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# The Role of Demand Profile in Optimizing Operational Planning

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***Abstract***
Heat demand is increasing every day due to urbanization, population growth, and rising living standards. This rising heat demand continually escalates operational costs day by day. The reduction in the expenses of heat production units is crucial because it directly affects energy affordability and profitability. The heat production units operate generally according to the end-user demand. The main goal is here to see how the variation in demand could have an impact on the operational cost and to determine what aspects of the demand variations need to be addressed to achieve cost-effective performance. Four categories for demand profiles are introduced: high demand, average demand, low demand, and extremely low demand. In this paper, the impact of the demand profile on the operational cost is discussed. An annual demand profile is taken into account. From these profiles, which are related to all days of the year, repeated samples are categorized, and samples are selected. For each of the selected patterns, the operational cost of the desired period is calculated and compared. For the calculation of the best scenario, a genetic algorithm-based algorithm is represented as a function of the consumed power and hourly electricity price. The results of the paper show that the extremely low demand profile outlined a better condition for saving in operational costs (44.6%) while the high demand profile represents the lowest potential for saving (26.5%). Investigation of the results shows that for more than 70% of the situations, the daily demand profile falls into the low demand profile, and this provides a great opportunity for more savings throughout the yearly operation of the unit.

***Keywords*:** demand profile, operational cost, day-ahead market, optimization.

## 1. Introduction

Renewable energy sources, such as wind and solar, are key players in the world's energy distribution and will absolutely contribute even more in the coming years [1]. The European Commission has projected that the share of renewable energy in the EU's final energy consumption will increase from 18.9% in 2018 to 32% by 2030 [2]. Changes in renewable generation and their abundance or decline can cause instabilities in electricity prices. Energy storage is being considered a solution to reduce electricity consumption costs due to providing the possibility of controlling production during electricity price variations. Storage can also increase the market outlook [3].

Variations in heat demand significantly affect energy system design. This is because of the impact of these changes on the balance between supply and demand. During peak demand times, energy systems must increase production, which typically requires more efficient and expensive resources. Conversely, during periods of low demand, excess energy can lead to inefficiency and waste of resources. These fluctuations require robust and resilient energy infrastructure, including advanced storage solutions and smart grid technologies, to ensure reliability and affordability [4]. Furthermore, understanding and predicting changes in heat demand can help optimize energy production, reduce greenhouse gas emissions, and increase the integration of renewable energy sources. Overall, managing changes in heat demand is crucial for creating sustainable and resilient energy systems [5].

Balancing electricity and heating systems comes with numerous challenges. One of the most important issues is the mismatch between supply and demand [6]. Heat demand is usually a function of ambient temperature and peaks in cold weather, while electricity demand can change due to various factors such as industrial activity and consumer behavior. Integrating renewable energy sources to maintain a sustainable supply faces many challenges. In addition, advanced storage solutions play a key role in managing excess energy. Effective coordination between the heat and power sectors, along with the implementation of smart grid technologies, is essential to overcome these challenges and ensure a reliable, efficient, and sustainable energy system.

In systems that have high operating hours and operate continuously, the operation cost of heating production units is crucial, especially when electricity prices are high. The storage tank could help to reduce the mismatches between supply and demand and help with energy affordability and profitability. With this background in mind, and to achieve cost-effective performance, the objective of this study is to investigate the following questions: How do variations in demand impact operational costs, and what are the key factors in demand profiles of the end-user influencing the operational costs of heat production units?

## 2. Methodology

The system of the study is a heat pump unit that is connected to a storage tank. The schematic is displayed in Figure 1. The heating demand of the consumer is indirectly met by tank storage. The system contains a compressor, condenser, a valve and an evaporator and the performance of the system would be characterized based on some parameters including the ambient temperature, sink and source temperature, refrigerant type, load matching, proper sizing and high-quality installation.

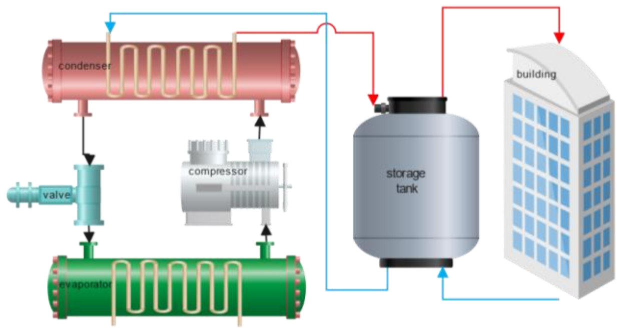


Fig. 1: Heat pump schematic integrated with the storage tank and the consumer.

To understand the direct relationship between the parameter of interest (demand profile) and the target parameter of the study (operational cost) and enables a fair comparison, one would have to suppose that the complicated performance of the unit would be more simplified. Thus, here keeping other factors constant helps us see how profile demand variation alone influences operational cost. For the modeling the heat pump, Lorenz efficiency of the heat pump is defined to be 0.4 [7]. The source temperature and the sink temperature also set to be 10℃ and 80℃. The Lorenz efficiency ($\eta_{Lorenz}$) is defined as the ratio of the actual COP of a heat pump to the Lorenz COP. The definitions of Lorenze efficiency and COP are represented as follows:

$$\eta_{Lorenz} = \frac{COP_{actual}}{COP_{Lorenz}} \tag{1}$$

$$COP_{Lorenz} = \frac{T_{sink}}{T_{source} - T_{sink}} \tag{2}$$

The genetic algorithm could be implemented here to represent the best possible solution for operational planning. The genetic algorithm is the approach selected here because of its extensive usage and successful application in various fields of energy system optimization [8]. The objective function defines the total electricity cost of a single day. The price of electricity for each hour is clear, the demand is also known and the interaction between the operation of the heat pump and the storage tank could make flexibility for the unit operation during different hours of the day. This objective function evaluates how well a solution solves the problem. The objective function that would be optimized here is the total electricity price (*tec*) during the operation. This total cost is achieved by multiplying the hourly electricity consumption (*c*) by the hourly electricity price (*p*). Thus, the genetic algorithm-based approach aims to minimize the total electricity price as expressed by Eq. (1).

$$tec = \min\left(\sum_{i=1}^{n}(c_i . p_i)\right) \tag{3}$$

When the storage tank is linked to the unit, the time of charging (operation time of the unit) could be changed based on variations in the electricity price. This would be performed based on the performance of the optimization algorithm. The algorithm works in this way, it provides a number of random guesses for the operation for each specific hour and tries to handle the system, respond to the heat demand of the unit, and save extra production in the storage tank. If the production would be less than the amount of heat pump production, then the storage tank would come into the network and and help the system to take the required heat of the need. Meanwhile, there are some limitations regarding the operation; the the state of the charge of the storage should not be a negative value and also could not be higher than the capacity of the storage tank. The amount of operation of the heat pump is identified by the guess values that come from the GA algorithm. algorithm. If the system works with the proposed value of the operation, that would be saved by the algorithm for further consideration and if it surpasses the limitations, the data would be put away and should not be considered anymore and new guess values would be replaced for the continuation of the process. In such a way, the operation of the unit is controlled by the proposed algorithm. Accordingly, the constraints for the storage tank would be defined in this way based on the state of the charge (*soc*).

$$soc(i) \geq 0\,,\;\; soc(i) \leq storage\ capacity \tag{4}$$

The state of charge of the storage tank in the next step is a function of the heat production (*pro*) in the unit and the hourly demand from the end user (*dem*) at the current time and could be defined in this way:

$$soc(t+1) = pro(t) - dem(t) \tag{5}$$

## 3. Heat Demand

The heat demand of a single building including domestic hot water and space heating has been represented in Figure 2(a) for a year. To get a better perspective regarding the whole demand, the accumulated values of required energy for each month of the year have been represented in Figure 2(b). In both figures, the space heating and domestic hot water are described, and they depict that the domestic hot water is relatively constant during the year while the space heating varies during the year based on the variation of the ambient temperature. Among all the demand profiles of 365 days of the year, 13 common demand patterns have been selected in Figure 2(c) which each represents the heating demand of a single day in the year. Among all selected patterns, four different patterns are selected to be the main representatives of all possible demand profiles occurring throughout the year. A comparison of the profiles divides the demand into four categories: high demand, average demand, low demand, and extremely low demand.

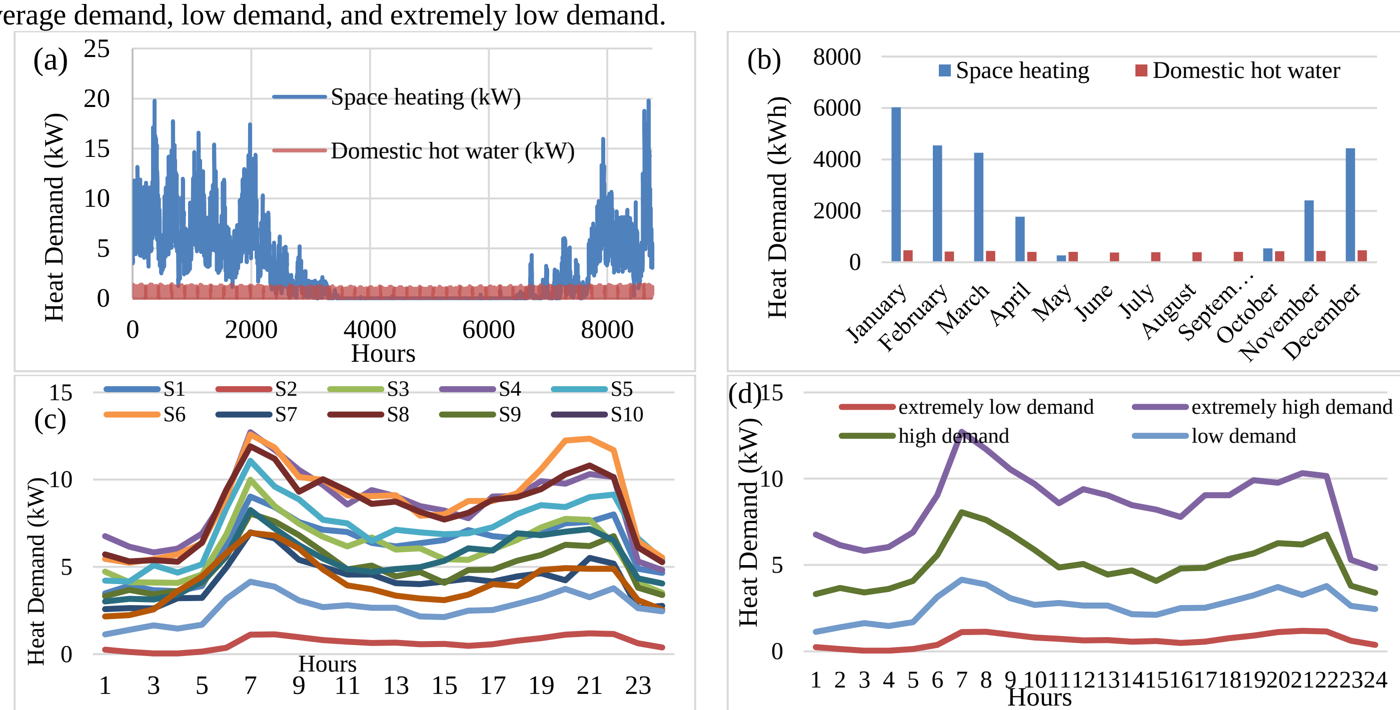


Fig. 2: Heat demand, (a) hourly profile, (b) monthly profile, (c) daily profile, and (d) selected four categories.

In this situation, with these defined demand profiles for a single building, one would try to see how the variation in demand could make an impact on the final total cost of electricity during the day and it would be determined what aspects of the demand variations need to be addressed to achieve cost-effective performance. assumption in this situation is that the electricity price is constant for each day and just the storage tank could to use the potential of the operational planning.

## 4. Results and Discussion

For a system that has a maximum demand of 13 kWh, a heat pump of the same size is characterized. Besides the unit, a storage tank with a capacity of 13 kWh has been implemented. To ensure that the optimization process and the achieved results are reliable, and they are not just the local minimum or suboptimal solutions and make sure that the simulation process is robust, a robustness check should be conducted. For this, the optimization is performed multiple times for each case. Then the consistency of the achieved results across different runs validated the reliability of the optimization process.

For this system, the results of the system's operation are represented in Figure 3. The amount of heat storage, the operation status of the unit, the electricity price profile for the specified period, and the demand are the profiles displayed in the figures. The system includes four demand profiles extracted from all represented demand profiles exhibited in Figure 2(a) and categorized in Figure 2(d). The electricity price profile is identified as a constant profile for all cases. The variation of the demand for these profiles is different and it could be observed that they are between 0 and 1.14, 1.13 and 4.15, 3.32 and 8.06, and 4.82 and 12.7 kWh for extremely low demand, low demand, average demand, and high demand respectively. The operation status of the unit shows the result of optimization which is how the system handles the operation to respond to the assumed profiles. When the demand is extremely low, which is the most common case occurring during the years (displayed in Figure 4), over half of the year the profile would be in such a way. The strategy for operation would be simple because the system doesn't need to operate too much. So, it recognizes the cheapest amount of electricity and operates the system at exactly these times. At most other times, the system switches off due to the extremely low demand profile. For this reason, the maximum amount of savings would be possible with respect to the other cases of the demand profile. When the demand changes and we go through a higher amount of demand which is about 4 times larger than the previous case, but still low demand based on the maximum nominal power of the unit, the system continues to function under a very light load. So, for the first hours of operation when the price of electricity is high, the unit operates partially not fully uniformly except for one single hour when the price is at the local minimum and the algorithm proposes a higher amount of load for the unit. Anyway, the variation in the workload is also not high in this case and it is between 0 to 0.5. The third case is when the demand is in the average range where the demand is between 0 and 8 kWh. The workload varies between 0.2 to 0.6. In this case, the algorithm suggests several switching on/off in such a way that when the electricity price is at the highest level, the unit production decreases to the minimum level of the proposed range. The last case is when the demand reaches its maximum level and a fluctuation between 5 and 13 kWh is noted in this scenario. The variation of the operating load of the unit would be between 0.38 to 0.81. Again, the algorithm recognizes the time of the cheap and expensive electricity price and adjusts the production accordingly in a wider range. Overall, what could be concluded from the figure is that the algorithm recognizes the location of the cheap and expensive electricity price and manages the switching on/off of the unit.

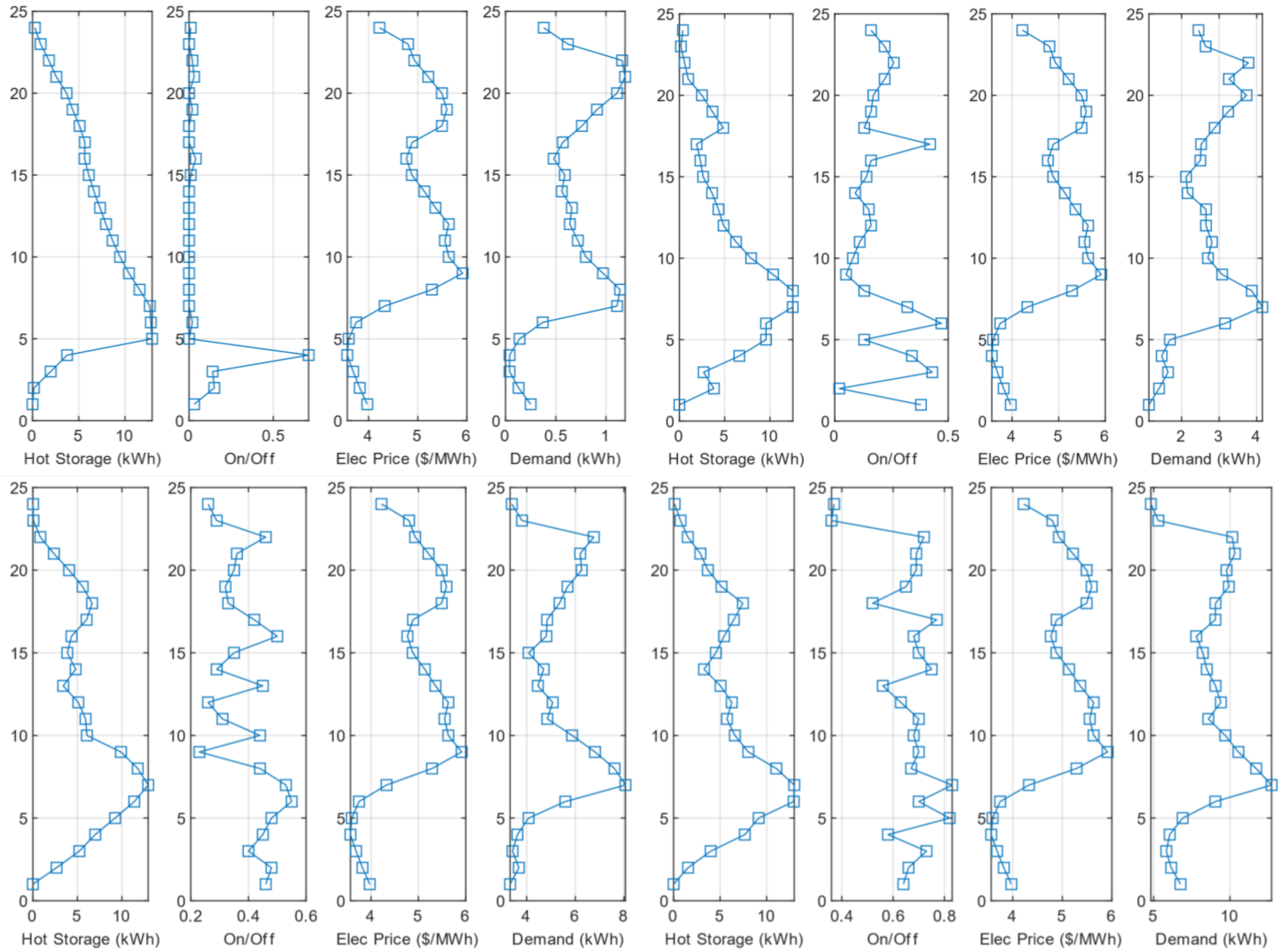

Fig. 3: the storage capacity, operation status, electricity price, and demand profile for four selected categories.

The previous figures displayed the potential for saving in terms of the total cost of electricity when the demand changes. Now, the question arises of how demand changes for all days of the year and how many days a year, there are the same profile for extremely low demand or with respect to the other introduced profiles. For this, the bar chart in Figure 4 exhibits the percentages of the days in a year that represent a specific demand profile. For 51% of days during the year, there is extremely low demand, specifically on summer days when the temperature is high, and the demand is low. For half a year, this profile has been identified, and a great opportunity appears for more savings with operational planning. For low, average, and high-demand profiles, the repetition percentages of the profile in a year are 16.71, 18.63, and 13.15% respectively. The figure also shows the potential for saving in operational costs. The maximum potential in saving is for the extremely low demand profile with 44.6%. The amount of savings in operational cost would be 30.5%, 28.4%, and 26.5% for low, average, and high demand profiles respectively.

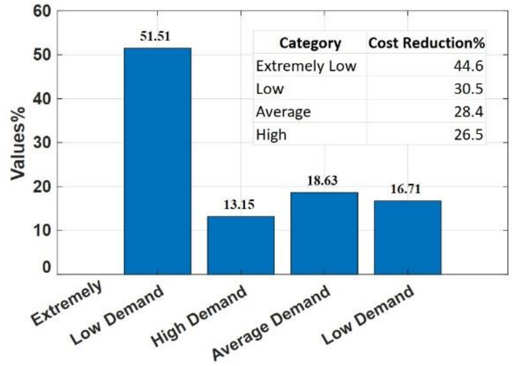

Fig. 4: Repetition of the demand profile in a yearly period and amount of saving in four selected categories.

For high demand, the minimum potential for saving is observed to be 26.5%, and for extremely low demand, the potential increases to 44.6%. Now to see the impact of storage size, for these worst and best cases, the capacity of the storage tanks has been changed to see how these parameters impact the total cost of electricity (Figure 5). Storage capacity has increased from the benchmark value of 13 kWh to 31.2 kWh. The calculation process is performed multiple times for each case to ensure the consistency of the results. It can be observed that when there is a high demand profile, the size of the storage tank has no impact on cost reduction, and increasing the tank size does not lead to any positive effects on lowering costs. When the extremely low demand profile is selected, it could be observed by increasing the storage capacity, the percentage of cost reduction increases, and by increasing the storage capacity to 2.4 times the benchmark value, a nearly 4% improvement in cost reduction is observed.

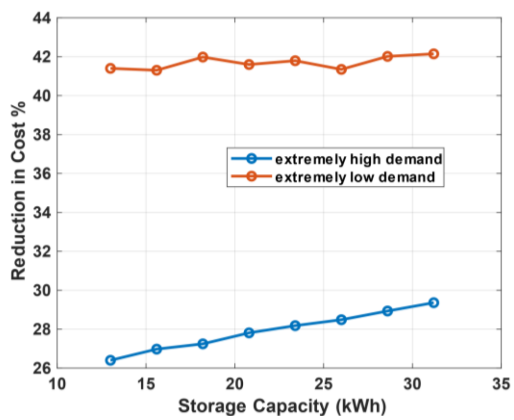

Fig. 5: Impact of storage capacity on reduction of the cost.

## 5. Conclusion

In this paper, a unit with a maximum heat demand of 13 kW including a storage unit with a capacity of 13 kWh is controlled by a proposed optimization algorithm to reduce the operational cost of the unit. The main goal is here to see how the variation in demand could have an impact on the operational cost and it needs to be determined what aspects of the demand variations need to be addressed to achieve cost-effective performance. Four categories for demand profiles are introduced based on the capacity of the unit. For the specified case, the analysis of the daily demand profiles of a year shows that in more than 50% of situations, the demand is categorized in the extremely low demand category that has the highest level of potential for cost reduction. It is a promising result that the most repeated cases among the demand profiles represent the highest cost reduction. From the other perspective, when the system is designed bigger than the nominal capacity of the the unit, it would be another way of forcing more daily demand profiles to fall into the extremely low demand category, and this brings the potential for more savings. The storage size is also an important parameter that can can provide the opportunity for higher savings, with a relatively lower cost when compared with the other expensive mechanical and electronic devices used in such systems. Meanwhile, this should be properly explained that the impact of the capacity of the storage tank would be more on the days with a higher demand profile and not when the demand is very low. In other words, storage capacity could not provide any opportunity in the case of extremely low demand. Last but not least, there is an issue with managing the switching on and off of the unit: it cannot be completely turned off or utilizing 100% of the heat pump capacity for most of the operational time, regardless of the category of extremely low demand that one could shut down the system for some hours. The reason for this is the small size of the storage tanks. Increasing the capacity of the storage tank enhances the potential of the unit by achieving higher flexibility by storing more thermal energy inside the storage tank.


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