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Stochastic MIP Modeling of a Natural Gas-Powered Industrial Park

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Abstract

We present an investment-decision tool for a natural-gas powered industrial park. The model maximizes the net present value in the industrial park by determining what type of plants to include in the park and what connections to build between them. A stochastic mixed-integer programming model was employed to handle uncertainty of future prices and costs of raw materials and finished products. The model is motivated by the Norwegian government's ambition to increase national consumption of natural gas, in particular for industrial use. A small case study was also included, focusing on model sizes and solution times.

Keywords: natural gas, stochastic, mixed-integer, industrial park, mosel-xpress

1. Introduction

Norway is the world's second largest natural gas exporter, and supplies a significant share of the European consumption of natural gas. It has long been a political ambition to increase the domestic utilization of natural gas, which is currently only 1.6% of the production (NPD [1]). This is mainly because of high export prices and the availability of environmentally friendly energy in Norway, namely, the hydroelectric power systems. In addition, natural gas usage brings about concerns over carbon emissions, as well as profitability of investments in a high-cost country such as Norway. The latter years however there has been an increase in prices for several of the materials that are relevant candidates for being produced in an industrial park in Norway. This has also lead to reopening of iron mines in the Northern regions of Norway and Sweden. The combination of available natural gas and raw materials such as iron ore in the same geographical area makes it interesting to analyze the potential for industrial operations.

In an industrial park, the proximity of the plants encourages the exchange of products, as well as the usage of by-products. Further, carbon capture could become cost-effective when several emitting plants are served by the same capture plant. Moreover, the closeness of several plants leverages the costs of installing communication networks, infrastructure, market development, workforce procurement and so on, making an industrial park more efficient to run than the isolated plants (Roberts [2]). On the other hand, there are also drawbacks with industrial parks such as technological uncertainties related to the integration of plants, environmental liability and the dependency between the companies. For example, if the design of the plants

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is customized for a certain industrial park configuration and the industrial park is changed afterwards (either a plant is shut-down or a new one is opened), the value of the original investments may be reduced. In addition, coordinating operations in the industrial park becomes a challenge when the different plants rely on each other. In this work, we have used a systemic perspective where we assume that a central planner is making all decisions in the park; with this method, we then find a benchmark solution. How close the companies in the industrial parks come to the benchmark solution will depend on the coordination and cooperation between them.

There exists relevant literature on industrial parks, including experiences and analyses on pollution control and reduction in Baas [3], resource savings in Chertow and Lombardi [4], and commodity sharing in Jacobsen [5]. Literature regarding the modeling of the individual plants is provided later in the model presentation.

The main contribution of this paper is the development of a decision support model for techno-economic analysis of industrial parks that can handle uncertain parameters. We also include a carbon-capture facility in the park, which allows for analysis regarding environmental impact as well as the impact of different carbon dioxide (CO_2) mitigating effects on the optimal park configuration and operation. In the model, we consider investments in the different plants and operation over the lifetime of the plants. For the operation, we consider aggregated time periods, but we have still included as much of the dynamics of operation in the plants as was possible within our framework. A full mathematical formulation of a deterministic version of the model is given in Midthun et al. [6]. For an analysis on the impact of carbon emissions, we refer to Nørstebø et al. [7].

In Section 2, we discuss the handling of uncertainty, and in Section 3 we present the functionality of the investment analysis model. Section 4 introduces a case study and Section 5 presents the main results, focusing on model dimensions and solution times. We then state some conclusions in Section 6.

2. Handling of uncertainty

While the solutions of deterministic models are optimal for the particular values of future parameters used in the models, they might turn out to be bad if the future is different from the given values. A *stochastic model* can, in contrast, take into account uncertainty of the future parameters and find a solution that is *robust* and/or *flexible* with respect to this uncertainty. In our case, we use a two-stage stochastic-programming model (Kall and Wallace [8], Birge and Louveaux [9]), with uncertainty modelled using *scenarios*, i.e. a discrete approximation of the underlying distribution. Note that this is different from doing sensitivity analysis: in that case, we would solve a deterministic model for each of the scenarios, obtaining as many solutions as we have scenarios; then we would try to deduce something about the optimal solution by analyzing them—which does not generally lead to optimal (or even good) solutions, as shown in Wallace [10].

2.1. Stochastic parameters and scenarios

In our formulation, we consider some future prices to be stochastic; these include prices for the main commodities, power, and also costs of emissions of CO_2 and nitrogen oxides (NO_X). In total, we have seven stochastic parameters in the model. However, our tests show that we can only solve the problem with a limited number of scenarios in a reasonable time: the analyzed instances vary from three to approximately thirty scenarios. For this reason, we have assumed that all stochastic parameters are completely correlated. Historical prices seem to indicate this is a justifiable assumption, but we have not performed formal proofs.

The scenario price of commodity c at time t of scenario s is then given as

$$P^s_{c,t} = M_c \, F^s_t \, EP_{c,t} \, ,$$

where F^s_t is the value of the stochastic factor at time t and scenario s and $EP_{c,t}$ is the expected (forecasted) price of the commodity at time t, i.e. the same value as in the deterministic model. Finally, the per-commodity value M_c models the variability factor of the commodity, relative to the natural gas prices.