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Article — Published Version

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Operations Research Forum

Provided in Cooperation with:
Springer Nature

Suggested Citation: Hobbie, Hannes; Dierstein, Constantin; Möst, Dominik; Schmidt, Matthew (2023) : Learning by Doing: Insights from Power Market Modelling in Energy Economics Courses, Operations Research Forum, ISSN 2662-2556, Springer International Publishing, Cham, Vol. 4, Iss. 2, https://doi.org/10.1007/s43069-023-00203-w

This Version is available at:
https://hdl.handle.net/10419/309269

Operations Research Forum (2023) 4:37
https://doi.org/10.1007/s43069-023-00203-w

TUTORIAL

Learning by Doing: Insights from Power Market Modelling in Energy Economics Courses

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Received: 2 August 2021 / Accepted: 2 February 2023 / Published online: 17 April 2023

Abstract

Much of energy economics curricula involves the study of techno-economic aspects of energy systems with an increasing focus devoted to fostering an understanding of the interactions between innovative technologies and adaptive markets. As the interplay of these dynamics and their impacts on market equilibria and outcomes is quite complex, optimization models are well-suited to facilitate their study. This paper presents two exemplary model approaches and associated case studies, which can be employed to study market developments driving long-term adaptations in the portfolio of power-generation assets as well as scheduling problems of individual plant owners with a focus on assessing the impact of changing market conditions on the profitability of investments. The combination of these two modelling approaches constitutes an innovative means of facilitating students' understanding of how individual decisions of different market stakeholders lead to welfare-maximizing market equilibria under the assumption of perfect competition. The models are discussed along with the experiences acquired employing them in various forms as project assignments. In summary, the integration of modelling exercises and assignments into the curriculum of energy economics courses has proven to be a practical means of reinforcing and broadening lecture material that is both interesting and rewarding for students.

Keywords Energy modelling · Electricity markets · Peak load pricing · Storage optimization · Energy economics

Mathematics Subject Classification (2010) 90-01 · 90-04 · 90-10

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1 Introduction

The field of energy economics has a strong interdisciplinary character. It requires not only a comprehensive understanding of the design and function of markets, but also the interplay between markets, technologies, and the physical properties of energy systems as well as the implications of policy and regulatory frameworks. The complexity of the various layers of interaction across markets and systems, e.g., technical and operational, policy design, short- and long-term planning, systems management, and market structures as well as the diversity of stakeholders involved, e.g., utilities, energy service companies, rate payers, network and market operators, regulatory bodies, and governments, lends itself to the purview of operations research. Operations research provides a rich set of models and methods to study the underlying dynamics at play.

Students completing courses in energy economics should master both foundational concepts and theoretical models while developing an appreciation for real-world applications and a comprehensive knowledge of empirical developments. Incorporating project assignments that take the form of model-based case studies provides an effective means of applying and extending the conceptual content of the lecture materials to real-world problems. Furthermore, students increase their familiarity with various units of measurement and their dimensions as well as gaining an awareness for the intricacies of acquiring and processing data. Commonly, fundamental or bottom-up models are employed that exhibit significant technical detail, e.g., generation capacity, efficiency rates, fuel sources, and ramp rates.

A distinction can be made between models that entail a system perspective or that of a single-firm or other market entity, e.g., households [1]. The latter case corresponds to a profit maximization problem, in which an individual entity, for instance, decides on the profit-maximizing deployment of its resources against exogenous market prices. The system perspective, on the other hand, imposes a system operator that deploys the individual resources in the system to maximize economic welfare. Employing a welfare maximization problem entails the assumption of perfectly competitive markets. When maximizing the profits of individual generator's employing a single firm dispatch optimization model, the firm's resulting production schedule resembles the deployment of the power stations derived by co-optimizing generation capacity investment and scheduling in an energy systems model. While not surprising in terms of economic theory, it is not quite intuitive at first glance for many students studying energy economics. Hence, providing students with modelling tasks from both modelling approaches constitutes an innovative way of employing power system models to facilitate the students' understanding of the interplay between the microeconomic principles of a single firm and market clearing procedures in competitive markets. In the following, the models and case studies introduced deal with power markets. As electricity markets in many parts of the world have undergone a process of restructuring, the assumption of perfect competition is empirically supported. Working under the assumption that electricity demand is inelastic, which is prevalent in most electricity markets due to the limited

short-term substitutability, the welfare maximization problem can be expressed as a cost minimization problem with an exogenously imputed demand.

Beyond the formulation of the model's objective, it is important to define the system boundaries and scope of the model. The system boundaries of the model refer to the energy systems and markets represented, e.g., extent of the energy value chain modelled or sector-specific representation. The scope of the model entails the level of spatial, temporal, and technical granularity included in the model.

In the following, we introduce two basic optimization models[1], ELTRAMOD-*stud*, a power market model that employs a system perspective and is formulated as a cost-minimization problem and STORMOD-*stud*, which models the scheduling problem of a single plant owner. In addition, the experiences acquired through their deployment in project assignments as part of the graduate-level course *Power System Economics* offered at the Chair of Energy Economics at TU Dresden are shared. The course consists of a set of lectures with corresponding tutorials and a project assignment employing model-based case studies. In general, the projects are assigned to groups of three to four students to be completed within a time frame of three to four months.

The remainder of the paper is organized as follows: In Section 2, basic concepts and terminology that form the basis of the case studies are explained. In Sections 3 and 4, ELTRAMOD-*stud*and STORMOD-*stud*are introduced, respectively, and the associated case studies are presented while learning objectives and outcomes are discussed. Section 5 concludes by offering general insights for educators from the experiences acquired employing model-based case studies in energy economics course curriculum.

2 Basic Concepts, Assumptions, and Terminology

2.1 Basic Teaching Concept

The models presented in this paper can be employed in various classroom settings. Depending on the level of knowledge of the students, it is advisable to provide preformulated mathematical equations or offer guidance in the implementation phase. In this case, the goal should be for students to make adjustments to the formulation and identify changes in the model output and analyze the underlying causal relationships and drivers. The more advanced the students' knowledge is in the field of energy economics and mathematical programming, they should be encouraged to develop the optimization model from scratch independently, i.e., formulate the respective system of equations and implement it in the selected programming language. In our own courses, the social planner's perspective (see Section 3) is usually

[1] The two models are formulated in the general algebraic modeling system (GAMS). Executable versions of the optimization models including input data can be downloaded here: https://doi.org/10.5281/zenodo.7740897 and https://doi.org/10.5281/zenodo.7740976.

developed independently by the students, whereas the basic formulation of the model cast as the single utility's perspective (see Section 4) is provided to the students. In all cases, students are required to collect the input data independently. A more detailed description of insights garnered in employing the models is provided in Section 5.

Results of the assignments are presented and discussed among the course participants to facilitate an understanding of the underlying economic principles at play in the two modelling approaches. In this manner, students are able to better understand how production decisions made by single firms impact economic market equilibria and how constraints affecting market equilibria in turn impact firms' decisions. Combining the learning outcomes of both modelling approaches creates an added value compared to focusing on a single modelling approach. This constitutes an essential objective of the teaching concept employed.

2.2 Optimal Dispatch of Generation with Inelastic Demand and Fixed Capacities

In the standard microeconomic model of perfect competition, the market equilibrium is determined by the intersection point of the respective supply and demand curves, resulting in the market clearing price. If the electricity market is perfectly competitive, the market equilibrium is considered Pareto efficient, i.e., no one market player can be made better off without making another worse off. Several conditions have to hold for the model of perfect competition (see [2]) to be applicable and these should be considered in the context of the respective electricity market under study.

From an economic point of view, under these conditions, the market is considered both allocatively, i.e., the price at the market equilibrium reflects the marginal costs of production, and productively efficient, i.e., the entry and exit of new producers result in a more efficient mix of resources deployed in the market over time [3]. In electricity markets, supply and demand curves can be derived from fundamental data. The aggregate supply function in the electricity market can be represented by a stepwise function, since marginal costs of single plants can be assumed to be nearly constant and different technologies entail varying marginal costs depending on the fuel used. As generation capacities, fuel costs, and plant efficiencies are generally well-known, the empirical shape of the aggregate supply curve can usually be estimated rather accurately. Due to the inflexibility of demand and the lack of storability, demand is quite often assumed to be entirely inelastic. Hence, supply and demand curves can be derived and the market clearing quantities and prices can be calculated by means of optimization models. A supply curve and (two different) inflexible demands are illustrated in Fig. 1. By arranging the marginal costs of the individual power plants in ascending order, the so-called merit order curve can be constructed. This curve represents the aggregate supply function of generators in the market.

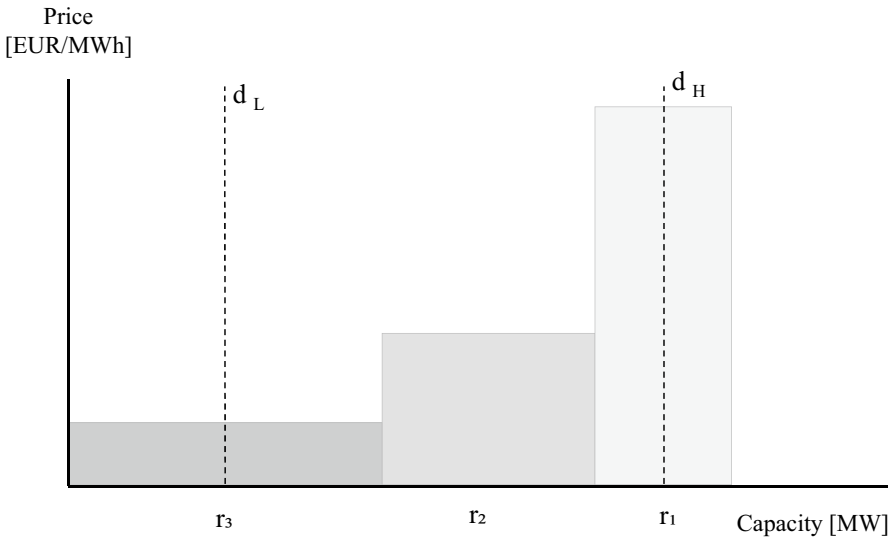

Fig. 1 Simplified merit order, source: own illustration

During off-peak hours when the demand is low indicated by d_L (typically during night and weekend hours), only the marginal cost of power plants with low marginal costs is covered and in turn dispatched (r_3). During peak demand hours indicated by d_H, the price is sufficiently high to cover the marginal cost of more expensive production units, i.e., the power plants r_3 and r_2 are fully utilized while r_1 still has some spare capacity.

2.3 Power Demand and Residual Load

As mentioned above, power demand is often assumed to be inelastic across all hours of the year. Power demand is characterized by daily (day/night), weekly (workday/weekend), and seasonal (winter/summer) patterns. The hourly demand must be satisfied at each moment in time by the available generation on the grid. As the marginal cost of electricity generation from renewable energy technologies is negligible and feed-in is by nature weather-dependent, production from renewables is subtracted from the power demand yielding the so-called residual demand. Hence, the residual load corresponds to the demand that must be covered by dispatchable power plants [4]. To provide an overview of the yearly (residual) demand, e.g., its peak and minimum demand, the hourly residual demand curve is sorted in descending order yielding the so-called residual load duration curve, which is illustrated in Fig. 2.

As can be observed in the graph, the x-axis indicates the number of hours that the residual load exceeds a certain value. Accordingly, it can be seen on the one hand that a very high residual load has to be served in only a few hours of the year, while on the other hand the residual load does not drop below a minimum value [5]. The residual load duration curve changes in accordance with the penetration

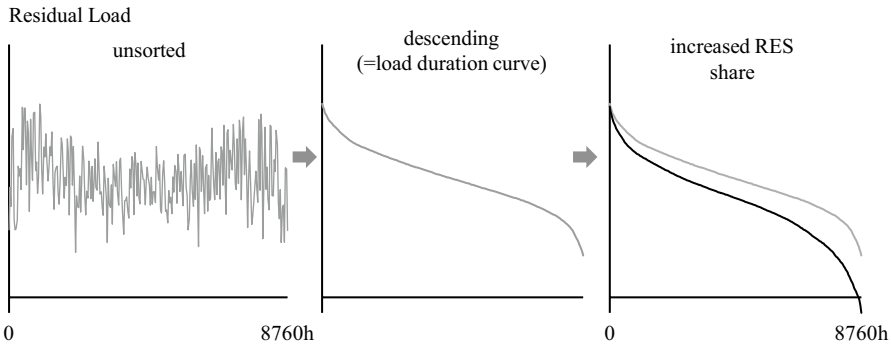

Fig. 2 Unsorted residual load, in descending order and with high RES share, source: own illustration

of renewable energy in the power system. It can observed that due to their intermittency the increasing shares of renewable energy hardly affect the peak load in the system while the curve pivots clockwise and becomes steeper with the curve intersecting the x-axis. This indicates that during some hours in the year the renewable energy supply exceeds the load on the grid (see Fig. 2). The surplus electricity can either be stored, consumed by flexible applications, e.g., demand-side management, exported to other markets, or curtailed [6].

2.4 Graphical Illustration of Long-Term Market Equilibrium

The supply and demand model described above is static in nature and treats capacities as being fixed. In the long term, the portfolio of generation assets and their capacities are subject to change and adaptation toward a long-term market equilibrium occurs. In terms of a system optimization model, this means that capacities no longer merely act as constraints on the market operation, but become decision variables that can be endogenously determined. In Fig. 3, three generic power generation technologies are illustrated with the help of screening curves. The slope of the curve corresponds to the variable costs, while the intercept of the curve corresponds to the annualized fixed cost for the respective technology. The gray line illustrates a technology with low fixed costs and high variable costs, a peaking technology, e.g., an open-cycle gas turbine; the dotted line represents a technology with medium fixed and variable costs, a mid-load technology, e.g., a coal-fired power plant or combined cycle gas turbine; and finally, the black line represents a technology with high fixed costs and low variable costs, e.g., a nuclear or lignite-fired power plant. For a given level of generation (full-load hours), the lowest curve indicates the least-cost option.

It can be observed in the diagram that up to the full-load hours denoted by t_1, the power plant technology r_1 is the most economical, up to the full-load hours of t_2, r_2 is the most cost-efficient option and as soon as a power plant technology is required to be deployed for more than t_2 full-load hours, r_3 is economically advantageous. Performing the analyzis, the optimal number of full-load hours per power plant technology can be determined. Since the residual load duration curve specifies exactly

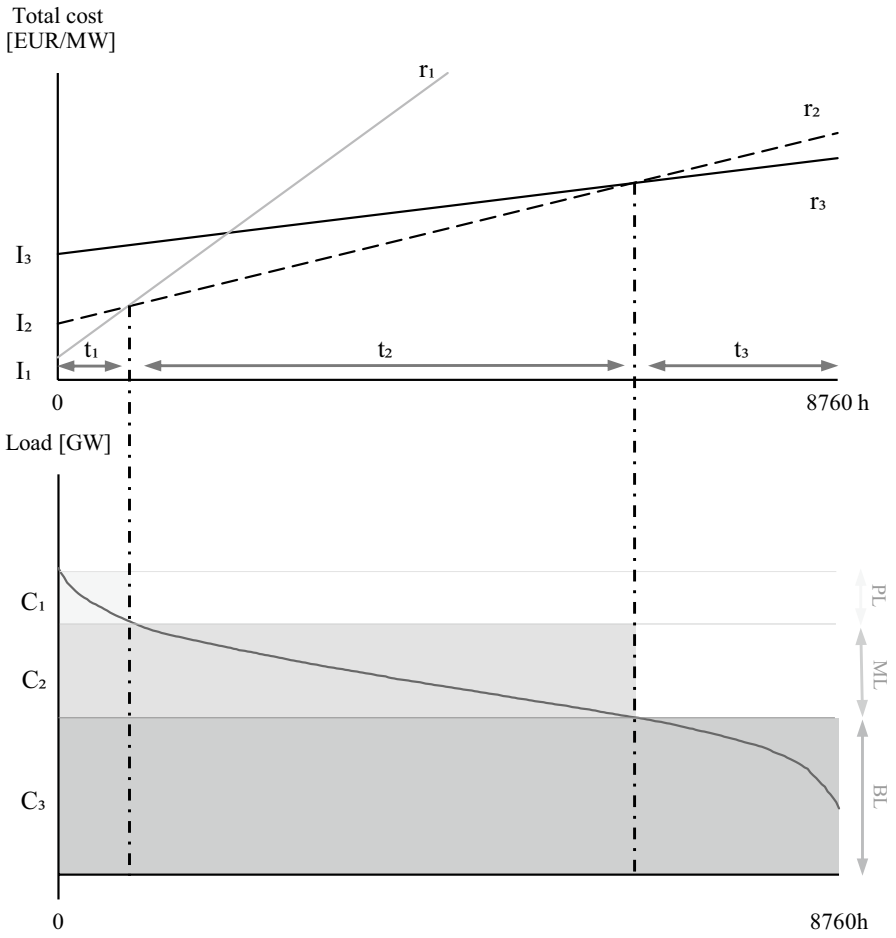

Fig. 3 Peak load pricing, source: own illustration

how many hours of electricity are required per year, the capacity for each power plant technology can be derived by the intersection of these full-load hours with the residual load duration curve, as shown in the lower part in Fig. 3. This results in the capacities C_3 for the power plant technology r_3 (base load with the high number of full-load hours), C_2 for the power plant technology r_2, and C_1 for the power plant technology r_1 (peak load, only a small amount of full load hours).

Changing the cost parameters of the three technologies would alter the intersection points and in turn the composition of the cost-optimal portfolio. A change in the residual load duration curve would only affect the optimal capacities of the individual technologies. In this long-term equilibrium model where peak-load or scarcity pricing is assumed, generation capacities perfectly adapt to the cost-efficient portfolio. It should be noted that in reality market inefficiencies and regulatory interventions often hinder the realization of a dynamically efficient equilibrium.

The simple graphical model provides an intuitive means of illustrating the underlying determinants of the cost-efficient generation capacity mix. That being said, the graphical analyzis abstracts from several relevant framework conditions of the power system. For example, the penetration of renewable energies and the deployment of storage technologies also decisively influence the composition of the power plant fleet. The dynamics at play are quite complex and require a model-based investigation [7], which provides the impetus for the project assignment discussed in the following section.

3 Social Planner's Perspective: Generation Capacity Expansion Planning

3.1 Learning Objectives

The model-based case study entails the following learning objectives. The students should develop an understanding for dispatch and investment decisions in electricity markets by drawing on the conceptual knowledge acquired in the lecture and transferring it to the study of current developments in power markets. Furthermore, they should learn, on the one hand, how increasing shares of renewable electricity generation affect the deployment of conventional power plants and, on the other hand, how these effects change when storage capacities are included. In terms of modelling, the students should learn how to implement a linear optimization model, which is a common class of models used in the field of energy economics [8]. To simplify the analyzsis, a so-called greenfield approach is assumed, i.e., no power plant fleet is assumed to exist. The optimization model builds all power plants from scratch based on the model's objective function and associated techno-economic constraints [9].

3.2 Motivation and Background of the Project Assignment

The expansion of renewable energy technologies is progressing worldwide, with wind and solar power predominating. Conventional power plant technologies remain an indispensable source of firm generation until a 100% renewable power supply becomes a reality. However, their deployment and capacity requirements are progressively changing in accordance with the expansion of renewable energy generation on the grid. The intermittent nature of renewable energy production plays a decisive role in determining which conventional power plants are displaced. This volatility simultaneously requires more flexibility in the system to compensate for the fluctuations in generation. On the one hand, this entails the deployment of more flexible power plant technologies such as gas turbines. On the other hand, storage facilities can be utilized to meet demand at times when less renewable generation is available. At the same time, coinciding periods of high demand and low renewable energy feed-in raise the question of how the power plant fleet should be designed to cope with such situations. The temporal deployment of power plants and the role

storage facilities can assume are subject to changing market conditions and depend on a complex interplay of many factors. Models aid in parsing these interdependencies and identifying which fundamental drivers should be taken into consideration in the future.

3.3 Mathematical Definition and Structure of ELTRAMOD-*stud*

3.3.1 Model Characteristics

The basic version of ELTRAMOD-*stud* entails a model endogenous power capacity expansion and power plant dispatch. Employing the assumptions of perfect competition and contestable markets discussed above, the cost-optimal generation capacity portfolio determined by ELTRAMOD-*stud* mimics the long-term market equilibrium under the assumption of immediate capacity adaptation. Capacity expansion models such as ELTRAMOD-*stud* are typically utilized to investigate long-term energy scenarios. The model can also be easily adjusted to derive short-term market equilibria, whereby the capacity variables are exogenously fixed.[2] Depending on the specific course level and modelling skills of students, the model can easily be extended to study further aspects of electricity systems, e.g., questions related to flexibility options and sector-coupling technologies or the implications of environmental policies.

3.3.2 Nomenclature

The power market model ELTRAMOD-*stud* comprises various endogenous variables and exogenous model inputs formulated with the help of different sets. The following defines all *sets* included in the model and *indices* related to them.

F: Fuels, $f \in F$
R: Technologies, $r \in R$

- R^{th} : Thermal-based generation technologies, $th \in R^{th} \subset R$
- R^{psp} : Pumped storage-based technology, $s \in R^{psp} \subset R$

T: Time steps, $T := \{t \mid t \in \mathbb{Z}_{>0},\ t \leq 8760\}$

Scalars and parameters of ELTRAMOD-*stud* that serve as exogenous model inputs are described in the following.

Storage characteristics:

- η_s : Pumped storage round trip efficiency, $\eta_s \in [0, 1]$
- β : Power-to-energy ratio (MWh/MW), $\beta \in \{6\}$

[2] It should be noted that determining long-term market equilibrium entails endogenously modelling the renewable energy capacity additions. However, due to the prevalence of policy-driven build-out targets, renewable energy capacities are often modelled as exogenous inputs.

Costs and related model inputs:

- a_r : Investment annuity (EUR/MW), $a_r \in \mathbb{R}_{\geq 0}$
- co^{curt} : Curtailment cost factor (EUR/MWh), $co^{curt} \in \mathbb{R}_{\geq 0}$
- co_r^{var} : Variable generation costs (EUR/MWh), $co_r^{var} \in \mathbb{R}_{\geq 0}$
- sc : Scaling factor, $sc = 1/1e6$

Power market demand and renewable generation:

- d_t^{res} : Residual electricity demand (MWh), $d_t^{res} \in \mathbb{R}_{\geq 0}$
- g_t^{res} : Aggregated renewable feed-in (MWh), $g_t^{res} \in \mathbb{R}_{\geq 0}$

Lastly, the following defines all model endogenous *variables* of ELTRAMOD-*stud*.

Costs and related model variables:

- CC : Total curtailment costs (1e6 EUR), $CC \in \mathbb{R}_{\geq 0}$
- CG : Total generation costs (1e6 EUR), $CG \in \mathbb{R}_{\geq 0}$
- CI : Total investment expenditures (1e6 EUR), $CI \in \mathbb{R}_{\geq 0}$
- TC : Total system cost (1e6 EUR), $TC \in \mathbb{R}_{>0}$

Technology capacity, dispatch, and related model variables:

- C_r : Total power plant capacity (MW), $C_r \in \mathbb{R}_{\geq 0}$
- CU_t : Curtailment quantities (MWh), $CU_t \in [0, g_t^{res}]$
- $G_{t,r}$: Technology specific generation (MWh), $G_{t,r} \in \mathbb{R}_{\geq 0}$
- $P_{t,s}$: Pump operation (MWh), $P_{t,s} \in \mathbb{R}_{\geq 0}$
- $SL_{t,s}$: Storage level (MWh), $SL_{t,s} \in \mathbb{R}_{\geq 0}$

3.3.3 Mathematical Equations

ELTRAMOD-*stud* assumes perfect competition resulting in optimal investment and dispatch decisions for a set of different power generation technologies serving an inelastic electricity demand. The system of equations governing ELTRAMOD-*stud* comprises a set of energy balances, capacity, and dispatch constraints as well as cost equations. The following describes the target function and associated cost equations. Teachers could first discuss with students which types of costs typically can be distinguished (fixed vs. operational cost) in long-term and short-term energy planning decisions and how model-based representations differ.

$$\min \quad TC \;=\; CI + CG + CC \tag{3.1}$$

$$CI \;=\; \sum_r \left(C_r \cdot a_r\right) \;\cdot\; sc \tag{3.2}$$

$$CG = \sum_{t,r} \left(G_{t,r} \cdot co_r^{var} \right) \cdot sc \tag{3.3}$$

$$CC = \sum_{t} \left(CU_t \cdot co^{curt} \right) \cdot sc \tag{3.4}$$

The target function minimizes the total investment and generation dispatch cost. The components of the target function are described separately based on Eqs. (3.2)–(3.4). The total investment in new generation technologies is calculated as the sum of the product of capacity variables C_r and the associated technology-specific annuity (3.2). It is important for students to understand how investments are translated into a corresponding annuity factor and which implications this has for modelling investment decisions. Teachers might give a brief introduction into finance theory to improve the students' understanding. Total generation cost CG is computed as the sum of the product of the hourly technology-specific dispatch $G_{t,r}$ and its associated variable cost (3.3). Intermittent renewable feed-in is subject to curtailment in periods of excess supply. The total curtailment cost CC is computed as the sum of the product of the quantity of curtailed energy CU_t in each time step and a penalty cost factor (3.4). To improve numerical efficiency, cost equations are scaled down with the scalar sc.

The power balance coordinates the market clearing process and is defined as follows:

$$\sum_{r} G_{t,r} - CU_t - \sum_{s} P_{t,s} = d_t^{res} \qquad \forall t \in T \tag{3.5}$$

The electricity demand is represented as a residual load. It is calculated beforehand as an exogenous model input by subtracting the sum of renewable energy generation from the electricity demand in each time step. The residual load d_t^{res} must be satisfied in each time step by the net difference between the total amount of generation dispatched and the curtailed renewable energy feed-in and the power consumed by pumped-hydro storage plants $P_{t,s}$. In addition, the amount of curtailment that can be performed in each time step is restricted to the aggregate renewable energy feed-in available on the grid. Experience has shown that discussing the merit order before introducing the modelling of the power balance supports student's understanding.

The dispatch of individual power plants in the model is subject to the following technical constraints.

$$G_{t,r} \leq C_r \qquad \forall t \in T, \forall r \in R \tag{3.6}$$

$$P_{t,s} \leq C_s \qquad \forall t \in T, \forall s \in R^{psp} \tag{3.7}$$

$$SL_{t,s} = SL_{t-,s} - G_{t,s} + P_{t,s} \cdot \eta \qquad \forall t \in T \setminus \{1\}, \forall s \in R^{psp} \tag{3.8}$$

$$SL_{t,s} \leq C_s \cdot \beta \qquad \forall t \in T, \forall s \in R^{psp} \tag{3.9}$$

$$SL_{t,s} = 0.5 \cdot C_s - G_{t,s} + P_{t,s} \cdot \eta_s \qquad \forall t \in \{1\}, \forall s \in R^{psp} \tag{3.10}$$

$$SL_{t,s} = 0.5 \cdot C_s \qquad \forall t \in \{8760\}, \forall s \in R^{psp} \tag{3.11}$$

The generation $G_{t,r}$ that can be dispatched by the respective power plant technologies in the model is restricted to the total available generation capacity C_r in each time step (3.6). Similarly, the available turbine capacity limits the pump operation of the storage technology $P_{t,s}$ implying a turbine/pump power ratio of 1 (3.7). Equations (3.8)–(3.11) define the technical specifications of the pumped-hydro storage unit. The (aggregate) storage level is determined by adding the power drawn to the upper reservoir $P_{t,s}$ via pumping minus that being discharged $G_{t,s}$ via the turbine to the storage level of the prior hour in each time step (3.8). Equation (3.9) imposes a limit on the maximal storage level. It is restricted to the product of the total pumped storage plant technology capacity and the energy-to-power ratio β. The boundary conditions (3.10)–(3.11) prevent unintended charging/discharging activities in the first and last time steps in the model. Typically, understanding the modelling of the storage unit included in ELTRAMOD-*stud* constitutes a challenge for students. It might help to illustrate the system effects of energy storage using a residual load duration curve. Moreover, it is important to point out how the storage operation affects the power balance and resulting values of cost variables in the target function.

3.4 Example Case Study

3.4.1 Scenario Definition

The model described above is deployed in the following case study that investigates the impact of varying renewable energy expansion scenarios and the integration of storage capacity options on the composition of the cost-optimal generation capacity portfolio. For this purpose, three expansion paths with increasing shares of wind and solar feed-in are considered, with and without storage options. This is reflected in the six scenarios RES^1_{noStor}, RES^2_{noStor}, RES^3_{noStor}, RES^1_{Stor}, RES^2_{Stor}, and RES^3_{Stor} constructed.

3.4.2 Assumptions and Data

The model draws on the following assumptions and data:[3] The German electricity system and power plant portfolio is used as a rough reference for the exemplary model application. Demand is modelled in hourly resolution for an entire year T, i.e., 8760 h. The annual demand amounts to 503.9 TWh. In terms of renewable energy feed-in, time series for wind and solar generation are incorporated into the model. In contrast to the demand, the time series do not entail absolute values,

[3] See Appendix for a detailed breakdown of the data.

Table 1 Installed capacities wind and solar

	RES^1	RES^2	RES^3
Wind	41.7 GW	74.3 GW	107 GW
Solar	38.6 GW	54.9 GW	59.9 GW

but rather the hourly availability of the installed wind and solar capacities, which fluctuates depending on the scenario on the basis of the values shown in Table 1. The multiplication of the installed capacities with the corresponding time series of the hourly availabilities ensures a consistent pattern across the scenarios while only increasing the quantity of feed-in from wind and solar energy. As already described in Section 2.3, the hourly difference between renewable energy feed-in and the demand is transformed into the hourly residual load d_t^{res}, which must be covered by the respective conventional power plant technologies included in the model.

For this purpose, five thermal power plant technologies *nuclear, lignite, hard-coal, combined cycle gas turbine (CCGT)*, and *open-cycle gas turbine (OCGT)* are at the disposal. In addition, the model can add and dispatch pumped-hydro storage units in scenarios in which a storage option is incorporated. To determine the cost curves shown in Section 2.4 and the marginal costs addressed in Section 2.2, specific technological and economical parameters are assigned to each technology. In addition to plant-specific efficiencies, these include fixed a_r, i.e., annualized capital expenditures, maintenance, staff and insurance costs, and variable costs co_r^{var}, i.e., fuel and operation costs. Furthermore, emissions are taken into account by implementing a CO_2 price of 6 EUR/t. Due to the fact that the residual load in some scenarios is negative in certain hours, curtailment costs co^{curt} of 100 EUR/MWh are applied. Likewise, the addition of pumped storage capacity is limited to 15,000 MW. This stems from the fact that pumped-hydro storage potential is strongly limited in reality due to topological conditions.

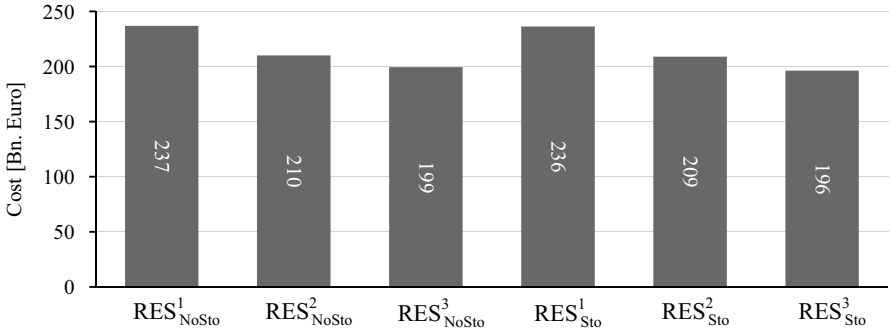

Fig. 4 Total costs for expansion and generation, source: own illustration

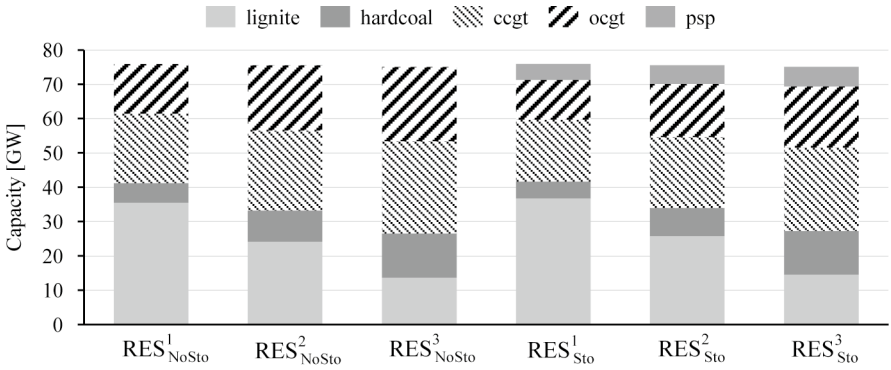

Fig. 5 Installed generation capacities, source: own illustration

3.4.3 Example Case Study Results

The model minimizes the total costs of electricity supply based on the objective function (3.1). The residual load, which must be satisfied by conventional power plant capacities, changes across the scenarios investigated. As shown in Fig. 4, total costs decrease with increasing penetration of renewable energies.[4] Incorporating storage technologies reduces these costs even further, since flexible power plant capacities can be dispensed with. This is economically advantageous as the pumped-hydro storage power plants can shift generation or demand to times with lower or higher renewable energy feed-in. Overall, the variability in the residual load can thus be flattened.

Changes in renewable energy penetration levels and storages affect the composition of the conventional power plant fleet as well. It can be observed that, despite their low variable costs, nuclear power plant capacities are not expanded due to the significant capital expenditures required. Furthermore, the expansion of renewable energies has almost no influence on the total installed capacity of conventional power plants (compare Fig. 5). This stems from the fact that the conventional power plant fleet has to provide firm capacity during hours with low feed-in from wind and solar power. Thus, adding storage options does not affect the total installed capacities (scenarios with the same RES feed-in result in the same installed capacities, e.g., RES^3_{Stor} and RES^3_{NoStor}).

Figure 5 also illustrates that with increasing levels of wind and solar feed-in, baseload power plants such as lignite are increasingly displaced by flexible power plants such as *OCGT* and *CCGT*. This is explained by the need to compensate for the intermittent solar and wind energy feed-in. The possibility of adding pumped storage power plants reduces this effect as storage capacities decrease the need

[4] Note that renewable investments are incorporated as exogenous model inputs via the residual load and thus do not contribute to the value of the objective function. These would need to be taken into account to provide a more accurate comparison of the total system costs.

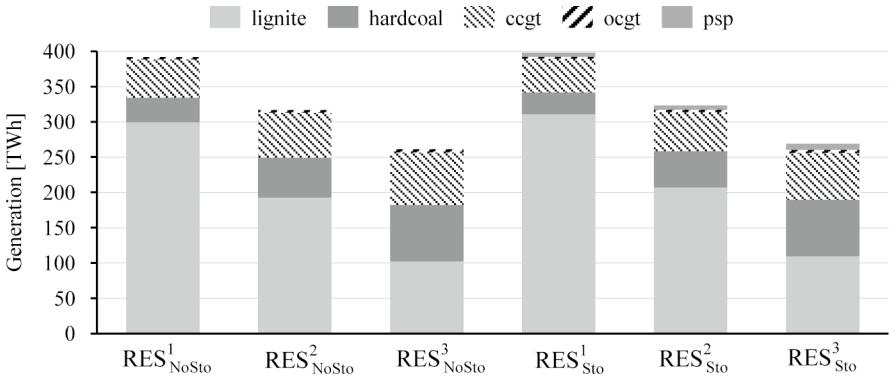

Fig. 6 Yearly generation per technology, source: own illustration

for flexible power plants. It is also noticeable that the generation of electricity is not proportional to the installed capacity. Thus, Fig. 6 clearly indicates that the residual load is predominantly covered by lignite, whose share decreases substantially with increasing generation from renewables and is complemented by hardcoal, while the flexible technologies CCGT and especially OCGT tend to generate less electricity. Again, this is due to the circumstance that these power plants are primarily utilized to compensate for the fluctuations in renewable feed-in. Likewise, pumped-hydro storage power plants provide relief for peak-load power plants. A comparison of the total electricity generation of scenarios with equivalent levels of renewable energy feed-in (e.g., RES^1_{Stor} and RES^3_{NoStor}) reveals that the total electricity generation in the scenarios with a storage option is generally higher. The reason for this is that the additional power required for recharging the storage has to be provided by the power plants.

This poses the question as to the reason why the pumped-hydro storage power plants do not exploit the surplus generation (negative residual load) from

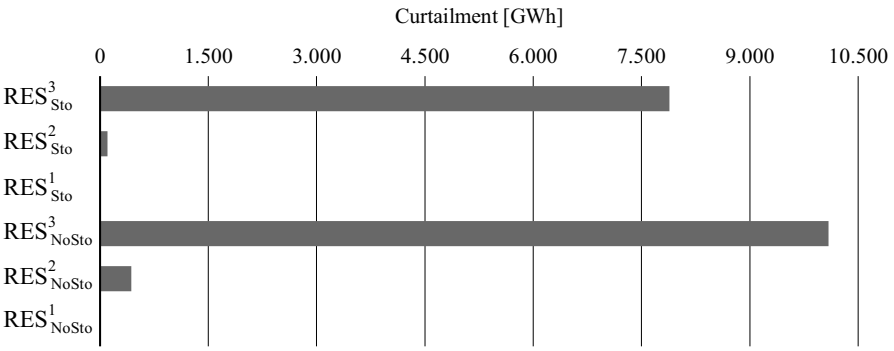

Fig. 7 Curtailment of renewables, source: own illustration

renewable energy feed-in for pumping, as described in Section 2.3. The model results indicate that this surplus energy can only be used to a limited extent, which is reflected in particular in the curtailment quantities (see Fig. 7). While storage facilities ensure that less electricity from renewables must be curtailed, even with moderate renewable energy feed-in levels, not all energy can be used (see Fig. 7). This development again shows the parallels between model and reality in which various strategies for an efficient integration of renewables are intensively discussed (e.g., Power-to-X).

3.5 Learning Outcomes

The case study presented offers students the ability to improve the understanding of the theoretical concepts of short- and long-term market equilibria and the factors driving developments in the power markets. Even these basic model applications can reproduce (or model) real-world conditions. Besides reinforcing the theoretical concepts learned in the lecture, students also familiarize themselves with general causal relationships in the electricity market: An increase in renewable energies can displace higher-emission power plant technologies such as lignite, but in order to achieve an actual reduction in installed capacity of conventional power plants and thus a change to a completely carbon neutral power plant fleet, storage technologies and further flexible technologies are necessary. The model also demonstrates that the expansion of renewable energies leads to hours with a negative residual load. This surplus could be utilized to displace conventional generation, but is currently still curtailed. The model can be applied to estimate and evaluate the magnitude of the surplus. As mentioned in the section above, in a long-term market equilibrium renewable energy capacities should likewise be endogenously determined. A CO_2 cap can be introduced to facilitate the expansion of renewables. In this case, the feed-in profiles of renewables can be expected to assume a greater importance to limit self-cannibalization [10]. These effects and trade-offs can be discussed with the students after they have applied the model and investigated the specific questions with regard to the electricity system. The model thus serves as a solid instrument to be employed in case studies to explore the effects of renewable energy and storage capacity expansion on power systems.

4 Single Utility's Perspective: Pumped-Hydro Energy Storage Scheduling

4.1 Learning Objectives

The student project serves to extend the lecture material covered and provide students with the opportunity to explore and reflect on current questions surrounding the electricity system, specifically the impact of the integration of increasing

shares of renewable energy sources. This particular project task pulls back from a system-wide economic perspective of the integration of renewable energy and delves into the business case for pumped-hydroelectric energy storage (PHES) operators, who currently provide the system with the only large-scale means of electricity storage. In particular, the students are tasked with assessing the impact of growing shares of renewable energy assets on the traditional price arbitrage strategies utilized by PHES operators. Beyond the content-based insights, the model-based assignment introduces students to a common class of optimization models used in the energy sector. The students gain familiarity with the techno-economic structure of optimization models and constraints governing the practical operation of a PHES unit.

4.2 Motivation and Background of the Project Assignment

Germany has set ambitious renewable build-out targets. As the penetration of renewable energies has increased, the grid is being subjected to greater levels of fluctuating feed-in due to the intermittent nature of wind and solar resources. Increasing supply variability and net load ramps are leading to increased demands on flexibility in the power system. In the long term, the market uptake of utility-scale storage capacities is considered pivotal toward facilitating the integration of high RES shares and ensuring supply security [6].

PHES constitutes one means of firming up the power supply on hourly and daily time scales. The operating principle of a PHES plant is based on the conversion of potential energy into kinetic energy as water masses flow from the upper basin through a turbine into the lower basin and vice versa. Pumped storage power plants exhibit high-load gradients and efficiencies [11]. In a deregulated electricity market, an energy storage facility is typically defined as a merchant unit, which maximizes its profits subject to technical constraints. PHES can be operated on both spot and control energy markets and thus contribute to the grid integration of intermittent feed-in from renewable energy. Currently, there are no comparable technologies in the field of large-scale storage with these technical characteristics [12].

4.3 Mathematical Definition and Structure of STORMOD-*stud*

4.3.1 Model Characteristics

In principle, storage technologies can be evaluated using different modelling approaches. On the one hand, as illustrated above, energy system models can be employed, which represent the entire energy system, and endogenously determine the cost-optimal capacity and dispatch of energy storage technologies. On the other hand, scheduling problems for individual storage units that involve determining bidding strategies that maximize revenues from selling and buying power can be evaluated on the basis of endogenously defined electricity prices [1].

In terms of classes of optimization models employed in power market applications, the dispatch or scheduling problem of an individual plant can be formulated as a profit maximization problem under fixed deterministic market prices assuming a perfectly competitive market structure. This problem can generally be expressed as a linear program (LP) or mixed integer linear program (MILP) [13]. Mixed integer (non-) linear programs are a special form of linear and non-linear programs. The incorporation of integers, often binary variables, results in a non-continuous, discrete optimization problem. Mixed-integer programs are frequently employed in energy market analyzis. The discrete variables represent different system states. Examples include on/off decisions, selling/buying, or shifting between operational modes of equipment [14].

Depending on the course level, in line with the learning objectives outlined above, the students are either tasked with developing the optimization model or are provided with a basic model to be adapted and extended to analyze the economic viability of a storage unit under historical changes in market conditions. The basic model only considers the day-ahead market as a marketplace to generate revenues for the storage operator. Extensions may include (uncertain) intraday market prices turning the optimization problem into a two-stage stochastic problem. This would entail the generation of a scenario tree for (uncertain) intraday prices and the reformulation of STORMOD-*stud* into a problem structure with day-ahead market trading taking place in the first stage and intraday trading in the second stage.

4.3.2 Nomenclature

STORMOD-*stud*includes a number of different features. The following defines the *index* and *set* that describe the temporal scope of the basic model version.

T: Time steps, $T := \{t \mid t \in \mathbb{Z}_{>0},\ t \leq 8760\}$

The next describes all *scalars and parameters* included as exogenous model inputs in STORMOD-*stud*.

Storage characteristics:

- η : Pumped-hydro storage round trip efficiency, $\eta \in [0, 1]$
- c^s : Maximum storage filling level (MWh), $c^s \in \mathbb{R}_{\geq 0}$

Pump characteristics:

- $c^{p,lo}$: Minimum pump operation (MW), $c^{p,lo} \in \mathbb{R}_{>0}$
- c^p : Maximum pump operation (MW), $c^p \in \mathbb{R}_{>0}$
- lc^p : Load change factor, $lc^p \in \mathbb{R}_{\geq 0}$

Turbine characteristics:

- $c^{t,lo}$: Minimal turbine operation (MW), $c^{t,lo} \in \mathbb{R}_{>0}$
- c^{t} : Maximal turbine operation (MW), $c^{t} \in \mathbb{R}_{>0}$
- lc^{t} : Load change factor, $lc^{t} \in [0, 1]$

Costs and related model inputs:

- pr_t^{da} : Spot market price (EUR/MWh), $pr_t^{da} \in \mathbb{R}$
- co^{p} : Operating pump cost (EUR/MWh), $co^{p} \in \mathbb{R}_{\geq 0}$
- co^{t} : Operating turbine cost (EUR/MWh), $co^{t} \in \mathbb{R}_{\geq 0}$
- sc : Scaling factor, $sc = 1/1e6$

All endogenous *variables* in STORMOD-*stud* are summarized in the following.

Costs and related model variables:

- GM : Gross margin (1e6 EUR), $GM \in \mathbb{R}_{\geq 0}$
- I^{t} : Electricity sales income (1e6 EUR), $I^{t} \in \mathbb{R}_{\geq 0}$
- E^{p} : Electricity purchase expenses (1e6 EUR), $E^{p} \in \mathbb{R}$

Storage-related variables:

- SL_t : Storage level (MWh), $SL_t \in \mathbb{R}_{\geq 0}$
- P_t : Pump operation (MW), $P_t \in \{0\} \cup [c^{p,lo}, c^{p}]$
- G_t : Turbine operation (MW), $G_t \in \{0\} \cup [c^{t,lo}, c^{t}]$

4.3.3 Mathematical Equations

STORMOD-*stud* models the scheduling problem of a single pumped-hydro storage operator facing day-ahead wholesale market prices. The model is formulated as a profit-maximization problem. The following set of equations describes the target function and associated equations. Students should be taught the concept of arbitrage as a business opportunity for storage operators before explaining the set of cost equations since arbitrage drives the scheduling decision in STORMOD-*stud*.

$$\max \quad GM \;=\; I^{t} - E^{p} \tag{4.1}$$

$$I^{t} \;=\; \sum_{t} \left(G_t \cdot \left(pr_t^{da} - co^{t} \right) \right) \;\cdot\; sc \tag{4.2}$$

$$E^{p} \;=\; \sum_{t} \left(P_t \cdot \left(pr_t^{da} + co^{p} \right) \right) \;\cdot\; sc \tag{4.3}$$

The objective of the optimization model entails the maximization of the contribution margin of the storage operator through the sale of power on the day-ahead market (4.1). The revenue consists of the net value of electricity produced via deploying the turbine at the prevailing hourly market price and the associated operating cost

and purchasing electricity for operating the pump to store hydro energy (4.2)–(4.3). In calculating the operating costs, a distinction is made between fixed and variable operating costs. It is important for students to understand the relationship that exists between market prices and underlying dynamics at play in the power system. During times of low prices, an oversupply of renewable energies can be typically observed incentivizing storage operators to store energy through the deployment of the pump unit. Market prices thus provide signals for its system-friendly operation. The same is true during times of capacity scarcity and high market prices, which incentivizes storage operators to offer additional energy to the market.

The maximization of the contribution margin is subject to a set of restrictions. The following details all technical limitations regarding charging/discharging of the storage basin.

$$SL_t = SL_{t-1} - G_t + P_t \cdot \eta \qquad \forall t \in T \setminus \{1\} \tag{4.4}$$

$$SL_t \leq c^s \qquad \forall t \in T \tag{4.5}$$

$$SL_t = 0.5 \cdot c^s - G_t + P_t \cdot \eta \qquad \forall t \in \{1\} \tag{4.6}$$

$$SL_t = 0.5 \cdot c^s \qquad \forall t \in \{8760\} \tag{4.7}$$

The filling of the storage is described on the basis of Eq. (4.4). The summation of all charging/discharging activities yields the storage level in each time step. The filling level of the storage reservoir is restricted to a maximum value (4.5). Furthermore, Eqs. (4.6)–(4.7) impose a limit on the storage level in the first and last hours included in the model. It is constrained to a filling level of 50% compared to the maximal value.

STORMOD-*stud* is a mixed-integer program using semi-continuous variables for the pump and turbine operation. In this manner, the variables P_t and G_t are constrained to a range between a minimum and maximum loads or assume a value of 0, i.e., the turbine or pump is switched off (see variable definition in the nomenclature for the exact specification of their domains). In order to prevent unintended activation rates and changes in the operation levels of the pump and turbine, the variables P_t and G_t are further constrained by the following load-change restrictions.

$$P_t - P_{t-1} \leq lc^p \cdot c^p \qquad \forall t \in T \setminus \{1\} \tag{4.8}$$

$$-P_t + P_{t-1} \leq lc^p \cdot c^p \qquad \forall t \in T \setminus \{1\} \tag{4.9}$$

$$G_t - G_{t-1} \leq lc^t \cdot c^t \qquad \forall t \in T \setminus \{1\} \tag{4.10}$$

$$-G_t + G_{t-1} \leq lc^t \cdot c^t \qquad \forall t \in T \setminus \{1\} \tag{4.11}$$

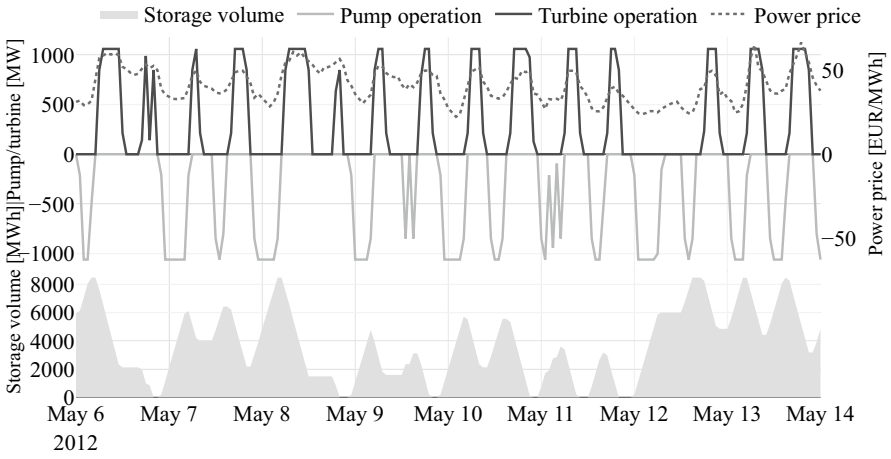

Fig. 8 Operation of the pump and turbine of the PHES unit against day-ahead wholesale market prices for an exemplary week in 2012 (above) and the development of the storage level across the same period (below), source: own illustration

A load-change factor *lc* constituting a relative proportion of the maximum operation power constrains changes in power levels of the pump (4.8)–(4.9) and turbine (4.10)–(4.11) between two consecutive time steps in each hour.

STORMOD-*stud* includes additional parametric data on economic characteristics of the storage plant. This could be utilized in conjunction with the model results on the gross margin to perform a detailed investment analyzis for a set of different spot-market price scenarios.

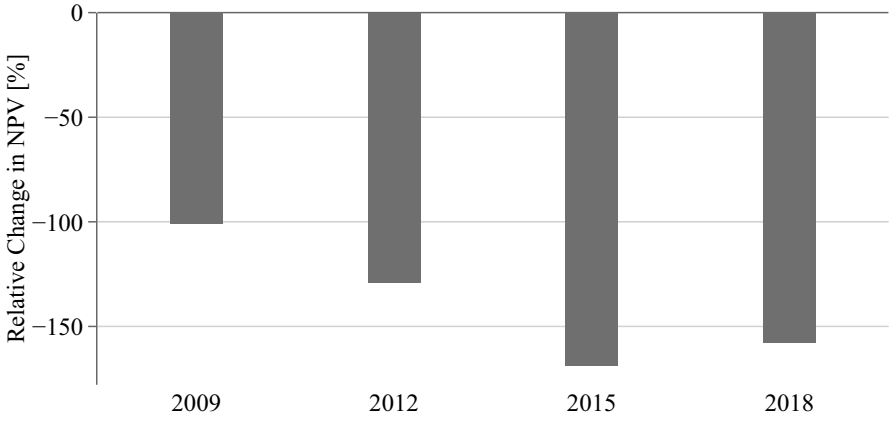

Fig. 9 Relative change in net present value (NPV) of an investment in the PHES under market conditions in the years 2009–2018 against the baseline of 2006, source: own illustration

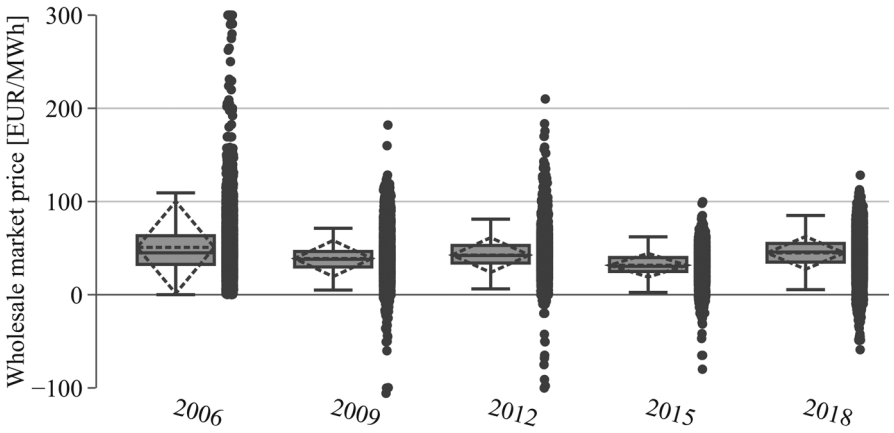

Fig. 10 Development of the distribution of German day-ahead wholesale power prices across the respective years considered in the model (dashed diamond-shaped regions in the box plots indicate the respective standard deviation), source: own illustration

4.4 Example Case Study Results

Based on the model application, the students are tasked with parsing the results toward evaluating the profitability of the traditional price arbitrage strategy utilized by PHES against the background of increasing shares of renewable power production.

To facilitate a better understanding of the scheduling decision of the PHES operator, students can investigate the impact of price signals on the pump and turbine operation of the PHES unit. Figure 8 displays the deployment of the pump and turbine of the PHES plant as well as wholesale power price movements for an exemplary week in 2012. It can be observed that the pump is mainly operated at night and on weekends—at times of low electricity prices. The turbine, on the other hand, is in operation at times of on-peak electricity prices.

Delving further into assessing the profitability of the PHES unit over time, a comparison of the net present value (NPV) of an investment in the plant indicates, as displayed in Fig. 9, a relative diminished profitability of the modelled PHES unit from 2006 to 2018. A supplementary sensitivity analyzis of relevant parameters could be conducted to provide further indication as to the extent to which specific assumptions, e.g., CAPEX, discount rate, impact the profitability of the exemplary PHES under study. Nevertheless, from the results it can be inferred that the prevailing market conditions in Germany in the past decade have compromised the traditional business model for PHES based on price arbitrage.

An explanation for this development is illustrated in Fig. 10, which depicts the distribution of wholesale power prices across the 5 years considered in the model-based analyzis. The plot indicates that prices have become more concentrated since 2006. The magnitude of the price spread has a determining impact on the contribution margin that can be generated via price arbitrage and thus impacts

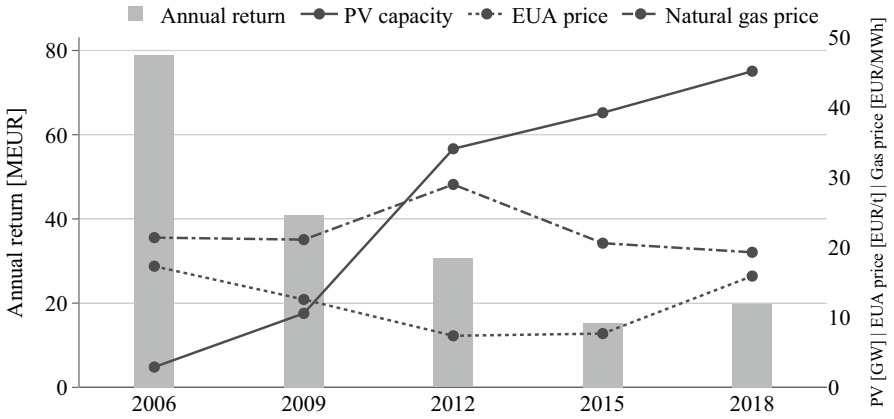

Fig. 11 Change in the annual return on the PHES unit, installed PV capacity, and gas and carbon allowance prices across the respective years considered in the model, source: own illustration

the ability to recover the investment and ensure an economic operation of the PHES unit. In order to ensure a profitable arbitrage, the power price incurred while in pumping mode is required to be at least 25–30% lower than the selling price to cover operation and maintenance (O&M) costs [15].

The changing market conditions reflected in the diminished price spread in the yearly time series should prompt students to explore the changing market conditions and the drivers behind the depressed power prices. The peak/off-peak price ratio has traditionally been dictated to a large extent by the price spread between coal and gas prices.

However, the impact of increasing shares of renewable energy on the grid (Fig. 11), especially the concurrence in daily PV feed-in and traditional peak system loads, has led to the reduction in on-peak electricity prices and spurred the erosion of the market share of natural gas generation. Since 2012, weak gas prices in combination with depressed emission allowance prices have further contributed to a narrowing of the price spread in turn the profitability of an investment in a PHES plant. As indicated in Fig. 11, in 2018 the price of emission allowances recovered, lending support to the price spread.

It should be noted that PHES plants can also derive other means of revenue via operating on intraday and reserve energy markets. Thus, absolute statements about the profitability of individual units cannot be drawn. The optimization problem could, however, be adapted to consider the profit-maximizing scheduling of the unit across the various markets.

4.5 Learning Outcomes

Performing the model-based analyzis, the students develop a better understanding of the merchant status of PHES in competitive electricity markets. Furthermore, the modeling exercise provides a hands-on means of assessing the business model based on

price arbitrage employed by PHES plants and how the profitability of PHES plants has been negatively impacted by changing market forces. This runs counter to the expectations of many students and entails a rather vexing policy outcome, as energy storage technologies are considered especially valuable in markets with higher penetration levels of renewable generation [16].

The learning outcomes should prompt further questions about market incentives for flexibility options in the future, which can be tied back into the lecture material. Pumped storage is likely to have better prospects in the long-term as higher shares of renewable penetration should make spot prices more volatile and incentivize flexible generation. This, of course, can be analyzed via a power market model, which is illustrated in the case study above.

5 Model-Based Case Studies Constitute Valuable Learning Tools in Energy Economics Courses

The field of energy economics is interdisciplinary in nature. Much of the course material covered comprises exploring techno-economic aspects of energy systems and increasingly facilitating an understanding of the interactions between innovative technologies and adaptive markets. In terms of power markets, these dynamics governing market outcomes can be complex and lend themselves to being analyzed by employing optimization models. The incorporation of modelling exercises in the curricula offers a fruitful means of grounding the theory conveyed in the lecture material and allows students to transfer their knowledge to studying current developments in power markets. In the paper, two case studies are presented to highlight different types of model-based analyzes that can be employed as project assignments.

Based on the course level, the assignments can be implemented as either model building or application exercises. Hence, the two models ELTRAMOD-*stud* and STORMOD-*stud* presented can be either provided to students as a basic model version to be adapted and extended or developed from scratch with guidance from the instructor. The application of a prepared model is less demanding for students but can still facilitate a basic modelling literacy as well as allow the students to explore the impact of changes in key parameters on the model results. As illustrated above, the models can be employed to study such topics as the scheduling problems of individual plant owners as well as market developments driving long-term adaptations in the portfolio of power-generation assets. In advanced courses, the students can be tasked with developing the model themselves. Of course, this increases the effort involved and presumes a greater degree of modelling proficiency and thus should be accompanied by a general introduction into optimization theory and the corresponding programming language to be deployed. In this case, the assignment entails several layers of investigation.

First, students should identify relevant real-world questions to be studied in an optimization framework. Students should draw on the lecture material to aid in defining a relevant research question to be addressed. As power markets are currently subject to a range of developments tied to the decarbonization of the power system, there are various avenues that can be explored. While the case studies illustrated above are modelled deterministically, stochastic methods can be introduced to extend the analyzis to capture market uncertainties that are becoming more prevalent.

Second, students need to translate their research questions into an optimization problem with its associated set of system of equations. This step involves condensing the problem into its constituent parts and determining the scope and level of granularity of the model required to adequately address the research questions developed. It is quite often the case that students are keen on increasing the level of detail in the model and need to be reminded that models are an abstraction of the real world; and thus, effort is better invested toward honing the model to address the relevant aspects of the questions under study. Experience has shown that regular consultations at the beginning stages of the project are valuable to guide students and ensure they maintain the proper focus.

Third, the exercise of formulating and implementing the optimization models in a programming language assists students in improving their mathematical proficiency as well as their coding literacy. As energy economics is an interdisciplinary field, the students usually bring a diverse set of educational backgrounds, e.g., economics, engineering, business administration, and informatics. The student's math skills differ accordingly; thus, it is essential that the group members can effectively convey mathematical concepts relevant to constructing the model. Nevertheless, the diverse array of skill sets can be beneficial toward completing the individual tasks, e.g., conceptualization, data collection and processing, programming, and evaluating and reporting results, in an efficient manner. While it is quite common that the model implementation is carried out by a subset of the students in the group, it is important to try and steer all members toward contributing or at least engaging in the process of developing the model.

Lastly, incorporating modelling assignments can spur some students to further their knowledge in the field, which might not happen if the course curriculum is confined to theory-based lecture material. While some students find the modelling work taxing, others take to the assignments and develop a deeper interest in power system modelling. This manifests itself in students completing more advanced courses offered and sets them up well to complete their thesis work in the field of study.

In summary, integrating modelling exercises and assignments in energy economics course curriculum has proved to be a practical means of reinforcing and extending lecture material that is both engaging and rewarding for students.

Appendix

Data for ELTRAMOD-*stud*

	TECHNOLOGY		
	[-]	[1/100]	[t/MWh_th]
	fuel	efficiency	emission
nuclear	uranium	0.309	0
lignite	lignite	0.37	0.404
hardcoal	hardcoal	0.417	0.354
ccgt	gas	0.542	0.202
ocgt	gas	0.34	0.202
psp	hydro	0.9	0

	ECONOMIC FIX			
	[EUR/MW]	[EUR/MW]	[EUR/MW]	[EUR/MW]
	invest	maintenance	staff	insurance
nuclear	2,950,000	0	13,125	51,525
lignite	1,700,000	36,218	8,663	10,065
hardcoal	1,600,000	29,250	12,150	8,625
ccgt	750,000	5,085	8,415	3,285
ocgt	650,000	2,780	3,700	2,520
psp	950,000	0	0	0

	ECONOMIC VAR		
	[EUR/MWh]	[EUR/MWh]	[EUR/MWh]
	operation	reserves	disposal
nuclear	10.3	1	1.5
lignite	0	1	0
hardcoal	0	0	0
ccgt	3	0	0
ocgt	3.5	0	0
psp	0	0	0

	ECONOMIC LIFETIME	INTEREST RATE	ANNUITY
	[a]	[1/100]	[EUR/MW * a]
	lifetime	interest	annuity
nuclear	60	0.1	295972.0522
lignite	35	0.1	176272.4987
hardcoal	35	0.1	165903.5282
ccgt	25	0.1	82626.05414
ocgt	25	0.1	71609.24692
psp	55	0.1	95505.16023

FUEL PRICE				
[EUR/MWh_th]	[EUR/MWh_th]	[EUR/MWh_th]	[EUR/MWh_th]	[EUR/t]
uranium	lignite	hardcoal	gas	carbon
3.24	6.20	8.93	23.36	6.00

Acknowledgements The authors would like to recognize Agata Giuffrida for her valuable support in preparing the figures contained in the paper.

Funding Open Access funding enabled and organized by Projekt DEAL.

Data and Code Availability Executable versions of ELTRAMOD-*stud* and STORMOD-*stud* including all input-data can be downloaded here: https://doi.org/10.5281/zenodo.7740897 and https://doi.org/10.5281/zenodo.7740976.

Declarations

Conflict of Interest The authors declare no competing interests.

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