Low-regret decisions for the steam supply in the chemical industry

Niklas Nolzena, Alexander Lademanna,b, Dennis Roskoscha, Stefano Moreta, Hagen Seeleb, Florian Joseph Baadera, André Bardowa,\*

aEnergy & Process Systems Engineering, Department of Mechanical and Process Engineering, ETH Zürich, Tannenstrasse 3, 8092 Zürich, Switzerland

bInstitute for Technical Thermodynamics, RWTH Aachen University, Schinkelstraße 8, 52062 Aachen, Germany

abardow@ethz.ch

**Keywords**: Heat pump, mixed-integer linear optimization, uncertainty analysis, utility system.

**Abstract**

The decarbonization of the chemical industry requires carbon-neutral steam production either via direct electrification, e.g., using heat pumps, or via indirect electrification, e.g., using green hydrogen. However, due to low technology-readiness levels, the cost and performance of such promising technologies are subject to high uncertainties. This uncertainty prevents the industry from investing, fearing economic regret. This study proposes a method for identifying low-regret decisions based on global sensitivity analysis. Low-regret decisions are defined as an investment in a specific technology that is economically near-optimal in all future scenarios. The proposed method comprises four steps: 1) Uncertainty characterization, 2) Parameter sampling, 3) Identification of low-regret decisions, and 4) Quantification of low-regret decisions. The method is applied to an industrial case study of a multi-energy system. We identify heat pumps and heat storage as low-regret decisions. The proposed method supports the decarbonization of the chemical industry by identifying low-regret decisions as starting points of the transition.

* 1. Introduction

Decarbonizing the chemical industry requires carbon-neutral steam production since the energy backbone of chemical sites is usually given by steam at different temperature levels. Currently, steam is usually produced at central sites by burning fossil fuels. Promising technologies are available to decarbonize the steam supply, e.g., via direct electrification by power-to-heat or indirect electrification using synthetic fuels, such as green hydrogen (Ruhnau et al., 2019). Today, these technologies are usually more expensive and require major investments. In addition, the decarbonization pathway is affected by substantial uncertainties, e.g., future costs and efficiencies of technologies at low technology readiness levels. As a result, the industry hesitates to take the required capital-intensive investments, fearing economic regret and lock-in effects. However, the transition to a low-carbon energy system needs to start as soon as possible.

This work presents a method that identifies and quantifies low-regret decisions for multi-energy systems. We define a low-regret decision as an investment in a specific technology that is economically near-optimal in all future scenarios. Thus, investments in low-regret technologies can be taken today to start the transition, while the remaining multi-energy system can be designed later once more information is available.

* 1. Method

To identify such low-regret decisions, we would, in principle, minimize the expected regret in stochastic optimization or the maximum regret in robust optimization. Each of these problems requires the solution of a two-stage design optimization: the first stage would set the low-regret decision variables, and the second stage adapts the remaining design and operational decisions. However, if uncertainties need to be captured through a large number of future scenarios, the two-stage design optimization is likely too computationally heavy to be solved.

In this contribution, we propose a method to identify low-regret decisions based on global sensitivity analysis (Saltelli et al., 2007). The proposed method comprises four steps: 1) Uncertainty characterization, 2) Parameter sampling, 3) Identification of low-regret decisions, and 4) Quantification of low-regret decisions.

1. **Uncertainty characterization:** The uncertainty of all model parameters is characterized by ranges either based on a literature review or detailed, non-linear process models, following the procedure described in Moret et al. (2017). Therein, parameters are grouped, i.e., parameters with similar uncertainty are assigned the same relative uncertainty range.
2. **Parameter sampling:** The uncertainty analysis draws samples varying all uncertain parameters. The resulting samples are used as input for the design optimization to derive each sample's optimal energy system design.
3. **Identification of low-regret decision:** The most frequently selected components across all system designs are identified as potential low-regret decisions. Note that, in principle, a set of components could also be identified as a low-regret decision.
4. **Quantification of low-regret decisions:** To evaluate the regret, we fix the potential low-regret decision in the design optimization. Subsequently, we re-optimize all regret samples, i.e., all samples in which the identified low-regret components have not been selected in the initial design optimization.

The economic regret $R$ is quantified for a sample as the difference between the optimal total annualized cost $TAC^{\*}$ and the total annualized cost with the fixed low-regret decision $TAC^{lrd}$. Here, the maximum cost difference of one sample indicates the maximum regret $R^{max}$, while the expected regret $\overline{R}$ denotes the average cost increase across all samples. For better interpretability, we introduce the maximum relative regret $R\_{\%}^{max}$, which is the maximum regret $R^{max}$ divided by the optimal total annualized cost of the respective sample $TAC^{\*}$. Furthermore, the expected relative regret $\overline{R}\_{\%}$ is obtained as the ratio of the expected regret $\overline{R}$ related to the average total annualized cost in case of perfect foresight $\overline{TAC}^{PF}$.

Table 1: Probability of regret $P(regret)$ as share of regret samples in all samples, average cost increase in case of regret $\overline{TAC}\_{loss}$, maximum cost increase $TAC\_{loss}^{max}$, expected relative regret $\overline{R}\_{\%}$, and maximum relative regret $R\_{\%}^{max}$ for the three identified low-regret decisions (LRD). As a reference, the total annualized cost $TAC$ in case of perfect foresight is $\overline{TAC}^{PF}= 135.4$ MEuro.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Components | $$P(regret)$$ | $$\overline{TAC}\_{loss}$$ | $$TAC\_{loss}^{max}$$ | $$\overline{R}\_{\%}$$ | $$R\_{\%}^{max}$$ |
|  |  | [%] | [kEuro] | [kEuro] | [%] | [%] |
| LRD-1 | $$COM\_{6 bar}$$ | 9.6 | 2668 | 4487 | 0.19 | 3.1 |
| LRD-2 | $$HS\_{6 bar}$$ | 34.3 | 39 | 820 | 0.01 | 0.6 |
| LRD-3 | $$COM\_{31 bar}$$ | 52.1 | 4349 | 7054 | 1.67 | 5.1 |

1. Case Study

The method is applied to a case study of an industrial energy system supplying a typical chemical park with time-varying demands for 6-bar steam (1.64 TWh/a), 31-bar steam (1.55 TWh/a), and electricity (2.00 TWh/a) (Bauer et al., 2022) using the SecMOD MILP framework (Reinert et al., 2023). For the global sensitivity analysis, we vary the efficiency, investment, and maintenance costs of all components. Furthermore, we vary the energy prices, the interest rate, the economic payback period, and the energy demands. As a result, the optimization problem comprises 374 uncertain parameters, which are grouped into 53 uncertain parameters. For each group, the uncertainty is characterized. Subsequently, the parameter space is discretized by 30 trajectories, resulting in a total of 1590 samples. These 1590 samples are used to identify low-regret decisions.

1. Results

The case study identifies heat pumps and heat storage as low-regret decisions (Table 1). Specifically, a combined-cycle heat pump for the 6-bar steam line ($COM\_{6 bar}$) with a capacity of 100 MW has no regret in 90 % of the samples. The combined-cycle heat pump comprises a subcritical heat pump and vapor re-compression unit. On the 31-bar steam line, a combined-cycle heat pump with a capacity of 100 MW ($COM\_{31 bar})$ has no regret in 48 % of the samples. This 31-bar heat pump has a higher expected relative regret of 1.67 % and a maximum relative regret of 5.1 %. Furthermore, heat storage ($HS\_{6 bar}$) shows no regret in 66 % of the samples, while both average and maximum relative regrets are low, 0.01 %, and 0.6 %, respectively. The small regret of the heat storage demonstrates the advantage of making the energy system more flexible.

Overall, all identified low-regret decisions for the three components have low expected and maximum cost increases. Thus, the proposed method identifies low-regret decisions for steam supply and can support decision-makers in accelerating the decarbonization of the chemical industry.

1. Conclusions

This study proposes a method to identify and quantify low-regret decisions for multi-energy systems. In this context, low-regret decisions refer to investment decisions that are economically near-optimal across a broad range of future scenarios. The method employs mathematical optimization and uncertainty analysis in four steps.

The method is applied to a case study of a multi-energy system with time-varying demands for 6-bar steam, 31-bar steam, and electricity. Therein, heat pumps and storage are identified as low-regret decisions with minimal overall cost increases.

In summary, the proposed method effectively identifies low-regret decisions for multi-energy systems. Thereby, the method provides valuable support to decision-makers in accelerating the decarbonization of the chemical industry.

Acknowledgments

N.N., F.B., A.B. acknowledge funding by the Swiss Federal Office of Energy's SWEET program as part of the project PATHFNDR. S.M. acknowledges support from the Swiss National Science Foundation under Grant no PZ00P2\_202117. H.S. acknowledges support from the German Federal Ministry of Economic Affairs and Energy (ref. no.: 03EN2031A).

References

Bauer, T., Prenzel, M., Klasing, F., Franck, R., Lützow, J., Perrey, K., Faatz, R., Trautmann, J., Reimer, A., Kirschbaum, S., 2022. Ideal‐Typical Utility Infrastructure at Chemical Sites – Definition, Operation and Defossilization. Chemie Ingenieur Technik 94 (6), 840–851. 10.1002/cite.202100164.

Moret, S., Codina Gironès, V., Bierlaire, M., Maréchal, F., 2017. Characterization of input uncertainties in strategic energy planning models. Applied Energy 202 (10), 597–617. 10.1016/j.apenergy.2017.05.106.

Reinert, C., Nolzen, N., Frohmann, J., Tillmanns, D., Bardow, A., 2023. Design of low-carbon multi-energy systems in the SecMOD framework by combining MILP optimization and life-cycle assessment. Computers & Chemical Engineering 172 (3), 108176. 10.1016/j.compchemeng.2023.108176.

Ruhnau, O., Bannik, S., Otten, S., Praktiknjo, A., Robinius, M., 2019. Direct or indirect electrification? A review of heat generation and road transport decarbonisation scenarios for Germany 2050. Energy 166, 989–999. 10.1016/j.energy.2018.10.114.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S., 2007. Global Sensitivity Analysis. The Primer. Wiley.