Electricity and CO2 Emissions System Price Modeling

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***Abstract*—We present two stochastic models optimizing a hydro-thermal power system; the first from the perspective of a global system and the second from a sub-system's (country or utility) perspective within a liberalized market. Particularly CO2 emission quotas and CO2 certificate prices are taken into account. The first model seeks to compute the electricity system marginal price as well as the CO2 emissions marginal price by minimizing the expected system's cost of operation. In the second model, the expected revenues of the sub-system within a liberalized electricity market are maximized while considering stochastic inflows, electricity, fuel and CO2 prices. The above-mentioned stochastic variables are represented via joint scenarios. The resulting stochastic linear program will be solved via hybrid SDP/SDDP.**

***Index Terms*—CO2 portfolio management, CO2 market price, CO2 quota, CO2 emission trading, energy, power systems optimization, SDDP, Stochastic Linear Programming**

I. Nomenclature

The nomenclature of this article is summarized in Table I. All data are given in capital letters while the variables are denoted in small letters. The ξ captures the stochastic or random aspects of the data.

TABLE I
Symbols Used for Both Models: Variables and Data

Symbol	Type	Unit	Meaning
$C_{tj}^{\mathrm{PP}}(\xi)$	stoch. data	€/MWh	cost for power production at thermal plant j at stage t
$P_t^{\mathrm{CO2,bm}}(\xi)$	stoch. data	€/ton	price for buying CO2 emission allowances via a trading market at stage t
$P_t^{\mathrm{CO2,sm}}(\xi)$	stoch. data	€/ton	price for selling CO2 emission allowances via a trading market at stage t
$P_t(\xi)$	stoch. data	€/MWh	price for selling power at stage t
$G_{tw}^{\mathrm{WP}}(\xi)$	stoch. data	MWh	generated power by wind turbine w in stage t
$A_{ti}(\xi)$	stoch. data	m^3	water inflow in hydro reservoir i during stage t
D_t	det. data	MWh	power demand at stage t
ρ_i	det. data	MWh/ (m^3/sec)	power coefficient for hydro plant i
B_j	det. data	€/ton	CO2 emissions per MWh produced at thermal plant j
$C^{\mathrm{CO2,f}}$	det. data	€/ton	CO2 emission fine/cost for exceeding the CO2 emission allowance
$C^{\mathrm{CO2,p}}$	det. data	€/ton	cost per ton CO2 emission certificate for switching to cleaner technology
$E^{\mathrm{CO2,a}}$	det. data	ton	CO2 emission allowance per annum
g_{tj}	variable	MWh	power generation of thermal plant j in time stage t
$e_t^{\mathrm{CO2,bm}}$	variable	tons	CO2 emissions allowances bought in a trading market
$e_t^{\mathrm{CO2,f}}$	variable	tons	CO2 emissions allowances 'bought' via fines
$e_t^{\mathrm{CO2,sm}}$	variable	tons	CO2 emissions allowances sold in a trading market
$e_t^{\mathrm{CO2,p}}$	variable	tons	CO2 emissions allowances 'bought' via a project from a country with no Kyoto target
v_{ti}	variable	m^3	water reservoir level of hydro plant i at the end of stage t
u_{ti}	variable	m^3	water used for power generation of hydro plant i in stage t
s_{ti}	variable	m^3	water spillage for hydro plant i in stage t

II. Introduction

THE EU power system faces important problems of CO2 emissions excess with respect to the Kyoto treaty. As it is widely known, CO2 is one of the most important inhibitors on the global warming phenomenon, for which the EU has been campaigning actively the last years. We can observe actions that are taken in all countries attempting to optimize the operation of the plants subject to the maximization of profits or the minimization of costs while considering the CO2 emissions. In addition, in order to improve the balancing of CO2 emissions, most of the countries are participating in a 'cap and trade' mechanism where utilities and other industries can optimize their CO2 allocation.

In 2006, the EU power system generation consisted of 54.7% thermal, 29.3% nuclear and 14.6% of renewable energy sources (EU 27), [1]. The thermal percentage, which accounts

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for the CO2 emissions, is related to a series of stochastic parameters such as price of coal, fuel and gas. The latter affect heavily the operation of the system and its optimization from a technical and financial point of view. Furthermore, for such a large system as the EU one, there are additional constraints that come from the electricity transmission system and the gas network that have to be considered appropriately.

A. CO2 Emission Trading

Climate change is recognized as a global problem and can only be solved globally. Hence, it is not important at which exact location the greenhouse gas emissions reduction is achieved, but more importantly, that the reduction is done in a cost efficient way. Therefore, emission trading schemes have been developed, giving greenhouse gases a 'price' - making it a tradable good. Carbon dioxide, CO2, is identified as one of the key drivers of global warming.

The power stations had the largest fraction with 21.3% of the anthropogenic annual greenhouse gas emissions in 2000; among 8 different sectors, with the second largest being the industrial processes with 16.8% [2].

1) Kyoto Protocol: The Kyoto Protocol [3] was adopted on December 11th, 1997 in Kyoto, Japan. It entered into force on February 16th, 2005. The Kyoto Protocol can be seen as a milestone in fighting global warming, as it commits industrialized countries to reduce greenhouse gas emissions.

The Kyoto Protocol aims to reduce emissions of six greenhouse gases: CO2, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, and sulphur hexafluoride [4]. Greenhouse gas emissions in the EU have to be reduced by 8% on 1990 levels during the first commitment period from 2008 to 2012 [4]; overall the emissions have to be reduced by 5.2% on 1990 levels [5].

The Kyoto Protocol offers the following three market-based mechanisms – the so-called *Kyoto mechanisms*:

- *Emissions Trading* or "the carbon market": Article 17 of the Kyoto Protocol allows countries to trade their excess capacity.
- *Joint Implementation* (JI) and *Clean Development Mechanism* (CDM): Part of the emission reduction can be achieved by conducting emission-reducing projects in other industrialized countries with Kyoto targets (JI) and in countries without targets (CDM).

2) EU Emission Trading Scheme: The European Union (EU) Emission Trading Scheme (ETS) is the largest multinational emission trading scheme in the world [6]. The governments of the EU Member States agree national emission caps and allocate the allowances to their industrial operators via so-called "national allocation plans"; the distribution of those has to be made carefully [7]. Plant operators have to monitor and annually report their CO2 emissions and they have to return the used emission allowances of CO2 in each year; although the CO2 emissions are given for several years in advance in order to avoid annual anomalies. Those installations which have allowances left over can sell them in the market or save them for future use. Those that exceed their total emissions have to pay a fine of 100 €/CO2 t emissions and their names are published.

The EU ETS is partitioned in three phases:

Phase 1. January 2007 - December 2007; test phase

Phase 2. January 2008 - December 2012; coincides with the first commitment period of the Kyoto Protocol; the EU target for greenhouse gas emissions reduction is at 8% of the 1990 level

Phase 3. January 2013 - December 2020.

In the following two models, the four years period of phase 2 of the EU ETS is considered.

B. Main Concept

Electricity companies within an emission trading scheme for CO2 allowances face new challenges, managing their portfolio of assets in an optimal way. The need for optimization tools was also empirically shown in [8], where a simulation of CO2 prices was performed.

The goal of the two presented mathematical optimization models in this paper is the optimal operation of a hydro-thermal system or subsystem within a CO2 trading scheme. As the CO2 prices are not known in advance, they are treated being stochastic.

Nevertheless, data such as electricity and CO2 prices have a rather short historical record in relation to the hydro data available. The latter leads to joint scenarios and hence transition matrices of questionable quality.

In order to overcome the above mentioned difficulty we shall calculate through a fundamental approach - operation optimization of the entire system - the CO2 prices and electricity prices that result from historical inflow scenarios, fuel price scenarios and demand that will be used as inputs. This leads to a 'fake' history of CO2 prices and electricity prices, capturing the correlation between the CO2 prices, electricity prices, hydro inflows and fuel prices [9], allowing calculating the transition matrices for the Markov Chains.

Therefore, we first consider an entire energy system. This system is highly interconnected, CO2 trading is active, there is a CO2 quota for each sub-system (country or utility) and the sub-systems can import/export electricity and exchange CO2 certificates among them. Such a system is given in Europe with the EU Emission Trading Scheme. The goal of this model is to forecast the electricity and CO2 prices for the whole system for a set of inflow and fuel price joint scenarios. However, the electricity and CO2 price forecast depend on each stage and state of the stochastic model; *i.e.*, it depends on the inflow and fuel joint scenario as well as the time stage considered.

As it is for computational reasons not possible in a model for the whole system to look at a country level in a great detail, a second model has to explore all the details for each country separately. Hence, once the electricity prices and the CO2 prices are calculated, they are combined with the inflow and fuel price scenarios. The latter joint scenarios are used as input to a revenue maximization algorithm applied to each sub-system, *i.e.*, country or utility. Hence, this latter model will make use of the electricity and CO2 prices calculated in the whole system model, thus, calculating the sub-systems optimal operation through maximization of the system's expected revenues. The latter is similar to considering the cost minimization of a sub-system such as a country in Europe subject to its stochastic variables and electricity demand. Nevertheless, in case of Europe, since we deal with a highly interconnected system with a common CO2 trading mechanism, the calculation of the electricity and CO2 certificate prices cannot take place without considering the entire system.

C. Literature Review

In [10], the authors consider different stochastic models for the spot price dynamics of CO2 emission allowances in the short-term. A multi-period stochastic optimization model for CO2 emissions trading planning of a combined heat and power producer is given in [11].

However, according to the existing state of the art in computational tools developments, there is no literature on mid-term optimization models taking into account stochastic CO2 prices, and especially not on treating CO2 prices and electricity prices stochastically at the same time.

This paper is organized as follows. In Section III, we present a mathematical programming model for expected cost minimization of a system taking into account CO2 emissions. An expected profit maximization approach for a sub-system is presented in Section IV. The solution methodology for both models is presented in Section V. We conclude with Section VI.

III. Operation Cost Minimization and CO2 Price Calculation of a System in the Mid-Term Horizon

The objective of optimization is the minimization of the expected operational cost of a system in the mid-term horizon. Technical specifications of the system, fuel prices, water inflows, power demand, and CO2 emission quotas have to be taken into consideration by the model.

We consider a given hydro-thermal system where the fuel prices and inflows are stochastic. Decisions can be made on the operation of the thermal and hydro power plants.

The time horizon of the model is 4 years with time stages of 1 week or 1 month, depending on the size of the model to be solved. As this is a mid-term horizon model, no investment decisions on changing generating capacity of power plants, *i.e.*, old and / or 'dirty' plants can be decommissioned and new plants can be added to the system, are explicitly modeled [12]. However, we can take into account the change of the power generation capacity and power generation cost via the time stages t, if we know in advance when power plants are added to, or removed from, the system.

The model will enable us to calculate the electricity system marginal price and the CO2 emission system marginal price per time period (stage).

The problem can be formulated as the following stochastic linear program

$$\begin{aligned}
\min \quad & \mathbb{E}\Bigg[\sum_t \sum_j C^{\mathrm{PP}}_{tj}(\xi)\, g_{tj} + \sum_t C^{\mathrm{CO2,f}} e_t^{\mathrm{CO2,f}} + \\
& \qquad + \sum_t C^{\mathrm{CO2,p}} e_t^{\mathrm{CO2,p}}\Bigg] && (1)\\
\text{s.t.} \quad & D_t - \sum_w G^{\mathrm{WP}}_{tw}(\xi) = \sum_j g_{tj} + \sum_i \rho_i u_{ti} \qquad \forall t && (2)\\
& v_{t+1i} = v_{ti} - u_{ti} - s_{ti} + A_{ti}(\xi) \qquad \forall t, i && (3)\\
& \sum_t \sum_j B_j g_{tj} - \sum_t \left(e_t^{\mathrm{CO2,f}} + e_t^{\mathrm{CO2,p}}\right) \le E^{\mathrm{CO2,a}} && (4)\\
& + \text{ other (linear) operational constraints} && (5)\\
& g_{tj}, e_t^{\mathrm{CO2,f}}, e_t^{\mathrm{CO2,p}}, u_{ti}, v_{ti}, s_{ti} \ge 0 \qquad \forall t, j, i && (6)
\end{aligned}$$

The electricity demand given by the demand forecast D_t, minus the power generated by the wind turbines, has to be met by either producing the electricity via thermal plants, g_{tj}, or via hydro plants, $\rho_i u_{ti}$, stated in constrains (2). The water balance constraints for stage t and hydro plant i is given in (3) with the stochastic water inflow $A_{ti}(\xi)$. Constraint (4) models the emission allowances. Coefficient B_j converts the generated electricity of the thermal plants to the emitted CO2, while variables $e_t^{\mathrm{CO2,f}}$ and $e_t^{\mathrm{CO2,p}}$ give additional CO2 allowances 'bought'. The coefficient $C^{\mathrm{CO2,f}}$ in the objective function (1) reflects a fine for exceeding the CO2 emission target/quote $E^{\mathrm{CO2,a}}$. The coefficient $C^{\mathrm{CO2,p}}$ is assumed to be given and represents the cost per certificate of 1 ton CO2 emissions for switching to cleaner technology. Hence, the cost in the objective function (1) are given by the sum of the expected cost of thermal power generation, the fines for exceeding the CO2 emissions and the cost for investments in cleaner technologies abroad.

The marginal electricity price and marginal CO2 emission price per stage t are then given as the dual (or Lagrange) multiplier of the demand constraints for electricity, equations (2) and of the CO2 balance constraint for CO2 prices, equation (4).

The linear operational constraints taking into account in this model are: minimum / maximum generation capacity of each thermal power plant j (lower and upper bound on g_{tj}), minimum / maximum volume storage capacity for each hydro plant i (lower and upper bound on v_{ti}), minimum / maximum turbine capacity for each hydro plant i (lower and upper bound on u_{ti}), and maximum spillage for each hydro plant i (upper bound on s_{ti}). A detailed discussion of this operational constraints can be found in [13], [14]. Adding the stage index t to the lower / upper bounds discussed, enables the model to capture given changes of the power plants' technical specifications, *i.e.*, due to a scheduled decommission of a plant. Furthermore, an upper bound on the CO2 emissions $e_t^{\mathrm{CO2,p}}$ is included in the model, taking into account any restrictions on the percentage of CO2 emission allowances used due to the implementation of cleaner technology.

Examples for systems discussed here are closed systems with respect to a CO2 trading market or the whole globe. Hence, Europe can be seen as such a system with the European

Trading Scheme as a CO2 trading market. In this case, the fine $C^{\mathrm{CO2,f}}$ could be a fine defined by an international treaty, *i.e.*, the Kyoto Protocol, while $C^{\mathrm{CO2,p}}$ are the cost of adopting CO2 emission reductions in countries having no CO2 emission reduction targets defined by the Kyoto Protocol [3] or the cost for switching to a clean technology such as carbon storage [15].

IV. Net Profit Maximization of a System in the Mid-Term Horizon

The objective of optimization is the maximization of the expected net profit, revenue minus operational cost, of a power sub-system in the mid-term. Technical specifications of the system, fuel prices, water inflows, CO2 emission quotas, and CO2 certificate prices have to be taken into consideration by the model.

We consider a given hydro-thermal system where the electricity prices, fuel prices, inflows and CO2 prices are stochastic. Decisions can be made on the operation of the thermal and hydro power plants and fuels as well as CO2 certificates can be bought and sold.

The time horizon of the model is 4 years with time stages of 1 week or 1 month. As in the cost minimization model of Sec. III, investment decisions on new power plants are not taking into account by this model as we are planning in a mid-term horizon.

The model will enable us to operate the system in an optimal – revenue maximal – way.

The problem can be formulated as the following stochastic linear program

$$
\begin{aligned}
\max \quad & \mathbb{E}\Bigg[\sum_t \sum_j \left(P_t(\xi) - C^{\mathrm{PP}}_{tj}(\xi)\right) g_{tj} + \\
& + \sum_t \sum_i P_t(\xi)\,\rho_i u_{ti} + \\
& + \sum_t P^{\mathrm{CO2,sm}}_t(\xi)\, e^{\mathrm{CO2,sm}}_t - \\
& - \sum_t P^{\mathrm{CO2,bm}}_t(\xi)\, e^{\mathrm{CO2,bm}}_t - \\
& - \sum_t C^{\mathrm{CO2,f}} e^{\mathrm{CO2,f}}_t - \\
& - \sum_t C^{\mathrm{CO2,p}} e^{\mathrm{CO2,p}}_t \Bigg] \qquad (7)\\
\text{s.t.} \quad & v_{t+1i} = v_{ti} - u_{ti} - s_{ti} + A_{ti}(\xi) \qquad \forall t, i \qquad (8)\\
& \sum_t \sum_j B_j g_{tj} - \sum_t \left(e^{\mathrm{CO2,bm}}_t + e^{\mathrm{CO2,f}}_t + e^{\mathrm{CO2,p}}_t\right) + \\
& + \sum_t e^{\mathrm{CO2,sm}}_t \le E^{\mathrm{CO2,a}} \qquad (9)\\
& + \text{other (linear) operational constraints} \qquad (10)\\
& g_{tj}, e^{\mathrm{CO2,sm}}_t, e^{\mathrm{CO2,bm}}_t, e^{\mathrm{CO2,f}}_t, e^{\mathrm{CO2,p}}_t, u_{ti},\\
& v_{ti}, s_{ti} \ge 0 \qquad \forall t, j, i \qquad (11)
\end{aligned}
$$

In the case of a power sub-system in the liberalized market, the objective is to maximize expected profits, rather than meeting the electricity demand and minimizing the generation cost. The profits for 1 MWh electricity generation from thermal plants is given by $P_t(\xi) - C^{\mathrm{PP}}_{tj}$, the stochastic electricity price in the spot market at stage t minus the generation cost for thermal plant j at stage t. As no generation cost for electricity from the hydro plants applies, the profits for the generation of 1 MWh associated with hydro plant i are given by $P_t(\xi)$. For the sub-system considered, a CO2 market is assumed to be existing, where CO2 emission rights can be traded at the stochastic sales price of $P^{\mathrm{CO2,sm}}_t$ per ton CO2 and the stochastic buy price of $P^{\mathrm{CO2,bm}}_t$ per ton CO2 at stage t. The water balance constraints are given by constraints (8) and the CO2 allowances are modeled via constraint (9). The linear operational constraints, given in (10), are the same as in the cost-minimization model of Sec. III.

Countries within an interconnected system, and large companies with a rich portfolio of assets, are examples for systems where such a model applies. The goal is to operate its system, a sub-system belonging to a system, in an optimal way while taking CO2 emissions into account.

V. Solution Approach Methodology

An overview of stochastic programming models in energy and their solution techniques are presented in [12]. Survey articles on solution methods for hydro-thermal optimization are given in [16], [17].

Stochastic Dynamic Programming (SDP) has been used initially to solve these type of stochastic programs [18]–[20]. However, the so-called curse of dimensionality [21] drove the development of decomposition methods [13], [22]. Stochastic Dual Dynamic Programming (SDDP) is a combination of Nested Benders' decomposition and SDP [23]. SDDP was developed in 1991 and it is still state of the art in solving hydro-thermal systems.

The basic idea of SDDP is to construct an approximation of the future benefits function that does not rely on interpolation techniques, in contrast to SDP, to determine the value of the functions between the grid points, but is based on extrapolation of a point and its slope. Besides approximating the future benefit function by piecewise linear functions, SDDP also relies on an iterative procedure to refine this approximation. In the so-called *backward phase*, a first approximation of the future benefit function is constructed using a limited number of discrete points, and the value of the objective function is stored. In the so-called *forward simulation* phase, the approximated future benefit function is used in a simulation. At the end of the simulation, the value of the objective function is stored and compared to the one obtained at the end of the backward phase. If the two values are within a predefined bound, then the procedure stops, otherwise new starting points are chosen and a new loop is needed to refine the future benefit function. More details about SDDP and its applications for practical problems can be found, for instance, in [23]–[27].

Nevertheless, considering jointly stochastic inflows and fuel spot prices the approach of nested Benders decomposition is not applicable due to the shape of the polyhedral. More specifically, the fuels state variables are present in the objective function and the inflows state variables are in the constraints. In the case of this article's application, varying the state variables within the objective function, the objective function varies concavely. In contrast, varying the RHS of the constraints, the objective function varies convexly. Hence the SDDP method is not applicable.

We will solve the models presented above using the algorithm of hybrid stochastic dynamic programming and stochastic dual dynamic programming [28], [29]. The latter algorithm can handle stochastic variables that are both in the objective function and the set of constraints while preserving a convex future benefit function.

Solution methods for mathematical models taking into account both stochastic inflows and stochastic fuel prices have not been reported in the literature. Similarly, there is no literature for solution methodologies for CO2 stochastic prices and fuel stochastic prices.

For the cost minimization model, presented in Section III, we will model inflows using an SDDP approach and fuel prices using an SDP approach. All stochastic variables will be represented by joint scenarios that according to the market structure can be considered as correlated or uncorrelated. In order to achieve the discretization of fuel prices we will use appropriate clustering methods that will define the various states of fuel prices for the SDP algorithm.

For the revenue maximization model, presented in Section IV, we will model inflows using an SDDP approach and electricity, fuel and CO2 prices using an SDP approach. All stochastic variables will be represented by joint scenarios that according to the market structure can be considered as correlated or uncorrelated. In order to achieve the discretization of electricity, fuel and CO2 prices, we will use appropriate clustering methods that will define the various states of electricity, fuel and CO2 prices for the SDP algorithm.

A. CO2 Quota Interpreted as Reservoir

Stochastic dual dynamic programming is a tailored algorithm for (linear) stochastic modeling, with the capacity to consider stochastic, sequential and time dependent problems such as hydro reservoirs and financial options. In both formulations, introduced in Section III and IV, the CO2 quotas can be interpreted in this reservoir framework as follows: At specific time periods, *e.g.* every January 1st, CO2 quotas are issued, filling the CO2 reservoir. During a certain period of time, *e.g.* yearly, we use the CO2 quotas until the reservoir is empty and we have to use another, infinite, CO2 reservoir, modeling the penalty for exceeding the CO2 quota. For each case we exceed the CO2 quota reservoir, the balance constraint is activated [30].

VI. Conclusion

In this paper we present the concept of two models that approach the complex mechanism of today's electricity markets. We consider the influence of electricity, fuel and CO2 prices in the operation of energy systems.

For reasons of model size, we tackle the problem by separating it into a system and into a subsystem problem. This allows us with the first model to calculate the interrelated factors of the system such as electricity and CO2 prices and with the second model to calculate the exact operation of subsystems, such as a country or a utility.

We approach the problem solution through the hybrid SDDP/SDP methodology for reason of problem size, combination of stochastic variables and time-coupling.

This work is part of an ongoing research. Hence, the next step will be the development of the exact methodology and mathematical implementation of the two above mentioned models within the framework of the SDDP algorithm. Specific focus should be given on the computational efficiency through the clustering methods and the calculation of transition matrices.

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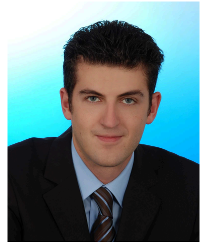

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