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Evaluating the Cost of Emissions in a Pool-Based Electricity Market

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Abstract

This paper proposes a methodology that quantifies the impact of emissions cost on the electricity price, the generation scheduling outcome, and the overall emissions in a pool-based electricity market. It employs a mid-term (yearly) generation scheduling model, by sequentially solving a Day-Ahead Scheduling problem, in which power plants internalize their emissions cost in the energy offers that they submit to the day-ahead market. It further explores several scenarios with respect to gas and carbon prices, as well as the realization of random outages that affect the availability of the generation units. An illustration on an instance of the Greek electricity market during the European Union Emissions Trading Scheme Phase III indicates that: (i) A carbon price equal to 30 €/tCO2e combined with low gas prices results in a 18.7% reduction of CO2 emissions, due to the substitution of lignite units by gas units in the energy generation mix. (ii) An increase in the carbon price by 1 €/tCO2e results in an increase of the weighted average electricity price ranging from 0.52 to 0.61 €/MWh. (iii) The average pass-through rate of the carbon costs onto the demand-side payments for carbon prices up to 15 €/tCO2e is close to 60%.

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Keywords: Electricity market, carbon price, emissions cost, generation scheduling.

Acronyms and Abbreviations

AGC	Automatic Generation Control
APTR	Average Pass-Through Rate
DAS	Day-Ahead Scheduling
$EFOR_D$	Equivalent Demand Forced Outage Rate
ETS	Emission Trading System
EU	European Union
GHG	Greenhouse Gas
MILP	Mixed Integer Linear Programming
NAP	National Allocation Plan
O&M	Operation & Maintenance
PV	Photovoltaic
RES	Renewable Energy Sources
SMP	System Marginal Price
TCC	Total Carbon Cost
tCO_2e	ton of CO_2 (carbon dioxide) equivalent
WAEP	Weighted Average Electricity Price

Nomenclature

Indices

b	Block of energy offer, b = 1, 2, …, 10
d	Day (time period), d = 1, 2, …, 365
h	Hour (time period), h = 0, 1, …, 24
u	Generation unit, u = 1, 2,…

Sets/Subsets

U	Generation units, indexed by u
U_{AGC}	Generation units that can operate in AGC mode ($U_{AGC} \subset U$)

Parameters:

$C^{\mathrm{G,Pen}}$ [€/MWh]	Cost of Penalty (Pen) related to energy Generation (G) in the energy balance constraint
$C_u^{\mathrm{G,Tot}}$ [€/MWh]	Total (Tot) variable Generation (G) cost of unit u
C_u^{Emis} [€/MWh]	Variable Emissions (Emis) cost of unit u
C_u^{Fuel} [€/MWh]	Variable Fuel cost of unit u
$C_u^{\mathrm{O\&M}}$ [€/MWh]	Variable Operation and Maintenance (O&M) cost of unit u

$C^{\text{PR,Pen}}$ [€/MW]	Penalty (Pen) related to the Primary Reserve (PR) requirement constraint
C_u^{SD} [€]	Shut-Down (SD) cost of unit u
$C^{\text{SR,Pen}}$ [€/MW]	Penalty (Pen) related to the Secondary Reserve (SR) up and down requirements constraints
$C^{\text{TR,Pen}}$ [€/MW]	Penalty (Pen) related to the Tertiary Reserve (TR) requirement constraint
ER_u [tCO_2e/MWh]	Emission Rate (ER) of unit u
MD_u [hours]	Minimum Downtime (MD) of unit u
MU_u [hours]	Minimum Uptime (MU) of unit u
$P^{\text{CO}_2\text{e}}$ [€/tCO_2e]	Carbon (CO_2) price
$P_{u,b,h}^{\text{G}}$ [€/MWh]	Price of energy Generation (G) offer of unit u, block b, hour h
$P_{u,h}^{\text{PR}}$ [€/MW]	Price of Primary Reserve (PR) offer of unit u, hour h
$P_{u,h}^{\text{SRR}}$ [€/MW]	Price of Secondary Reserve Range (SRR) offer of unit u, hour h
$Q_u^{\text{AGC,Max}}$ [MW]	Technical Maximum (Max) of unit u under AGC
$Q_u^{\text{AGC,Min}}$ [MW]	Technical Minimum (Min) of unit u under AGC
Q_h^{Exp} [MWh]	Exports (Exp) in hour h
$Q_u^{\text{G,Max}}$ [MW]	Technical Maximum (Max) of unit u
$Q_u^{\text{G,Min}}$ [MW]	Technical Minimum (Min) of unit u
$Q_{u,h}^{\text{G,Mand}}$	Mandatory (Mand) non-priced Generation (G) of unit u, hour h
Q_h^{Imp} [MWh]	Imports (Imp) in hour h
$Q_u^{\text{PR,Max}}$ [MW]	Primary Reserve (PR) Maximum (Max) of unit u
Q_h^{Pump} [MWh]	Pumping (Pump) in hour h
Q_h^{RES} [MWh]	RES in hour h
$Q_u^{\text{SRR,Max}}$ [MW]	Secondary Reserve Range (SRR) Maximum (Max) of unit u
$Q_u^{\text{TR,Max}}$ [MW]	Tertiary Reserve Maximum (Max) of unit u
Req_h^{PR} [MW]	Primary Reserve (PR) requirement in hour h
Req_h^{SRD} [MW]	Secondary Reserve Down (SRD) requirement in hour h
Req_h^{SRU} [MW]	Secondary Reserve Up (SRU) requirement in hour h
Req_h^{TR} [MW]	Tertiary Reserve (TR) Requirement in hour h

$SysL_h$ [MWh]	System Load in hour *h*
$X_{u,h}^{\mathrm{ST,Avail}}$	Availability (Avail) Status (St) of unit *u*, hour *h.* Values: 0 or 1.
$X_u^{\mathrm{St,0}}$	Initial Status (St) of unit *u* (in hour 0). Values: 0 or 1.
$Y_u^{\mathrm{Off,0}}$ [hours]	Number of hours that unit *u* has been "OFFLINE" (Off) in hour 0
$Y_u^{\mathrm{On,0}}$ [hours]	Number of hours that unit *u* has been "ONLINE" (On) in hour 0

Decision variables:

EnCost [€]	Aggregate Energy Cost
PenCost [€]	Aggregate Penalty Cost
$Q_{u,b,h}^{\mathrm{G}}$ [MWh]	Generation (G) of unit *u*, block, *b*, hour *h*, (not including mandatory injections)
$Q_{u,h}^{\mathrm{G,Tot}}$ [MWh]	Total (Tot) Generation (G) of unit *u*, hour *h*
$Q_h^{\mathrm{G,Def}}$ [MWh]	Deficit (Def) variable related to the energy balance constraint in hour *h*
$Q_h^{\mathrm{G,Sur}}$ [MWh]	Surplus (Sur) variable related to the energy balance constraint in hour *h*
$Q_{u,h}^{\mathrm{PR}}$ [MW]	Primary Reserve (PR) of unit *u*, hour *h*
$Q_h^{\mathrm{PR,Def}}$ [MW]	Deficit (Def) variable related to the Primary Reserve (PR) requirement constraint in hour *h*
$Q_{u,h}^{\mathrm{SRD}}$ [MW]	Secondary Reserve Down (SRD) of unit *u*, hour *h*
$Q_h^{\mathrm{SRD,Def}}$ [MW]	Deficit (Def) variable related to the Secondary Reserve Down (SRD) requirement constraint in hour *h*
$Q_{u,h}^{\mathrm{SRU}}$ [MW]	Secondary Reserve Up (SRU) of unit *u*, hour *h*
$Q_h^{\mathrm{SRU,Def}}$ [MW]	Deficit (Def) variable related to the Secondary Reserve Up (SRU) requirement constraint in hour *h*
$Q_{u,h}^{\mathrm{TR}}$ [MW]	Tertiary Reserve (TR) of unit *u*, hour *h*
$Q_h^{\mathrm{TR,Def}}$ [MW]	Deficit (Def) variable related to the Tertiary Reserve (TR) requirement constraint in hour *h*
ResCost [€]	Aggregate Reserves Cost
SDCost [€]	Aggregate Shut-Down Cost
SMP_h [€/MWh]	System Marginal Price (SMP) in hour *h* – Dual variable related to the energy balance constraint
TotSysCost [€]	Total System Cost
$X_{u,h}^{\mathrm{AGC}}$	AGC condition of unit *u* in hour *h* – Dependent binary variable: 1

= In AGC mode, 0 = Not in AGC mode

$X_{u,h}^{\mathrm{St}}$	Status (St) of unit *u*, hour *h* – Binary variable: 1 = ONLINE, 0 = OFFLINE
$X_{u,h}^{\mathrm{SD}}$	Shutdown signal for unit *u* in hour *h* – Dependent binary variable: 1 = Shut-Down (SD), 0 = No Shut-Down
$Y_{u,h}^{\mathrm{Off}}$ [hours]	Number of hours that unit *u* has been OFFLINE (Off) in hour *h* since last shutdown – Integer variable
$Y_{u,h}^{\mathrm{On}}$ [hours]	Number of hours that unit *u* has been ONLINE (On) in hour *h* since last startup – Integer variable

1. Introduction

In 2003, the *European Union* (EU) introduced the *Emissions Trading Scheme* (ETS) [1] in an effort to reach the Kyoto Protocol *Greenhouse Gas* (GHG) emissions reduction targets. The scheme was instantiated in January 2005, and to date, remains the world's largest emissions trading market. EU ETS covers around 45% of EU's GHG emissions and limits emissions from more than 11,000 heavy energy-using installations, such as power stations, industrial plants, and aviation activities in 31 countries (EU-28 plus Norway, Iceland, and Liechtenstein) [2].

EU ETS works on the "cap-and-trade" principle and consists of several consecutive trading periods or phases. Phase I (2005-2007) was the initial pilot "learn-by-doing" phase. Phase II (2008-2012) coincided with the first commitment period of the Kyoto Protocol. In the first two phases, the installations initially received a certain amount of free allowances according to the *National Allocation Plans* (NAPs). In each phase, allowances may be bought in case of shortage, or sold or saved in case of surplus, on a yearly basis. A review of early research on EU ETS, summarizing evidence from its operating mechanism and economic effect, as well as details on its history, structure and functioning is presented in [3, 4]. A review of mandatory GHG emissions trading schemes in operation worldwide up to 2010, which apart from EU ETS included the US Regional Greenhouse Gas Initiative, the New Zealand Emissions Trading Scheme, the Tokyo Metropolitan Trading Scheme, and the New South Wales Greenhouse Gas Abatement Scheme, is presented in [5].

The largest part of GHG emissions is created by the electricity sector. Although GHG emissions in the EU decreased by 22.4% over the period 1990-2016, the electricity and heat production sector share still remains the largest, accounting for about one third of the EU total emissions [6]. Initially, it was expected that EU ETS Phase III (2013-2020), launched in 2013, would signal important changes to the development of the electricity sector, since no free allowances (as in the case of NAPs) would be allocated to electricity generation units [7]. The energy generation cost in particular was thought to be significantly impacted by the emissions cost, as a real cost resulting from purchasing the total amount of emissions allowances from carbon markets or other Kyoto-protocol mechanisms. In 2013, however, the carbon price dropped to as low as 3 euros per ton of CO_2 equivalent, mainly due to the economic slowdown and the fact that the market was heavily oversupplied. Following a long period of prices steadily below 10 euros, recent reforms “revived” the carbon market, and prices have been rising since late 2017, reaching a peak of almost 30 euros in July 2019, before dropping to approximately 20 euros in April 2020, due to the pause in global activities caused by the Corona virus pandemic (see Figure 1). Hence, the impact of the carbon price on the electricity sector is attracting renewed attention.

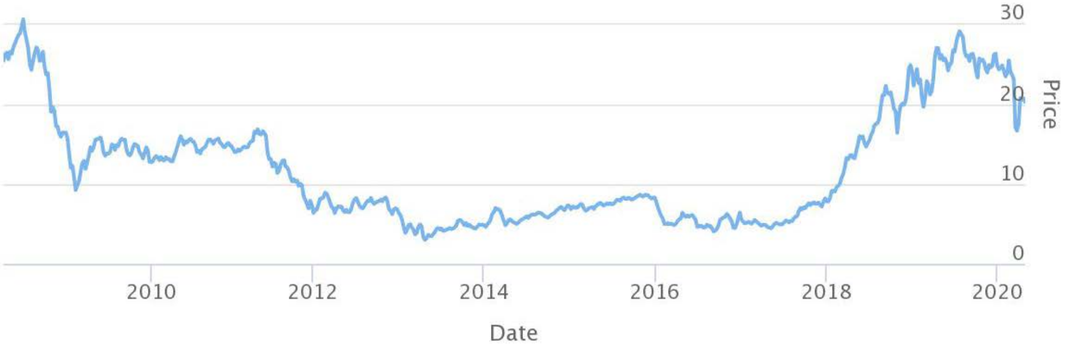

Figure 1. Carbon price (in €/tCO_2e), 2008-2020. Source: https://sandbag.org.uk/carbon-price-viewer/.

Carbon pricing and emissions trading has been a popular research topic [8-10]. Notably, discussions abound on the connections between carbon emissions, emission trading schemes and renewable targets [11], and CO_2 abatement [12, 13]. The ambitious new EU targets to achieve at least 40% cuts in GHG, at least 32% renewables in energy consumption, and at least 32.5% energy efficiency by 2030, which have led to the new EU framework "Clean energy for all Europeans package" [14], have further stimulated the interest in studying the aforementioned connections.

Since the EU ETS has been the main driver for thermal power plants to integrate the cost of their emissions into their offers in electricity markets, particular emphasis has been placed on the carbon cost "pass-through" on electricity prices, most importantly the day-ahead electricity prices, which are considered to provide the main price signal. European electricity markets have employed different schemes for their day-ahead market trades and the scheduling of the production / demand resources. In most cases, the day-ahead market is a voluntary energy-only market, with portfolio offers / bids operated by a Power Exchange, which follows bilateral and forward market contracts concluded beforehand and concern longer time frames. This has been the standard paradigm in most Northern / Central European markets, where the decentralized approach has been the prevailing scheduling and dispatch method. Although the European Target Model [15] does not specify the market design, European markets have moved to a power exchange. Nevertheless, the day-ahead market still provides the main price signal, as is also the case in pool-based markets. In pool markets, a Day-Ahead Scheduling problem is solved, employing a unit commitment and economic dispatch problem that schedules both energy and reserves, while respecting system and generation unit technical constraints. In a pool-based market design, the market-clearing price represents the short-term marginal cost for electricity generation, whereas the generation units are guaranteed revenue sufficiency through cost recovery mechanisms and related uplifts [16-18], and the capital and investment costs in the long-term through a capacity assurance mechanism. In power exchanges, on the other hand, the electricity prices reflect both (short-term and long-term) cost components, since usually no out-of-market cost recovery mechanism and/or capacity markets exists.

This paper explores the interface between the carbon market and a pool-based electricity market. It studies the effects of carbon costs on system operation conditions and market prices, employing a Day-Ahead Scheduling model, in which power plants internalize their emissions cost in the energy offers that they submit to the day-ahead market. It quantifies the impact of the emissions cost on the electricity price, the generation scheduling outcome, and the overall emissions, and presents results from an instance of the Greek electricity market under EU ETS Phase III.

The remainder of this paper is organized as follows. Section 2 discusses the relevant literature. Section 3 presents the methodology, including the Day-Ahead Scheduling model, the impact of emissions cost in a pool-based market, and the data sources of a test case that is based on an instance of the Greek electricity market during EU ETS Phase III. Section 4 presents and discusses the numerical results and the main outcomes on the pass-through rates. Section 5 concludes and points out issues for further research.

2. Literature Review

The existing literature on the interface between carbon and electricity markets mainly uses historical data from Phases I and II of the EU ETS to study the formation of carbon prices [19-22] and analyze their impact on electricity prices. In the context of EU ETS, carbon cost pass-through rates have been calculated across several EU countries, using a variety of methodologies. Several studies employ empirical, statistical, and econometric models to analyze the relationship between carbon and electricity prices [23-35]. In addition, some approaches use market equilibrium and simulation models. The COMPETES (COmpetition and Market Power in Electric Transmission and Energy Simulator) model, a static short-run equilibrium model that represents competition between decentralized power producers in 20 EU member states in a transmission-constrained European power market, is used in [24, 25, 36, 37]. A Nash-Cournot oligopolistic market equilibrium model is employed in [38] to investigate the impact of permit allocation on the CO_2 cost pass-through. An electricity market model based on stochastic dynamic programming is used in [39], a market equilibrium problem using quadratic optimization is formulated in [40], and agent-based simulation is used in [41, 42]. The impact of EU ETS on electricity pricing is investigated in [43, 44], using both theoretical and empirical analysis, emphasizing market power and market structure. The literature also includes several case studies in Europe (e.g., Germany [29, 34], the Netherlands [34], Spain [33], Nordic and Baltic countries [26, 45], and on emission trading elsewhere (e.g., Australia [46-49], South Korea [46], China [50, 51], Japan [52], California [53]).

Empirical, statistical and econometric models [23-35] are popular mainly due to the data availability of electricity market results, which are run on daily basis, e.g., day-ahead electricity prices, generation schedules, as well as the availability of emission data, e.g., carbon prices, and technology-driven emission rates. However, these approaches rely heavily on stylized model assumptions – e.g., a rough distinction between peak and off-peak hours, assumptions on various demand elasticities, etc. – whose choice significantly affects their outcome. In addition, empirical, statistical, and econometric models employ historical data to assess pass-through rates, and as such they are affected by the market conditions and price realizations of their study period; hence their ability to explain changes in conditions and different realizations, i.e., their “out-of-sample” performance, remains questionable. Among the above works, [33-34] and [54] have emphasized the role of the marginal generator in estimating the pass-through rates and the importance of identifying the marginal generation unit and the corresponding marginal emissions [55]. However, an accurate estimation of the marginal generator in a pool-based setting requires modeling of the Day-Ahead Scheduling problem, which provides the main market signal and governs the generation scheduling outcome. Even though the cost of emissions is fully integrated in the energy offers, and the "add-on" rate as defined by [24] can be 100%, this cost may not pass completely onto the demand-side payments; a different "work-on" rate is thus implied, since the wholesale electricity price depends on the impact of the marginal generation unit. Hence, empirical, statistical, and econometric works, although they may correctly identify the importance of the marginal generator, they fall short of capturing the system operation conditions and day-ahead market requirements, which in turn affect, to a great extent, the impacts of carbon costs on market prices and scheduling.

In pool markets, the analysis of the effects of emissions costs on market prices, unit scheduling and final emissions reduction, requires the use of simulation models that capture the salient features of the generation scheduling resulting from solving a unit commitment and economic dispatch problem. In this direction, [56] includes the costs of buying and selling CO_2 allowances in the generation scheduling process, as well as emission constraints. The emphasis of this work is on allowance trading; pass-through rates and mid-term implications are not discussed. A hydro-thermal power system optimization model considering CO_2 emissions quotas and certificate prices is presented in [57]. This work considers the mid-term model of 4 years, in a stochastic setting, with time stages of 1 week or 1 month. In this respect, this mid-term model suppresses important features of the day-ahead market, which play a major role in the short-term scheduling outcome. For instance, it is shown in [58] that the benefits in the reduction of emissions resulting from an increase in the carbon price may be offset by a consequent rise in cycling costs (see also [59] for a relevant case study on the “hidden cost” of renewables). It is also worth mentioning that, typically, in a day-ahead model, the uncertainty introduced by high renewable penetration [59-62] is dealt with appropriate requirements for reserves. Including the unit commitment decisions and the salient technical constraints of the generation units, which take into account the power system operations flexibility [61], provides more accurate results on the costs associated with the commitment and dispatch of conventional generation to complement renewable injections. Hence, in this context, the investigation of the impact of generation unit outages, becomes even more important, because, apart from their impact on the actual commitment and dispatch, they also affect the availability of reserves.

The case study presented in this paper considers an instance of the Greek generation sector during EU ETS Phase III. Traditionally, the horsepower of the Greek electricity sector has been domestic lignite [63]; the generation mix has also included combined cycle and open-cycle gas turbines, gas/oil-fired units, large hydro plants, and renewable installations (wind, solar, small hydro plants, biomass, and cogeneration). A study of the Greek power sector from a least-cost electricity planning perspective is presented in [64], whereas an overview of its CO_2 emissions is presented in [65]. The Greek electricity market makes an interesting case because it followed a pool market setting with energy and reserve co-optimization [66, 67], through EU ETS Phase III. Although a zonal model was initially foreseen, considering a North-to-South transmission corridor constraint, this constraint has hardly ever been binding. A recent econometric study for the Greek electricity market [68] shows that depending on the model assumptions, the carbon pass-through rates may range from incomplete (lower than 50%), using baseline methodologies, to complete (of about 100%), using an instrumental variable approach in the spirit of [33].

The results presented herein significantly extend our prior work and preliminary results [69] by: (i) providing a thorough review of approaches with emphasis on the pass-through rates, (ii) formulating a general methodology and a scheduling model that is applicable to a pool-based market but can be customized to accommodate any market-specific rules, and (iii) providing new and extensive numerical results that exhaustively consider and quantify the impact of outages on each fuel price and gas price scenario.

The contributions with respect to the existing literature are summarized as follows. The paper proposes a methodology to evaluate the impact of the cost of emissions on the mid-term generation scheduling, electricity prices, and carbon cost pass-through rates. Compared to empirical, statistical or econometric models, the proposed methodology provides a more accurate means of determining the marginal generator, since it considers the co-optimization of energy and reserves in a unit commitment and economic dispatch model, while also being highly suitable for systems with high renewable penetration (which require a high level of reserves). In addition, since it does not depend on historical data to explain the future, as the aforementioned models do with occasionally poor “out-of-sample” performance, the proposed methodology can be applied even if the power system generation mix changes significantly, e.g., if the share of renewables increases substantially. Furthermore, the selection of a yearly time horizon, while maintaining the complexity of the daily operation, balances between short-term and mid-term models, also catering for different seasonality conditions, and smoothening time-varying pass-through rates, to obtain average results. The confidence of the obtained results is further enhanced by considering the unit availability as affected by random outages. Lastly, the methodology is illustrated through an application on an instance of the Greek electricity market during the EU ETS Phase III and provides results on the market outcome, the impact on electricity prices, and the pass-through rates under a mix of gas and carbon price scenarios. Although the results of the Greek electricity market cannot be directly compared with the econometric study in [68], which considers a period with relative low carbon prices and various other assumptions, our estimated pass-through rates are within the range of values obtained under the different methods considered in [68]. Arguably, the sensitivity analysis with respect to gas and carbon prices employed in this work provides a more intuitive explanation of the pass-through rates.

3. Methodology

In this section, we present the optimization model of the Day-Ahead Scheduling problem (in Subsection 3.1), we quantify the impact of the cost of emissions (in Subsection 3.2), and we provide the relevant data sources (in Subsection 3.3).

3.1 The Day-Ahead Scheduling Model

The Day-Ahead Scheduling problem constitutes the basis of the day-ahead market. It is solved on a daily basis, simultaneously for all 24 hours of the next day. Its solution determines the hourly energy and reserve clearing prices, as well as the unit scheduling (energy and reserves). The objective is to minimize the total system cost based on the energy and reserve offers of the generating units to cover the system load and meet the reserve requirements and the generation unit technical constraints. The generation units submit energy offers for each hour of the following day as a stepwise function of up to ten non-decreasing price-quantity pairs (blocks); the cost of emissions is internalized in these offers (by accounting for the applicable emission rate and carbon price). The units also submit reserve offers as a single price-quantity pair for each hour, as well as their technical characteristics and limitations (e.g., technical minimum and maximum, reserve capabilities, minimum uptime and downtime, etc.), which are taken into account in the problem.

For the purposes of this study, the model is kept simplified yet complex enough to capture all the important characteristics of the market. Additional characteristics that are deemed important in specific markets (e.g., transmission constraints, interconnection capacities, etc.) can be straightforwardly incorporated. To facilitate the readability, we present below a brief overview of the problem decision variables. These include: (i) non-negative continuous variables for the generation unit energy and reserve schedules, and for the system slack (deficit or surplus) variables that are used to ensure a feasible solution (relaxing system constraints with a high penalty); (ii) discrete variables for the generation units. We elaborate on the decision variables below.

Generation unit continuous variables include: (i) $Q^{\mathrm{G}}_{u,b,h}$ (in MWh), denoting the generation (output) of unit u, block b, hour h, without including any mandatory injections; (ii) $Q^{\mathrm{G,Tot}}_{u,h}$ (in MWh), denoting the total generation (output) of unit u, hour h (the difference refers to any mandatory injections that may apply to specific units, e.g., hydro plants); (iii) $Q^{\mathrm{PR}}_{u,h}$ (in MW), denoting the primary reserve of unit u, hour h; (iv) $Q^{\mathrm{SRD}}_{u,h}$ (in MW), denoting the secondary reserve down of unit u, hour h; (v) $Q^{\mathrm{SRU}}_{u,h}$ (in MW), denoting the secondary reserve up of unit *u*, hour *h*; (vi) $Q_{u,h}^{\mathrm{TR}}$ (in MW), denoting the tertiary reserve of unit *u*, hour *h*.

System-related continuous variables include the following slack (deficit or surplus) variables: (i) $Q_{h}^{\mathrm{G,Def}}$ (in MWh) ,denoting the potential deficit in the energy balance constraint in hour *h*; (ii) $Q_{h}^{\mathrm{G,Sur}}$ (in MWh), denoting the potential surplus in the energy balance constraint in hour *h*; (iii) $Q_{h}^{\mathrm{PR,Def}}$ (in MW), denoting the potential deficit in the primary reserve requirement constraint in hour *h*; (iv) $Q_{h}^{\mathrm{SRD,Def}}$ (in MW), denoting the potential deficit in the secondary reserve down requirement constraint in hour *h*; (v) $Q_{h}^{\mathrm{SRU,Def}}$ (in MW), denoting the potential deficit in the secondary reserve up requirement constraint in hour *h*; (vi) $Q_{h}^{\mathrm{TR,Def}}$ (in MW), denoting potential deficit variable related to the tertiary reserve requirement constraint in hour *h*.

Binary variables of generation units include: (i) $X_{u,h}^{\mathrm{St}}$, denoting the status (condition) of unit *u*, hour *h* (1: Online; 0: Offline); (ii) $X_{u,h}^{\mathrm{SD}}$, denoting a shutdown of unit *u* in hour *h* (1: Shutdown, 0: No shutdown); (iii) $X_{u,h}^{\mathrm{AGC}}$, denoting the AGC condition of unit *u* in hour *h* (1: In AGC mode, 0 = Not in AGC mode).

Integer variables of generation units include: (i) $Y_{u,h}^{\mathrm{Off}}$, indicating the number of hours unit *u* has been offline in hour *h* since the last shutdown; (ii) $Y_{u,h}^{\mathrm{On}}$, indicating the number of hours unit *u* has been online in hour *h* since the last startup.

<u>Objective Function</u>: The Day-Ahead Scheduling problem aims to minimize the total system cost, *TotSysCost*, as defined in (1.a) - (1.d). The terms of the objective function include the aggregate energy cost *EnCost* (1.a), the aggregate reserves cost *ResCost* (1.b), the aggregate shutdown cost *SDCost* (1.c), and a penalty cost *PenCost* (1.d) to avoid problem infeasibility.

$$\text{minimize}\, TotSysCost = EnCost + ResCost + SDCost + PenCost \,, \tag{1}$$

where

$$TotEnCost = \sum_{u,b,h} P^{\mathrm{G}}_{u,b,h} \cdot Q^{\mathrm{G}}_{u_i,b,h} \,, \tag{1.a}$$

$$ResCost = \sum_{u,h} \left[P^{\mathrm{PR}}_{u,h} \cdot Q^{\mathrm{PR}}_{u,h} + P^{\mathrm{SRR}}_{u,h} \cdot \left(Q^{\mathrm{SRU}}_{u,h} + Q^{\mathrm{SRD}}_{u,h} \right) \right], \tag{1.b}$$

$$SDCost = \sum_{u,h} X^{\mathrm{SD}}_{u,h} \cdot C^{\mathrm{SD}}_{u} \,, \tag{1.c}$$

$$PenCost = \sum_{h} \begin{bmatrix} C^{\mathrm{G,\,Pen}} \left(Q^{\mathrm{G,\,Def}}_{h} + Q^{\mathrm{G,Sur}}_{h} \right) + C^{\mathrm{PR,Pen}} \cdot Q^{\mathrm{PR,Def}}_{h} \\ + C^{\mathrm{SR,Pen}} \left(Q^{\mathrm{SRU,Def}}_{h} + Q^{\mathrm{SRD,Def}}_{h} \right) + C^{\mathrm{TR,Pen}} \cdot Q^{\mathrm{TR,Def}}_{h} \end{bmatrix}. \tag{1.d}$$

The aggregate energy cost (1.a) includes the contribution of all blocks of energy offers cleared, where $P^{\mathrm{G}}_{u,b,h}$ (in €/MWh) denotes the energy offer price of unit *u*, block *b*, hour *h*. The aggregate reserves cost (1.b) includes the cost for the provision of: (i) primary reserve, where $P^{\mathrm{PR}}_{u,h}$ (in €/MW) denotes the primary reserve offer of unit *u*, hour *h*; (ii) secondary reserve up and down, where $P^{\mathrm{SRR}}_{u,h}$ (in €/MW) denotes the price for the secondary reserve range offer of unit *u*, hour *h*. The aggregate shutdown cost (1.c) considers the shutdown cost of unit *u*, C^{SD}_{u} (in €), equal to the warm startup cost to deter solutions in which generation units are easily shut down, because such solutions may adversely affect the system cost in the Day-Ahead Scheduling problem of the following day if the time required to start up the stopped units is large [70]. The penalty cost (1.d) employs penalty (big M) coefficients which relax system constraints (energy balance and reserve requirements) through the introduction of slack (deficit and surplus) variables for energy and reserves. The penalties refer to energy $C^{\mathrm{G,Pen}}$ (in €/MWh), primary reserve $C^{\mathrm{PR,Pen}}$ (in €/MW), secondary reserve $C^{\mathrm{SR,Pen}}$ (in €/MW), and tertiary reserve $C^{\mathrm{TR,Pen}}$ (in €/MW), and their values can be set to represent different priorities in the constraint relaxation.

The system constraints include the energy balance and reserve requirements constraints (2) and (3), respectively.

Energy Balance:

$$\sum_u Q_{u,h}^{\text{G, Tot}} + Q_h^{\text{Imp}} + Q_h^{\text{RES}} + Q_h^{\text{G, Def}} - Q_h^{\text{G,Sur}} = SysL_h + Q_h^{\text{Exp}} + Q_h^{\text{Pump}}, \qquad \forall h. \qquad (2)$$

Constraint (2) defines the energy balance for each hour of the following day. Namely, the sum of the generation for all units $\sum_u Q_{u,h}^{\text{G,Tot}}$, plus the imports Q_h^{Imp} (in MWh), plus the renewable generation Q_h^{RES} (in MWh) should equal the system load $SysL_h$ (in MWh), plus the exports Q_h^{Exp} (in MWh), plus the pumping declarations Q_h^{Pump} (in MWh). Deficit and surplus variables, $Q_h^{\text{G, Def}}$ and $Q_h^{\text{G, Sur}}$, respectively, ensure feasibility.

Reserve Requirement Constraints:

Primary Reserve: $$\sum_u Q_{u,h}^{\text{PR}} + Q_h^{\text{PR,Def}} \geq Req_h^{\text{PR}}, \qquad \forall h, \qquad (3.a)$$

Secondary Reserve Up: $$\sum_u Q_{u,h}^{\text{SRU}} + Q_h^{\text{SRU,Def}} \geq Req_h^{\text{SRU}}, \qquad \forall h \qquad (3.b)$$

Secondary Reserve Down: $$\sum_u Q_{u,h}^{\text{SRD}} + Q_h^{\text{SRD,Def}} \geq Req_h^{\text{SRD}}, \qquad \forall h, \qquad (3.c)$$

Tertiary Reserve: $$\sum_u Q_{u,h}^{\text{TR}} + Q_h^{\text{TR,Def}} \geq Req_h^{\text{TR}}, \qquad \forall h. \qquad (3.d)$$

Constraints (3.a) - (3.d) ensure the adequacy of the different types of reserves to meet the requirements for: primary reserve, Req_h^{PR} (in MW), secondary reserve up, Req_h^{SRU} (in MW), secondary reserve down, Req_h^{SRD} (in MW), and tertiary reserve Req_h^{TR} (in MW). The deficit variables relax the reserve requirements constraints, with appropriately selected penalty coefficients to maintain the following order: (i) tertiary reserve; (ii) secondary reserve; (iii) primary reserve, and (iv) energy balance, which is the last constraint to be relaxed.

The generation unit specific constraints include the following:

Total Generation Output:

$$Q_{u,h}^{\mathrm{G,Tot}} = Q_{u,h}^{\mathrm{G,\,Mand}} + \sum_{b} Q_{u,b,h}^{\mathrm{G}}\,, \qquad \forall u,h\,. \tag{4}$$

Equality (4) states that the total generation equals a non-priced, mandatory component, $Q_{u,h}^{\mathrm{G,Mand}}$, e.g., the mandatory hydro injections, plus a component (block offers) that is scheduled/decided by the optimization problem.

Technical Maximum/Minimum:

$$Q_{u,h}^{\mathrm{G,Tot}} + Q_{u,h}^{\mathrm{PR}} + Q_{u,h}^{\mathrm{SRU}} + Q_{u.h}^{\mathrm{TR}} \le Q_{u}^{\mathrm{G,\,Max}} \cdot \left(X_{u,h}^{\mathrm{St}} - X_{u,h}^{\mathrm{AGC}} \right) + X_{u,h}^{\mathrm{AGC}} \cdot Q_{u}^{\mathrm{AGC,\,Max}}, \qquad \forall u,h\,, \tag{5.a}$$

$$Q_{u,h}^{\mathrm{G,Tot}} - Q_{u,h}^{\mathrm{SRD}} \ge Q_{u}^{\mathrm{G,Min}} \cdot \left(X_{u,h}^{\mathrm{St}} - X_{u,h}^{\mathrm{AGC}} \right) + X_{u,h}^{\mathrm{AGC}} \cdot Q_{u}^{\mathrm{AGC,Min}}, \qquad \forall u,h\,. \tag{5.b}$$

Constraints (5.a) and (5.b) represent the technical maximum and minimum limits, while also considering the provision of reserves and the AGC limits, for unit *u*, hour *h*. Parameters $Q_{u}^{\mathrm{G,\,Max}}$ (in MW) and $Q_{u}^{\mathrm{G,\,Min}}$ (in MW) denote the technical maximum and technical minimum, respectively, of unit *u*. Parameters $Q_{u}^{\mathrm{AGC,\,Max}}$ (in MW) and $Q_{u}^{\mathrm{AGC,\,Min}}$ (in MW) denote the AGC maximum and AGC minimum limits of unit *u*. Usually, these limits are stricter than the technical maximum and minimum limits.

Reserve Capability:

Primary Reserve: $$Q_{u,h}^{\mathrm{PR}} \le X_{u,h}^{\mathrm{St}} \cdot Q_{u}^{\mathrm{PR,Max}}, \qquad \forall u,h\,, \tag{6.a}$$

Secondary Reserve Range: $$Q_{u,h}^{\mathrm{SRU}} + Q_{u,h}^{\mathrm{SRD}} \le X_{u,h}^{\mathrm{AGC}} \cdot Q_{u}^{\mathrm{SRR,Max}}, \qquad \forall u,h\,, \tag{6.b}$$

Tertiary Resrve: $$Q_{u,h}^{\mathrm{TR}} \le X_{u,h}^{\mathrm{St}} \cdot Q_{u}^{\mathrm{TR,Max}}, \qquad \forall u,h\,. \tag{6.c}$$

Inequalities (6.a) - (6.c) represent the reserve capabilities for unit *u*, hour *h*. Parameters $Q_{u}^{\mathrm{PR,Max}}$, $Q_{u}^{\mathrm{SRR,Max}}$, and $Q_{u}^{\mathrm{TR,Max}}$ denoter the maximum capabilities (in MW) of unit *u*, for the provision of primary, secondary reserve range, and tertiary reserve, respectively. Primary and tertiary reserve provision requires the generation unit to be online, i.e., $X_{u,h}^{\mathrm{St}}=1$; in addition, for the provision of up/down secondary reserve, the generation unit should be in AGC mode, i.e., $X_{u,h}^{\mathrm{AGC}}=1$.

<u>Minimum Uptime/Dowtime</u>:

$$\left(Y_{u,h-1}^{\mathrm{On}}-MU_u\right)\left(X_{u,h-1}^{\mathrm{St}}-X_{u,h}^{\mathrm{St}}\right)X_{u,h}^{\mathrm{St,Avail}}\geq 0, \qquad \forall u,h, \qquad (7.a)$$

$$\left(Y_{u,h-1}^{\mathrm{Off}}-MD_u\right)\left(X_{u,h}^{\mathrm{St}}-X_{u,h-1}^{\mathrm{St}}\right)\geq 0, \qquad \forall u,h. \qquad (7.b)$$

Constraints (7.a) and (7.b) define minimum uptime and minimum downtime constraints for unit *u*, hour *h*. Parameters MU_u (in hours) and MD_u (in hours), denote the minimum uptime and minimum downtime, respectively, for unit *u*. When a generation unit starts up (shuts down), it must remain online (offline) for a certain number of hours, measured by time counters $Y_{u,h}^{\mathrm{On}}$, and $Y_{u,h}^{\mathrm{Off}}$. By multiplying constraint (7.a) with the unit availability $X_{u,h}^{\mathrm{St,Avail}}$ (binary availability parameter with 1: available; 0: not available), the minimum uptime requirement is dropped when the unit is not available (e.g., due to maintenance or outage).

<u>AGC Mode</u>:

$$X_{u,h}^{\mathrm{AGC}}\leq X_{u,h}^{\mathrm{St}}, \qquad \forall u,h, \qquad (8.a)$$

$$X_{u,h}^{\mathrm{AGC}}=0, \qquad \forall u\notin U_{\mathrm{AGC}},\ h. \qquad (8.b)$$

Constraints (8.a) and (8.b) imply that the AGC-mode variable can be set to 1, indicating that the unit is in AGC-mode only if the unit is online, whereas it should be set to zero in case the unit is not capable of providing secondary reserve (i.e., when it does not belong to the set of generation units with AGC capability).

<u>Availability</u>:

$$X_{u,h}^{\mathrm{St}} \le X_{u,h}^{\mathrm{St,Avail}}, \qquad \forall u,h. \tag{9}$$

Constraint (9) declares the unit availability. The unit status should be zero when the unit is not available, i.e., the right hand side is zero.

<u>Dependent Variables</u>:

Shutdown Signal: $$X_{u,h}^{\mathrm{SD}} = X_{u,h-1}^{\mathrm{St}}\left(1 - X_{u,h}^{\mathrm{St}}\right), \qquad \forall u,h, \tag{10.a}$$

Hours Online: $$Y_{u,h}^{\mathrm{On}} = \left(Y_{u,h-1}^{\mathrm{On}} + 1\right) X_{u,h}^{\mathrm{St}}, \qquad \forall u,h, \tag{10.b}$$

Hours Offline: $$Y_{u,h}^{\mathrm{Off}} = \left(Y_{u,h-1}^{\mathrm{Off}} + 1\right)\left(1 - X_{u,h}^{\mathrm{St}}\right), \qquad \forall u,h. \tag{10.c}$$

Equalities (10.a) - (10.c) define dependent variables for unit *u*, hour *h*, which declare shutdown signals $X_{u,h}^{\mathrm{SD}}$, and count the hours that a unit has remained online, $Y_{u,h}^{\mathrm{On}}$, or offline $Y_{u,h}^{\mathrm{Off}}$.

<u>Initialization</u>:

$$X_{u,0}^{\mathrm{St}} = X_{u}^{\mathrm{St,0}}, \qquad \forall u, \tag{11.a}$$

$$Y_{u,0}^{\mathrm{On}} = Y_{u}^{\mathrm{On,0}}, \qquad \forall u, \tag{11.b}$$

$$Y_{u,0}^{\mathrm{Off}} = Y_{u}^{\mathrm{Off,0}}, \qquad \forall u. \tag{11.c}$$

Lastly, equalities (11.a) - (11.c) define the initial values, in hour 0 for the aforementioned variables.

Note that constraints (7.a) - (7.b) and (10.a) - (10.c) are nonlinear. It is shown in [71, Appendix A] that these constraints can be replaced by equivalent linear inequalities, through the introduction of auxiliary variables. The formulation that results after the above replacements is a Mixed Integer Linear Programming (MILP) problem. The progress of MILP solvers in recent years resulted in adopting MILP models to solve a unit commitment and economic dispatch problem.

Once the MILP problem is solved, the resulting Linear Programming problem, which is obtained by fixing the integer variables at their optimal values and dropping the constraints that involve only integer variables, i.e., constraints (7.a) - (11.c), allows for the calculation of clearing prices using marginal pricing theory [72]. The energy clearing price, referred to as the *System Marginal Price* (SMP) in hour h, SMP_h (in €/MWh), is determined as the shadow price of the energy balance constraint (2).

3.2 Impact of Emissions Cost

In this section, the simulation methodology to evaluate the impact of the emissions cost in pool-based electricity markets is described. Based on the Day-Ahead Scheduling model, a mid-term generation scheduling is developed by simulating the day-ahead electricity market on a daily basis for an entire year (365 days). The Day-Ahead Scheduling problem is solved for each day, using the information of the previous day system status.

The day-ahead energy offers reflect several components of the variable energy cost. Provided that the generating units integrate the cost of emissions in their day-ahead energy offers, the variable cost of thermal unit u consists of three components: (i) the variable costs for fuel, (ii) Operation and Maintenance (O&M), and (iii) emissions, as follows:

$$C_u^{\mathrm{G,\ Tot}}\left(\frac{€}{\mathrm{MWh}}\right) = C_u^{\mathrm{Fuel}} + C_u^{\mathrm{O\&M}} + C_u^{\mathrm{Emis}}, \tag{12}$$

where the variable emissions cost is given by multiplying the emissions rate of the generation unit, ER_u, with the carbon price, $P^{\mathrm{CO_2e}}$, i.e.,

$$C_u^{\mathrm{Emis}}\left(\frac{€}{\mathrm{MWh}}\right) = ER_u\left(\frac{\mathrm{t\,CO_2e}}{\mathrm{MWh}}\right)\cdot P^{\mathrm{CO_2e}}\left(\frac{€}{\mathrm{t\,CO_2e}}\right). \tag{12.a}$$

It should be mentioned that for consistency reasons, even though this paper deals almost exclusively with CO_2 emissions, emissions are measured in tons of CO_2 equivalent

(tCO_2e), as would be the case with general GHG emissions, and the carbon price is indicated in €/tCO_2e.

Two key factors that will affect the scheduling output are the fuel (gas) price and the carbon price. Hence, a scenario-based approach is employed to evaluate different combinations of gas and carbon prices. Specifically, three scenarios are considered for the gas price: low, moderate and high, and seven scenarios for the carbon price, ranging from 0 to 30 €/tCO_2e with a step of 5 €/tCO_2e.

As the carbon price increases, the merit order of the generation units may change, resulting in a different generation scheduling outcome with reduced emissions. More specifically, a power plant that would otherwise be committed to serve base load and would be operating most of the time, may have to shut down more often, as it will have an increased variable cost at higher carbon prices. Nevertheless, the actual impact on the electricity price in a pool-based market will depend on the cost-recovery mechanism in effect. This issue will be discussed further in the following section.

There are several sources of uncertainty in a mid-term generation scheduling model. This work focuses on unit availability which is mostly affected by the occurrence of random outages (assuming that the maintenance schedule is announced and known in advance). An outage will affect the availability of generation units, and, depending on the type and technical characteristics of each unit, the Day-Ahead Scheduling solution will be affected accordingly. Typically, the outage rate is characterized by the *Equivalent Demand Forced Outage Rate* ($EFOR_D$) value of each unit, which measures the probability that the unit will not be available in the next day due to a forced outage. To simulate the failures and repairs of the units, Bernoulli-distributed random outages are generated for each day based on the $EFOR_D$ of each unit, which means that the time to failure of a generation unit is assumed to be geometrically distributed. Each outage requires a unit-specific repair time for the unit to become available. Using thirty different scenarios for the realizations of the random outages, the level of confidence in the obtained results is enhanced.

The combination of the seven scenarios for the carbon price, the three scenarios for the gas price, and the thirty scenarios for the random outages, yield a total of 630 problem instance scenarios (7·3·30 = 630). Figure 2 gives a pictorial representation of the total generated scenarios (630 scenarios) and shows a flowchart of the iterative procedure used to obtain the yearly results. The term “initial values” refers to the values of equalities (11.a) - (11.c) of the Day-Ahead Scheduling problem (status, and time periods that each unit has been on/off-line), which are necessary for the initialization. These values are set equal to the respective values at the end of the previous day and are drawn from the respective solution of the Day-Ahead Scheduling problem.

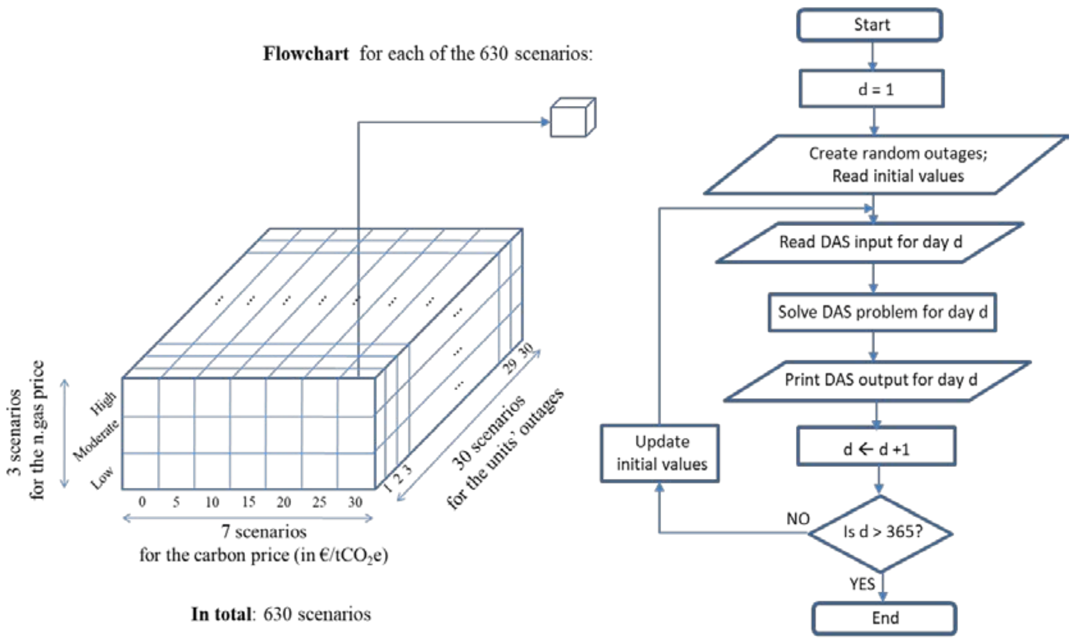

Figure 2. Scenarios generated for the simulation, and flowchart of the iterative procedure followed for each scenario. Source: Authors’ Elaboration.

The key price signal of the pool-based electricity market is the day-ahead electricity price, i.e., the SMP, which represents the marginal (as-bid) cost for producing one additional MWh at a specific hour. In the employed mid-term scheduling model, the *weighted average electricity price* (WAEP) represents the demand payments for purchasing electricity in the wholesale market. The WAEP is computed by weighing the SMP in each hour with the aggregate demand share in that hour, for the entire simulation horizon, i.e., over all 8,760 hours of the horizon, as is shown by expressions (13) and (13.a), where the sum over *d, h,* refers to all days, *d*, in a year and all hours, *h,* in a day. The aggregate demand share in each hour is the aggregate demand in that hour divided by the sum of the aggregate demands over all 8,760 hours of the horizon.

$$WAEP\left(\frac{€}{\text{MWh}}\right)=\frac{\sum_{d,h}\left(SMP_{d,h}\cdot Dem_{d,h}\right)}{\sum_{d,h}Dem_{d,h}}, \tag{13}$$

where

$$Dem_{d,h}=SysL_{d,h}+Q_{d,h}^{\text{Exp}}+Q_{d,h}^{\text{Pump}} \tag{13.a}$$

A measure of interest is the *total carbon cost* (TCC) percentage that passes onto demand-side payments, which refer to the payments of the demand side to the market operator. Using the WAEP, this measure is essentially the pass-through rate – as defined in the literature (e.g., [24]) – of the carbon costs to the WAEP (i.e., the average electricity price seen by the demand in the yearly period). In the context of this paper, this measure is a referred to as *average pass-through rate* (APTR) – with “average” indicating the yearly period and the WAEP – and is defined as follows:

$$\begin{aligned}APTR(\%)&=\frac{\left(WAEP-WAEP^{0}\right)\sum_{d,h}Dem_{d,h}}{TCC}\cdot 100\%\\&=\frac{\sum_{d,h}\left(SMP_{d,h}-SMP_{d,h}^{0}\right)\cdot Dem_{d,h}}{P^{\text{CO}_2\text{e}}\cdot\sum_{d,h}Emis_{d,h}}\cdot 100\%\end{aligned} \tag{14}$$

where $WAEP^{0}$ and $SMP_{d,h}^{0}$ denote the WAEP and SMP values when $P^{\text{CO}_2\text{e}}=0$, and $Emis_{d,h}$ denotes the aggregate emissions in day *d*, hour *h* calculated by the aggregate emissions of all units using the respective emission rates and generation quantities.

3.3 Data Sources

In this section, a test case of a pool-based market within EU ETS is described. representing an instance of the Greek generation sector during EU ETS Phase III, considering historical data for the year 2013. All prices are current prices.

The total installed capacity is approximately 14.2 GW and consists of about 9 GW from thermal units 3 GW from 15 hydro units, and 2.2 GW from RES (mainly wind parks and PVs) [73]. The thermal units consist of 17 lignite units of about 4.3 GW and 15 gas units of about 4.7 GW. The system hourly minimum and maximum loads are equal to 3.2 GW and 9.7 GW, respectively, and the yearly energy consumption is 52.633 TWh. Average hourly net imports and RES injections are assumed equal to 300 MW and 400 MW, respectively. To remove potential biases from day-ahead forecasts, we included the actual (historical) values for load profiles and RES injections. Reserve requirements are set at 80 MW for primary reserve, 100 – 350 MW for secondary reserve and 5% of the system load for tertiary reserve. An overview of the various reserves (ancillary services) in the Greek electricity market is provided in [71] (note that currently primary, secondary, and tertiary reserve are referred to as frequency containment, automatic frequency restoration and manual frequency restoration reserve, respectively). The maintenance schedule and the $EFOR_D$ are obtained from historical data. The outage repair time is set at two days. Hydro units are considered as an aggregate plant, with a 2.6 GW adjusted capacity considering an average hydro $EFOR_D$ whose energy offer for the non-mandatory injections is set above the last thermal power plant. Yearly mandatory hydro injections amount to 4.2 TWh which represent a moderate year (neither too dry nor too wet).

Aggregate data for the generation units are shown in Table 1. The interested reader is referred to Appendix A for a more detailed presentation of the units' technical and economic characteristics. More specifically, Table 1 presents the total capacity, the ranges of the emissions rates (in tons of CO_2 equivalent per MWh) per unit category, and the ranges of the energy offers (assuming a single price-quantity pair for each unit) under the zero-carbon price scenario for the three different gas price scenarios: low, moderate and high. The low and the high gas price scenarios are derived from the moderate one with a 10% decrease and increase respectively.

Table 1
Emissions rates and energy offers under the zero-carbon price scenario

Fuel type	**Units**	**Total Capacity (MW)**	**Emissions Rates (tCO_2e/MWh)**	**Energy Offers (€/MWh)**		
				Gas Price Scenario		
				Low	**Moderate**	**High**
Lignite	1-17	4,314	1.04-1.96		24-37	
Gas	18-27	4,190	0.37-0.49	51.6-75.6	57.1-81.1	62.7-86.7
	28-29	339	0.53	78.5-86.2	87.0-95.6	95.6-105.0
	30-32	147	0.60	79.2	87.9	96.5

Source: Authors' Estimates.

Units 1-17 are lignite units, with low energy costs, and high emission rates. Units 18-27 are mainly combined cycle gas turbine units with prices that depend on their specific technology and characteristics. Units 28-29 are older technology gas units, with higher minimum uptimes/downtimes, higher costs, and higher emission rates compared with combined cycle units. Lastly, units 30-32 are open cycle gas turbine units, also referred to as "peakers" or fast-start units; these units also have higher costs than the combined cycle, also higher emission rates, but a much faster response.

Since the values listed in Table 1 represent only the first two terms in the right hand side of (12), the final generation unit energy offers are derived by adding the third term that represents the cost of emissions, which is given by (12.a) for each of the seven scenarios for carbon prices. The final energy offers (price per MWh offered) for the thermal power plants are presented in Figure 3 (in two groups regarding the fuel type: lignite and gas). Figure 3 demonstrates how the generation unit merit order changes as the carbon price increases, for the three gas price scenarios: low (Figure 3a), moderate (Figure 3b), and high (Figure 3c).

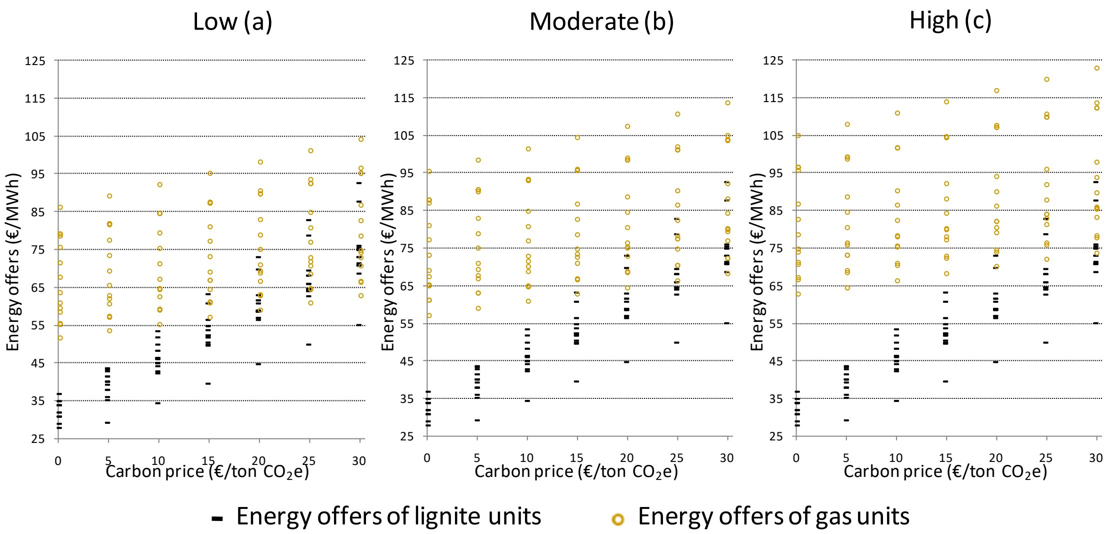

Figure 3. Energy offers of lignite and gas units versus carbon price for the three gas price scenarios. Source: Authors' Elaboration.

To remove potential gaming exercised through the reserve offers and the resulting impact on the SMP This work assumed zero-priced reserve offers. The initialization is such that the dispatching is not affected. Namely, all generation units are online for a long enough time so that they can be shut down immediately.

The penalty coefficients in the objective function (1.d) of the slack variables associated with the violation of constraints (2) - (3.c) are set at 25,000 (€/MWh), for the energy balance, and at 20,000 (€/MW), 15,000 (€/MW) and 10,000 (€/MW) for the primary, secondary and tertiary reserve, respectively. If a slack variable becomes positive, the SMP is set at an administratively defined price cap. Of note, that we did not encounter any such violations in our case study.

4. Results and Discussion

This section presents and discusses the numerical results of the test case. The Day-Ahead Scheduling problem was modelled using AMPL [74] mathematical programming language and solved with CPLEX solver. Each optimization problem had approximately 13K variables (4K binary and 4K integer) and about 30K constraints. As was already mentioned, a total of 630 (= 3·7·30) independent scenarios were solved: seven scenarios for the carbon price, three scenarios for the gas price, and thirty scenarios for the outages. Each of the 630 scenarios required the solution of 365 Day-Ahead Scheduling problems, and the average computational time to solve each yearly scenario on a Dell i7 @ 2.4 GHz, was about 30 minutes.

In what follows, the average (over the thirty scenarios for the outages) yearly results of various market outcome measures are presented versus the carbon price on electricity prices, emissions and energy mix, for different scenarios of the gas price. At the end of this section, the confidence intervals of these averages are discussed.

Figure 4 shows the WAEP versus the carbon price for the three scenarios of the gas price, using the values of energy offers presented in Figure 3. Each cluster of marks in Figure 4 represents the WAEP values for the thirty different scenarios of random outages, for a particular combination of carbon price and gas price. The impact of the carbon price on WAEP is estimated quite accurately by a linear regression line of the average WAEP values of each cluster on the carbon price, as shown in Figure 4. The slopes of the regression lines indicate that if the carbon price is increased by 1 €/tCO_2e, the resulting increase of WAEP ranges from 0.52 to 0.61 €/MWh depending on the gas price scenario.

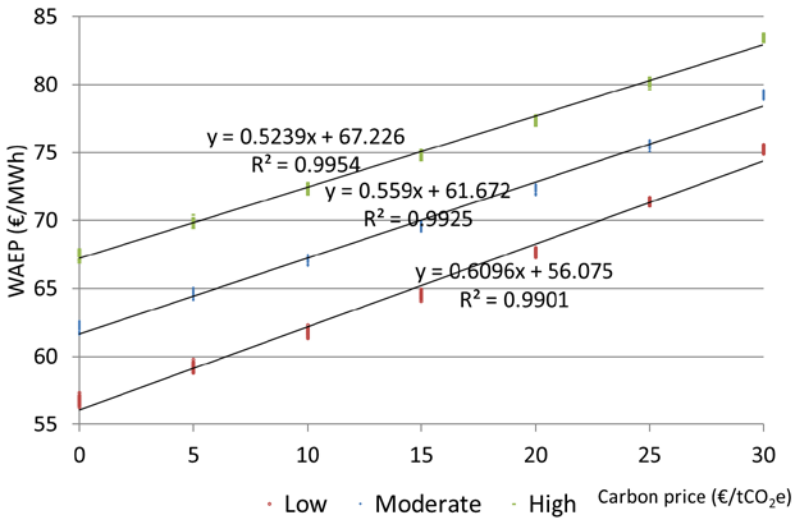

Figure 4. WAEP (in €/MWh) versus carbon price (in €/tCO_2e) for the three gas price scenarios. Source: Authors' Estimates.

Figure 4 also indicates that an increase in the gas price from moderate to high (10% increase) results in a 5.4-8.6% increase in WAEP; similarly, a decrease in the gas price from moderate to low (10% decrease) results in 5-8.6% decrease in WAEP. These WAEP changes are smaller as the carbon price increases.

Figure 5 shows the emissions reduction (percentage) for each carbon price and gas price scenario.

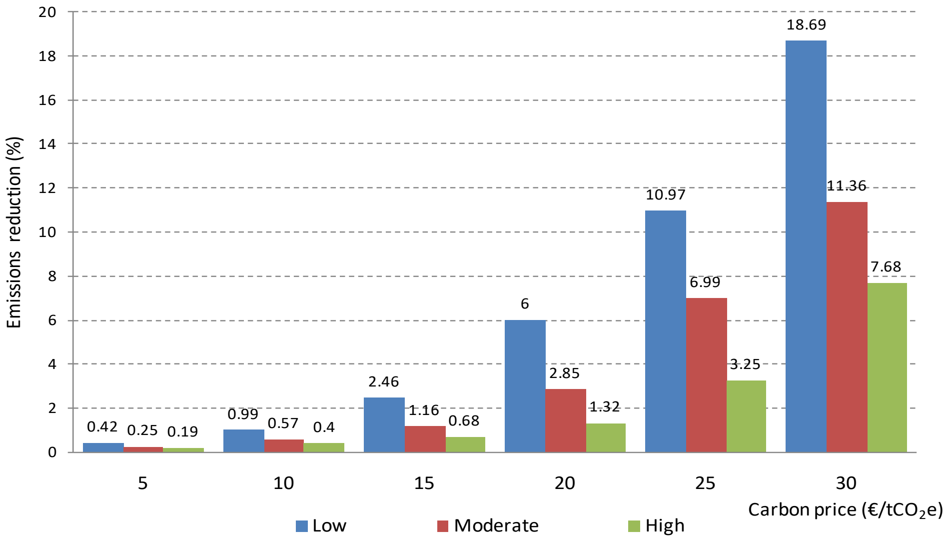

Figure 5. Emissions reduction (percentage) versus the carbon price for the three gas price scenarios. Source: Authors' Estimates.

Notably, the percentage of emissions reduction increases – at an escalating rate – as the carbon price increases. For carbon prices of as high as 15 €/tCO_2e, the reduction does not exceed 2.5%, and becomes negligible (below 1%) for prices lower than 10 €/tCO_2e. The reason is that the fuel cost difference between lignite and gas is large enough, so that it takes a combination of a high enough carbon price (thus high cost of emissions) and a low enough gas price to cover this difference. Under such a combination, the lignite units may be forced by the optimization problem to shut down, resulting in significant emissions reduction. It is also observed that, for the same carbon price, the lower the gas price, the higher the emissions reduction. In the case of a carbon price equal to 30 €/tCO_2e that is combined with a low enough gas price, the overall CO_2 reduction reaches 18.7%.

Figure 6 shows the *average pass-through rate* (APTR) versus the carbon price for the three gas price scenarios. It is observed that APTR is generally higher for the low gas price scenario, since the cost of emissions becomes a comparatively large component of the variable cost, despite the fact that the total amount of emissions decreases in absolute terms at lower gas prices. For carbon prices up to 15 €/tCO_2e, the average percentage is close to 60%. Even though the cost of emissions is fully integrated in the energy offers, i.e., the "add-on" rate is 100%, this cost does not pass completely onto the demand-side payments, i.e., the "work-on" rate depends on the impact of the marginal generation unit. At off-peak hours, the SMP is set by the lignite units and the impact is higher. However, at peak-load hours, gas units set the SMP and the impact is much lower.

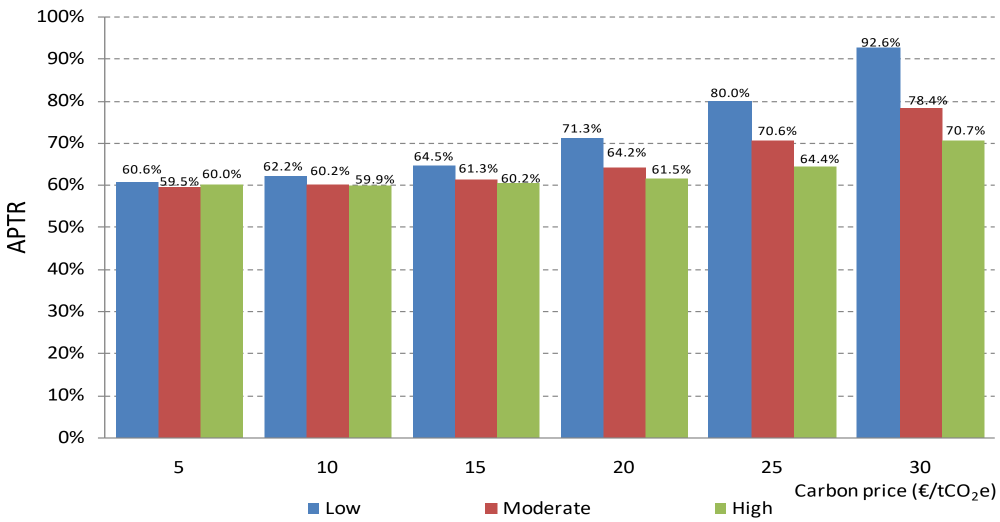

Figure 6. APTR versus carbon price for the three gas price scenarios. Source: Authors' Estimates.

Figure 7 shows the energy mix for the three gas price scenarios. It can be seen that even for the highest carbon price (30 €/tCO_2e), the share of lignite is above 50% in the high gas price scenario (Figure 7c). In the moderate gas price case (Figure 7b), the share of lignite is still close to 55% for carbon prices as high as 15 €/tCO_2e, and is slightly less than 50% for the highest carbon price of 30 €/tCO_2e. In the low gas price case (Figure 7a), the share of lignite falls quite rapidly (substituted by gas) as the carbon price increases, approaching 42% for the highest carbon price of 30 €/tCO_2e.

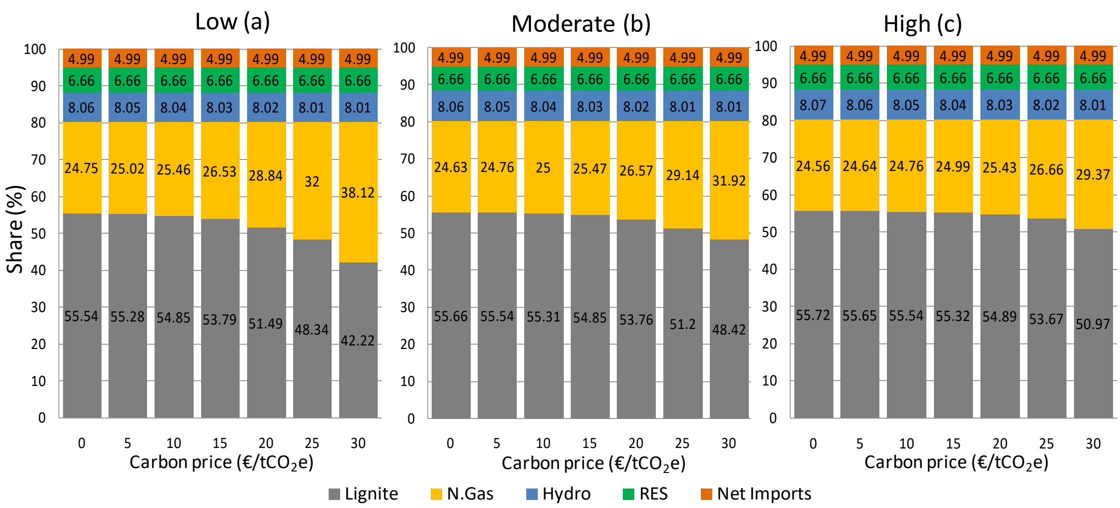

Figure 7. Energy mix versus carbon price for the three gas price scenarios. Source: Authors' Estimates.

The conventional (thermal/hydro) annual energy production, in absolute terms, is equal to 46.501 TWh; by including also the contribution of RES and the net imports, the total annual energy injection reaches 52.633 TWh. Hydro units contribute slightly over 8% (approximately 4.23 TWh), the RES injections and the net imports contribute about 3.504 TWh (6.7%) and 2.628 TWh (5%), respectively. The total thermal generation is approximately 42.27 TWh, which represents about 80.3% of the overall total energy production.

The yearly emissions in case of zero carbon price are approximately equal to 44.887, 44.949, and 44.999 $MtCO_2e$ for the cases of low, moderate, and high gas price, respectively. The highest carbon price (30 €/tCO_2e) reduces the emissions by about 8.389, 5.106 and 3.458 $MtCO_2e$ for the low, moderate and high gas price scenario, respectively. The relevant percent reductions in CO_2 emissions are illustrated in Figure 5.

Figure 8 shows the average emissions per thermal MWh and per total produced MWh (by all generation units, including hydro and renewables). As expected, the coefficient of average emissions decreases faster for the low gas price scenario (compare with the natural gas share in the low gas price scenario in Figure 7 as well as with the emission reduction trend in the low gas price scenario in Figure 5). It is interesting to note that at a carbon price of 30 €/tCO_2e, the coefficient is slightly under 0.87, 0.95, and 0.99 tCO_2e/MWh (thermal), in the low, moderate and high gas price scenario, respectively. For a carbon price less than 15 €/tCO_2e, it is close to 1.05 tCO_2e/MWh (thermal) and 0.88 tCO_2e/MWh (total) for the three gas price scenarios.

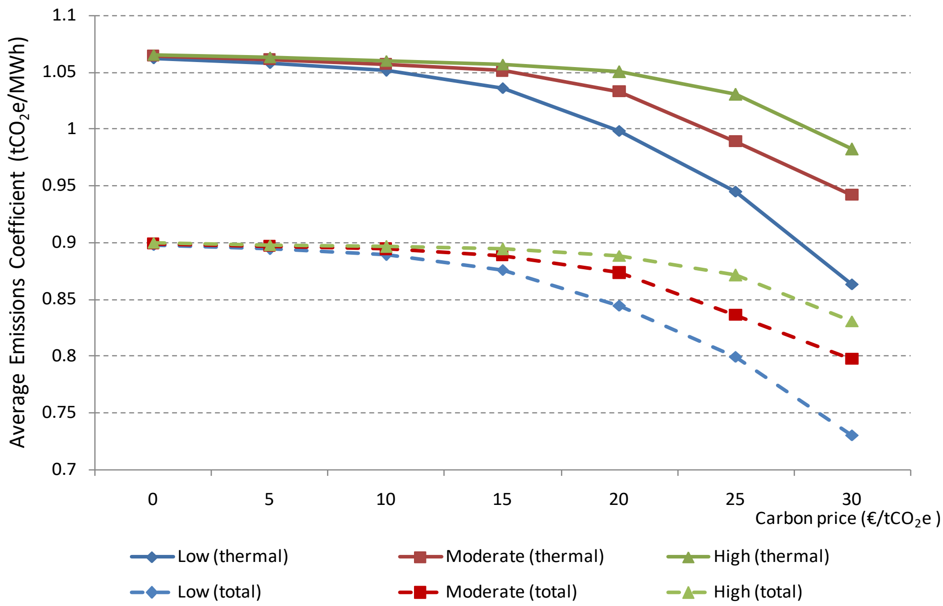

Figure 8. Average emissions coefficient in tCO_2e/MWh for the thermal and total generation versus carbon price for the three gas price scenarios. Source: Authors' Estimates.

As already mentioned above, to enhance the confidence level of the results with respect to the unit outages, thirty simulation runs were performed for each of the twenty-one scenarios concerning carbon and gas price levels. In each simulation run a different unit outage scenario was simulated. In Table 2, the average and confidence intervals (95%, 99%, and 99.9%) of the main results are presented with respect to the outages for one selected scenario (moderate gas price and carbon price equal to 15 €/tCO_2e).

Table 2
Confidence intervals of the main results for the case of moderate gas price and carbon price equal to 15 €/tCO_2e

		Confidence Interval		
Results	**Average**	**95%**	**99%**	**99.9%**
Average SMP (€/MWh)	69.568	± 0.076	± 0.100	± 0.128
Emissions (ktCO_2e)	44,426.7	± 57.4	± 75.5	± 96.4
Lignite production share (%)	54.85	± 0.10	± 0.14	± 0.17
Gas production share (%)	25.46	± 0.10	± 0.14	± 0.18

Source: Authors' Estimates.

The confidence intervals of the main results shown in Table 2 are extremely tight, even for the case of 99.9%, suggesting that randomness of unit outages does not have a significant impact on the yearly results. A potential explanation involves the following reasons. Firstly, the majority of the units do not exhibit frequent outages. The $EFOR_D$ (average) which was used in the simulations, was 12.7% and 6% for the lignite and combined cycle units, respectively. Secondly, there exists a fair amount of generation units of the same category (for instance, the lignite units) with similar characteristics, implying that the impact of any unit outage from a certain category during any particular day is mostly the same. Finally, the probability of two or more simultaneous unit outages from the same category is relatively small.

5. Concluding Remarks

A simulation methodology for estimating the impact of the cost of emissions on the mid-term generation scheduling outcome in a pool market was presented. A simple Day-Ahead Scheduling model was provided, and a scenario-based approach was employed to investigate across different gas and carbon prices, as well as the realization of random outages on an adapted instance that is based on the Greek electricity generation sector. The methodology can be adjusted to fit any pool-based electricity market, and it implicitly captures uncertainty due to renewables by considering the reserve requirements in the optimization model. In addition, it can capture the impact that this uncertainty will have on the unit commitment and dispatch of conventional generation units, hence revealing the cost that is associated with intermittent renewable sources.

Arguably, under an efficient market operation, the applicability of this model extends to power exchange settings, particularly in what concerns the generation schedules and overall emissions. Notably, even in power exchanges, a unit commitment and economic dispatch model is still solved by system operators, to determine the physical scheduling of the generation units. Although this model is solved on top of (after) the day-ahead market to complement its outcome, an efficient market operation is expected to result in similar outcomes to those in pool markets. In fact, the empirical evidence from the recent transition of the Greek market to a power exchange suggests that the unit scheduling and the day-ahead prices were not significantly impacted; this is not a surprise, since the power system generation mix and market participants remained the same. In this respect, it is expected that, since the energy offers in a power exchange internalize the cost of emissions, the results of the average pass-through rates are not significantly affected by the change in the market rules.

The analysis highlighted the fact that integrating the cost of emissions in the variable cost of the generation units may not result in significant emission reduction, unless low gas prices are combined with relatively high carbon prices, in which case the main CO_2 pollutants (lignite units) become less cost effective and may be substituted by gas units. It also revealed the difference between the "add-on" rate of emissions, which is 100% since the cost of emissions is fully integrated in the energy offers, and the "work-on" rate, which depends on the impact of the marginal generation unit that determines the SMP and is generally lower, i.e., the cost of emissions does not pass completely onto the demand-side payments. The APTR of the carbon costs onto the demand-side payments is relatively stable for carbon prices up to 15 €/tCO_2e; for higher carbon prices, the APTR increases as the carbon price increases, whereas it decreases as the gas price increases. Finally, the attained results indicate that the random outages realizations have an insignificant impact on the yearly results.

The qualitative and quantitative results of this study provide useful insight to policy makers, investors on both conventional and renewable generation, and market participants. Further research on this topic includes the examination of the short-term impact on the hourly prices, the computation of profits/losses of each participant category derived by the inclusion of emissions costs, the investigation of the strategic bidding behavior of producers. Last but not least, it should be mentioned that a similar scenario-based approach can be rather straightforwardly employed to explicitly investigate the impact of (i) the uncertainty due to renewable injections [59, 62], (ii) a wet or dry year that will affect the hydro production, and (iii) the reliability (i.e., outages) of the gas network [75].

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Appendix A. Generation Unit Detailed Data

Table A.1

Detailed Generation Unit Data

Unit	Emission Rate [1](tCO2e/ MWh)	Energy offer in €/MWh @ moderate gas price & 15€/tCO2e	Technical Maximum (MW)	Technical Minimum (MW)	Primary Reserve Capability (MW)	Secondary Reserve Up Capability (MW)	Secondary Reserve Down Capability (MW)	Tertiary Reserve Capability (MW)	AGC Min (MW)	AGC Max (MW)	Minimum Uptime (hours)	Minimum Downtime (hours)	Shutdown Cost (€)	EFORD (%)
1	1.23	52.46	274	165	24	0	0	30	0	0	24	8	45000	8.484
2	1.23	52.47	274	165	24	0	0	30	0	0	24	8	45000	5.92
3	1.23	52.48	283	165	24	0	0	30	0	0	24	8	45000	6.262
4	1.23	52.49	283	165	24	0	0	30	0	0	24	8	45000	12.788
5	1.23	50.46	342	200	24	0	0	30	0	0	24	8	45000	5.583
6	1.33	54.96	273	152	24	0	0	30	0	0	24	8	45000	9.637
7	1.33	54.97	273	152	24	0	0	30	0	0	24	8	45000	12.318
8	1.04	39.6	289	150	24	0	0	45	0	0	24	8	45000	10.557
9	1.4	52.01	275	153	24	0	0	45	0	0	24	8	80000	16.134
10	1.4	52.02	275	153	24	0	0	45	0	0	24	8	80000	13.379
11	1.4	52.03	280	160	24	0	0	45	0	0	24	8	80000	8.723
12	1.4	50.04	280	160	24	0	0	45	0	0	24	8	80000	17.964
13	1.45	53.78	116	80	24	0	0	12	0	0	24	8	17000	26.517
14	1.45	49.75	274	160	24	0	0	30	0	0	24	8	48000	16.111
15	1.3	56.52	12	5	0	0	0	7	0	0	24	8	6000	6.42
16	1.96	63.45	255	195	24	0	0	75	0	0	24	8	65000	19.237
17	1.79	60.91	256	195	24	0	0	75	0	0	24	8	65000	8.936
18	0.4	73.4	550	155	36	200	200	180	175	530	8	3	24000	3.96
19	0.37	66.8	377	240	24	100	100	137	260	357	8	3	14000	4.974
20	0.4	70.9	476	144	30	280	280	180	164	456	8	3	16000	6.994
21	0.37	66.68	389	240	24	0	100	139	260	357	8	3	14000	6.199
22	0.49	72.48	326	150	24	0	0	176	0	0	8	3	14000	6
23	0.37	74.68	410	240	24	0	100	170	260	380	8	3	14000	6
24	0.37	78.68	422	240	24	0	100	180	260	380	8	3	14000	6
25	0.37	82.68	420	240	24	0	100	180	260	380	8	3	14000	6
26	0.37	86.68	420	240	24	0	100	180	260	380	8	3	14000	6
27	0.37	62.68	400	240	24	0	100	160	260	370	8	3	14000	6
28	0.6	96.04	151	65	12	0	0	45	0	0	16	8	11000	6.081
29	0.6	104.56	188	105	12	0	0	45	0	0	16	8	22000	2.981
30	0.53	95.8	49	0	0	0	0	49	0	0	0	0	1500	10.794
31	0.53	95.81	49	0	0	0	0	49	0	0	0	0	1500	10.794
32	0.53	95.82	49	0	0	0	0	49	0	0	0	0	1500	10.794

Source: Authors' Estimates.

[1] The emission rates, measured in tCO2eq per MWh, are declared characteristics for each generation unit. Their values are obtained by yearly measurements performed by the generation units, and hence, the detailed calculation methodology is not subject to this paper's scope. Nevertheless, we refer to a recent document of ACER (EU Agency for the Cooperation of Energy Regulators) for guidelines on the calculation of emission limits [76], and also to an online calculator from the US Environmental Protection Agency [77] for equivalent ways to express emissions.