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A Stochastic Discrete Choice Dynamic Programming Model of Power Plant Operations and Retirement

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Abstract

We present a methodology to estimate fixed cost parameters relevant to the decision to operate, mothball or retire an open-cycle gas turbine (OCGT) using a dynamic discrete choice model, based on fuel and electricity prices, as well as technical data and the operational status of OCGTs in the PJM market area. With operational and mothballed OCGTs, we find for both, age of the power plant and plant vintage statistically significant positive correlations with the fixed operation and maintenance (O&M) costs. We also show a statistically significant negative relationship between the installed capacity and the fixed O&M costs, confirming that an increase in scale results in lower specific costs. The estimated fixed O&M cost parameters for an operational OCGT vary from 15.3 USD/kW/yr for new, large, high-efficiency units, to 50.8 USD/kW/yr for older, small, low-efficiency units. Mothballing a plant reduces these costs by 75% to 95%, depending on plant vintage and size. Decommissioning an OCGT was found to be cash flow negative, which means that the associated cost exceeds any scrap value the equipment may have on secondary markets. Our estimated cost parameters depend on operational status, capacity, vintage, and age of a generation unit. This differentiation is valuable for a better understanding of costs in the context of competition policy. It would also allow for a more realistic parameterisation of power market models. Using the estimates and market data, we also compute the probabilities of operating, mothballing or retiring an OCGT. Sensitivity analyses regarding changes in prices of capacity, electricity, and natural gas reveal that the operating decisions for OCGTs are significantly affected by the profitability potential, most notably by electricity prices.

JEL classification: C61, D24, L94

Keywords: dynamic discrete choice models, electricity markets, fixed cost estimation, maximum likelihood estimation, open-cycle gas turbine (OCGT)

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1. Introduction

The objective of this paper is to estimate fixed cost parameters relevant to the decision to operate, mothball or retire an open-cycle gas turbine (OCGT) in the Pennsylvania, New Jersey, Maryland Power Pool (PJM)[1] using a dynamic discrete choice model supplied with data on fuel and electricity prices, as well as technical data and the operational status of OCGTs in the PJM market area.

Characterised by low investment but high variable costs, OCGTs are usually operated as peaking power plants that come online only when electricity prices are high enough to cover their variable costs. Due to their position at the top end of the merit order[2] of the market, they are often the price-setting technology in peak hours. Furthermore, new OCGTs are often the price setting technology in capacity remuneration mechanisms such as PJM's Reliability Pricing Model (RPM) designed to incentivise the deployment of sufficient firm capacity to maintain security of supply at times of very high demand. The upshot of this is that OCGTs are a pivotal technology when it comes to the potential of market participants to exert market power on both electricity and capacity markets, i.e. by withholding capacity in critical hours on the electricity market, or in auctions on the capacity market. In order to assess the structure and competitiveness of both electricity and capacity markets, regulators need robust data on the cost structures of peaking power plants in particular. However, publicly available reports on the operating costs of power plants, published by public organisations such as the Energy Information Administration (EIA, 2016), the International Energy Agency (IEA, 2015, 2020), market operators (PJM, 2014, 2018a), as well as private engineering and consulting firms (e.g. NREL (2012) or Lazard (2020)), tend to focus on newly built plants and usually provide point estimates for an average unit only. The dynamic discrete choice model described in this paper, on the other hand, can be used to generate a larger set of more differentiated cost estimates for a single technology such as an OCGT, dependent on plant characteristics such as age, capacity or vintage. Additionally, it is able to provide estimates for the operation and maintenance (O&M) costs of mothballed plants, as well the cost associated with the final decommissioning of plants. Better cost estimates improve market transparency, potentially lowering market entry barriers for the general benefit of competition on the market.

Furthermore, such differentiated cost estimates for generating units of varying operational status, capacity, age, and vintage are valuable parameters for the modelling of energy systems. The fight against climate change, not least via a growing share of intermittent generation in the power supply, increases the

[1] PJM is the independent system operator (ISO) for all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia. PJM operates the high-voltage transmission system, the wholesale market for electricity and an auction-based mechanism for the provision of secure capacity.

[2] The term *merit order* describes the short-run supply curve of an electricity market.

importance of such models. They provide insights into questions on network stability, investment decisions, and greenhouse gas emissions and would benefit from more differentiated costs data, as provided in this paper.

Dynamic discrete choice models assume that rational, forward looking, risk-neutral agents maximise expected payoffs across time. Based on the principle of *revealed preference* (Aguirregabiria and Mira, 2010), they allow for the estimation of unknown parameters in an agent's profit function using data on agent choices and choice outcomes. For the model to replicate operator behaviour and produce valid cost estimates, the market under investigation needs to be competitive, i.e. market participants have to behave as price-takers whose decisions are determined by costs and prices only, rather than strategic considerations. Otherwise, the cost estimates might be biased. We assume that as a large and liquid market, PJM is sufficiently competitive for the model to generate valid cost estimates and therefore suitable to estimate the O&M costs of peaking power plants. To support this assumption, we analyse PJM's annual state of the market reports for the 2008 to 2017 period. The annual reports find that electricity prices in PJM are set mostly by marginal units at or close to their marginal cost of production. They conclude that in all years, both energy and capacity market outcomes are broadly consistent with competitive behaviour among the market participants (Monitoring Analytics, 2020).

Since OCGTs are largely standardised, the cost estimates derived in this paper should apply to OCGTs in other United States or OECD electricity markets as well. Thus, they could provide useful information to researchers and regulators assessing the competitiveness of other electricity or capacity markets.

Econometric dynamic discrete choice models are applied to a wide range of microeconomic problems. Some of the seminal works are, Wolpin (1984) on fertility and child mortality, Rust (1987) on the optimal replacement of bus engines, Das (1992) on capital utilisation and retirement decisions in the cement industry, and Keane and Wolpin (1997) on the educational and occupational choices of young men. Other notable works include Hartmann and Viard (2008) on switching costs in frequency reward programmes, Nevo et al. (2016) on the consumer response to usage-based broadband pricing and Peters et al. (2017) on firm R&D spending. Aguirregabiria and Mira (2010) provide an overview of dynamic discrete choice estimation procedures commonly used in the literature.

In an electricity industry context, dynamic discrete choice models are used to assess investment, operational, and retirement decisions associated with electricity generators. In particular, they are used to study the impact of external shocks on managerial decision-making and to estimate unknown cost parameters in a variety of contexts. Rothwell and Rust (1997), for instance, model the long-term decision problem (operate or decommission) of a nuclear power plant operator in order to determine the optimal lifetime of existing plants. They take account of major unplanned outages (*problem spells*) in their model specification and assume that such outages become more likely as a plant ages. Cook and Lin Lawell (2019) use a dynamic structural model to analyse the impact of government policy on the investment in, decommissioning or replacement of small-scale wind turbines in Denmark. They find that government policy had a greater impact on the growth of wind power in Denmark than technological improvements, and that specific policy changes had a substantial impact on the timing of expansion, shutdown and replacement decisions made by wind turbine operators.

According to the principle of revealed preference (Aguirregabiria and Mira, 2010), the decisions of production units can be used to estimate unknown cost parameters, provided some other parameters are known. Fleten et al. (2019), for example, use data on startup and shutdown events, natural gas and electricity prices in the northeastern United States (including PJM), covering the years 2001–2009, to estimate maintenance and state switching costs for OCGTs with the help of a dynamic discrete choice framework. Based on the derived estimates, they calculate the avoidable cost rate (ACR) associated with switching from an operational to a mothballed and from a mothballed to a decommissioned state and find that the estimated ACRs are lower than the clearing prices observed in PJM's market for secure capacity. Based on this, they conclude that consumers are likely overpaying for the provision of secure capacity in the PJM Interconnection.

Building on the methodological approach of Das (1992), our study expands on the work of Fleten et al. (2019). Unlike the latter, we explicitly model how fixed costs relate to characteristics of the generating unit, such as plant age and plant size. This means that our model allows us to quantify hidden cost parameters (fixed O&M costs) for different plant sizes and vintages. Furthermore, we incorporate capacity prices for the years 2008–2017 into our model, recognising that these represent a significant source of additional revenue for OCGTs, which operate only in peak hours.

Using a dynamic model to estimate power plant costs has several advantages: costs are usually estimated based on engineering studies of plant designs, or operator questionnaires. Furthermore, they are usually provided only for operational units. Through the use of a dynamic model, we generate parameter estimates based on the actual behaviour of market participants. Therefore, we can estimate costs that are not usually included in engineering studies or surveys, for instance costs of plants in a mothballed state or costs/revenues associated with the final retirement of a production unit (decommissioning costs/scrap value). In addition, using the estimated cost parameters, the fitted model itself can be used to predict the behaviour of plant operators in response to changes in exogenous parameters, such as fuel or electricity prices.

For both operational and mothballed OCGTs, we find statistically significant, positive relationships between the age of the power plant and the inverse of the efficiency of the turbine (which serves as a proxy for the plant vintage) and the fixed O&M costs. We also show a statistically significant, negative relationship between the installed capacity and the fixed O&M costs, confirming that an increase in scale results in lower specific costs. Decommissioning an OCGT was found to be cash flow negative, which means that the associated cost exceeds any scrap value the equipment may have on secondary markets.

The paper is structured as follows: the model, its assumptions and the underlying data are presented in section 2. The estimated parameters, as well as a simulation based on these parameters follow in sections 3. Section 4 contains sensitivity analyses using the fitted model. Section 5 concludes the paper.

2. Methodology

2.1. Assumptions and Data

PJM operates three separate markets in its area of operations: a wholesale market for electricity, a market for secure capacity, and a market for ancillary services. The day-ahead market forms the core of PJM's wholesale market for electricity. Prices are derived by matching offers from generators with bids from consumers, with the most expensive offer cleared setting the price. The day-ahead market is augmented by a real-time market, which allows market participants to make final adjustments to their positions shortly before delivery. The PJM capacity market—called the Reliability Pricing Model (RPM)—is designed to ensure that sufficient levels of secure capacity are available to meet the projected peak demand of a given year, plus a reserve margin. The main capacity auction (base residual auction) is held three years in advance of the delivery period. 95 percent of the capacity required by PJM is purchased in the base residual auction. The remaining 5 percent are acquired in a series of incremental auctions. Capacity cleared in the auctions is committed to be available in the delivery period, which ranges from June 1st to May 31st of the following year. This means that the plant has to be operational, and can neither be mothballed nor decommissioned. Participation in the capacity market is mandatory for existing generators and optional for yet to be commissioned newly built generators. Each generator that has cleared a sell offer in one of the auctions will receive a daily payment that is equal to the MW amount cleared times the respective auction's clearing price for the delivery period (pay-as-cleared). A penalty applies in case of non-delivery (PJM, 2018b).

For the model-based analysis, we use average hourly real-time electricity prices used for the PJM interconnection (PJM, 2020b), as well as the respective year's capacity price (PJM, 2020a)[3]. Monthly natural gas prices for the states serviced by PJM are taken from (EIA, 2020b). The average annual values are presented in Table 1.

We use detailed power plant data provided by the Energy Information Administration (EIA) in their Annual Electric Generator Reports (EIA-860). The annual data set includes the commissioning date, operational status, location, generation capacity and fuel type of individual units. The operational status of the units include being operational, being in standby mode or being out of service and being retired. We consider the standby and out of service status in the data set as mothballed status.

In practice, the economic lifespan of OCGTs is around 25 years and the maximum technical lifespan is considered to be 30 years (IEA ETSAP, 2010). However, in the EIA data, a significant number of units (225 out of 740 units) had commissioning dates which indicated turbine units older than 30 years. As those commissioning dates were most likely not updated with retrofit dates, we assume those units to have received retrofits at some point, which is not specified in the data sheet. Thus, we assume major retrofits to occur every 30 years after a plant's original commissioning.

OCGTs, traditionally characterised by low fuel-to-electricity conversion efficiencies, have seen significant improvements in efficiency due to advances in technology over the past decades. As such, it can be assumed that efficiency of a turbine strongly depends on the era the turbine was commissioned in. Within this context, we assign the observed units into *vintage classes* corresponding to their commissioning years. We consider three vintage classes representative of the technology progress, and hence the efficiency of the turbines. Units built between 1972–1999 are assigned an efficiency of 0.28, units built between 2000–2014 an efficiency of 0.35, and those built from 2015 onward 0.40. The efficiency of retrofitted plants is assumed to correspond to that of new plants commissioned in the same year as the retrofit. The efficiency of a retrofitted plant corresponds to that of a plant commissioned at the time of the retrofit.[4]

Similarly, in order to reduce model complexity, we consider the capacities of observations in several classes. The observed capacities are clustered into four capacity sizes corresponding to the mean values of the quartiles of the data. The assumed vintage classes with their corresponding efficiencies and the

[3] Annual capacity prices are weighted averages of seasonal capacity prices. A RPM season runs from June to May.

[4] We are aware that the assumption of fixed efficiencies may not represent the real efficiencies of some units; especially those with commissioning dates bordering the dates of another vintage class. Considering more vintage classes with interpolated efficiency assumptions would result in a more realistic representation, but with exponentially increasing duration for model convergence. Hence, we found limiting the number of vintage classes to three to be a necessary simplification that allows for reasonable model convergence duration. The vintage classes are based on OCGT vintage classes used in the DIMENSION electricity market model maintained at the Institute of Energy Economics at the University of Cologne (Richter, 2011).

considered mean capacities for the clusters of observations are provided in Table 2. For each vintage class, there are four capacity clusters, which makes a total of 12 unit types.

The yearly energy payments (in USD per MW) that the considered unit types receive on the electricity market are estimated as the sum of hourly positive spark spreads throughout a year. These correspond to the integral of the price duration curve above the total variable costs of the unit. These costs comprise variable fuel costs and variable operation and maintenance costs. The variable fuel costs are assumed to be the cost of fuel (i.e. the price of natural gas) divided by the efficiency. Average variable operation and maintenance costs are assumed to be 5.5 USD/MWh (EIA, 2020a). Hence, the short run profit indicator, S, corresponds to the sum of positive spark spreads throughout a year plus the respective capacity payment.

Table 1: Proportion of operated, mothballed and decommissioned units, and the development of mean capacities, electricity and natural gas prices, spark spreads, and capacity prices throughout the considered period

Year	No. of units	OP	MB	DC	Age	Capacity	P_{el}	P_{ng}	Spark spread	Capacity payment
		%	%	%	years	MW	USD/ MWh	USD/ MWh	thousand USD/MW	thousand USD/MW
2008	606	70.6	10.9	18.5	7.9	60.8	66.12	33.76	17.20	25.71
2009	520	84.6	11.3	4.0	8.7	63.6	37.00	25.39	9.45	39.35
2010	530	82.8	11.3	5.8	9.6	63.9	44.57	22.81	31.52	48.23
2011	555	79.8	10.8	9.4	10.6	63.1	42.52	22.31	32.04	53.84
2012	533	89.7	7.5	2.8	11.3	63.6	32.79	19.04	34.35	25.92
2013	543	90.4	6.1	3.5	12.1	62.9	37.15	17.87	23.93	7.72
2014	531	90.0	7.9	2.1	13.1	63.4	49.33	19.19	83.17	25.07
2015	535	84.9	5.8	9.3	14.0	63.9	34.12	16.14	75.05	47.51
2016	519	89.2	5.8	5.0	15.1	66.2	28.10	13.15	55.03	37.99
2017	531	87.4	4.9	7.7	16.1	64.3	29.48	15.02	32.18	30.89

Table 2: Vintage classes depending on the commissioning year and the capacity clusters assumed for the OCGT units

Vintage	Efficiency	Capacity (MW)
up to 1999	0.28	24, 48, 81, 150
2000 to 2014	0.35	24, 48, 81, 150
2015 onward	0.40	24, 48, 81, 150

2.2. Model

The model structure is closely related to the model presented in Das (1992).[5] A power plant operator's decision problem consists of choosing a sequence of decision rules $I = i_t = f_t(x_t, \epsilon_t, \theta)$ for each time period

[5]Our model is implemented in the Python programming language and solved using the L-BFGS-B algorithm (Byrd et al., 1995; Zhu et al., 1997).

t, which maximises the expected discounted sum of profits of the managed power plant unit, as expressed in Equation 1:

$$\max_{I} \; E_0 \left\{ \sum_{t=0}^{T} \beta^t \, u(x_t, i_t, \epsilon_t, \theta) \right\} \tag{1}$$

where E_0 is the expectation based on today's information, T is the lifespan of a plant, and β is the discount rate.[6] The instantaneous profit function of a unit, $u(\cdot)$, depends on the vector of exogenous variables, x_t (installed capacity of the unit, its age, its commissioning year, and the short-run profit indicator determined by the electricity prices, fuel prices, other variable O&M costs, and capacity payments); the vector of the unobserved random components, ϵ associated with the decisions i; and the vector of parameters to be estimated, θ.

Equation 1 is also called the value function, $V_t(x_t, i_t, \epsilon_t, \theta)$, which corresponds to the recursive solution of the Bellman equation, where the operator picks i_t from a set of three choices, $C = \{op, mb, dc\}$. Those are whether to operate, mothball, or decommission the unit:

$$V_t(x_t, \epsilon_t, \theta) = \max_{i \in C} \{u(x_t, i_t, \epsilon_t, \theta) + \beta \, EV_t(x_t, i_t, \epsilon_t, \theta)\} \tag{2}$$

where the expected value EV_t is:

$$EV_t(x_t, i_t, \epsilon_t, \theta) = \int_{x_{t+1}} \int_{\epsilon_{t+1}} V_{t+1}(x_{t+1}, \epsilon_{t+1}, \theta) \, dPr(x_{t+1}, \epsilon_{t+1} \mid x_t, i_t, \epsilon_t) \tag{3}$$

As also shown in Rust (1988), under certain regularity conditions the optimal choice then corresponds to Equation 4, where the aim is to estimate the vector of parameters θ.

$$f(x_t, \epsilon_t, \theta) = \arg\max_{i \in C} \{u(x_t, i_t, \epsilon_t, \theta) + \beta \, EV_t(x_t, i_t, \epsilon_t, \theta)\} \tag{4}$$

In this respect, the instantaneous profit function can be written as:

$$u(\cdot) = \begin{cases} K \cdot S_t - F_{t,op} + \epsilon_{t,op} & i = op \\ -F_{t,mb} + \epsilon_{t,mb} & i = mb \\ -F_{t,dc} + \epsilon_{t,dc} & i = dc \end{cases} \tag{5}$$

When a unit runs, the positive term of its payoff consists of its capacity K, multiplied with the short-run profit indicator, S_t, which already contains any variable costs.

[6] In line with Das (1992), we assume a discount factor of 0.9.

The negative term of the payoff of an operating unit equals its fixed O&M costs. They are assumed to linearly depend on the capacity K of the unit. The larger the unit capacity, the higher the fixed O&M costs. Similarly the costs are assumed to linearly depend on the age of the unit, A. The older the unit, the higher the fixed costs. Further, we assume that as plant technology improves, those costs decrease. We map plant efficiency to the vintage class of a plant. Since units with newer technology have higher efficiencies, the specific fixed O&M costs are assumed to be inversely related with the unit efficiency η. The simplifying assumption of a linear relationship is consistent with the literature (Fleten et al., 2019). The fixed O&M costs for an operating unit can then be expressed as follows:

$$F_{t,op} = \theta_{K,op}\, K + \theta_{A,op}\, A_t + \theta_{\eta,op}\, \frac{1}{\eta} \qquad \theta_{K,op}, \theta_{A,op}, \theta_{\eta,op} > 0 \tag{6}$$

A mothballed unit does not have variable costs and is assumed to have fixed costs only. The O&M costs of a mothballed plant are expected to be significantly reduced compared to those of an operating unit, hence the incentive to mothball a temporarily unprofitable plant. The fixed costs in this case are similarly assumed to be a function of unit capacity, age and vintage class:

$$F_{t,mb} = \theta_{K,mb}\, K + \theta_{A,mb}\, A_t + \theta_{\eta,mb}\, \frac{1}{\eta} \qquad \theta_{K,mb}, \theta_{A,mb}, \theta_{\eta,mb} > 0 \tag{7}$$

The fixed cost associated with decommissioning are assumed to linearly depend on unit capacity as shown in Equation 8. The cost term F_{dc} can be positive or negative, depending on whether the cost of decommissioning exceeds the salvage value obtained on secondary markets for combustion turbines.

$$F_{dc} = \theta_{dc}\, K \tag{8}$$

The vector of estimable parameters of the problem is then $\theta = (\theta_{K,op}, \theta_{A,op}, \theta_{\eta,op}, \theta_{K,mb}, \theta_{A,mb}, \theta_{\eta,mb}, \theta_{dc})$, where the exogenous variables are $x_t = (K, A_t, S_t, \eta)$.

The parameters of the vector θ are estimated by maximising the likelihood function:

$$L(\theta \mid i, x) = \prod_{n=1}^{N} \prod_{t=1}^{T_n} Pr(i_{n,t} \mid x_{n,t}, \theta) \tag{9}$$

where $Pr(i_{n,t} \mid x_{n,t}, \theta)$ are the optimal choice probabilities, given the vector i contains every unit's choice and the vector x includes the state variables for each period. The total number of units is denoted by N, and T_n corresponds to the number of observations for unit n.

The capacity K of a unit and its efficiency η are assumed to be constant over time. The age of a unit however changes over the time periods. If the decision i_t is not to retire, then the age increases by one each year, i.e. $A_{t+1} = A_t + 1$. If the decision i_t is to retire or the maximum age of 30 years is reached then an absorbing state is reached, i.e. $A_{t+1} = A_t$. The absorbing state of the age variable assumes that after reaching the end of a turbine's lifespan, i.e. after 30 years or after decommissioning, an additional year no longer has an effect on costs.

We assume that prices of capacity, natural gas, and electricity jointly follow a first-order Markov process, denoted by $Pr(P_{capa,t+1}, P_{el,t+1}, P_{fuel,t+1} \mid P_{capa,t}, P_{el,t}, P_{fuel,t})$. Therefore, the short-run profit indicator, S, can be assumed to follow the process $Pr(x_{t+1} \mid x_t)$. Consequently, for each unit type we have the process $Pr(A_{t+1} \mid A_t, i_t) \cdot Pr(x_{t+1} \mid x_t)$, where the change in age is deterministic. By assumption, the non-deterministic transition probabilities correspond to the respective relative frequencies of x_t in the data set.

The conditional independence assumption[7] reduces the problem from $EV(x_t, i_t, \epsilon_t, \theta)$ to $EV_t(x_t, i_t, \theta)$. The value function can thus be reexpressed as:

$$V_t(x_t, \epsilon_t, \theta) = \max\{V_{t,op}(x_t) + \epsilon_{t,op}, \quad V_{t,mb}(x_t) + \epsilon_{t,mb}, \quad V_{t,dc}(x_t) + \epsilon_{t,dc}\} \tag{10}$$

The individual value functions for the respective decisions (i.e. operate, mothball, decommission) can then be written as follows:

$$\begin{aligned}
V_{t,op}(x_t) &\equiv K \cdot S_t - (\theta_{K,op}\, K + \theta_{A,op}\, A_t + \theta_{\eta,op}\, \frac{1}{\eta}) + \beta\, EV_t(x_t, \theta) \\
V_{t,mb}(x_t) &\equiv -(\theta_{K,mb}\, K + \theta_{A,mb}\, A_t + \theta_{\eta,op}\, \frac{1}{\eta}) + \beta\, EV_t(x_t, \theta) \\
V_{t,dc}(x_t) &\equiv -\theta_{dc}\, K
\end{aligned}$$

Based on the assumption that the density of ϵ for a given x follows an extreme value distribution, our choice probabilities can be expressed as:

$$\begin{aligned}
Pr(op \,|\, x_t, \theta) &= \frac{e^{V_{t,op}(x_t)}}{M_t} \\
Pr(mb \,|\, x_t, \theta) &= \frac{e^{V_{t,mc}(x_t)}}{M_t} \\
Pr(dc \,|\, x_t, \theta) &= \frac{e^{V_{t,dc}(x_t)}}{M_t}
\end{aligned} \tag{11}$$

where $M_t = e^{V_{t,op}(x_t)} + e^{V_{t,mb}(x_t)} + e^{V_{t,dc}(x_t)}$ and $EV_t(x_t, \theta)$ stems from the unique solution of:

[7] See Rust (1987) for detailed information on this assumption.

$$EV_t(x_t, \theta) = \int \log(e^{V_{t+1,op}(x_{t+1})} + e^{V_{t+1,mb}(x_{t+1})} + e^{\theta_{dc}})\, Pr(x_{t+1} \mid x_t, i_t)\, dx_{t+1} \tag{12}$$

3. Results

3.1. Parameter Estimates

The combination of the discrete choice dynamic programming algorithm and the maximum likelihood estimation procedure generates the following parameter estimates for $\theta_{A,op}$, $\theta_{K,op}$, $\theta_{\eta,op}$, $\theta_{A,mb}$, $\theta_{K,mb}$, $\theta_{\eta,mb}$ and θ_{dc} (see Table 3).

Table 3: Parameter estimates, standard errors and t-ratios

	$\theta_{A,op}$	$\theta_{K,op}$	$\theta_{\eta,op}$	$\theta_{A,mb}$	$\theta_{K,mb}$	$\theta_{\eta,mb}$	θ_{dc}
Estimate	311.1***	14,213***	244,931***	99.98***	111.7	85,073***	1,004***
Standard Error	(34.90)	(2,041)	(39,917)	(0.017)	(665.9)	(29,009)	(7.795)
T-ratio	8.92	6.96	6.14	5,743	0.17	2.93	128.8

The standard errors and t-ratios are derived using parametric bootstrapping. The t-ratios (with 49 degrees of freedom) indicate that the estimates for $\theta_{A,op}$, $\theta_{K,op}$, $\theta_{\eta,op}$, $\theta_{A,mb}$, $\theta_{\eta,mb}$ and θ_{dc} are statistically significant at the 99% confidence level. The parameter estimate for $\theta_{K,mb}$ is found not to be statistically significant.

The parameter $\theta_{A,op}$ interacts with the age, the parameter $\theta_{K,op}$ with the installed capacity and the parameter $\theta_{\eta,op}$ with the efficiency of the power plant. They are part of the fixed O&M cost term of the profit function of an operational OCGT. The fixed O&M costs are expressed in USD/MW/year and scale linearly with the three parameters.

The statistically significant estimate for $\theta_{A,op}$ (311.1) shows that an OCGT's fixed O&M costs are positively correlated with the power plant's age, but the economic impact of the estimate is small.[8] This is consistent with the assumption that the wear and tear associated with long-term operation necessitates increased maintenance as the turbine ages. The mean age of the turbines in our sample increases from 8 years in 2008 to 16 years in 2017. Furthermore, plant fixed O&M costs are also assumed to scale linearly with capacity and the inverse of the efficiency of the turbine. Larger turbines are assumed to be more costly to maintain, while efficiency serves as a proxy for the plant vintage: Newer, more modern and efficient plants likely have lower maintenance costs per unit of capacity than older units. All other things being equal, a

[8]Multiplying an estimate with its respective state variable shows the impact of the estimate on the economics of the plant. Cf. Tables 4 and 5.

higher efficiency would therefore translate to lower fixed O&M costs per unit of capacity. The parameter estimates for $\theta_{K,op}$ (14,213) and $\theta_{\eta,op}$ (244,931) confirm these relationships.

For the operator of a mothballed plant all costs are fixed costs. The statistically significant estimate for $\theta_{A,mb}$ (99.98) shows that the fixed costs increase with the age of the plant. However, we are unable to detect a statistically significant relationship between fixed costs and the capacity of the plant ($\theta_{K,mb}$). As expected, we find that mothballing significantly reduces a plants cost footprint.

The parameter θ_{dc} interacts with the plant capacity and describes the costs associated with the permanent shutdown of a plant. It is estimated as 1,004 USD/MW. Since the parameter estimate of θ_{dc} is positive, we are able to deduce that the process of decommissioning a plant is cash flow negative, which means the costs are higher than the potential revenue from selling old equipment such as the turbine on a secondary market.

Table 4 displays the model-derived fixed O&M costs for selected operational OCGTs in USD/kW/yr, based on the capacity clusters and plant-vintage-based efficiencies used in this study.[9]

Table 4: Fixed O&M cost estimates for an operational 10-year-old OCGT, by vintage class and capacity cluster (USD/kW/yr)

Vintage	Efficiency	24 MW	48 MW	81 MW	150 MW	300 MW
up to 1972	28%	50.8	32.5	28.8	20.1	15.8
1973 to 2000	35%	43.5	28.9	25.9	18.9	15.5
2001 to 2015	40%	39.9	27.0	24.5	18.3	15.3

As shown above, the costs negatively correlated with the vintage/efficiency of a plant. The older and less efficient the turbine, the higher the associated costs. At the same time, costs scale inversely with the capacity of a plant: the larger the unit, the lower the specific fixed O&M cost per unit of capacity. Our model estimates fixed O&M costs with a range from 15.3 USD/kW/yr for a relatively new and efficient, large (300 MW) gas turbine, to 50.8 USD/kW/yr for a small, relatively old low efficiency 24 MW turbine.

Table 5: Fixed O&M cost estimates for a mothballed 10-year-old OCGT, by vintage class and capacity cluster (USD/kW/yr)

Vintage	Efficiency	24 MW	48 MW	81 MW	150 MW	300 MW
up to 1972	28%	12.8	6.4	3.9	2.1	1.1
1973 to 2000	35%	10.3	5.2	3.1	1.7	0.9
2001 to 2015	40%	9.0	4.6	2.7	1.5	0.8

[9] We also show out of sample predictions for plants with a capacity of 300 MW, as turbines of this size are commercially available. See, for example, PJM (2014) and PJM (2018a).

The estimated fixed O&M cost for different capacity cluster/plant vintage combinations of mothballed OCGTs are shown in Table 5. They vary from 0.8 USD/kW/yr for a new, large 300 MW OCGT to 12.8 USD/kW/yr for a small, old unit. As with operating units, the larger a unit, the lower the specific fixed O&M cost. Overall, fixed O&M costs in the mothballed state are estimated to be around 25% of the fixed O&M costs in the operating state for smaller, older plant. The fixed O&M costs are as little as 5% for a large new unit. This shows that the relative benefit of mothballing is greater for larger plants.

The derived parameter estimates are broadly in line with what can be found in the relevant literature. PJM's own reports on the cost of newly built capacity (PJM, 2014, 2018a) give figures ranging from 12.2 to 25.5 USD/kW/yr for the fixed O&M cost of a newly built operational gas turbine-equipped peaker plant, which is in the lower half of the range of estimates given by the dynamic model. It should be noted that the PJM estimates are for new, large (+300 MW) plants, while the data set analysed using our model contains a significant number of smaller, older, lower efficiency units, which, as shown in Table 4, are likely to have higher specific fixed O&M costs.

Similarly, EIA (2016) states a fixed O&M cost estimate of 10 USD/kW/yr for a simple combustion turbine and 17.5 USD/kW/yr for a more advanced turbine. This is slightly below our own estimates. Again, this is not surprising, since these estimates too are for new plants, while most units in our data set are of older vintages.

Estimates of the costs of a mothballed unit or of decommissioning OCGTs are harder to come by. A report by the Dutch transmission system operator TenneT (2019) states that mothballing cuts the fixed O&M expenses of large (800 MW) *combined cycle* gas turbine (CCGT) power stations by roughly 95%. Our estimates suggest that the relative savings are of a similar magnitude for large OCGTs.

According to Raimi (2017), the costs of decommissioning gas fired power stations in the US range from 1,000 USD/MW to 50,000 USD/MW, with a mean value of 15,000 USD/MW. The source does not differentiate between simple OCGTs and the more complex CCGTs, but it appears reasonable to assume that the lower end of the range is more likely to be representative of the costs associated with decommissioning the smaller and less capital-intensive OCGTs. This is in line with our estimate of 1,004 USD/MW.

3.2. Fit of the model and model predictions

Using the parameter estimates described above, we are able to compare the model predictions to the data. In Figures 1, 2, and 3, we plot the estimated probability to operate, mothball or retire an OCGT against the actual observations for each of the observed years, providing a qualitative indication of the goodness of fit of the model.

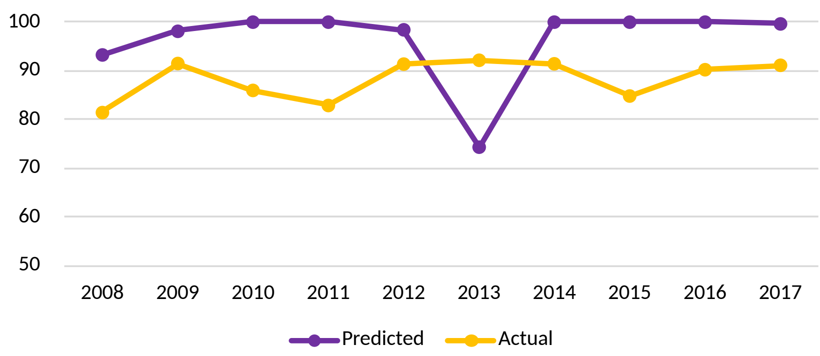

Figure 1: Probability of operating: model predictions vs actual observations (Percent)

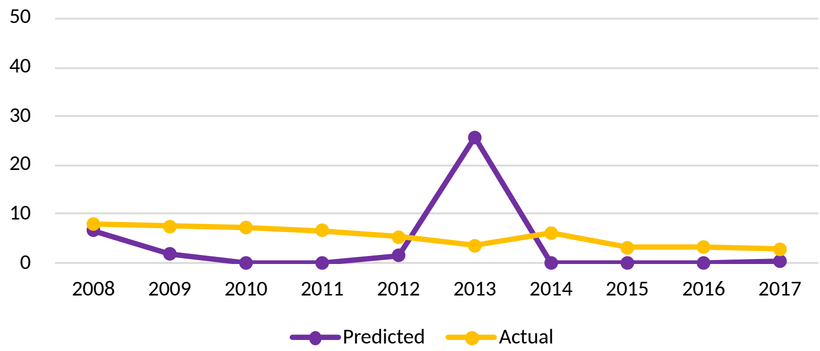

Figure 2: Probability of mothballing: model predictions vs actual observations (Percent)

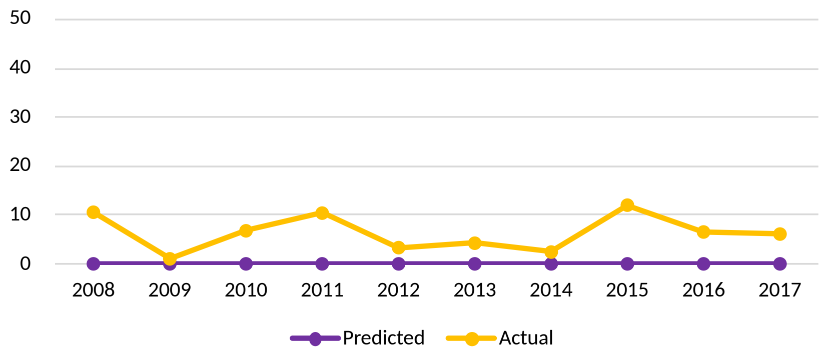

Figure 3: Probability of decommissioning: model predictions vs actual observations (Percent)

It is evident that the model over-predicts the probability to operate. Mothballings are predicted to occur only in 2008, 2009, 2012, and 2013. In the data, mothballings are observed in all years, although there is a declining trend in line with the long-run decline of natural gas prices and the improving relative competitiveness of gas-fired power plants. The model assumes that operators value the present more than the future, therefore the decision to mothball in a bad year would be rational. This is reflected in the behaviour of the model: the spike in estimated mothballings in 2008 can be explained by the prevailing high natural gas price (33.76 USD/MWh), the second peak in 2013 with low capacity payments (7.72 USD/kW/yr) in the PJM. In both years, profits are low enough to make mothballing the most economical choice in older vintage classes. A key assumption underpinning the model is that operators assign an equal probability to all future outcomes, in this case any of the ten years covered by the data set. Eight of these years are good profit years. In reality, however, operator expectation about the future may very much be shaped by recent trends and forecasts. In 2008, operators were probably still deciding based on the past experience of a high gas price world. From 2008 onward, for example, there has been a continuous decline in the gas price. 2008 is in fact the only year in the data set with a gas price above 30 USD/MWh. Operators would therefore assign a lower probability to such an outcome–a sharp increase in the gas price–than to the possibility of gas prices remaining low.

While the cost estimates are in line with the literature, the model does not predict any decommissionings, even though they can be observed in all of the years considered. The fact that in reality, retirements are more likely to occur than predicted by the model might also be explained by unobserved shocks, such as major failures in units that are potentially close to the end of their technical lifespan.

Despite the highlighted model limitations, it should be noted that in the data, mothballings account for less than 10% of the observations between 2008 and 2014 and less than 5% of the observations between 2015 and 2017. Decommissionings are similarly rare in any given year. There are peaks in 2008, 2011 and 2015 where they account for close to 10% of the total observations, but in most other years, the probabilities here are also lower than 5%. Taking the relative infrequency of both mothballings and decommissioning in the data into account, the predictive power of the model appears reasonable.

4. Sensitivity Analysis

The model estimates can be used to perform sensitivity analyses with respect to changes in the state variables of the model. Figures 4 to 6 display the impact—ceteris paribus—of a percentage change in capacity prices, electricity prices, and natural gas prices, respectively, on the probability of operating, mothballing or retiring a plant. These three state variables strongly influence the economics of the plant operator's decision problem. The sensitivity analyses are carried out as follows: the three state variables are analysed separately. For all time periods, the respective state variable is altered to the indicated percentage level. Subsequently, we run the model using our estimated cost parameters. Finally, the overall percentage shares of the three operational states are calculated from the probabilities delivered by the model runs.

In summary, an increase in the capacity or electricity prices elevates the probability of choosing to operate, and an increase in natural gas prices raises the probability of choosing to mothball or retire a plant.

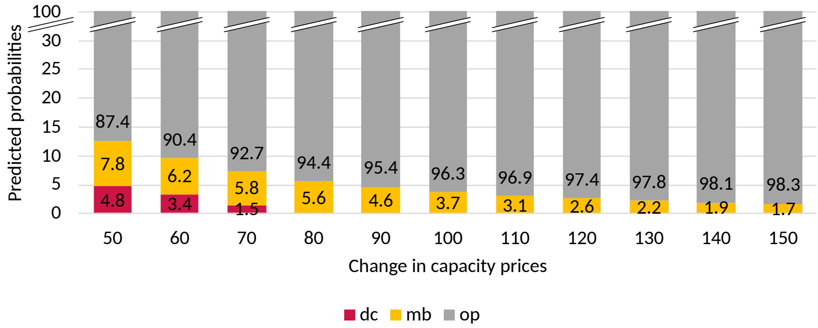

Figure 4: Predicted probabilities in response to a change in capacity prices (Percent)

Figure 4 shows that the probability to operate declines to 87.4% when the capacity prices decline to 50% of their respective values over the 2008-2017 period under investigation. At the same time, the probability of mothballing increases from 3.7% to 7.8%, while the probability of decommissioning increases to 4.8%. At the average capacity price level, decommissionings are—all else equal—never the most profitable choice and the related probability is thus 0%.

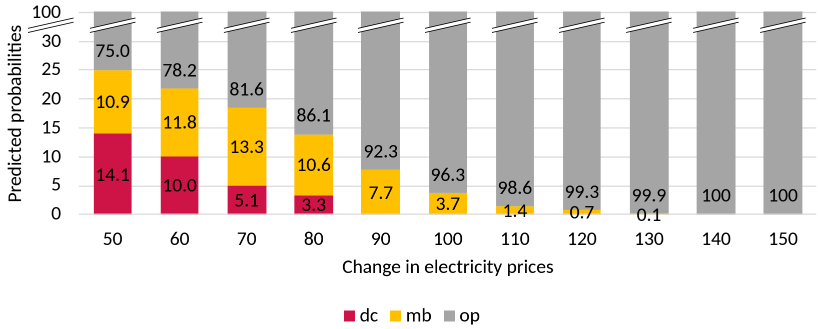

Figure 5: Predicted probabilities in response to a change in electricity prices (Percent)

In Figure 5, the electricity prices vary between 50% and 150% of the electricity price level over the periods under investigation. In the context of the sensitivity analyses, a decline in the electricity prices has the strongest effect on the probability to decommission. It increases to 14.1% when the prices of electricity are at the 50% level. The probability of mothballing peaks with a value of 13.3% at prices that are at the 70% level. At even lower prices, it declines again as decommissioning becomes a more profitable choice relative to it. This suggests that sustained periods of significantly lower electricity prices would likely lead to an increase in the number of plants exiting the market.

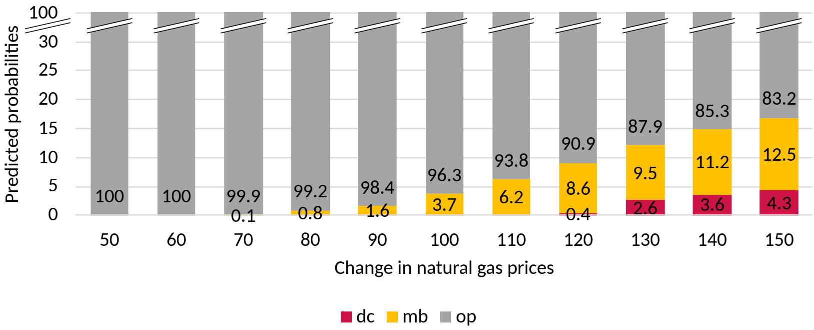

Figure 6: Predicted probabilities in response to a change in natural gas prices (Percent)

In Figure 6, natural gas prices vary between 50% and 150% of the original natural gas price level for the years 2008–2017. The probability of mothballing increases from the original 3.7% to 12.5% with a 50% rise in gas prices. The probability of retiring the plant first becomes larger than zero (0.4%) at the 120% natural gas price level. After a jump to 2.6% at the 130% price level it finally reaches 4.3% at the 150% price level.

In conclusion, the sensitivity analyses confirm that the original price levels describe a fairly profitable situation for OCGTs. For instance, only large deviations of the state variables over the entire observed period lead to projected decommissionings (at least -20% in electricity prices, +20% in natural gas prices, and -30% in capacity prices).

5. Conclusion

The paper at hand presents a methodology to estimate fixed cost parameters relevant to the decision to operate, mothball, or retire an OCGT using a combination of a discrete choice dynamic programming algorithm and a maximum likelihood estimation procedure. The model uses data on capacity, fuel, and electricity prices, as well as technical data and the operational status of OCGTs in the PJM market area.

For both operational and mothballed OCGTs, we find statistically significant, positive relationships of the fixed O&M costs of the power plant with the age of the plant, as well as with the inverse of the efficiency of the plant (which serves as a proxy for the plant vintage). As expected, we also found a statistically significant, negative relationship between the installed capacity and the fixed O&M costs of operational plants, confirming that an increase in scale results in lower specific costs. The estimated fixed O&M cost parameters for an operational OCGT vary from 15.3 USD/kW/yr for new, large, high efficiency units, to 50.8 USD/kW/yr for older, small, low efficiency turbines. Mothballing a plant reduces these costs by 75% to 95%, depending on plant vintage and size. Decommissioning an OCGT is found to be cash flow negative, which means that the associated cost exceeds any scrap value the equipment may have on secondary markets. The estimates are broadly in line with those provided by other sources, most notably PJM's own independent reports on the cost of new peaking capacity (PJM, 2014, 2018a). Yet, our results offer the additional benefit of a differentiation by technical attributes of a power plant. This differentiation is valuable for a better understanding of costs in the context of competition policy. It also allows for more accurate energy system modelling with the goal of more realistic analyses of network stability, investment decisions, and greenhouse gas emissions.

Using the estimates, we also analyse the sensitivity of operational choices of an OCGT with regard to changes in model inputs, namely capacity prices, electricity prices, and natural gas prices. The sensitivity analyses confirm the model to behave as expected, with a decrease in the capacity or electricity prices, first the probability of mothballing, and at lower price levels, also the probability of decommissioning an OCGT increases. The reverse is true for natural gas prices. Here, a price increase results in rising probabilities for plant mothballings and retirements.

A limitation of the approach used in this paper is that it relies on the assumption that the markets for electricity and capacity in PJM are perfectly competitive in order to derive robust parameter estimates. If players exert market power by withholding capacity (e.g. by mothballing otherwise profitable power plants), the costs estimated by the model could be exaggerated. However, the general alignment of the estimated parameters with cost estimates from other sources that employ different methodologies suggests this to be unlikely. Additionally, PJM's own state of the market reports underline that both the electricity and the capacity market have been broadly competitive throughout the period under investigation (Monitoring Analytics, 2020).

Future extensions of this work may consider additional choices a plant operator may make. Owing to a lack of data, for instance, the paper does not consider retrofits that improve the operating efficiency, lower costs or extend the operational lifetime of a power plant. Retrofits improve the forward-looking profit margin of a power plant. Based on expectations about future profits, it may be rational for such an investment to be undertaken, adding a fourth alternative to the choice of operating, mothballing or retiring.

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