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Control policies for managing energy storage systems under uncertainty based on industrial case studies

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Abstract

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Control policies for managing energy storage systems under uncertainty based on industrial case studies

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Abstract

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1 Introduction

The problem of storing energy now to be used later arises in such a wide range of settings that it has become a foundational problem, as ubiquitous in energy systems as inventory theory is in operations management. Storage problems have to be solved in the presence of different types of uncertainty: uncertain generation from renewable sources, stochastic (and heavy-tailed) real-time prices, infrequent failures of generators or transmission lines, as well as inaccurate forecasts of temperatures and loads (Powell, 2014). In this report, we examine some control strategies used by industry to manage energy storage systems in the face of these sources of uncertainty. We use two case studies based on industrial visits to provide a framework to model the problem, explain which control strategy is currently used by industry and alternative control policies that are worth considering.

2 Literature review

Energy storage is a form of inventory problem, which is the original stochastic control problem used by Bellman to motivate his work on dynamic programming (Bellman et al., 1955). Several researchers have focused on finding provably optimal control policies for special classes of storage/inventory problems. For example, Harsha and Dahleh (2014) showed that for storage problems with stochastic supply and demand, one storage device, and time-varying prices, the optimal control policy has a dual threshold structure. Other works on structural analysis of optimal polices for storage problems are Zhou et al. (2016, 2019); van de Ven et al. (2013). Alternatively, most papers aim at designing suboptimal, but effective, solution strategies for a wide range of settings. These solution approaches include policy function approximations (Warrington et al., 2012; Han et al., 2016), cost function approximations (Simao et al., 2017; Thalassinakis and Dialynas, 2004), model predictive control (Arnold and Andersson, 2011), and approximate dynamic programming (Durante et al., 2017). Powell and Meisel (2015) have shown that all classes of policies may work best for a given energy storage problem, depending on the characteristics of the problem. For this reason, when solving a particular problem, it is important to screen over different classes of policies to find the one that works best.

3 Case study: A district heating network

This case study is based on the visit to the incineration plant in Heimdal, which uses residual waste to heat the water used for district heating in the city of Trondheim. From Heimdal, hot water runs in pipes to large parts of the city. Among the institutions receiving district heating are St. Olav's Hospital, the Norwegian University of Science and Technology, Lerkendal Stadium, Nidaros Cathedral, and most residential areas in the city.

In this problem, an operator of a district heating network must satisfy a recurring energy demand with a time-varying supply of energy from a waste incineration plant, unlimited supply of energy from electric boilers that consume electricity from the grid at a stochastic price, and a local thermal storage device. The objective is to control the system to minimize the cost of electricity over time. The PI&D diagram in shown in Appendix A. However, we will model a simplified version of this problem, whose configuration is illustrated in Figure 1. This simplified model in terms of energy flows will allows us to be more precise when modeling the problem and describing the control policy currently used.

3.1 Mathematical model

To represent sequential energy allocation decisions in the context of this energy storage problem, we follow the modelling framework outlined in Powell (2019), which includes five key components: state variables, decision variables, exogenous information, state transition function, and objective function.

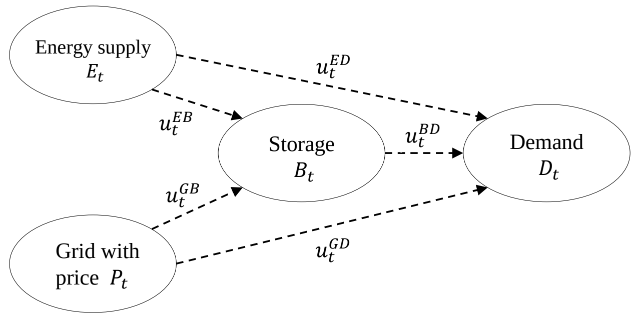

Figure 1: Illustration of the energy storage problem. There are four nodes: energy supply, the grid, storage, and demand; three exogenous variables: energy generation, the price of electricity, and the demand; and five decision variables representing energy allocations at each time step.

3.1.1 State variables

The state x_t of the system at time t contains all the information we need to know (from history) to model the evolution of the system and that is relevant for future optimization. We distinguish between the initial state x_0 and the dynamic state x_t for $t > 0$. The initial state contains all static parameters and initial values of dynamic parameters. The dynamic state x_t contains information that is evolving over time.

In this problem, the initial state x_0 contains the initial values of energy supply E_0 (in MWh), energy demand D_0 (in MWh), electricity price P_0 (in kr/MWh) and storage level B_0 (in MWh). Additionally, it includes the static parameters that characterize the storage device: the energy capacity $B_{\max}$ (in MWh), the charging efficiency η_c, the discharging efficiency η_d, the maximum charging rate γ_c (in MWh per time period), and the maximum discharging rate γ_d (in MWh per time period). Therefore,

$$x_0 = (B_0, E_0, D_0, P_0, B_{\max}, \eta_c, \eta_d, \gamma_c, \gamma_d).$$

The dynamic state x_t contains the current energy supply E_t, energy demand D_t, electricity price P_t and storage level B_t. Therefore,

$$x_t = (B_t, E_t, D_t, P_t).$$

3.1.2 Decision variables

The decision variable u_t encapsulates all energy allocation decisions made at time t. Energy is bought from the grid at the current spot market price. Energy from the waste incineration plant can either be stored or used to satisfy the current demand.

Decisions are made with a policy π, a function which maps the state of the system x_t to a feasible decision, i.e., $u_t = \pi(x_t)$.

Let u_t^{IJ} denote the amount of energy transferred from I to J at time t, where superscript E stands for energy supply, D for demand, B for battery (storage device) and G for grid. Therefore, the decision vector is given by

$$u_t = (u_t^{ED}, u_t^{GD}, u_t^{BD}, u_t^{EB}, u_t^{GB}).$$

In our model, the decisions are subject to several constraints. We require that all energy flows are nonnegative for all t:

$$u_t^{ED}, u_t^{GD}, u_t^{BD}, u_t^{EB}, u_t^{GB} \geq 0. \tag{1}$$

Furthermore, the total amount of energy stored in the device at time t must not exceed the energy capacity available or the maximum charging rate, whichever is smaller:

$$u_t^{EB} + u_t^{GB} \leq \min\{B_{\max} - B_t, \gamma_c\}. \tag{2}$$

We also make the assumption that all demand at time t must be satisfied:

$$u_t^{ED} + \eta_d u_t^{BD} + u_t^{GD} = D_t. \tag{3}$$

Additionally, the amount of energy drawn from the storage device to satisfy the demand must not exceed the amount of energy that is available in the device at time t or the maximum discharging rate, whichever is smaller:

$$u_t^{BD} \leq \min\{B_t, \gamma_d\}. \tag{4}$$

Finally, flow conservation requires that the amount of energy transferred from the waste incineration plant is not greater than the amount of energy being generated at time t:

$$u_t^{EB} + u_t^{ED} \leq E_t. \tag{5}$$

The set of all constraints (1) - (5) defines the feasible decision space.

3.1.3 Exogenous information

Exogenous information variables, also known as disturbances, represent what we learn from an exogenous source after we make each decision. We denote the exogenous information arriving between t and $t+1$ as ω_t and it is therefore random at time t. In our problem,

$$\omega_t = (\hat{E}_t, \hat{D}_t, \hat{P}_t),$$

where $\hat{E}_t$ is the change in the energy supply between t and $t+1$, $\hat{D}_t$ is the change in the energy demand between t and $t+1$, and $\hat{P}_t$ is the change in the electricity price between t and $t+1$.

To complete the model, we would have to provide the probability distribution for the exogenous variables $P(\omega_t | x_t, u_t)$. These stochastic models can be constructed from historical data of energy supply, energy demand, and electricity prices in Trondheim.

3.1.4 State transition function

Also known as the system model, the state transition function is a mapping from our current state x_t to the next state x_{t+1}, given our decision u_t and the realization of the exogenous information ω_t:

$$x_{t+1} = f(x_t, u_t, \omega_t).$$

The transition function for the energy in the storage device is given by

$$B_{t+1} = B_t + \eta_c(u_t^{EB} + u_t^{GB}) - u_t^{BD}, \tag{6}$$

which is an energy balance in the storage device. The transition dynamics for the energy supply, energy demand, and price are given by

$$E_{t+1} = E_t + \hat{E}_t, \tag{7}$$

$$D_{t+1} = D_t + \hat{D}_t. \tag{8}$$

$$P_{t+1} = P_t + \hat{P}_t. \tag{9}$$

3.1.5 Objective function

The objective function captures our performance at a particular time, and characterizes the problem of finding optimal policies.

In this problem, we incur costs when purchasing electricity from the grid. Therefore, our cost from being in the state x_t and making the decision u_t at time t is given by

$$C(x_t, u_t) = P_t(u_t^{GB} + u_t^{GD}).$$

Since we aim to minimize costs with real-time electricity prices over a finite horizon, our objective function is given by

$$\min_{\pi \in \Pi} \mathbb{E} \left[\sum_{t=0}^{T} C(x_t, u_t) \middle| x_0 \right],$$

where $x_{t+1} = f(x_t, u_t, \omega_t)$ is given by equations (6) - (9). Letting Π be the collection of all mappings from state to decisions that satisfy the set of constraints (1) - (5), we minimize over the set of all admissible policies $\pi \in \Pi$ to determine an optimal policy. In most cases, finding an optimal policy is just an aspiration and we focus instead on designing suboptimal, altough effective, policies.

3.2 Control policy currently used in Heimdal

The operators in Heimdal currently use a simple threshold policy that depends on the electricity price to manage the system.

The energy from the waste incineration plant is first used to satisfy the current demand:

$$u_t^{ED} = \min\{D_t, E_t\}.$$

If generation exceeds demand, the surplus energy is stored in the storage device, respecting the capacity and charging constrains:

$$u_t^{EB} = \min\{E_t - u_t^{ED}, B_{\max} - B_t, \gamma_c\}.$$

If the current demand cannot be satisfied with energy from the waste incineration plant and the storage device, the electric boilers are used by purchasing electricity from the grid at the current price:

$$u_t^{GD} = D_t - u_t^{ED} - u_t^{BD}.$$

When electricity prices are low (below certain threshold θ_{low}), the storage device is charged purchasing energy from the grid, respecting the capacity and the charging constraints:

$$u_t^{GB} = \begin{cases} \min\{B_{\max} - B_t - u_t^{EB}, \gamma_c\}, & \text{if } P_t < \theta_{\text{low}} \\ 0, & \text{if } P_t \geq \theta_{\text{low}} \end{cases}$$

When electricity prices are high (above certain threshold θ_{high}), the storage device is discharged to satisfy the current demand, respecting the capacity and the discharging constraints:

$$u_t^{BD} = \begin{cases} \min\{D_t - u_t^{ED}, B_t, \gamma_d\}, & \text{if } P_t > \theta_{\text{high}} \\ 0, & \text{if } P_t \leq \theta_{\text{high}} \end{cases}$$

Pulling it all together, the control policy currently used in Heimdal is given by

$$\pi(x_t|\theta) = \begin{cases} u_t^{ED} = \min\{D_t, E_t\} \\ u_t^{BD} = \begin{cases} \min\{D_t - u_t^{ED}, B_t, \gamma_d\}, & \text{if } P_t > \theta_{\text{high}} \\ 0, & \text{if } P_t \leq \theta_{\text{high}} \end{cases} \\ u_t^{GD} = D_t - u_t^{ED} - u_t^{BD} \\ u_t^{EB} = \min\{E_t - u_t^{ED}, B_{\max} - B_t, \gamma_c\} \\ u_t^{GB} = \begin{cases} \min\{B_{\max} - B_t - u_t^{EB}, \gamma_c\}, & \text{if } P_t < \theta_{\text{low}} \\ 0, & \text{if } P_t \geq \theta_{\text{low}} \end{cases} \end{cases}$$

The policy is parameterized by $\theta = (\theta_{\text{low}}, \theta_{\text{high}})$, which are the thresholds on the electricity prices. Therefore, choosing the right values for these parameters will determine the performance of the policy. We believe that this policy is very effective for Heimdal, where the energy supply is almost stationary (the waste incineration plant burns waste almost at a constant rate) and the electricity prices in Trondheim are not very spiky, as in other spot electricity markets. This policy exploits well the structure of the problem employing a “buy low, sell high” philosophy and allows the operators to re-tune the policy whenever operating conditions change in the plant or in the spot electricity market.

3.3 Alternative control policies

If we had access to forecasts of any of the exogenous variables (energy supply, energy demand, or electricity prices), we could use this information in a lookahead policy such as economic model predictive control. This method solves the control problem over a horizon H at time t using a point forecast of the future, then implements only the decision for time t and repeats the process at $t + 1$, when new information has arrived. However, for this case study it is unclear if a lookahead policy will outperform significantly a well-tuned simple threshold policy as the one currently in used. We have investigated this problem in a recent master thesis (Jeong, 2020) and the simulation results showed that the simple threshold policy well-tuned outperformed different forms of model predictive control for this particular problem.

4 Case study: An agricultural school

This case study illustrates the use of energy storage in an agricultural school in Mære. The school needs heating for office spaces, greenhouses, and farm animals. There are two thermal storage devices, which operate on different time scales: short-term and long-term (seasonal) storage. These devices are charged by waste heat collected from ambient heat, lighting, sun radiation, and plant transpiration, using chill beams and underfloor harvesters installed in the buildings. The available surplus heat is highly stochastic and it depends on factors such as whether conditions and room occupancy. The main difference with respect to the previous case study is the use of two storage devices, which work on different time scales. The objective is to minimize the total expected energy cost. The PI&D diagram is shown in Appendix B.

4.1 Mathematical model

Due to the complexity of this system, we will not derive a simplified model in terms of energy flows as we did in the previous case study. This implies that we will be more descriptive, but following the same modeling framework.

4.1.1 State variables

The state of the system is given by all the temperatures and mass flow rates in the network, the heating and cooling demand, the surplus heat available, the temperatures of the storage devices and the price of electricity.

4.1.2 Decision variables

The decision variables are the heat flows in the system. Of particular importance is whether to charge/discharge the thermal energy storage devices and when to use the dry cooler, aerotempers, and the electric boiler. In a low-level representation of the system, the decision variables are actually valve openings and speeds of compressors and pumps.

4.1.3 Exogenous information

The exogenous information (random variables) is the change in the heating demand in the building and green houses, the change in the ambient heat available from the aerotempers, the change in the heat recovered from the dry cooler and the chnage in the price of electricity from one time to the next.

4.1.4 State transition function

The system model is given by the mass and energy balances in the system, as well as the stochastic models that govern the state transitions in the exogenous variables.

4.1.5 Objective function

The objective is to minimize the total expected cost of operating the system, which implies minimizing the expected electricity cost from the heat pumps and the electric boilers over time.

4.2 Control policy currently used in Mære

The current control strategy for the storage devices in Mære is based on balancing the temperatures in the system. To see this in more detail, let us consider the subsystem “Mære 1” in the PI&D diagram in Appendix B. In this subsystem, the heat pumps connect the low temperature side (in green) with the high temperature side (in red). The low temperature side is where heat from the dry cooler and the aerotempers is recovered and also where the thermal energy storages charge/discharge energy. The thermal energy storages are charged if their temperature is lower than the circuit temperature and discharge otherwise. This is what we mean by balancing the temperatures in the system. The heat sources (dry cooler and aerotempers) are activate whenever their temperature is higher than the temperature in the circuit. All this heat is upgraded by the heat pump to meet the heating demand in the buildings. The electric boiler is only active whenever the temperature in the heat pump is not enough to meet the building demand. The control strategy for the thermal energy storages, the dry cooler and the aerotempers is the same for the subsystem “Mære 2”.

4.3 Alternative control policies

Model predictive control with information about the weather conditions and stochastic models for cooling and heating demand based on historical data could improve the performance of the system.

5 Conclusion

These two case studies have shown that the control policies most used in practices are simple parametric functions derived from experience or heuristics and not solution strategies that are based on solving optimization problems online. In the case of Heimdal, we see little room for improvement over the existing policy, which has proven to give better performance than different implementations of model predictive control in Jeong (2020). Our assessment for Mære is different. In this problem, the existence of two energy storage devices operating on different time scales (daily and seasonal storage) makes the problem more complicated. More research is needed to analyze the structure of the optimal solution for this problem class. The existence of weather forecasts and historical data on the building energy demand motivates the implementation of a lookahead policy like economic model predictive control. In this case, we believe there is room for improvement over the current policy.

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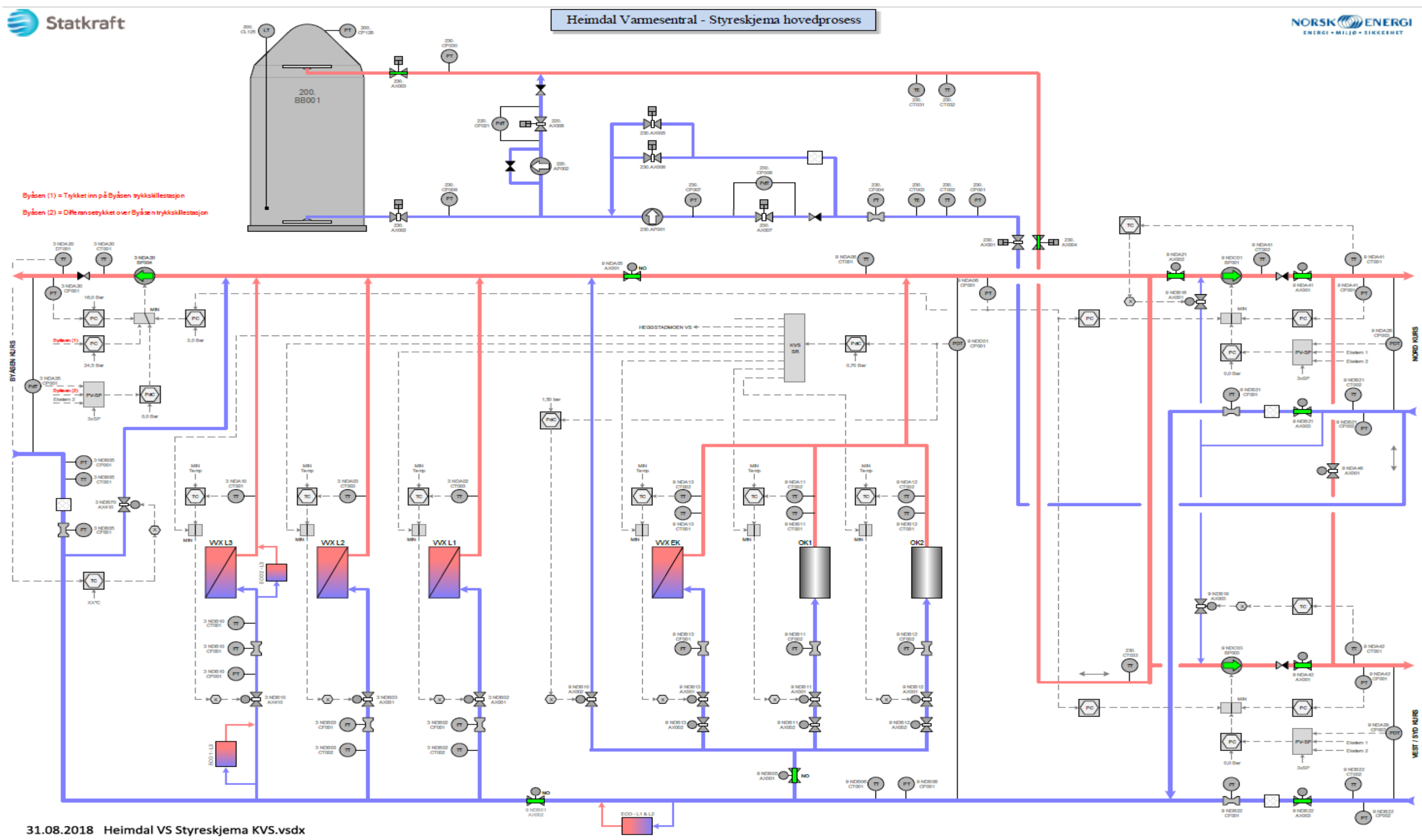
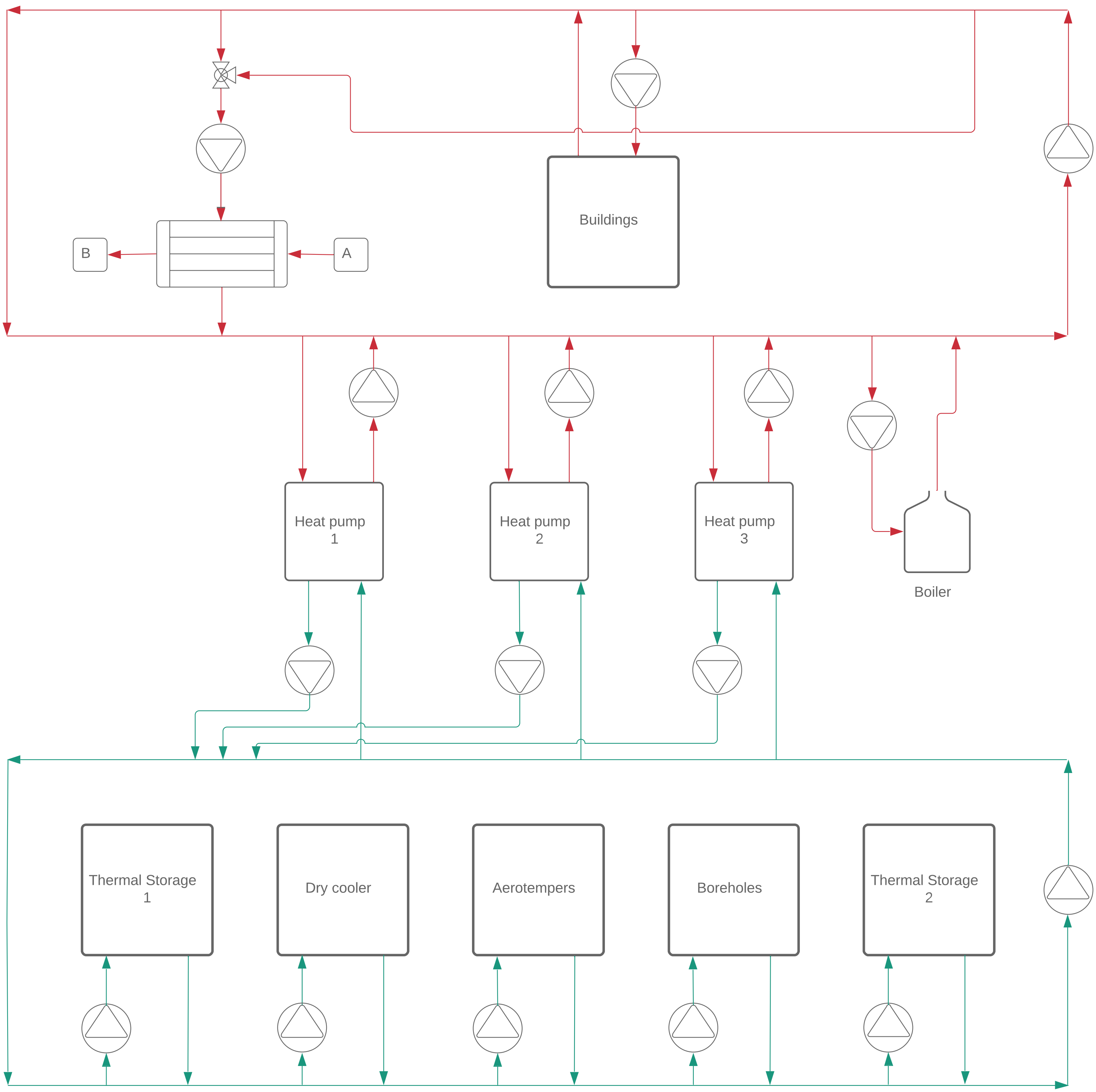
A PI&D diagram for Heimdal case study



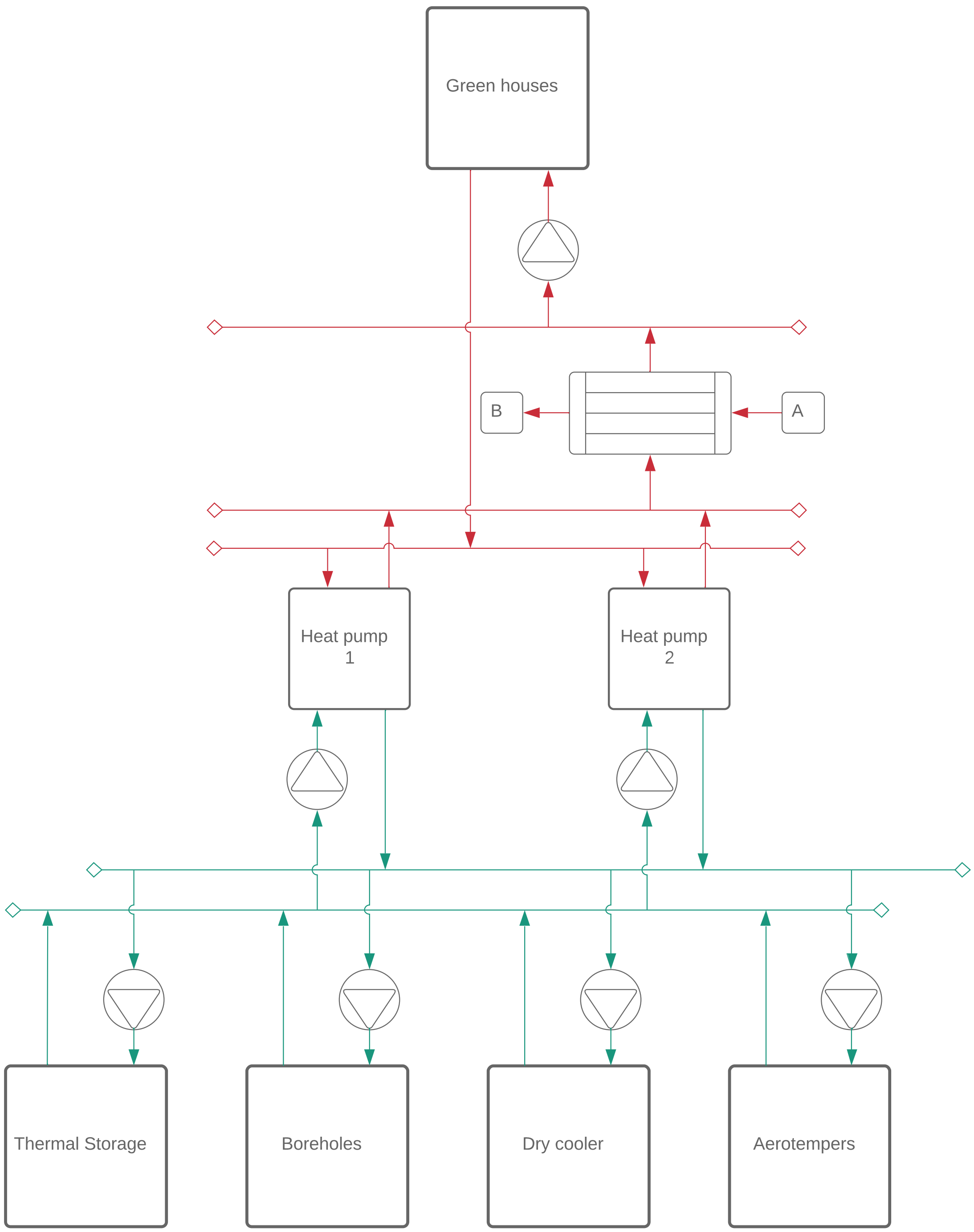
Statkraft
Heimdal Varmesentral - Styreskjema hovedprosess
NORSK ENERGI
ENERGI • MILJØ • SIKKERHET
200.
BB001
Byåsen (1) = Trykket inn på Byåsen trykkskillestasjon
Byåsen (2) = Differansetrykket over Byåsen trykkskillestasjon
BYÅSEN KURS
NORD KURS
VEST / SYD KURS
HEGGSTADMOEN VS
KVS
SR
VVX L3
VVX L2
VVX L1
VVX EK
OK1
OK2
ECO - L1 & L2
MIN Temp
16,0 Bar
24,5 Bar
3,0 Bar
0,70 Bar
1,50 bar
0,0 Bar
31.08.2018 Heimdal VS Styreskjema KVS.vsdx

B PI&D diagram for Mære case study



Maere 2 Energy Simplified P&ID

Opeyemi Bamigbetan, Gether AS | December 19, 2019



Maere 1 Energy Simplified P&ID

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