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Letters

Energy supply scheduling in manufacturing systems using Quantum Annealing

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ABSTRACT

Optimizing a manufacturing company's in-house energy demand amidst fluctuating electricity prices and uncertainties in renewable energy supply as well as volatile manufacturing planning situations is a challenging task. To tackle this issue, a novel approach is developed for scheduling the energy supply in manufacturing systems with the objective of reducing energy costs. The approach employs Quantum Annealing to determine the optimal mix of in-house generation, purchased electricity, and energy storage. The effectiveness and scalability of the approach are demonstrated through the validation using two simplified use cases, showcasing its potential in solving complex energy supply optimization problems.

1. Introduction

Energy prices have increased steadily in recent years due to stricter regulations as well as rising demand [1]. This leads to increasing costs in production. In particular, companies in countries with comparatively high energy prices must reduce their energy costs to remain competitive [2]. There are two options to reduce energy costs; either the energy efficiency of manufacturing operations can be increased, which is the subject of numerous studies, or electricity can be purchased more cheaply, which has hardly been examined so far [3,4]. To reduce energy costs, in-house generation can be implemented or expanded, e.g. by implementing photovoltaics, or the procurement strategy can be changed. Also, contracts can be renegotiated, to purchase cheaper energy from the energy supplier. Both strategies, however, are exposed to strong uncertainties, as in-house generation depends on the current weather and the market price is subject to strong volatility. Hence, using energy storage systems that store surplus energy and discharge when needed, e. g. to compensate peak loads, is often beneficial [5,6]. On the one hand, this compensates for weather fluctuations. On the other, electricity can be purchased on the spot market at current daily prices and can either be used immediately or stored for later use. But, to achieve a cost reduction, the charging and discharging as well as the production planning and control (PPC) must be adjusted to the own generation and the purchase price. In addition, rescheduling may become necessary if projections become more concrete or change.

In terms of optimization methods to reduce the energy cost of manufacturing systems, most approaches focus on PPC such as energy-aware job shop scheduling solved by genetic algorithm [7]. Chen et al. use an improved multi-objective evolutionary algorithm based on decomposition to solve a hybrid flow shop scheduling problem with onsite PV power generation and battery system [8]. Materi et al. propose a time-dependent model to optimize manufacturing parameters and thus align the power required by the manufacturing system with the renewable energy supply to obtain the maximum monthly profit [9]. However, the approaches aimed at energy supply scheduling in manufacturing systems with multiple energy resources are rarely discussed. Karimi and Kwon are aiming to reduce energy costs using a mathematical optimization-based systematic approach to analyze the effect on energy cost [10]. Wang et al. proposed a heuristic approach for integrated energy supply and demand scheduling to cover uncertainties [11]. In grid systems, energy supply scheduling or energy flow optimization is primarily solved by conventional metaheuristic approaches, which can be time-consuming or lack the precision required for complex or large-scale problem sizes [12]. These limitations present obstacles for implementation in day-to-day business operations.

A new promising approach to solve such problems is therefore Quantum Annealing (QA), as already demonstrated by approaches such as Ajagekar et al. and Schworm et al. [13,14]. QA is a meta-

Abbreviations: QA, Quantum Annealing; CQM, Constraint quadratic model.

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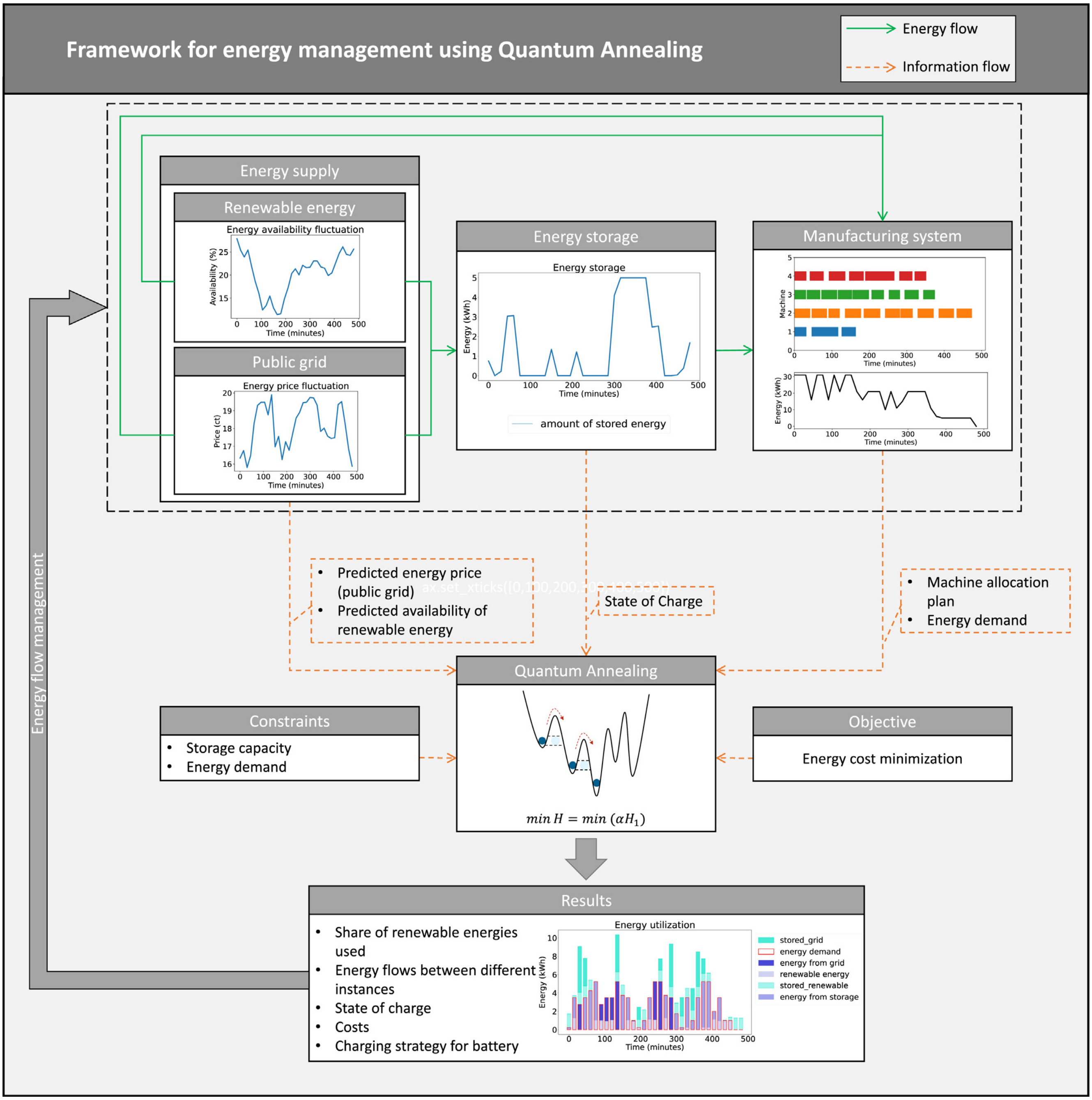


Fig. 1. Proposed Framework.

heuristic that aims at finding optimal or near-optimal solutions in a very short time and hence has advantages over classical approaches [15,16]. Therefore, the presented approach aims to minimize the costs for electricity of manufacturing systems by determining the cost-minimal electricity mix of in-house generation, purchased electricity, and storage.

2. Quantum annealing based energy supply optimization

2.1. Framework

The approach based on quantum annealing aims to select an energy management strategy that minimizes energy costs. The corresponding framework is depicted in Fig. 1. A typical energy system in the manufacturing industry can be divided into various energy sources, energy storages, and consumers. It is essential to ensure that the energy demand of the consumers is met at all times. To determine a cost-minimizing strategy, inputs such as predicted energy prices and predicted renewable energy generation, the state of charge of energy storage units, a machine occupancy schedule, and the resulting energy demand are required. Additionally, constraints for the specific QA energy minimization problem must be integrated. The generated strategy determines the energy flows between the different system components using QA for cost-minimizing energy management.

2.2. Use case

To demonstrate the ability of QA to solve energy supply problems in a manufacturing system, two simplified use cases are defined. Starting point forms a scenario described in the frame-

Table 1
The related parameters, variables, and formulations in CQM.

Parameters	Initial storage	$S_{initial}$
	Electricity price at time t	$P_{e,t}$
	Time range	$T = [0, i, 2i, \cdots, 480min]$(1)
	Renewable energy generation capacity at time t	$E_{r,t}$
	Energy demand at time t	$E_{d,t}$
	The capacity of energy storage	C_s
Real variables	Energy usage from grid at time t	$X_{u,g,t} \in [0, E_{d,t}]$(2)
	Amount of stored energy from grid at time t	$X_{s,g,t} \in [0, E_{d,t}]$(3)
	Amount of stored energy from renewable sources at time t	$X_{s,r,t} \in [0, E_{r,t}]$(4)
	Energy usage from renewable sources at time t	$X_{u,r,t} \in [0, E_{r,t}]$(5)
	Current energy storage capacity at time t	$X_{s,c,t} \in [0, E_{c,t}]$(6)
	Energy usage from storage at time t	$X_{u,s,t} \in [0, E_{c,t}]$(7)
Energy demand constraint	$\sum_{t\in T} E_{d,t} = \sum_{t\in T} X_{u,g,t} + \sum_{t\in T} X_{u,r,t}$(8)	
Distribution constraint	$\sum_{t\in T} X_{u,r,t} + \sum_{t\in T} X_{s,r,t} \leq \sum_{t\in T} E_{r,t}$(9)	
Storage constraint	$\sum_{t\in T} X_{s,c,t} = \sum_{t\in T} \left(\sum_{\substack{t' \in T \\ t' < t}} (X_{s,r,t'} + X_{s,g,t'}) - \sum_{\substack{t' \in T \\ t' \leq t}} X_{u,s,t'} \right)$(10)	
Cost objective	$H_1 = \sum_{t\in T} P_{e,t} \cdot (X_{u,g,t} + X_{s,g,t})$(11)	
Objective function	$minH = \alpha H_1$(12)	

work with a given energy demand, renewable energy availability, initial energy storage, and electricity price from the grid over an 8 h shift. To compute a feasible energy combination the shift is discretized in time periods (Eq. (1)). In the first use case, three different time discretizations are used to explore the scalability of the approach: $i \epsilon [15min, 60min, 120min]$. Therefore, trends for energy demand, prices, and availability are generated for each time period and an optimized supply is computed. In the second use case, a constant time step of $i = 15min$ is considered and analog to the fist use case energy-related factors are generated. However, at $t = 120min$, a change in energy availability is simulated, which forces the system to reschedule. This is how the flexibility of the approach is investigated. Defined parameters and trends of the use cases can be found in the supplementary material.

Moreover, for the problem formulation, the following constraints are considered:

- **Energy demand constraint:** Used energy from renewable resources, storage, and power grid must fulfill the energy demand.
- **Distribution constraint:** The sum of stored energy and used energy from renewable sources cannot exceed the generated energy capacity of the renewable sources.
- **Storage constraint:** Stored energy in storage is the difference between the sum of the previously stored energy and the sum of used energy. Stored energy cannot be used at the same time.

For simplicity, it is assumed that the purchase of energy from the power grid is associated with costs and that renewable energies are freely available. The objective is to minimize the energy cost by finding an optimized energy flow for the manufacturing system. For representing energy flows and capacities, real variables are most suitable, therefore, a constraint quadratic model (CQM) formulation is used to construct the optimization problem. Parameters, variables, constraints, and objectives are summarized in Table 1. For computation, the D-Wave[1] hybrid CQM-solver is used since it is specifically tailored to this type of problem and can compute problem sizes larger than a pure quantum annealer. Real variables are used to represent energy usage and storage from the grid, renewable energy, and energy storage, each with corresponding limits based on energy demand, renewable energy generation capacity, and energy storage capacity (Eqs. (2)–(7)). Using the flexible constraint manipulation approach in CQM, the constraints of this optimization problem are denoted in independent equations (Eqs. (8)–(10)). Eq. (11) illustrates the cost objective to minimize the total energy cost. The objective functions of CQM are stated in terms of minimizing the Hamilton formulation with non-negative scalar weights, which is used to determine the effect of various objectives for multi-objective problems. For this optimization problem, which has a single objective, the value of the scalar weight α for Hamilton $H1$ is set to 1.

The proposed approach computes each scenario of the use cases and derives an optimized energy supply over the time periods. The results, including energy prices and trends of storage as well as used energy over the 8 h shift are summarized in Table 2. The total energy demand of a time interval is marked with a red frame and is made up of the various sources of energy. Computing times and energy costs are also shown for comparison purposes.

In the analysis of the results, QA shows its scalability through the three scenarios from use case 1. Remarkable at this point is that despite exponentially increasing problem size, the computing time for finding a solution increases only slightly. Furthermore, the results of the second use case show that QA allows initially planned energy distributions to be adapted according to new environmental conditions. In this context, QA similarly delivers a new solution within a few seconds as well. Thus, the use of QA allows the rescheduling described at the beginning to be carried out in a matter of seconds and to be adapted to changing conditions of a manufacturing system.

3. Conclusion

In this paper, a QA-based approach is proposed to optimize the energy supply by providing a cost-effective energy mix for manufacturing systems. Using influencing factors such as availability of renewable energy, and volatile electricity prices, different use cases are computed to investigate the scalability and flexibility of the approach. QA has shown to be capable of computing problem sizes of varying complexity within seconds and demonstrates its suitability for flexible rescheduling in response to changing environmental conditions. Consequently, QA bears the potential for building a fast and efficient energy management system for manufacturing that can respond to changing conditions with flexible rescheduling.

The object of further research will be the comparison with state-of-the-art algorithms to show the validity of the approach.

Table 2
Results of the use cases.

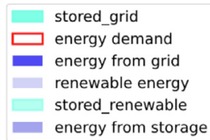
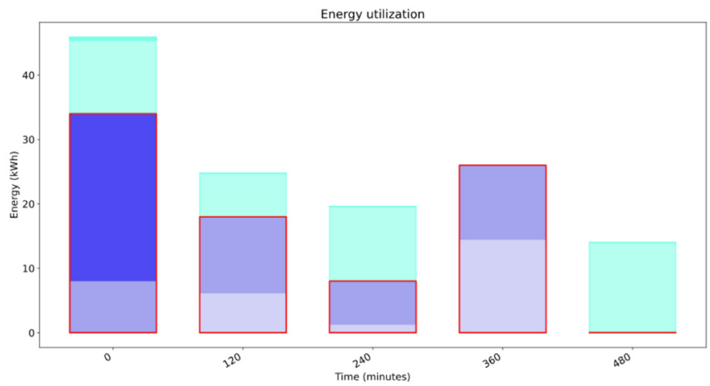
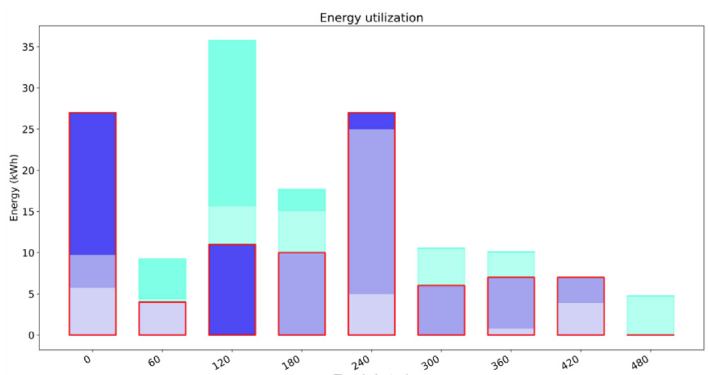
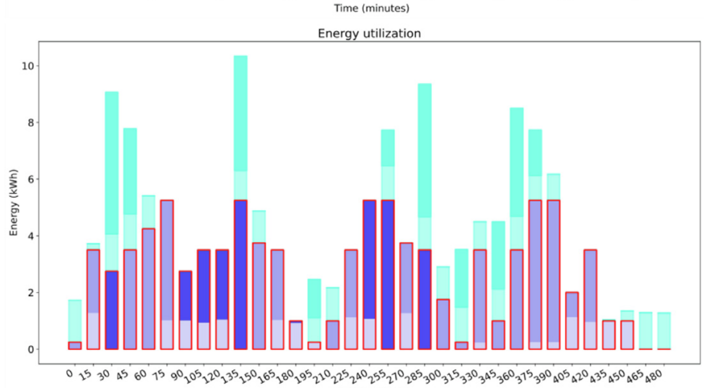
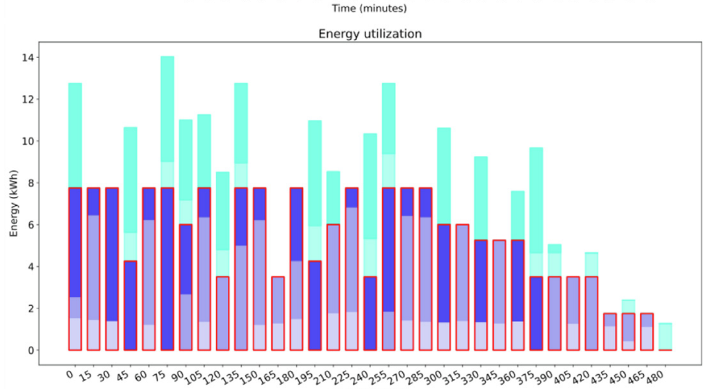
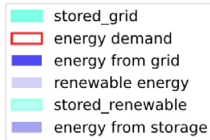
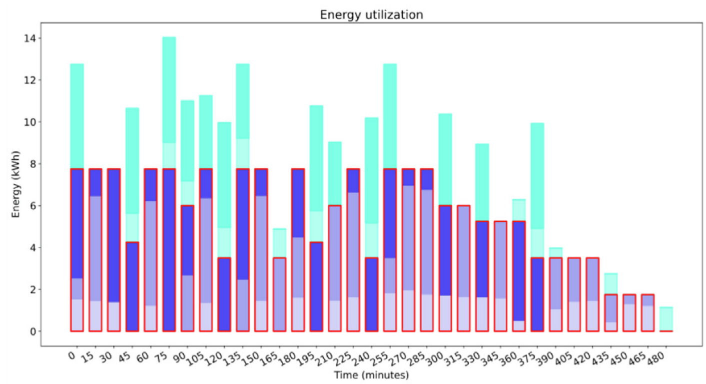
Use case	Time interval	 Energy supply	Computing time in s/ Energy cost in ct
1	t = 120 min		4.30/371
	t = 60 min		4.38/738
	t = 15 min		4.84/655
2	Initial plan		4.71/2015

Table 2 (*continued*)

<table>
<tr><th>Use case</th><th>Time interval</th><th>

Energy supply</th><th>Computing time in s/ Energy cost in ct</th></tr>
<tr><td></td><td>Rescheduling t = 120 min</td><td>
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</table>

Moreover, the combination with a scheduling approach like [14] could be beneficial, since energy requirements can already be included in the process scheduling. To create a more accurate model, peak load reduction techniques will be incorporated. These techniques play a critical role in determining prices, where it's essential to prevent grid overloads. Additionally, within this context, considering capital depreciation offers a valuable means of enabling a more equitable price comparison. Further research is needed to find out how a multi-objective approach can be implemented in order to represent and optimize real industrial problems.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.mfglet.2023.09.005.

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