out}(t) dt$$

2.2 Shifting load - Postponement / advancing consumption

Demand response strategy may be introduced for an industrial site. This may be based on dynamic pricing, estimates on emissions from energy, or combining pricing and emissions at each time of the day. The last option was reported to achieve the balance between cost and emissions since focusing on the cost tended to increase the carbon emission while considering the emission solely could lead to higher cost, as proposed by Zhang et al [8]. Figure 3 illustrates both strategies.

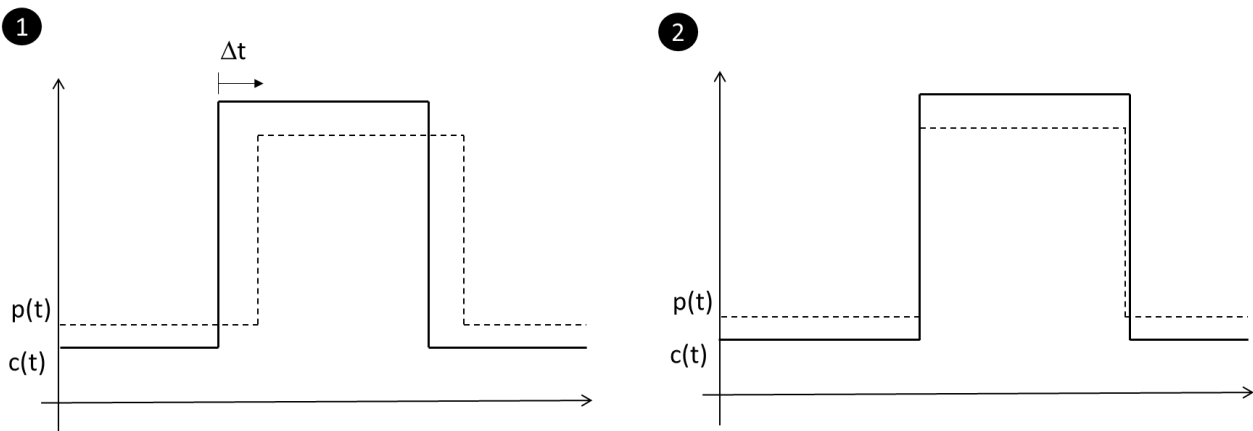


Figure 3: Postponement and advancing consumption strategies

After postponement or advancing the consumption, the consumption is $c_{shift}(t)$ is for each time period t . The maximum shifting capacity is constrained by $c_{max}(t)$. The amount of total energy shifted over the day should not change the total consumption, $\sum_{t=1}^{24} c_{shift}(t) = \sum_{t=1}^{24} c(t)$.

2.3 Local energy storage

Use of energy storage is one potential strategy, when available. In case of low cost or low emissions, energy may be stored in a battery. In practice such as a controlling system could be based on storage of electricity in a battery or storing heat in a heat element. The parameters for this strategy are:

- S - Maximum capacity of energy stored in a battery [kWh]
- $SOC(t)$ - State of charge of the battery at each time t [kWh]-
- n Storage efficiency factor, percentage of energy retrieved from stored energy [%]
- Storage charging and discharging may include speed factor $P_{charge}(t)$ and $P_{discharge}(t)$ [kWh/h]
- Using storage may also have a cost $c_{storage}(t)$ and emission factor $e_{storage}(t)$.

2.4 Optimisation model - shifting and storage

Now based on the parameters introduces, an optimization model may be developed. Storage of the battery capacity is handled as follows:

$$SOC(t) = SOC(t - 1) + P_{charge}(t) * \eta - P_{discharge}(t)/\eta$$

Initial battery status at $SOC(0) = SOC_{init}$ and the capacity is constrained $0 \leq SOC(t) \leq S$

Input to grid - Energy needed from the grid with the storage capacity is

$$G_{in}(t) = \max(0, c_{shift}(t) - p(t) - P_{discharge}(t))$$

Output to grid, which refers to oversupply of local production to the grid is

$$G_{out}(t) = \max(0, p(t) - c_{shift}(t) - P_{charge}(t))$$

Shifting the consumption strategy is constrained by speed of charging and discharging:

$$c_{shift}(t) = c(t) + \Delta c(t)$$

$$c_{max}(t) \geq \Delta c(t)$$

and total energy should not be changed during the period

$$\sum_{t=1}^{24} c(t) = 0$$

For a factory the total cost function can be defined as follows:

$$C_{total} = \sum_{t=1}^{24} (G_{in}(t) * b(t) - G_{out}(t) * s(t) + (P_{charge}(t) + P_{discharge}(t)) * c_{storege}(t))$$

And a respective total emissions function similarly:

$$E_{total} = \sum_{t=1}^{24} (G_{in}(t) * e(t) - (P_{charge}(t) + P_{discharge}(t)) * e_{storege}(t))$$

As both cost and emissions need to be taken into account, objective function J combines the total cost from direct energy costs and sales as well as GHG emissions costs as a market price:

$$\min J = C_{total} + E_{total} * e_{cost}$$

subject to

- (1) $c_{shift}(t) - p(t) = G_{in}(t) - G_{out}(t) + P_{charge}(t) - P_{discharge}(t)$
- (2) $c_{shift}(t) = c(t) + \Delta c(t)$
- (3) $c_{max}(t) \geq \Delta c(t)$
- (4) $SOC(t) = SOC(t - 1) + P_{charge}(t) * \eta - P_{discharge}(t)/\eta$
- (5) $0 \leq SOC(t) \leq S$
- (6) $P_{charge}(t), P_{discharge}(t), G_{in}(t), G_{out}(t) \geq 0$

2.4 Energy model with multiple sites

System effects may take place when multiple industrial sites are operating in the same grid and can operationalise a cooperative load-shifting policy (Figure 4). Assume multiple sites consuming energy at each hour of the day as a function of $c(t)$, each site can shift energy consumption by c_{shift} which is constrained by c_{max} at each site. Energy price $b(t)$ at each hour. The price is same for all consuming sites.

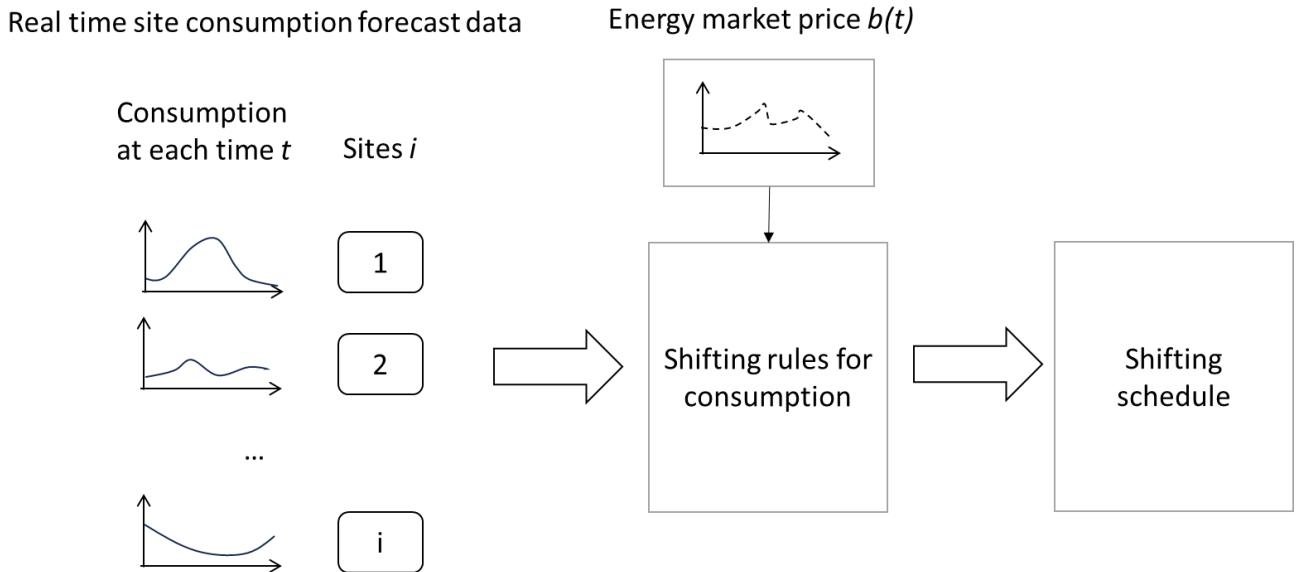


Figure 4: Multiple operations sites connected with each other to synchronize scheduling

The system level model can be developed based on demand at each site i with the following parameters:

- $c_{i_base}(t)$ - Local consumption quantity at each hour t for each i site [kWh]
- $c_{i_shift}(t)$ - shifted consumption quantity at each hour t for each i site [kWh]

- c_{i_max} - maximum energy consumption limit for shifting at site i [kWh]
- $b_i(t)$ - Buying price for energy from grid for each i site [eur/kWh]

Based on this an objective function for the problem as cost minimization problem can be formulated:

$$\min C = \sum_t \sum_i b(t) * c_i(t)$$

subject to

- (1) $c_{max}(t) \geq c_{i,shift}(t), \forall i, \forall t$ - each battery at each site
- (2) $c_i(t) \geq c_{i,base}(t) - c_{i,shift}(t)$ - shifting max own consumption demand
- (3) $c_i(t) \geq 0, c_{i,shift}(t) \geq 0, \forall i, \forall t$, consumption is non-negative

Based on this we can also estimate the average price of saved energy.

$$AC(t) = \frac{\sum_i (b(t) * c_i(t))}{\sum_i c_i(t)}$$

3 SIMULATION SOFTWARE FOR INDUSTRIAL CASE

Various complex situations may take place especially when multiple industrial sites are connected to the same grid. In order to test various scenarios of local energy production, storages and shifting policies, computerized simulation approach is needed. We have developed a playground for building such simulations. A common market for electricity and emissions profiles can take place, and at the same time each industrial site can have own demand patterns. Figure 5 illustrates a screenshot of the system where several sites can be configured to the simulation playground.

The structure of the consumption and site-level data is stored on a local database along with the consumption and production data. One possible decision point can be changing the load. User can change the hourly electricity and DR factor. DR factor shows flexibility, e.g., 0.9 DR factor means that 10% of electricity consumption during peak hour will be reduced and shifted to the low peak. Figure 6 shows impact of such change for a sample day.

Optimisation algorithms may be tested on top of the data model and strategies can be tested from both cost and emissions perspectives. The development of the simulator and the playground is ongoing and the solution has not been released yet.



Figure 5: Screenshot of the energy and emission analysis software

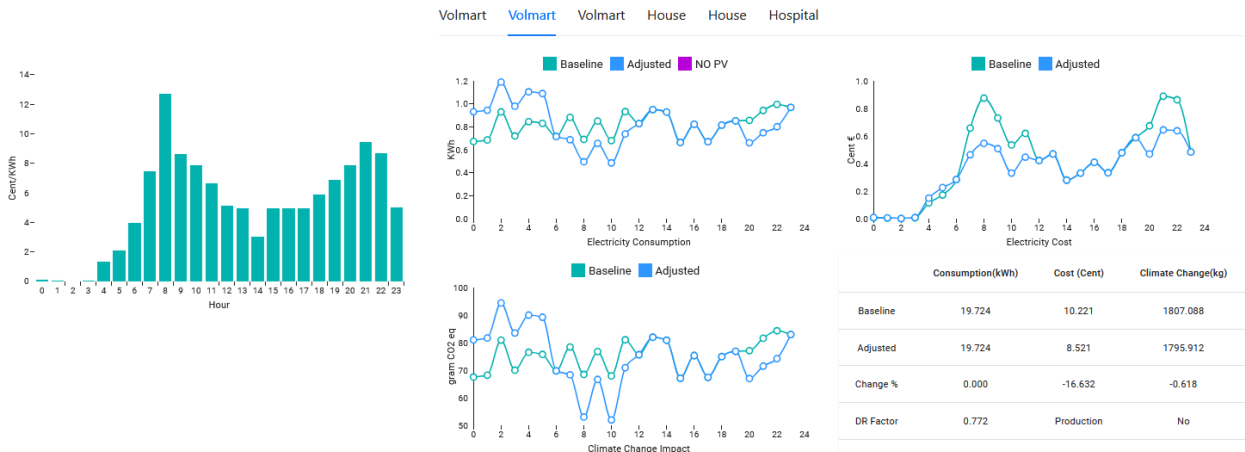


Figure 6: The data of each building in the simulation tool. The results of load distribution after change DR factor



4 CONCLUSIONS

The use of energy has both cost and emission perspectives for industrial operators. Companies producing goods should pay attention to both and employ suitable decisions to support their objectives. The trade-off situations between economic objectives and environmental impacts should be made transparent for decision makers. The modelling and simulator development work has suggested that:

- (1) Cost optimisation and emissions minimisation are strategies which may be controversial from each other.
- (2) Demand response, use of energy storage and coordinated exchange of information among stakeholders may all provide opportunities to reduce costs and/or reduce emissions.

Development of simulation tool may provide a solution for complex interactions as problems may become non-linear and stochastic components cannot be avoided.

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