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Full Length Article

Importance of fuel in the valuation of lignite-based energy projects with risk assessment from geology to energy market

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ABSTRACT

This research aims to discuss complex economics of lignite-based energy projects with respect to risk and uncertainty, optimisation, sustainable land use and the importance of lignite as fuel that may be expressed in situ as a deposit of energy. The sensitivity analyses and Monte Carlo simulations performed in this article include estimated land acquisition costs, geostatistics, 3D deposit block modelling, electricity (product) price, power station efficiency, the unit cost of lignite processing at the power station, CO_2 allowance costs, mining unit cost and also geological risk considered as kriging estimation error for lignite reserves. The investigated parameters have a nonlinear influence on the final results and hence the economically viable amount of lignite in the optimum ultimate pit varies. The optimum ultimate pit area varies across scenarios from 11.2 km^2 (or even 9.1 km^2) up to 14.3 km^2. The performed simulations allowed each optimum ultimate pit to be calculated from a unique set of project parameters based on their distributions. For the highest surface cost scenario, there is 95% probability of obtaining undiscounted net value of €1277 million and also there is only 5% chance to obtain the net value of €5524 million.

1. Introduction

1.1. Literature review

With high fixed costs, the transition to higher efficiency power generation becomes an important issue, if the profitability of lignite-based energy projects is to be maintained in a low carbon future. Lignite reserves represent a subset of resources which could be mined economically with regard to realistic mining and economic conditions at the time of reporting. In order to identify lignite reserves, at least the ultimate pit shell has to be designed [1]. Owing to ultimate pit optimisation (Lerchs and Grossmann [2], Underwood and Tolwinski [3], Dowd and Onur [4], Khalokakaie et al. [5]) and to modelling, a graphical feedback of a pit extent for each scenario is produced. This graphical visualization enables analyses of occupied land and might be helpful in terms of mining-induced displacement and resettlement, as investigated by Rew et al. [6], Downing [7], Terminski [8], or in preparation of spatial development plans for strategic mineral deposits, as in Blachowski [9]. Continuous mining project optimisation led to the development of new simultaneous stochastic optimisation frameworks by Goodfellow and Dimitrakopoulos [10,11] where raw materials (minerals) extracted from various mineral deposits are transformed into a set of sellable products.

Being the second most important energy source, coal covers about 30% of global primary energy consumption. Hard coal and lignite are the leading energy sources in power generation with 40% of global power generation relying on this fuel. 75% of coal plants worldwide utilise subcritical technology. An increase in the efficiency of coal-fired power plants throughout the world from an average of 33% to 40% could cut global carbon dioxide emissions by 1.7 billion tonnes each year [12]. According to Zhao et al. [13], the key to reducing environmental impact is the efficiency not only of energy production but also of energy consumption.

Over the last decade, it has been increasingly difficult to track carbon policy changes and incorporate them in long-term coal energy projects, especially in Europe. Climate change scenarios have an impact on investment decisions, under both the NPV rule and the model for optimal timing of the investment as investigated by Truong and Trück [14]. Targets of the 2020 Climate and Energy Package (Directive 2009/29/EC, 2009/28/EC, 2009/31/EC and Decision No. 406/2009/EC of the Parliament and the Council) set three key objectives for 2020. These objectives are: by 20% of the EU greenhouse gas emissions from 1990 levels, increase in the share of EU renewables up to 20%, and 20% improvement in the EU's energy efficiency. In order to keep the increase

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of temperature below 2 °C, Paris Agreement [15] assumes priced carbon emissions, regulation of energy production and consumption and also funding to research and development projects.

With this attitude toward climate change in Europe and as indicated in Thomson Reuters forecast [16,17], carbon tax may be expected to increase. However, crucial aspects include not only emissions but also environment monitoring. Analyses performed by Tol [18,19] show that if concentrations are to be kept below 450 ppm CO_2eq, the global carbon tax is supposed to reach some \$210/tCO_2 in 2020. Such a carbon tax would double the price of energy in Europe. For comparison, the recent price of permits in the emissions is about €5/tCO_2.

Being a predominantly indigenous fuel, mined and used in the same country, lignite allows the security of supply. Joint analyses and optimisation of vertically integrated lignite mining companies and power plants maximize the project value as investigated by Roumpos [20] and Jurdziak and Kawalec [21–23]. It is important to acknowledge many possible scenarios while developing projects for new potential lignite-based greenfield electricity generation. The lithotype associations composition is important for mining activities and multi-use of lignite. Bitumen-rich association significantly increases the lignites calorific value, whereas large amounts of fibrous xylites are characterised by a lower calorific value than other lithotypes and are also undesirable in lignite mining and further combustion [24].

As for low rank coal beneficiation, drying significantly increases the net unit efficiency, and also reduces carbon emissions [25].

Due to levelised cost of energy (LCOE), economic effectiveness of electricity generation technologies can be compared regardless of their scale and lifetime.

$$LCOE = \frac{\sum_{t=1}^{n} [(I_t + M_t + F_t)/(1+r)^t]}{\sum_{t=1}^{n} [(E_t/(1+r)^t]} \tag{1}$$

where I_t are investment expenditures in the year t, M_t operations and maintenance expenditures in the year t, F_t fuel expenditures in the year t, E_t electrical energy generated over the year t, r discount rate, n expected lifetime of the system or of the power station.

Fuel price and plant availability play a key role in plant economics. Recent calculations of LCOE found in Pettinau et al. [26] present a techno-economic comparison between the most promising power generation technologies. In particular, three different power generation technologies have been considered in their conventional (without CCS) and CO_2-free configurations, i.e. ultra supercritical (USC) pulverized coal combustion, oxy-coal combustion (OCC) and integrated gasification combined cycle (IGCC). Process simulation, based on Aspen Plus and Gate Cycle commercial tools, allowed the calculation of plant performance, including the energy penalty due to the CCS system (10.9% points for USC and 8.7% points for IGCC). In parallel, a detailed economic assessment shows that, among the commercial-ready technologies, USC could be the most convenient solution for power generation without CCS (with LCOE of €38.6/MWh, significantly lower than €43.7/MWh of IGCC), whereas IGCC becomes competitive for CO_2-free systems (with a LCOE of €59.6/MWh, to be compared with €63.4/MWh of USC). Moreover, oxy-coal combustion, which is currently not mature enough for commercial-scale applications, promises to become strongly competitive for CCS applications due to its relatively low levelized cost of electricity (€62.8/MWh). This kind of analysis typically presents strong uncertainties, owing to the variability of several key parameters (e.g. fuel and CCS prices, determined by the fluctuation in the international markets, or the improvement of the technologies) [26].

Extensive comparison of 18 generation technologies discounted as of 2013 may be found in Zaporowski [27] from where it also can be acknowledged that lignite remains one of the most competitive energy sources.

1.2. Contribution of this work

Performed joint analyses and optimisation of the investigated vertically integrated lignite mining company and of the power plant maximise the project value which contributes to investment decision-making processes and sustainable land use so as to avoid any land use without careful economic study. Lignite quality index adjusted to energy is introduced with assigned resources risk considered as kriging estimation error, thus enabling the differentiation of lignite through deposit in value chain. Research results presented in this paper as the relative impact of these parameters on the project, spider graphs as well as tornado diagrams help to investigate the impact of project parameters related to lignite on its economic viability. The self-prepared surface cost map that was processed together with the lignite deposit was derived from a vector cadastral map file format. Estimated land buyout cost was assigned to each of the land parcels. Data stored within the surface cost map model cover also detailed land use, land parcel or building ID number. As Lerchs-Grossmann optimisation is performed, the resulting optimum ultimate pit returns maximised undiscounted project value. Additional spatial data can be added to the surface cost model map if needed. Owing to the fact that the surface cost map is based upon a cadastral map, investors may be sure that each of the hundreds of calculated scenarios and resulting pit extents returns a list of parcels and buildings with cadastral boundaries which need to be acquired in order to start the mining operations. Such approach allows faster negotiations.

2. Methodology

In order to identify lignite reserves, at least the ultimate pit shell has to be designed [1]. Assuming that a digital, economic block model of a lignite deposit has been built (based on a quality model as well as on economic parameters), it can be processed with the use of open pit optimisation algorithms (e.g. Lerchs and Grossmann). The total amount of electric energy that can be obtained from the lignite in the deposit depends on the ultimate pit reserves as well as on the efficiency of the power station. Therefore, the coal-by-wire approach has been applied to model the integrated power generation company consisting of a surface lignite mine and a power station that produces electric energy. In order to estimate lignite energy project value, a lignite quality index was introduced to classify lignite through deposit. In the next step, quality index was multiplied by a factor that converts base tonne of lignite to the energy that may be generated from it. As a result, lignite deposit is converted into a deposit of energy with assigned uncertainty given by function error based upon kriging errors of the estimation of lignite deposit quality parameters.

2.1. Lignite block model and geological risk

To create an economic block model of the lignite deposit, quality parameters derived from boreholes samples (Fig. 1) were investigated. Statistics for lignite calorific value are shown in Fig. 2 ranging from 3443 to 11,761 kJ/kg with the mean of 8897 kJ/kg. Kriging estimation of quality parameters was performed under intrinsic stationarity assumption. As an estimation procedure, kriging gives the best linear unbiased prediction of any of the parameters and by solving kriging equations which give an explicit representation of the optimal coefficients (weights) in terms of the variogram, kriging variance (kriging error) is minimized [28]. Predicted value at any point is a linear combination of the measured values, that is, the kriging estimate is a linear predictor. Once defined the covariance model or variogram, valid in all field of analysis, then we can write an expression for the estimation variance of any estimator in function of the covariance between the samples and the covariances between the samples and the point to estimate. Minimized kriging error is given by the following formula: