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Integration of Heat Pump Storage Systems in Manufacturing Systems via Data Farming and Monte Carlo Simulation

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The electrification of industrial energy demand is essential for effective climate protection and a successful energy transition. In production systems with fluctuating heating and cooling demands, heat pumps can make a significant contribution to electrification and increased efficiency in a demand-oriented production with automated standby operation. In order to dimension a suitable heat pump storage system, well-founded statistical information about the production system is required. For the creation of stochastic heating and cooling demand profiles, numerous material flow simulations were therefore carried out as part of a case study, whereby the simulated time is always a production week in seconds resolution with shutdown at the weekend. Input data for the simulation are real energy measurement data from an energy monitoring system. The results of the Monte Carlo simulation show that relatively small heat pumps and storages can ensure the reliable heat and cold supply of the manufacturing system thanks to the superposition and mutual compensation of numerous sources of uncertainty in the manufacturing system. In the case study presented in this paper, covering a constantly running HP in only 95 % of all possible cases instead of the entire 100 % leads to a drastic reduction in storage volume by a factor of about 25.

1. Introduction

In general, there is a wide range of economic applications of heat pumps (HPs) in industrial processes (Olsen et al., 2017). Since HPs require continuous operation, many approaches deal with the dimensioning of heat and cold storage systems in order to meet the challenge of (effectively) non-continuous processes (e.g. Stampfli et al., 2018). Junge et al. (2017) and Seevers et al. (2018) highlighted the possible energy efficiency potentials of heat pump storage solutions (HPS) integrated into the energy supply structure of gear manufacturing systems. In a typical production line in manufacturing systems, the integration of HPS is a complex problem due to the high non-continuity - especially when implementing a standby control system (Goy, 2016) - and several other influencing factors that increase the range of variation (Seevers et al., 2018). In order to optimise such non-stationary material flows with discrete production processes in terms of costs and energy demand, a material flow analysis is usually required. However, material flow simulation and optimisation is a complex problem, even if several simplifying assumptions are made and energy efficiency considerations are completely neglected (Kiesmüller and Zimmermann, 2018).

In the context of increasing electrification in all sectors, heat sources at a low temperature level, such as the cooling of machine tools, are becoming increasingly important in contrast to conventional fossil waste heat sources due to the electrification of energy and production systems (Hoffmann et al., 2015). To the authors' knowledge, there is so far no approach to material flow optimisation that takes into account the energetic advantages of thermal coupling of heat sources and sinks such as machine tools and washing machines. This paper will also not offer a solution for a holistic optimisation of the material flow system and the design of the energy supply systems. In contrast to existing approaches, however, it shows a methodology that takes into account decisive factors influencing the robust design of storage and pump sizes as well as existing framework conditions due to material flow system optimisations.

In Seevers et al. (2018), the exemplary case study of a very small production line showed that heating and cooling demands can be linked quite well with a certain HPS dimensioning. However, many sources of uncertainty complicate a deterministic and stable dimensioning of the HPS system. Therefore, existing

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approaches like Junge et al. (2017) or Watanabe (2013) aim at creating a framework to simplify the coupling of machine tools and washing machines. These simplifications lead to the need of several HPs and storages to be installed within a manufacturing system to ensure high production reliability.

In contrast to such simplified approaches, which lead to high investment costs, the novelty of this study lies in the dimensioning of a single HPS, which couples all heat sinks and sources in one production system. Furthermore, both different standby strategies and complex material flow interdependencies should be considered by means of a Monte Carlo (MC) based material and energy flow simulation. By using MC methods, the simulation results contain information about the degree of uncertainty, which supports a robust design of the systems (Dunkelberg et al., 2019). Due to the numerous uncertainty input factors mentioned above, which significantly influence the heating and cooling demands of the entire material flow system, a very wide range of possible thermal demand profiles can easily arise. In order to cover all these possibilities, immensely large heat and cold storages would probably have to be installed. The aim of this paper is therefore to find a robust HPS dimensioning that optimally covers the majority (e.g. 95 %) of all possible demand profiles generated by the MC based material flow simulation. The rest can then be buffered via separate heating and cooling units.

The methodological approach of this paper is described in section 2. In section 3 a case study is shown where real sensor data from a production line is used for statistical robust dimensioning of a HPS. The results of this case study are discussed in section 4. Finally, section 5 concludes this paper.

2. Methods

The methodology used in this paper is shown in Figure 1. Basically it consists of three key components: First the definition and selection of relevant input data to the discrete event simulation as well as the definition of the type of experimental design (e.g. (full) factorial design of experiments (DoE) or MC simulation). The first component can be found in Figure 1 in the left part. In the case of a MC driven simulation, as it is the focus of this paper, the input factor specification contains the definition of the distribution type (normal, Weibull, equal etc.), estimated mean and standard deviation.

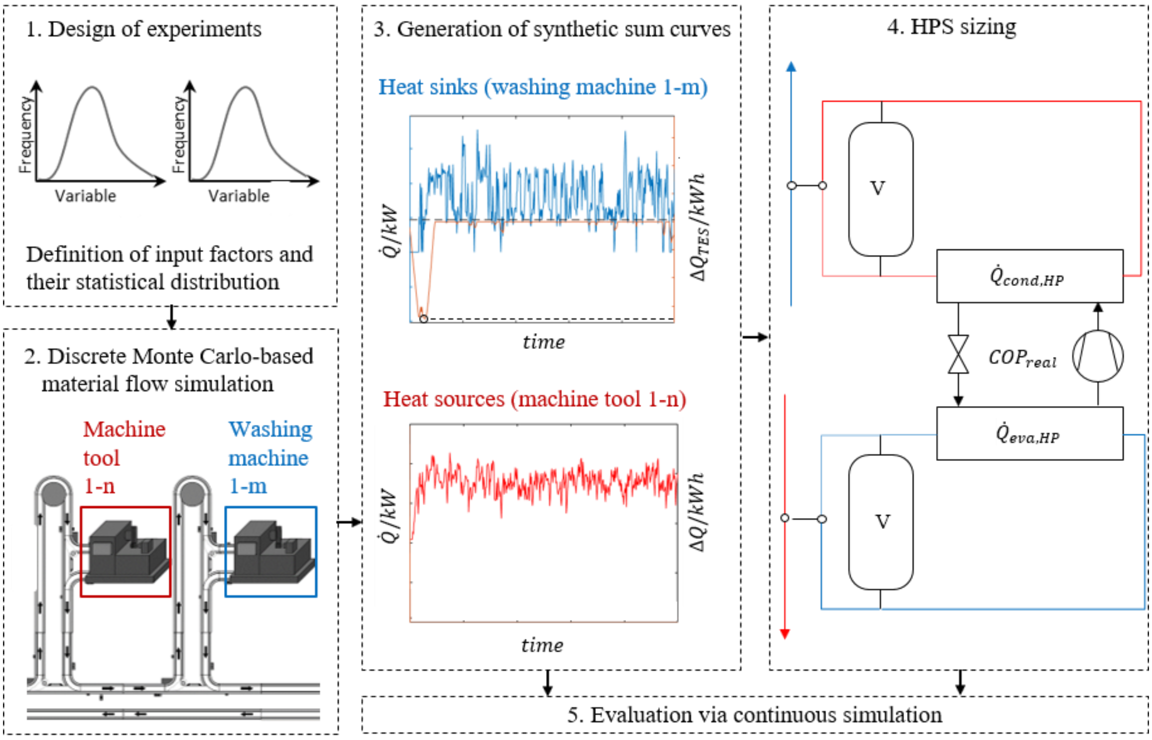

Figure 1: Methodological overview

The material flow discrete event simulation of the manufacturing system including the generation of the heat source and sink demand sum profiles also belong to key component 1. The events which are simulated can be associated with a degree of uncertainty. In practice, e.g. provisioning of new parts to the manufacturing line or machine failures are subject to great uncertainty. Dependent on the course of these discrete uncertain events, the machining stations in the simulated manufacturing system enter different operational states. These operational states entail certain levels of cooling or heating demand respectively. The sum curves of cooling and heating demands are the material flow simulation output. Every simulation run generates both one sum profile for all cooling demands and one sum curve for all heating demands in the respective manufacturing system. In this manner, a high number of scenarios can be considered. The size of the manufacturing system to be simulated and thus the number of heat sources and heat sinks can be adjusted by means of a modular design with little effort. The methodology is therefore easily scalable to different systems. Statistical methods can be used to estimate the minimum number of simulation runs (Byrne, 2013)

For each simulation output of two time series (cooling and heating demand sum curves) the dimensioning of HP and storages according to the Pinch method takes place in key component two of our methodology. In Seevers et al. (2018) the detailed description and the used calculation formulas can be found.

The first step is to analyze the availability of heat sinks and source for the integration of a HP. Figure 1(b) displays the average sum load $\dot{Q}$ of the sink and source streams. Secondly, it must be check whether the heat demand can be fully covered by pumping the existing heat source capacity to the target sink temperature. For the condition $\dot{Q}_{e,Si} \leq \dot{Q}_{HP,prod}$, the condensation capacity of the HP is determined according to (3). Otherwise, the emitable heating capacity $\dot{Q}_{e,Si}$ depends on the absorbable heat source $\dot{Q}_{a,So}$ and $\dot{Q}_{cond,HP}$ is calculated by (2).

$$\dot{Q}_{cond,HP} = \min\left(\dot{Q}_{e,Si};\ \dot{Q}_{HP,prod}\right) \tag{1}$$

$$\dot{Q}_{HP,prod} = \frac{\sum_{t=1}^{t_{SROP}} \dot{Q}(t)_{a,So} \cdot dt}{t_{SROP} \cdot \ (1 - \frac{1}{COP_{real}})} \tag{2}$$

$$\dot{Q}_{e,Si} \ = \frac{\sum_{t=1}^{t_{SROP}} \dot{Q}(t)_{e,Si} \cdot dt}{t_{SROP}} \tag{3}$$

Due to the temporal incongruency between the constant output of the HP and the no-continuous demand of the sink, a thermal energy storage (TES) must be used to bridge the gap. Since the balance of the transferred heat must be equal after a Stream-wise Repeating Operating Period (SROP), the capacity $Q_{TES,i}$ to be buffered is calculated from the maximum difference between demand and HP according to Figure 1 and algorithm 1.

Algorithm 1: TES sizing for heat sink

1: **Input:** $\dot{Q}(t)_{e,Si}$, $\dot{Q}_{HP,cond}$, t_{SROP}, ΔT_{min}
2: **Output:** V_{TES}
3: $\Delta\dot{Q}(t)_{Si}$ = $\dot{Q}_{HP,cond}$ - $\dot{Q}(t)_{e,Si}$
4: **for** t = 2: t_{SROP}
5: if $Q(t-1)_{TES}$ + $\Delta\dot{Q}(t)_{Si} * \Delta t$ < 0
6: $Q(t)_{TES}$ = 0
7: else
8: $Q(t)_{TES}$ = $Q(t-1)_{TES}$ + $\Delta\dot{Q}(t)_{Si} * \Delta t$
9: end
10: end
11: $Q_{TES,max} = \max\left(Q(t)_{TES}\right)$
12: **return** $V_{TES} = \frac{Q_{TES,max}}{1{,}16\frac{kWh}{m^3K}\cdot\Delta T_{min}}$

Key component 3 is the evaluation of the possible HPS sizes. After the first simulation runs based on the statistical analysis of the simulation output, one HP dimensioning is chosen from the distribution of all possible HP dimensions. In the second, step with this chosen HP dimension possible heat sink and source storage sizes have to be calculated for each single simulation output set of (cooling and heating demand) sum curves according to algorithm 1 which shows exemplarily the heat sink storage calculation.

Based on the statistical distribution of needed storage sizes a decision can be made which storage to choose. After Key component 3 the evaluation of heat recovery rates and the estimation of the probability of energy efficiency potentials should follow. This can be done by thermal continuous simulations which goes beyond the scope of this paper.

3. Case study

The investigated manufacturing line consist of 16 machines (see in detail Goy (2016)). Nine machines are machine tools with a cooling demand. Four machines are washing machines with heating demand. In average, the heating demands are significantly smaller than the cooling demands. This is the reason why in every scenario no heat source storage was needed. The remaining cooling demand of the line that cannot be supplied by the HP is provided by an additional cooling unit. Machines 14-16 are simple laser marking systems with negligible heating and cooling demands. There are three different kinds of parts machined in this material flow system. The production is designed for a 3-shift operation and 1600-1800 parts per day. However, the parts production per day can vary widely. Therefore, the parts provisioning is a crucial input factor to the MC simulation. The weekly production of parts (including faulty parts) of all three part types on the production line ranges from about 3600 to 12000 with an average value of 7225 (200 simulation runs, each with $t_{SROP} = 1\ week$).

Two standby scenarios are considered for the respective manufacturing line: No standby manger (1) and a relatively easily implementable state-of-the-art standby manager which reduces the power demand of machines when they are waiting for parts (2). Two scenarios with 200 simulation runs correspond to 400 sum curve sets as a result of the material flow simulation. Beside the parts produced, the most relevant input factors to the manufacturing system are related to production interruptions due to machine failure. Therefore, the empirical distributions of mean time to repair (MTTR) and the machine availability (A) are taken into consideration for each of the 16 machines (see the distributions of MTTR exemplarily in Figure 2). With given A and MTTR, the mean time before failure (MTBF) can be calculated. Inside the simulation an "Erlang distribution" is used for the MTTR and a "negative exponential distribution" is used for the MTBF.

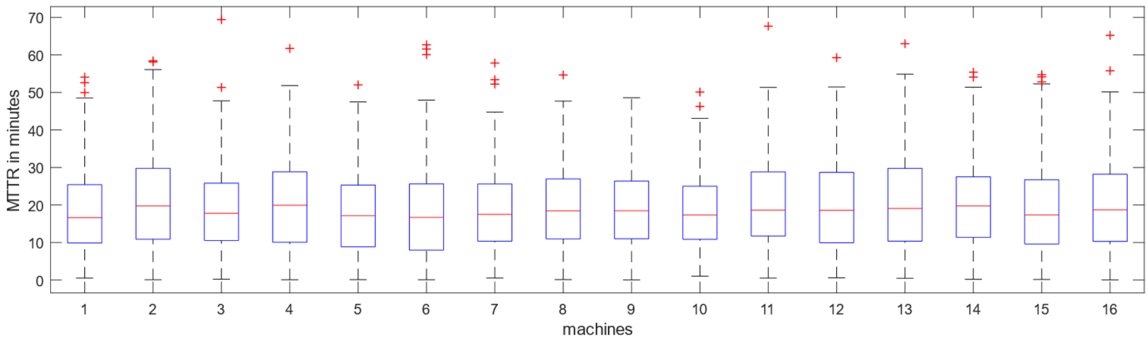

Figure 2: Empirical distributions of MTTR for 16 machines

4. Results and discussion

In the first step the HP has to be dimensioned for every simulation run. The distribution of possible HP dimensions for the first scenario is shown in Figure 3. The vertical black lines depict the selection of two HPs. One HP has a higher value for $\dot{Q}_{HP,cond}$ than 5 % of all other HP sizes and one HP has a higher value for $\dot{Q}_{HP,cond}$ than 10 % of all other HP sizes. The values are almost equal at around 60 kW. In standby scenario 2, the distribution of HP sizes is much broader, from 28 to 48 kW condensing capacity, as the cooling and heat demands fluctuate more strongly. However, the 5 % and the 10 % HP sizes (32,5 kW and 33,5 kW) do not differ to any relevant extent in this scenario either.

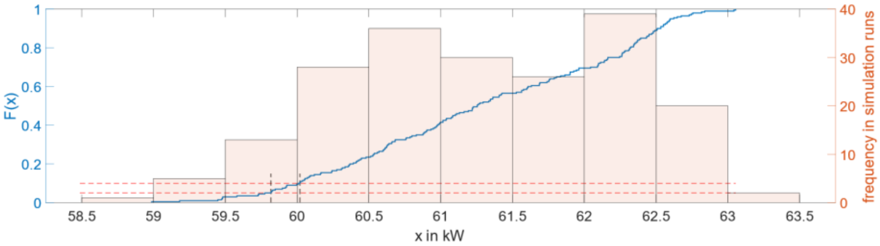

Figure 3: HP dimensions ($\dot{Q}_{HP,cond}$) for the 200 simulation runs in standby scenario 1.

The storage size of the heat sink, if it is designed for each individual simulation run with the HP best suited to the individual case, has a large range and on average a very large storage volume for scenario 2. In Figure 4 the histogram and the cumulative distribution is shown. In order to fully cover all 90 % of all probable demand profiles with the individually dimensioned HP, a massive storage capacity of over 8 m³ would be required.

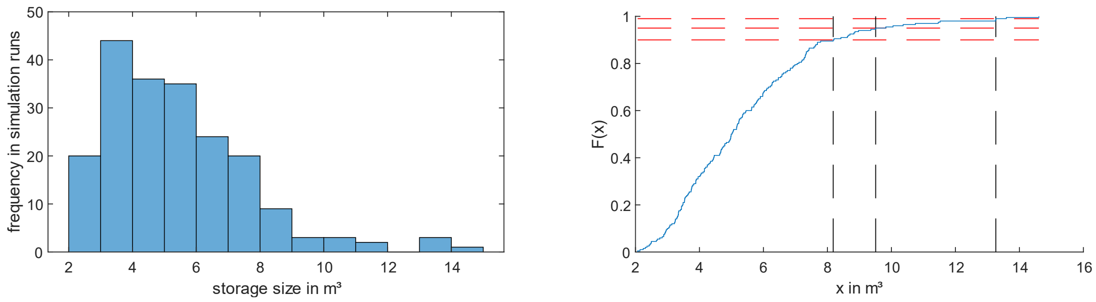

Figure 4: Heat sink storage sizes in m³ for standby scenario 2 and varying HP sizes

After having chosen the 5 % and 10 % HP sizes for both scenarios, four statistical distributions of the heat sink storage sizing are the output of another 4*200=800 storage dimensioning calculations. In Figure 5 two empirical cumulative distribution functions of the “5 % HP” are illustrated.

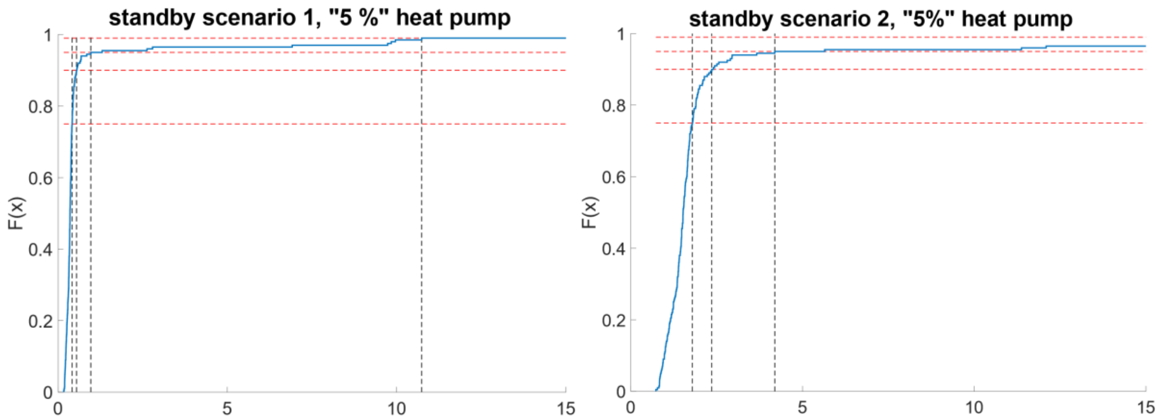

Figure 5: Heat sink storage sizes in m³ for standby scenarios 1 and 2

In both scenarios, even the small increase in HP size of only about 1 kW led to significantly larger storage volumes with the same confidence level (red lines). In standby scenario 1 with the same confidence level of 95 %, the required storage capacity increases from approx. 1 m³ to approx. 6 m³. In standby scenario 2 even from 4 m³ to 90 m³. The standby scenario 2 with the practical standby manager leads to significantly larger storage dimensions due to the higher fluctuations. This highlights the importance of avoiding oversizing the HP. In Scenario 2, almost independent of the size of the HP, with a storage capacity of approx. 2 m³, in 75 % of all cases the constantly running HP can be used 100 % of the time and does not have to be switched off at any time. Without standby operation in scenario 1, a heat sink storage tank of approx. 0.5 m³ is even sufficient to buffer 90 % of all cases to 100%. Even smaller storage tanks and thus lower space requirements and investment costs would also be conceivable. However, in such a case the HP would have to be switched off more often. It is therefore possible to evaluate efficiency potentials as well as economic efficiency by means of thermal simulations. If the absolute extreme values, e.g. in a full factorial DoE, were used as the basis for the storage tank sizes, this would lead to heat sink storage tank sizes of approx. 25 m³ in standby scenario 1 and 110 m³ in standby scenario 2 for the 5 % HP.
With up to 95% of the cases covered by the storage, the relatively small HPS dimensions are remarkable for a large gear manufacturing line with considerably large and highly fluctuating energy demands. They support the core statements of the research of Stoltze et al. (1995) that a theoretically large number of heat storages (double the number of process streams) can be reduced to a few.

5. Conclusions and outlook

With the application and further development of the methodology presented by Seevers et al. (2018) this paper showed to what extent MC-based material flow simulation can be used to achieve a reliable and highly system-efficient power supply for electrified production. In addition, it was shown how a robust HPS dimensioning can be calculated, which can cover all sources of uncertainty as accurately as possible via data farming. A constantly running HP in at least 95 % of all possible cases instead of the total 100 % leads in the case study shown in this paper to a drastic reduction in storage volume: in standby scenario 1 only approx. 1 m³ instead of 25 m³, in standby scenario 2 only approx. 4 m³ instead of 110 m³. In both cases this is a reduction by a factor of about 25. On this basis of the MC based material and energy flow simulations, planning engineers as well as energy managers and auditors can make statistically well-founded decisions. This can help to refute classic arguments against energy efficiency measures such as planning uncertainty, quality and process reliability concerns.

Both for the planning of new material flow systems and for the retrofitting of existing ones, the developed methodology and discrete event simulation environment offers comprehensive transferability to a large number of conceivable case studies. Material flow systems of any type, design and size and their heating and cooling demands can be simulated. Many influencing factors can also be taken into account. The more comprehensive consideration of all influencing factors will also require further research. In this context, it is necessary to make an uncertain estimate of the future and currently not yet measurable cooling and heat demand when planning new material flow systems. Based on empirical and theoretical models fed with comprehensive energy monitoring data, there is a need for research to estimate these cooling and heating demands as reliably as possible for the varying operational states of different machine types.

Moreover, it should be investigated to what extent material flow optimisation approaches, considering e.g. production parts buffer size and spare parts provisioning (Kiesmüller and Zimmermann, 2018), can be combined with the optimised planning of standby control and HPS. A faster delivery of spare parts, for example, ensures a more continuous material flow, which would be advantageous for HP operation. In contrast, large machining part buffers tend to lead to more discontinuous operation, making stricter standby operation more attractive and limiting HPS integration.

References

Byrne, M.D., 2013. How Many Times Should a Stochastic Model Be Run? An Approach Based on Confidence Intervals. Proceedings of the 12th International conference on cognitive modeling, Ottawa.

Dunkelberg, H., Sondermann, M., Meschede, H., Hesselbach, J., 2019. Assessment of Flexibilisation Potential by Changing Energy Sources Using Monte Carlo Simulation. Energies 12, 711.

Goy, S., 2016. Stand-by-Betrieb von Maschinen und Anlagen. Entwicklung eines Stand-by-Managers zur energieeffizienten Produktionssteuerung. Kassel University Press GmbH; Kassel University Press.

Hoffmann, C., Gerhardt, N., Sandau, F., Zimmermann, B., Pape, C., Bofinger, S., 2015. A Business Model for the Energiewende. A Rejoinder to the "Cost Argument". Fraunhofer IWES, Kassel.

Junge, F., Helfert, M., Abele, E., Vogel, F., 2017. Increase in energy efficiency of industrial production processes through thermal crosslinking of cutting-machine tools and cleaning machines by heat-pump technology, 12th IEA Heat Pump Conference 2017, Rotterdam.

Kiesmüller, G.P., Zimmermann, J., 2018. The influence of spare parts provisioning on buffer size in a production system. IISE Transactions 50, 367–380.

Olsen, D., Abdelouadoud, Y., Liem, P., Hoffmann, S., Wellig, B., 2017. Integration of Heat Pumps in Industrial Processes with Pinch Analysis, 12th IEA Heat Pump Conference 2017, Rotterdam.

Seevers, J.-P., Schlosser, F., Peesel, R.-H., Hesselbach, J., 2018. Dimensioning of Heat Pump Systems Based on Pinch Analysis and Energy Monitoring Data. Chemical Engineering Transactions, 787–792.

Stampfli, J.A., Atkins, M.J., Olsen, D.G., Wellig, B., Walmsley, M.R.W., Neale, J.R., 2018. Industrial Heat Pump Integration in Non-Continuous Processes Using Thermal Energy Storages as Utility – An NLP Enhancement of the Graphical Approach. Chemical Engineering Transactions, 1789–1794.

Stoltze, S., Mikkelsen, J., Lorentzen, B., Peterson, P.M., Qvale, B., 1995. Waste-Heat Recovery in Batch Processs Using Heat Storage. Journal of Energy Resources Technology 117, 142–149.

Watanabe, C., 2013. Trends in industrial heat pump technology in Japan. 3rd Conference of AHPNW, HUST, Hanoi, Vietnam.