The effects of bulk electricity storage on the PJM market

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Abstract

Recent advancements in battery technologies may make bulk electricity storage economically feasible. We analyze the value of two electrochemical storage technologies and traditional pumped hydropower storage in the 2010 PJM day-ahead energy market, using a reduced-form unit commitment model. We find that large-scale storage would increase overall social welfare in PJM. However, the annualized capital costs of storage would exceed social welfare gains. Consumers would save up to $4 billion annually due to reduced peak prices and reduced reliance on expensive peaking generators. These savings are equivalent to ~10% of sales in the PJM day-ahead energy market. Savings come largely at the expense of generator surplus. Existing market mechanisms are insufficient to encourage the socially optimal quantity of storage. Storage reduces the profitability of generators and the need for peaking generation capacity. Storage modestly increases emissions of CO_2 and other pollutants in a system with 2010 PJM characteristics.

Keywords: Electricity storage, wholesale market, arbitrage, consumer benefit, emissions, The PJM Interconnection

1. Introduction

Electric power systems today have limited storage capacity. Both in the USA and worldwide, storage makes up less than 3% of generation capacity [1]. This lack of storage forces grid operators to continuously balance generation and load, and prevents the electricity sector from operating as a conventional competitive market that relies on inventory.

Pumped hydropower storage (PHS) is the predominant storage technology today, making up 99% of all deployed storage capacity. The Federal Energy Regulatory Commission (FERC) has issued preliminary permits to an additional 55 PHS facilities, with a combined capacity of 47 GW [2]. R&D investments have led to rapid improvements in advanced battery technologies. Recent advancements suggest batteries with long cycle life may approach cost parity with pumped hydropower [1].

Inexpensive electricity storage has the potential to transform electricity markets. Storage can provide a variety of high-value services, including ancillary services such as frequency regulation [3]. Although profitable, these relatively small market opportunities are expected to saturate quickly: in PJM, average hourly regulation procurement is less than 1 GW, or ~1% of total load [4]. At that point, storage operators and manufacturers will consider larger volume, lower value applications. One such application is arbitrage in wholesale energy markets.

In wholesale markets, storage profits by buying electricity when prices are low and selling at peak hours. For small amounts of storage, this arbitrage will not affect prices or generator dispatch order. A large body of research exists on how small, price-taking storage devices can maximize profits in wholesale markets. This research has looked at storage in several applications, including the value of electric vehicle batteries for grid storage [5] and the economics of storage in the New York state electricity market [6].

How large amounts of storage will change wholesale markets is less well understood. Existing studies have found that the benefits of 1 GW of storage are 10% - 20% less than price-taking storage in PJM, assuming a linear relationship between load and electricity price [7]. Recent research [8] used a unit commitment model to study the effect of up to 800 MW of electricity storage on the Irish power system (12% of peak annual demand), finding that storage reduces production costs, but increases average electricity prices due to storage capital costs. Using a game-theoretic approach, Schill and Kemfert find that while the utilization of storage depends on the operator's market power, storage generally increases consumer welfare and reduces producer surplus in the German market [9]. Sioshansi analyses the value of large-scale wind and energy storage deployments in the ERCOT (Texas) market and the effects of market power [10].

Here we analyze the effect of bulk storage on the PJM's day-ahead wholesale energy market and capacity market. Storage has the potential to effectively provide power at peak load hours, which would reduce wholesale energy prices and expenditures on capacity markets. We estimate the value of large storage deployments in the PJM Interconnection's day-ahead energy market and capacity market with a reduced-form unit commitment model. The viability of storage in PJM is likely to be representative, as PJM is the world's largest competitive electricity market with $35 billion in transactions and 167 GW of installed capacity in 2010 [4].

We build upon existing research by investigating the feasibility of three different storage technologies: pumped hydropower storage, aqueous hybrid ion (AHI) batteries (an example of the class of aqueous intercalation batteries), and sodium sulfur (SS) batteries. We investigate how storage will affect overall consumer welfare. We also investigate the effect on consumer costs on the day-ahead wholesale market and capacity market, the profitability of bulk storage, and its effect on the revenues of generators. We constrain the analysis to short-term effects; we assume storage does not cause changes to the PJM generation fleet or net load (we do include the additional load imposed by charging the storage). Finally, we investigate how bulk storage will affect emissions of CO_2, nitrous oxides (NO_X), and sulfur dioxide (SO_2).

2. Methods

2.1. Unit commitment and economic dispatch model

We developed a reduced-form unit commitment and economic dispatch (UCED) model, called PHORUM, to simulate the 2010 PJM day-ahead market. This software is open source and freely available online[*]. PHORUM is a mixed integer linear program (MILP) that calculates the least-cost combination of generators and storage to meet load at each hour on the day-ahead market, subject to generator and transmission constraints. We assume that under a scenario with large capacities of storage, system operators will control the dispatch of storage to maintain grid reliability.

PJM calculates locational marginal prices (LMPs) for more than 10,000 nodes [4]. The nodal pricing system allows PJM to account for transmission constraints that result from locational variation in supply and demand. In general, transmission constrains the flow of power from Midwestern states to coastal load centers, resulting in higher LMPs along the coast. Congestion costs make up approximately 5% of costs in the PJM day-ahead energy market [4]. Details of transmission assets are designated as Critical Energy Infrastructure Information and not publically available. However, PJM provides hourly data on the capacity of seven transmission interfaces, each made up of multiple 500 kV lines, which form critical congestion paths that made up 49% of all congestion costs in 2010 [4].

Based on the seven transmission interfaces, we divided PJM into five transmission buses to account for transmission constraints (Fig. 1). We aggregated the seven PJM interfaces into six transmission lines between regions. We ignored other transmission constraints, and assumed lossless power flow between buses. We assumed that within each bus, transmission is unconstrained and all LMPs are equal. 2010 LMP data shows that within our defined buses, zonal LMPs are highly correlated (Appendix A, Figure 10), supporting this assumption. Other researchers have used this technique of dividing PJM into regions [11]. More details can be found in Appendix A.

[*] PHORUM can be downloaded at https://github.com/rlueken/PHORUM

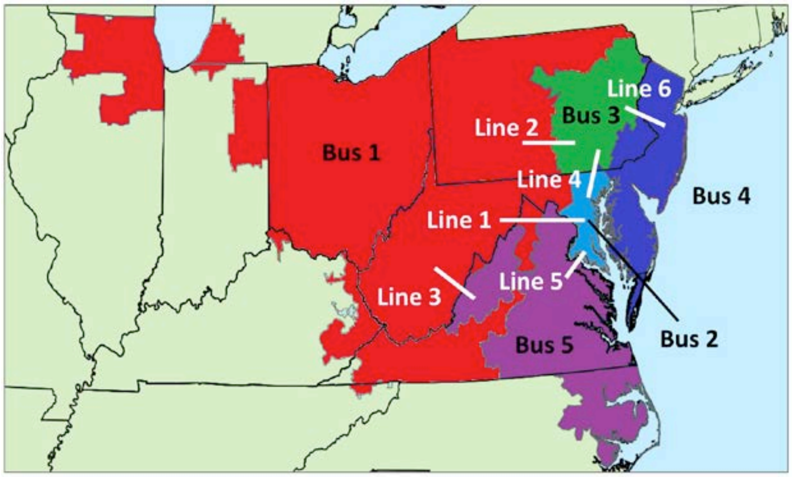

Fig. 1 Reduced form model of the PJM Interconnection

We simulated 1,017 generators and four existing PJM pumped hydroelectric storage (PHS) facilities: Bath County (VA, 2.8 GW), Yards Creek (NJ, 400 MW), Muddy Run (PA, 1 GW), and Smith Mountain (VA, 240 MW). These facilities total 4.5 GW of capacity, approximately 2.5% of total generation capacity [12]. Generators smaller than 5 MW were excluded. We assumed demand is perfectly inelastic; the short-term elasticity of demand is highly inelastic [13]. We constrained the analysis to short-term effects; we assumed storage does not cause changes to the PJM generation fleet or net load.

PHORUM tracks emissions of CO_2, NO_X, and SO_2 from each generator, using emission rate data from the EPA Emissions & Generation Resource Integrated Database (eGRID) [9]. We assumed emission rates are linear with output level and independent of time of year or ambient temperature. We also did not account for variations in NO_X output for ozone season. We tracked emissions associated with generator startups [14]; however, startup emissions are less than 1% of total emissions.

We ran 365 daily optimizations, each minimizing costs over a 48-hour period. The optimizations were rolled over, with the 25th hour of the previous optimization becoming the first hour of the next. This rollover ensured that minimum runtime/downtime constraints held between days. Storage state of charge is constrained to 50% for the first hour of the first optimization and the 48th hour of each optimization. PJM's actual dispatch process minimizes costs over one day only; cross-day decisions are made manually by the day-ahead operator [15]. Appendix A contains more details on how variables are passed across day boundaries.

We assumed perfect information over the 48-hour optimization. In reality, the system operator has perfect information for the first 24 hours of each period (the day ahead forecast), but not hours 25-48 (the day ahead forecast for the second day). The assumption of perfect information inflates the value of storage; in reality, forecast error in load and wind generation will lead to suboptimal use of storage. Optimizing storage operations over a longer period of time would increase the value of storage; however, accurately predicting load more than 48 hours out may be difficult. The relatively high charging and discharging speed of storage gives system operators the ability to flexibly respond to unforeseen forecast errors in real time [3]. We do not simulate the real time market, and therefore do not capture this value.

Two types of data were used: hourly data and generator data. Hourly data from PJM were used to calculate net hourly load at each bus and transmission limits between buses. Net hourly load considers such factors as imports, exports, and must-take wind generation. Generator data were used to characterize each generator, and were derived from multiple sources, including eGRID, EPA National Electric Energy Data System (NEEDS) database, and PJM reports. Data on fuel prices, aggregated by state and by month, were from the Energy Information Agency. Appendix A contains details on all data sources.

To maintain reliability, PJM co-optimizes the day-ahead energy market and a separate day-ahead scheduled reserve (DASR) market. Rather than co-optimizing the energy and DASR markets, we approximated hourly reserve requirements by adding 3.6 GW to hourly load. 3.6 GW is equivalent to PJM's hourly synchronized reserve requirement: the total capacity of largest unit in RFC (bus 1), the largest unit in the Mid-Atlantic control zone (buses 2-4), and the largest unit in Dominion (bus 5) [16]. This approximation overstates the load each hour, and therefore increases hourly LMPs. However, the error caused by this approximation is minimal; compared to a scenario in which reserve requirements are not added to load, average LMPs increase by less than 5%. When compared to actual 2010 LMPs, including reserves as load also results in lower error than not including reserves as load. Section 3 contains more details on model validation. Mean hourly LMP error is 0%, suggesting this approximation does not induce bias into our results. The approximation was necessary to keep computation time manageable.

Table 1 Model Nomenclature

Constants

$D_r(t)$	Consumer demand at time t in bus r [MW]
$IMP_r(t)$	Net imports from other regional transmission operators (RTOs) at time t to bus r [MW]
$ND_r(t)$	Net load demand at time t in bus r [MW]
$SR_r(t)$	Spinning reserve requirement at time t for bus r [MW]
$WG_r(t)$	Wind generation at time t in bus r [MW]
$\overline{P_{rm}}(t)$	Max power flow on interface rm [MW]
$\overline{C}_k$	Max SoC of storage unit k [MWh]
$C_k(0)$	Initial SoC of storage unit k [MWh]
$\overline{P_k}$	Max charge/discharge rate from storage unit k [MW]
ρ	Round trip efficiency of storage units [%]
$\boldsymbol{FC_i}$	Fuel cost of generator i [$/MMBtu]
G_i	Number of periods generator i must be initially online due to its minimum up time constraint
HR_i	Heat rate of generator i [MMBtu/MWh]
L_i	Number of periods generator i must be initially offline due to its minimum down time constraint
OM_i	Variable O&M costs of generator i [$/MWh]
$\overline{P_i}, \underline{P_i}$	Max and min output from generator i [MW]
$P_i(0)$	Initial level of generator i [MW]
$\dot{\boldsymbol{P}}_{\boldsymbol{i}}$	Ramp rate of generator i [MW/h]
S_i	Startup cost of generator i [$]
$U_i(0)$	Initial state of generator i (1 if online, 0 otherwise)
UT_i, DT_i	Minimum uptime / downtime of generator i

Variables

$p_{r,rm}(t)$	Power imported (+) or exported (-) from bus r via interface rm [MW]
$c_k(t)$	SoC of storage unit k at time t [MWh]
$pd_k(t)$, $pc_k(t)$	Power discharged or charged by storage unit k at time t [MW]
$p_i(t)$	Power generated by generator i at time t [MW]
$s_i(t)$	Startup cost of generator i at period t [$]
$u_i(t)$	State of generator i at time t (1 if online, 0 otherwise)

Sets

I_r	Set of indices of the generators in bus r
K_r	Set of indices of the storage units in bus r
R	Set of buses
RM	Set of indices of the transmission interfaces
T	Set of indices of the time periods

Table 2 Model Formulation

Minimize (1)

$$\sum_{t\in T}\sum_{r\in R}\sum_{i\in I_r} 1.1 p_i(t)*(HR_i*FC_i+OM_i)+s_i(t)$$

subject to

System Constraints

$$ND_r(t)=\sum_{i\in I_r} p_i(t)+\sum_{k\in K_r}(pd_k(t)-pc_k(t))+\sum_{rm\in RM} p_{r,rm}(t) \quad \forall t\in T,\forall r\in R \tag{2}$$

$$-\overline{P_{rm}}(t)\le p_{r,rm}(t)\le \overline{P_{rm}}(t) \quad \forall r\in R,\forall rm\in RM,\forall t\in T \tag{3}$$

Storage Constraints

$$c_k(t+1)=c_k(t)+\sqrt{\rho}*pc_k(t)-\frac{pd_k(t)}{\sqrt{\rho}} \quad \forall k\in K,\forall t\in T \tag{4}$$

$$0\le c_k(t)\le \overline{C_k} \quad \forall k\in K,\forall t\in T \tag{5}$$

$$0\le pd_k(t)\le \overline{P_k} \quad \forall k\in K,\forall t\in T \tag{6}$$

$$0\le pc_k(t)\le \overline{P_k} \quad \forall k\in K,\forall t\in T \tag{7}$$

$$c_k(0)\le C_k(0) \quad \forall k\in K \tag{8}$$

Generator Constraints

$$p_i(0)=P_i(0) \quad \forall i\in I \tag{9}$$

$$u_i(0)=U_i(0) \quad \forall i\in I \tag{10}$$

$$s_i(t)\ge S_i*(u_i(t)-u_i(t-1)) \quad \forall i\in I,\forall t\in T \tag{11}$$

$$s_i(t)\ge 0 \quad \forall i\in I,\forall t\in T \tag{12}$$

$$\underline{P_i}*u_i(t)\le p_i(t)\le \overline{P_i}*u_i(t) \quad \forall i\in I,\forall t\in T \tag{13}$$

$$p_i(t)\le p_i(t-1)+\dot{P}_i*u_i(t-1)+\underline{P_i}*(u_i(t)-u_i(t-1)) \quad \forall i\in I,\forall t\in T \tag{14}$$

$$p_i(t-1)-p_i(t)\le \dot{P}_i*u_i(t)+\underline{P_i}*(u_i(t-1)-u_i(t)) \quad \forall i\in I,\forall t\in T \tag{15}$$

$$\sum_{t=1}^{G_i}[1-u_i(t)]=0 \quad \forall i\in I \tag{16}$$

$$\sum_{n=t}^{t+UT_i-1} u_i(n)\ge UT_i[u_i(t)-u_i(t-1)] \quad \forall i\in I,\forall t\in G_i+1\ldots T-UT_i+1 \tag{17}$$

$$\sum_{n=t}^{T}\{u_i(n)-[u_i(t)-u_i(t-1)]\}\ge 0 \quad \forall i\in I,\forall t\in T-UT_i+2\ldots T \tag{18}$$

$$\sum_{t=1}^{L_i} u_i(t)=0 \quad \forall i\in I \tag{19}$$

$$\sum_{n=t}^{t+DT_i-1}[1-u_i(n)]\ge DT_i[u_i(t-1)-u_i(t)] \quad \forall i\in I,\forall t\in L_i+1\ldots T-DT_i+1 \tag{20}$$

$$\sum_{n=t}^{T}\{1-u_i(n)-[u_i(t-1)-u_i(t)]\}\ge 0 \quad \forall i\in I,\forall t\in T-DT_i+2\ldots T \tag{21}$$

$$ND_r(t)=D_r(t)+SR_r(t)-WG_r(t)+IMP_r(t) \quad \forall t\in T \tag{22}$$

Our formulation owes much to earlier work [17, 18] and is similar to the model used by PJM to dispatch power on the day-ahead market [19]. The objective function, Eq (1), minimizes the total social cost of providing electricity, which includes the variable costs and startup costs. The equation includes the 10% cost adder that PJM allows all generators to add to their hourly bid [20]. Eq (2) sets separate supply/demand constraints for each bus. The LMPs at each bus are the negative Lagrange multiplier (shadow price) of these constraints.

Eq (3) sets transmission limits between buses. Equations (4-8) are storage constraints that limit the capacity, charge/discharge rates, and set initial charge levels. Eqs (9-10) set initial conditions for generators. Eqs (11-12) triggers startup costs when a generator turns on, and (13) constrains generation capacity while the generator is online. Eqs (14-15) constrain generator ramp rates. Eqs (16-18) ensure generators satisfy uptime constraints: (16) sets initial uptimes, (17) constraints uptimes for subsequent hours, and (18) forces generators that turn on near the end of the day to stay on over the final time periods. Eqs (19-21) are analogous to (16-18), but for generator downtimes. Eq (22) calculates net hourly load in each region, considering wind generation and imports/exports to PJM.

2.2. Storage modeling

We modeled three storage technologies: pumped hydropower, aqueous hybrid ion (AHI) batteries, and sodium sulfur (SS) batteries. We modeled each technology with four parameters: capacity (in GW), round-trip efficiency (RTE), duration (how long storage can provide the rated capacity before going flat), and location (bus 1-5). We varied capacity from 0.5 – 80 GW (0.4% - 60% of peak annual demand).

Data on storage technologies is uncertain for three reasons. First, AHI and SS battery technologies are relatively new and extensive commercial data are not yet available. Second, performance and cost of large storage projects vary greatly. Third, the RTE of electrochemical batteries depends on how quickly they are charged and discharged; charging more slowly improves efficiency [21]. To incorporate these uncertainties, we modeled two cases for each technology, as shown in Table 3. The lower bound scenario assumes pessimistic technical assumptions and fast charging/discharging (low RTE, low duration, high capital cost); the upper bound scenario assumes optimistic technical assumptions and slow charging/discharging (high RTE, high duration, low capital cost). Cycle counts are held constant between upper and lower bound scenarios. Parameter assumptions are from [1, 22, 23].

Table 3 Modeled storage technologies [1, 22, 23]. Costs in 2010 dollars

Technology	Duration (hours)	% Round trip efficiency	Maximum cycle count	Cost [$/kWh]
Aqueous hybrid ion (AHI) battery				
Lower bound	4	80%	10,000	300
Upper bound	20	90%	10,000	300
Sodium sulfur (SS) battery				
Lower bound	6	75%	4,500	550
Upper bound	8	86%	4,500	535
Pumped hydropower				
Lower bound	4	70%	>13,000	430
Upper bound	12	85%	>13,000	250

We deployed storage to each of the five buses in proportion to fraction of total annual load on that bus (45% bus 1, 10% bus 2, 8% bus 3, 24% bus 4, 14% bus 5). We assumed storage could be deployed in any grid location and in any capacity. We also assumed storage is dispatched by the system operator, who has perfect information of prices over the 48-hour optimization. We made several simplifying assumptions in our model of storage devices, ignoring storage degradation, minimum depth of discharge, operational costs, and standby losses. By ignoring these complications, we somewhat overestimated the value of storage. We set storage state of charge to 50% for the first hour of the year and the last hour of each optimization.

We calculated the lifespan of each storage technology with Eq (23). We assumed one ‘cycle’ is equivalent to discharging energy equal to the device’s capacity. We assumed all devices are decommissioned after 40 years, putting an upper bound on lifespan.

$$Lifespan = \min\left(\frac{total\ cycle\ count * kWh\ capacity}{annual\ kWh\ discharged}, 40\right) \qquad (23)$$

2.3. Effects of storage on market participants

We modeled the effect of bulk storage by first simulating a ‘business as usual’ case, the actual operations of the 2010 PJM day-ahead energy market. We then added bulk storage and examine how prices, dispatch order, and emissions changed. From the annual simulations, we quantified the following effects that storage has on participants in the PJM wholesale market.

2.3.1. Consumer benefits

We analyzed the benefits that storage provides to consumers on the PJM day-ahead wholesale energy market and capacity market. We quantified energy market savings as the reduction in total annual consumer expenditures on the energy market, as calculated by Eq (24).

$$Consumer\ energy\ costs = \sum_{hour}\sum_{bus} LMP_{hour,bus} * Load_{hour,bus} \qquad (24)$$

In PJM, generators receive payments on the capacity market for providing firm capacity towards reliability. Bulk storage reduces the amount of capacity that is needed; as more storage is deployed, fewer peaking plants are needed and could in theory be decommissioned. We quantified the savings to consumers if these unused plants are decommissioned with the 2010/2011 PJM capacity auction price of $175/MW-day [24]. We did not endogenously model effects of storage on capacity auction clearing prices, but performed sensitivity analyses on the benefits under a range of clearing prices (see section 5). Storage is currently ineligible for capacity payments in PJM [25]. Other research has estimated the capacity value of storage by using other methods [26, 27, 28].

Finally, we calculated the net consumer benefits of storage: changes in the money transacted on the wholesale energy and capacity market minus the annualized cost of storage. A positive net consumer benefit means consumers are made better off by storage on the wholesale and capacity markets. We annualized capital cost using an 8% cost of capital and storage lifespan calculated with Eq (22).

2.3.2. Effect on generators

Bulk storage changes the dispatch of generators, altering how much electricity generators produce and how much revenues they receive. For each generator in PJM, we compared annual electricity production and revenues for a scenario with storage to the business as usual scenario.

2.3.3. Storage profitability

Storage profits in this application by arbitraging between high and low prices on the wholesale energy market. Storage profits were calculated as in Eq (25).

$$StorageProfit = \sum_{buses}\sum_{hours}(LMP_{bus,hour} * Discharge_{bus,hour} - LMP_{bus,hour} * Charge_{bus,hour}) - AnnualCost \quad (25)$$

2.3.4. Overall social welfare

We define changes in overall social welfare as reductions in total energy market costs minus the annualized capital cost of storage. Reductions in total energy market costs, measured as improvements to the system operator's cost minimization (Eq. 1), are the net effect of storage on consumers, generators, and storage operators. Changes in the capacity market are excluded, as any consumer savings in the capacity market are a direct transfer from generators. Our social welfare analysis excludes implications of adding storage on other markets and the effects of changes in emissions of CO_2, NO_X, and SO_2.

2.3.5. Emissions

We quantified the change in annual emissions of CO_2, NO_X, and SO_2 due to storage by comparing the total annual emissions from each PJM generator in a scenario with storage to the business as usual scenario.

3. Validation

To validate that PHORUM captures the salient factors that determine electricity price and dispatch order, we constructed a business as usual (BAU) scenario that simulates the market as it was in 2010. We then compared the LMPs from the BAU simulation to the actual 2010 day-ahead market LMPs, aggregated by bus. We measured accuracy with two metrics: hourly error and daily arbitrage error. The first tracks the model's accuracy in predicting prices each hour (Eq 26). The second tracks how well PHORUM predicts the minimum and maximum daily prices (Eq 27).

The model consistently modestly under-predicts arbitrage and therefore under-predicts the value of storage. We investigated the implications by comparing the total annual revenue a price-taking storage device would receive under the simulated LMPs and the actual 2010 LMPs. Annual revenue to storage with a two-hour duration (charges the two lowest priced hours and discharges the two highest priced hours each day) is 3% less under the simulated LMPs than the actual 2010 LMPs; revenue for 20-hour duration storage is 10% less. We conclude that although our results will be biased to somewhat underpredict the value of storage, results are close enough to the observed data to validate the model's usefulness for this application.

Table 4 Validation equation and variables

Equation		Variables	
$$Hourly\ Error = \frac{LMP_{modeled} - LMP_{actual}}{LMP_{actual}}$$	(26)	$LMP_{modeled}$	Modeled hourly LMP
		LMP_{actual}	Actual 2010 hourly LMP
$$Daily\ Aritrage\ Error = \frac{\Delta LMP_{max,modeled} - \Delta LMP_{max,actual}}{\Delta LMP_{max,modeled}}$$	(27)	$\Delta LMP_{max,modeled}$	Modeled maximum daily difference in hourly LMPs
		$\Delta LMP_{max,actual}$	Actual 2010 maximum daily difference in hourly LMPs

Table 5 Validation Results

	Bus 1	Bus 2	Bus 3	Bus 4	Bus 5	Average
Hourly Error (%)						
Mean	1%	0%	8%	5%	-15%	0%
Standard Deviation	24%	24%	24%	23%	21%	23%
Arbitrage Error (%)						
Mean	4%	-6%	9%	15%	-34%	-2%
Standard Deviation	72%	64%	68%	71%	52%	65%

4. Results

4.1. Consumer benefits

Storage benefits consumers in two ways: by reducing costs in the wholesale energy market, and by reducing reliance on expensive peaking generators. Table 6 shows how consumer benefits increase as more storage is deployed.

Storage reduces wholesale energy costs by lowering locational marginal prices (LMPs) at high-load hours. Annual wholesale energy savings reach $2 billion. More than 75% of total savings are reached with 20 GW of storage. These savings are up to 6% of total 2010 PJM wholesale energy costs of $35 billion. Storage also reduces LMP volatility; large deployments reduce volatility by more than 50%.

Storage reduces consumer capacity costs by replacing peaking plants, which in theory could be decommissioned. Up to 30 GW, or 20% of total PJM capacity, could be retired (Fig. 2). Capacity savings approach $2 billion, assuming the 2010/2011 PJM capacity auction price of $175/MW-day (PJM 2012). The majority of these benefits are achieved by 20 GW of storage.

Decommissioning plants due to bulk storage would not significantly affect PJM reserve margins. According to the North American Electric Reliability Corporation (NERC), any storage primarily used for energy (not regulation or transmission) qualifies as reserves [29]. Therefore, PJM reserve margins do not fall below 15% for any level of storage deployment, as additions in storage capacity offset the generation capacity that is decommissioned.

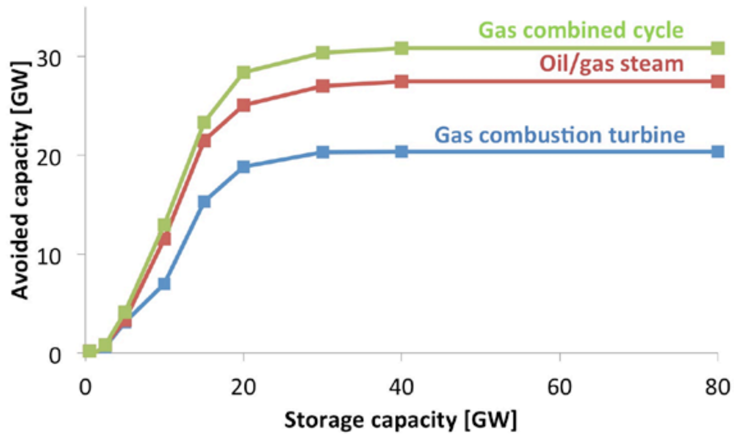

Fig. 2 Cumulative peaking capacity that is never needed due to storage, and could in theory be decommissioned. Storage technology is AHI battery, 90% round trip efficiency, 20-hour duration

Table 6 Consumer savings due to storage. Energy savings are savings in the wholesale day-ahead energy market. Capacity savings are the avoided capacity payments to plants that storage has replaced, valued at the 2010/2011 capacity auction price of $175/MW-day. Ranges represent lower and upper bounds. 2010 dollars

			Storage Capacity [GW]		
Savings [$B]	**1**	**10**	**20**	**40**	**80**
Sodium sulfur batteries					
Energy	0.2	1.2 – 1.7	1.6 – 2.2	1.7 – 2.0	1.7 – 1.9
Capacity	0.0 – 0.1	0.7 – 0.8	1.5 – 1.7	1.6 – 1.8	1.7 – 1.9
Total	0.2 – 0.3	1.9 – 2.5	3.1 – 3.9	3.3 – 3.8	3.4 – 3.8
Aqueous hybrid ion batteries					
Energy	0.1 – 0.4	0.8 – 1.7	1.4 – 2.0	1.9 – 2.0	1.8 – 2.0
Capacity	-0.1 – 0.0	0.5 – 0.8	1.0 – 1.8	1.7 – 2.0	1.7 – 2.0
Total	0.0 – 0.4	1.3 – 2.5	2.4 – 3.8	3.6 – 4.0	3.5 – 4.0
Pumped hydropower					
Energy	0.1 – 0.4	0.7 – 1.4	1.2 – 2.0	1.5 – 1.9	1.6 – 1.7
Capacity	-0.1 – 0.0	0.5 – 0.8	0.9 – 1.7	1.6 – 1.9	1.6 – 1.9
Total	0.0 – 0.4	1.2 – 2.6	2.1 – 3.7	3.1 – 3.8	3.2 – 3.8

We next calculated net consumer benefit, defined as total consumer benefit minus annualized storage costs. Fig. 3 shows that AHI batteries can provide positive net consumer benefits depending on parameter assumptions, while the net benefit of SS batteries is always negative. Under optimistic technical assumptions and operating conditions (slow, high efficiency charging and discharging), AHI can provide positive net benefits up to 35 GW of deployment. First movers provide large benefits, as they displace the most inefficient and expensive peaking generators. The net benefits of AHI are similar to that of traditional pumped hydropower. Differences in capital costs are the primary driver of the variation in net consumer benefit (Section 5.2).

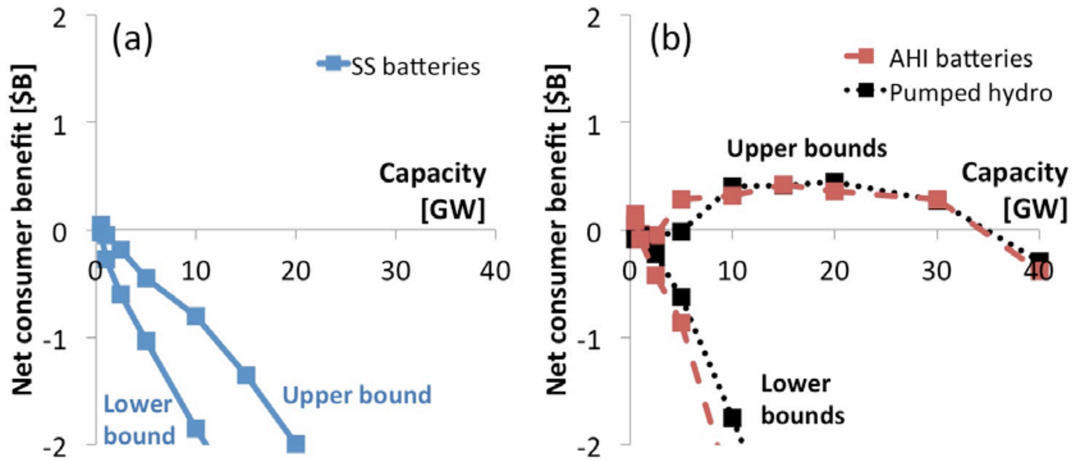

Fig. 3 Net annual consumer benefit (total consumer benefit – annualized storage cost). (a): sodium sulfur (SS) batteries; (b): aqueous hybrid ion (AHI) batteries and pumped hydropower. Net benefits vary depending on assumptions of storage parameters and cost. Net benefits of AHI batteries similar to that of conventional pumped hydro. 2010 dollars

4.2. Effect on generators

By reducing prices on the wholesale energy market and reducing reliance on peakers, storage reduces generator revenues. As shown Table 7, generation from peaking plants (combustion turbine, oil/gas steam, and combined cycle) falls as they are displaced by storage. Output from coal plants increases as they charge storage at off-peak hours. Revenues to all generators on the wholesale energy market fall as storage capacity increases; total revenues fall by more than 10% in high storage cases. In addition, generator revenues on the capacity market are reduced by an amount equal to consumer savings on the capacity market (Table 6). Our findings agree with other research that shows the increases in consumer welfare due to storage come with significant reductions in producer surplus accruing to generators [7, 30].

Table 7 Generator output and energy market revenue, business as usual (BAU) scenario and a scenario with 80 GW of aqueous hybrid ion (AHI) storage (90% round trip efficiency, 20-hour duration). Revenues in 2010 dollars

	Generation [TWh]		**Energy Market Revenues [$M]**	
Generator type	**BAU**	**AHI storage**	**BAU**	**AHI storage**
Nuclear	260	260	$9,200	$8,950
Hydropower	8	8	$380	$370
Coal steam	420	432	$5,350	$4,820
Natural gas combined cycle	48	42	$650	$20
Natural gas combustion turbine	4	0	$131	$0
Oil/gas steam	1	0	$20	$0

4.3. Storage profits

Fig. 4 shows that storage revenues peak with considerably less than 20 GW of storage deployed; as more storage is deployed, less arbitrage opportunities are available, and revenues drop. If used only for arbitrage, net annual profits are negative, regardless of the technology used or capacity deployed. For both

AHI and SS batteries, debt service on capital costs greatly exceeds wholesale energy market revenues (Table 8).

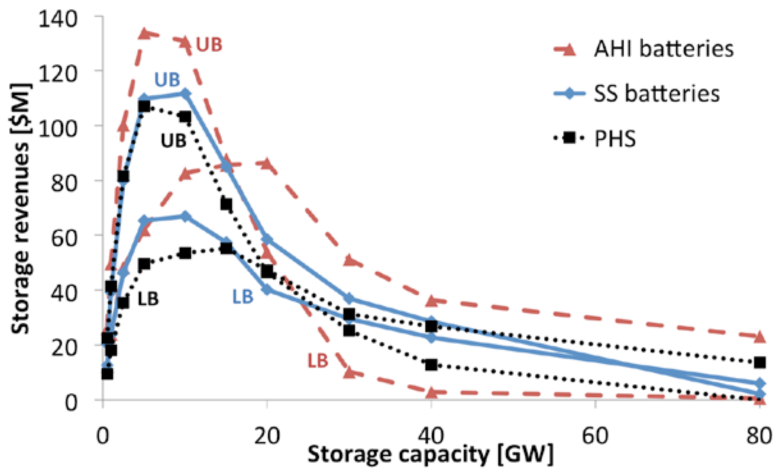

Fig. 4 Annual wholesale market arbitrage revenues to storage operators. Revenues vary depending on upper bound (UB) or lower bound (LB) assumptions of storage parameters and cost. Revenues peak with less than 20 GW of storage deployed. 2010 dollars

Table 8 Annual net profits of storage technologies to storage operator. Ranges represent lower and upper bounds. 2010 dollars

Capacity [GW]	**AHI battery annual profits [$B]**	**SS battery annual profits [$B]**	**PHS annual profits [$B]**
1	[0, 0]	[0, -1]	[0, 0]
10	[-5, -1]	[-4, -3]	[-2, -1]
80	[-40, -8]	[-28, -20]	[-20, -7]

4.4. Overall social welfare

Adding storage to the system increases overall social welfare on the wholesale energy market. Total energy market savings monotonically increase as more storage is deployed (Fig. 5). Total market savings are much smaller than improvements in consumer welfare (Table 6), as the majority of consumer welfare benefits are transfers from generators. Although storage increases total social welfare, the annualized capital costs of storage exceed these savings (Table 9).

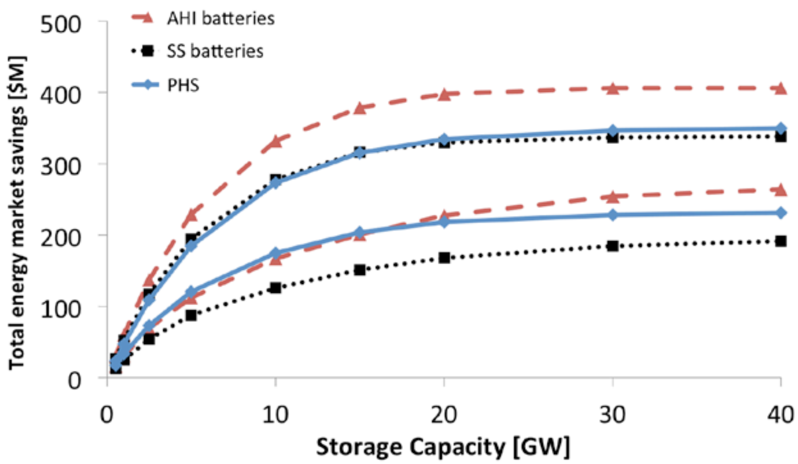

Fig. 5 Total savings on the wholesale energy market due to storage. 2010 dollars

Table 9 Change in overall social welfare on the energy market minus annualized storage capital cost. Ranges represent lower and upper bounds. 2010 dollars

Capacity [GW]	AHI battery [$B]	PHS [$B]	SS battery [$B]
1	[0, 0]	[0, 0]	[0, 0]
10	[-5, -1]	[-4, 0]	[-4, -3]
20	[-10, -2]	[-9, -2]	[-8, -5]
40	[-20, -4]	[-17, -3]	[-15, -10]
80	[-40, -8]	[-35, -7]	[-30, -21]

4.4. Effect on emissions

Storage modestly increases emissions (Table 10). This is for two reasons. First, storage is primarily charged off-peak by coal plants, which have higher emissions than the peaking gas plants they replace. Second, additional electricity must be generated to compensate for the losses inherent in storing electricity. However, the effect of storage on emissions will depend on underlying market dynamics (see section 5).

Table 10 Annual emission increases and associated damages due to storage in the 2010 PJM wholesale energy market. Storage technology is aqueous hybrid ion (AHI) batteries, 90% round trip efficiency, 20-hour duration.

AHI battery capacity [GW]	Change in Emissions [MT] (%)		
	CO_2	NO_X	SO_2
1	2,400,000 (0.5%)	2,500 (0.6%)	16,600 (0.9%)
10	5,400,000 (1.2%)	4,700 (1.2%)	58,000 (3.0%)
80	6,600,000 (1.5%)	5,600 (1.4%)	71,800 (3.7%)

5. Sensitivity Analysis

We tested the robustness of our results with four sensitivity analyses:

- Sensitivity of consumer benefits to storage round trip efficiency and duration
- Sensitivity of net consumer benefits to the capital cost and lifespan of storage
- Sensitivity of consumer benefits to capacity market prices
- Sensitivity of consumer benefit and emissions to fuel prices and the amount of wind deployed.

5.1. Sensitivity to round trip efficiency and duration parameters

To test for sensitivity to RTE and duration, we performed a one-way sensitivity analysis. We varied RTE of a generic storage device from 64%-100% and duration from 4-20 hours. These ranges capture the majority of storage technologies being discussed today. Fig. 6 shows that increasing storage RTE increases total consumer savings on the wholesale energy and capacity markets. Increasing duration does not increase savings, but allows a given level of savings to be reached with less storage capacity.

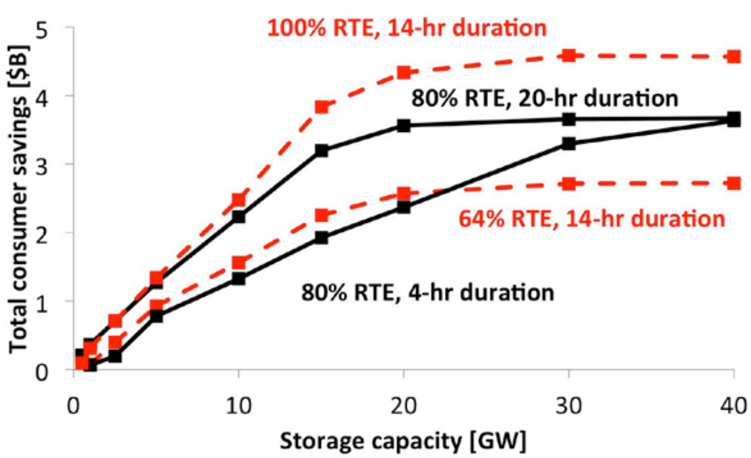

Fig. 6 Sensitivity of total annual consumer savings to storage round trip efficiency (RTE) and duration. 2010 dollars

5.2. Sensitivity to capital costs and lifespan

We next tested for sensitivity to the capital cost and lifespan of storage technologies. We fixed the capital cost at $300/kWh for both SS and AHI battery technologies and analyzed the resulting net consumer benefit. Because the lifespan of SS batteries varies from 14 – 40 years depending on the amount deployed, we examined sensitivity of net consumer benefit to SS battery lifespan by setting lifespan to 40 years, the same as AHI batteries. Variations in net consumer benefit are solely due to differences in technology parameters (efficiency and duration). Fig. 7 shows that SS batteries become competitive with AHI batteries if equal capital costs are assumed. Improving SS battery lifespan to 40 years increases net consumer benefit by up to 20% for deployments less than 20 GW. Because the RTE and duration parameters of AHI vary greatly depending on how the battery is operated, the range of net consumer benefits is wider than SS.

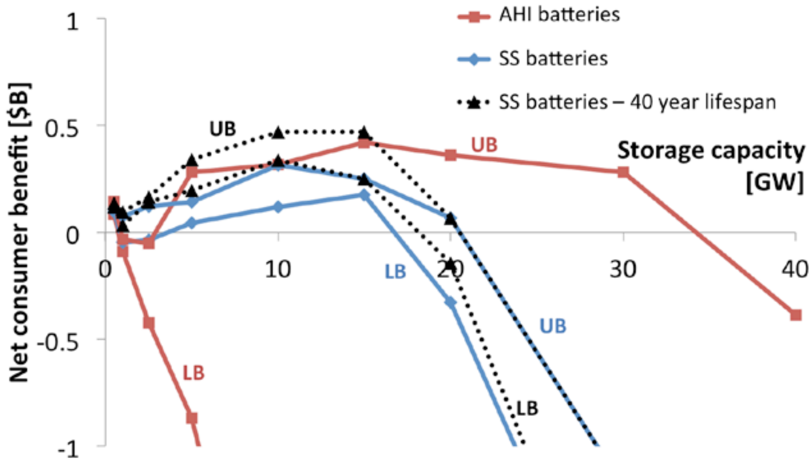

Fig. 7 Net annual consumer benefit for sodium sulfur (SS) and aqueous hybrid ion (AHI) batteries, assuming a capital cost of $300/kWh for both technologies. Dashed lines are SS net annual consumer benefits, assuming 40-year lifespan. Net benefits vary between upper bound (UB) and lower bound (LB) depending on assumptions of storage parameters. 2010 dollars

5.3. Sensitivity to capacity market prices

Capacity prices in PJM have varied significantly since capacity auctions were established in 2007. Prices have varied from a high of $174/MWh in the 2010/2011 auction to a low of $16/MWh in the 2012/2013 auction [24]. The value of storage to consumers is highly dependent on capacity market prices, as half of the total consumer benefits of storage are due to reductions in capacity market expenditures (Table 6). Reducing the modeled capacity market price from $174/MWh to $16/MWh would reduce modeled total consumer benefits by half.

Future capacity prices are highly uncertain, and historic prices show no clear trend. Environmental regulations such as the Clean Air Interstate Rule are expected to put upward pressure on capacity prices; PJM projects 20 GW of coal capacity will be forced to retire due environmental regulations [31]. However, the rapid growth of demand response (DR) will put downward pressure on capacity prices. DR's participation in the PJM capacity market has expanded from 700 MW in 2008/2009 to 19 GW in 2015/2016 [24]. How these and other forces will affect capacity prices in the coming years will significantly affect the consumer benefits of storage.

5.4. Sensitivity to fuel price

The above analysis uses 2010 fuel prices. However, fuel prices have changed dramatically since 2010 due to the expansion of the shale gas industry. In particular, the average delivered price of natural gas to PJM generators has dropped by roughly 30% (as of late 2012) [32]. To test the robustness of our results, we ran a simulation with fuel prices from August 2011 – July 2012. All other variables were left unchanged.

Without storage, changing from 2010 to 2011/2012 fuel prices reduces total consumer expenditures in the energy market from $35B to $30B. The new fuel prices also cause the generator dispatch order to change. Coal generation decreases by 14%; this drop is filled primarily by combined cycle gas generation (our model results match the observed switch from coal to gas well).

Storage provides greater benefits under the 2011/2012 fuel price scenario; on average, benefits are 10% higher. The increased benefits are due to higher savings in the wholesale energy market; capacity savings are largely unchanged. Based on this analysis, the conclusion that storage provides substantial benefits to consumers is robust to variations in fuel price, including current low natural gas prices.

Without storage, emissions of CO_2, NO_X, and SO_2 are lower in the 2011/2012 fuel price scenario than the 2010 scenario due to the decrease in coal generation. Adding storage increases emissions of CO_2 and SO_2 in both scenarios, although increases are smaller in the 20111/2012 fuel price scenario (Table 11). Storage increases emissions of NO_X in the 2010 scenario, but does not change NO_X emissions in the 2011/2012 fuel price scenario. Adding storage to the 2011/2012 fuel price scenario increases emissions from coal generators, which are largely offset by decreased emissions from peaking generators. NO_X emissions are unchanged, as reductions from peaking plants are as large as increases from coal plants.

5.5. Sensitivity to amount of wind deployed

Finally, we investigated how the benefit of storage changes in a scenario with high penetrations of wind. Over the next decade, PJM anticipates a large expansion of wind in order to meet state renewable portfolio standards. We investigated the benefits of deploying 40 GW of 90% RTE, 20-hour duration AHI storage in two scenarios: the base 2010 scenario (1.5% of energy supplied by wind), and a scenario with 20% of energy from wind. For the 20% wind scenario, we used the data from the Eastern Wind Integration and Transmission Study [33] to identify hourly generation from likely wind sites in PJM member states. We then added sites in order of decreasing capacity factor until total wind generation was 20% of load.

In the base scenario, storage induces \$3.2 billion in consumer benefits; in the 20% wind scenario, total benefits increase ~10% to \$3.6 billion. This increase is due to reductions in wind curtailment. Without storage, 5% of wind energy is curtailed; with storage, no wind is curtailed. Therefore, we conclude that the benefits of storage are unlikely to increase dramatically in high wind scenarios.

Without storage, emissions are significantly lower in the 20% wind scenario than the base scenario. Adding storage in the 20% wind scenario increases CO_2 and SO_2 emissions by less than 1%; NO_X emissions slightly decrease (Table 11). The net CO_2 emission increase is due to a 2% increase in CO_2 emissions by coal plants, which is largely offset by a 93% reduction in CO_2 emissions from peaking combustion turbine and oil/gas steam plants. Although researchers have shown that hybrid wind/storage systems can provide low emission baseload power [34], our findings agree with studies that show adding storage into high-wind systems can increase emissions. Tuohy and O'Malley find that storage increases the level of carbon emissions at wind penetrations less than 60% in the Irish system [26] [27]. Sioshansi finds that adding large amounts of storage (10 GW) to the ERCOT system in the presence of high wind (10 GW) increases emissions of CO_2, NO_X, and SO_2, assuming a competitive market [35].

Table 11 Emissions of CO_2, NO_X, and SO_2 in the business as usual (BAU) scenario - 2010 fuel prices, a scenario with 2011/2012 fuel prices, and a scenario with 20% of energy from wind. Storage is 40 GW aqueous hybrid ion (AHI) batteries (90% RTE, 20-hr duration)

	BAU scenario emissions [Million tons]			**2011/2012 fuel price scenario emissions [Million tons]**			**20% wind scenario [Million tons]**		
	CO_2	NO_X	SO_2	CO_2	NO_X	SO_2	CO_2	NO_X	SO_2
No storage	466	0.43	2.09	432	0.36	1.71	337	0.31	1.46
Storage	473	0.44	2.16	434	0.36	1.73	338	0.30	1.46

6. Discussion

Although storage increases overall social welfare on the wholesale energy market, the annualized capital cost of storage exceeds these benefits. However, storage creates large benefits for consumers, ~10% of the value transacted in PJM's day-ahead energy market. These benefits are primarily transfers from generators on the wholesale and energy markets. Net consumer benefits, or total benefit on wholesale energy and capacity markets minus annualized capital costs, are positive under optimistic technical and operating assumptions for AHI batteries but negative for SS batteries. The positive benefits of AHI batteries could be distributed in three ways: they could be given to consumers as reduced energy costs, to generators to compensate for revenue losses, or to storage operators as profit. Even if all net benefits are given to generators, they are insufficient to completely compensate for lost revenues.

Due to the high capital costs, operating storage on wholesale markets is unprofitable for storage operators if used solely for arbitrage. Fig. 8 illustrates that under current market design, storage revenues are much smaller than total welfare increases, and therefore the socially optimal amount of storage is not achieved. Other researchers have noted the limitations of existing market designs in signaling the value of energy storage [36].

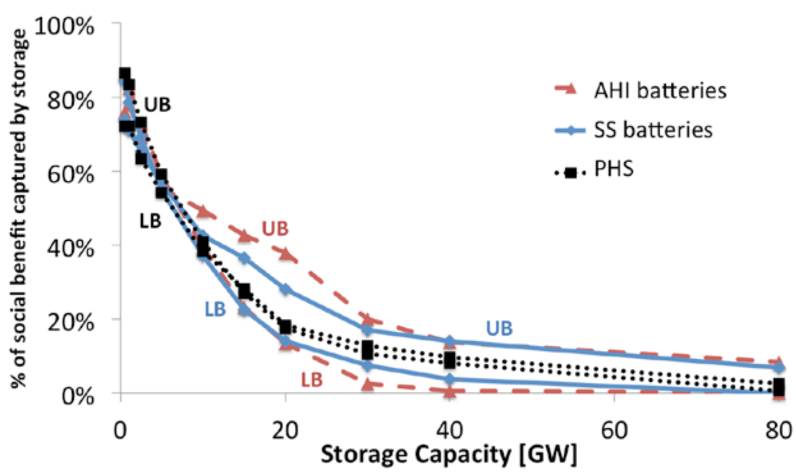

Fig. 8 Percentage of the total social welfare benefits captured by storage operators. Storage operators capture only a small fraction of the benefits they create at high levels of deployment. Results vary between upper bound (UB) and lower bound (LB) depending on assumptions of storage parameters.

Sioshansi has shown that consumer or generator ownership of storage is not welfare maximizing [30, 37]. Consumers overuse storage, as they neglect the producer surplus losses the storage creates. Generators underuse storage, as they seek to minimize producer surplus losses. Merchant operated storage does result in social welfare maximization, assuming perfectly competitive storage and generation. We propose four strategies that might be used in various combinations to encourage storage deployment closer to the societally optimal level by merchant operators.

First, regional transmission operators (RTOs) should ensure that storage assets are eligible for capacity market payments, where such markets exist.

Second, RTOs could establish rules that allow profit maximizing behavior. For example, storage operators could be permitted to bid into the market the prices at which they are willing to charge or discharge. Our analysis assumes RTOs will dispatch storage in order to minimize total social costs, as they currently dispatch generators.

Third, RTOs or governments could directly subsidize storage operators. This subsidy would be based on the overall social welfare benefits that storage provides.

Finally, system operators could attempt to incentivize storage by removing all price caps and allowing for high price spikes. During these few hours of very high prices, some argue that storage could possibly recoup enough money to be profitable [38].

7. Conclusion

Storage increases overall social welfare on the wholesale energy market. However, the annualized capital cost of storage exceeds these benefits. Storage provides substantial benefits to consumers in two ways: by reducing prices in the wholesale energy market, and by reducing the need for peaking generators. 20 GW of storage would reduce consumer expenditures by more than $2.5 billion annually and allow 30 GW of peaking capacity to be retired. However, storage reduces the profitability of all generators. Generation from peaking gas and oil plants decreases, while generation from coal plants increases. Storage modestly increases system emissions of CO_2 and other pollutants in the 2010 PJM market. No current storage technologies are profitable if solely used for arbitrage on the PJM day-ahead market.

The current market design results in merchant storage operators receiving only a small fraction of the total social welfare they create at high levels of deployment. Four strategies might be used by PJM and the public utilities commissions and governments in its territory to encourage storage deployment closer to the socially optimal level: (1) ensure storage is eligible for capacity payments; (2) establish rules that allow profit-maximizing behavior for storage; (3) directly subsidize storage for the overall social welfare benefits it provides; and (4) remove all price caps and allow for high price spikes if this is shown to be effective.

Future research could improve the accuracy with which storage is modeled in the unit commitment model framework by (1) modeling transmission congestion within each of the 5 buses; (2) considering wind uncertainty by using a stochastic unit commitment model; and (3) co-optimizing the energy and reserve markets.

Acknowledgements

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Appendix A: Detailed model description

Our analysis used a five-bus model of PJM. Each of the five buses consists of one or more of the 19 PJM zones (Fig. 9). When defining buses, more data are now available than were available to earlier researchers, so we were able to incorporate additional granularity. The London Economics International (LEI) analysis [11] includes three transmission interfaces (Western, Central, and Eastern), and five regions. PHORUM includes three additional transmission interfaces: Bedington – Black Oak, AEP-DOM and AP South. Fig. 10 shows all PJM transmission interfaces. We one more bus than the LEI study, bus 5 (Dominion/VA), but did not model Delmarva Power and Light (DPL) as a separate region. Finally, we did not divide the METED zone across multiple regions, as did LEI. DUK (Duke Energy) zone was integrated into PJM Jan 1, 2012 and was not included in the analysis.

We made three modifications when dividing the PJM transmission interfaces into PHORUM's transmission lines: (1) the Western Interface is made up of four 500kV lines, each connecting different buses. Therefore, we divided the Interface's capacity into quarters and apportion the capacity to lines as appropriate; (2) the 500X(5004+5005) Interface is made up of two 500kV lines that are contained within the Western Interface. Therefore, we did not model the 500X(5004+5005) interface as it is included in the Western Interface; and (3) we combined the Bedington-Black Oak, AP South, and AEP-DOM Interfaces into a single line between buses 1 and 5. We made the simplifying assumption that the capacity of each line is independent of how much current it carries. Table 12 summarizes the assignment of PJM zones and interfaces to PHORUM buses and transmission lines. 2010 LMP data shows that within our defined buses, zonal LMPs are highly correlated, supporting our assumptions of bus locations and unconstrained transmission within each bus (Fig. 11). Aggregating PJM into five transmission buses will obscure the high arbitrage potential, and therefore storage revenue, at a few localized nodes. However, we assume large deployments of storage will saturate these localized opportunities and act to equalize LMPs at all nodes within the bus.

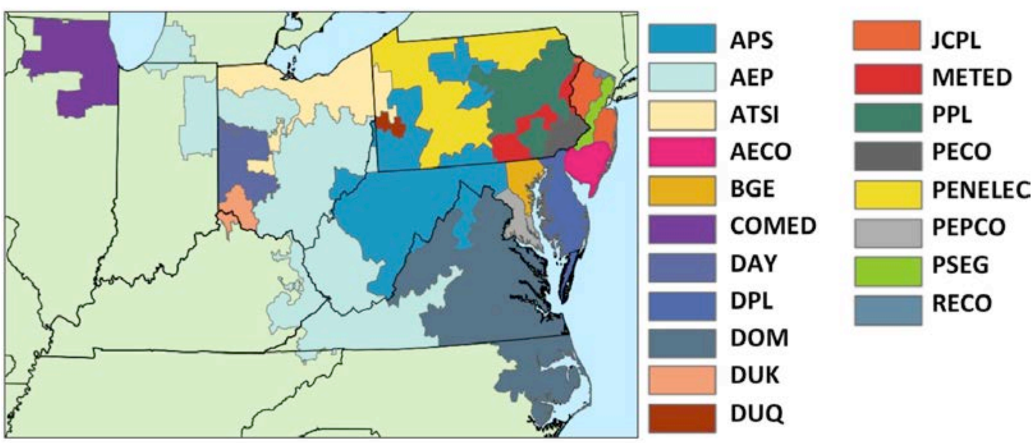

Fig. 9 The PJM Interconnection and its constituent zones [39]

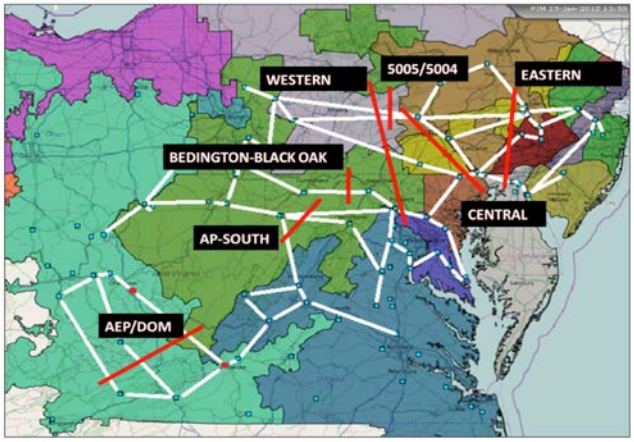

Fig. 10 PJM 500kV transmission lines (white lines) and transmission interfaces (red lines) [40, 41]. Most interfaces contain multiple 500kV lines

Table 12 Assignment of PJM zones to PHORUM buses and PJM interfaces to PHORUM transmission lines.

Bus	**PJM Zones**
Bus 1	AEP, APS, COMED, DAY, DUQ, PENELEC, ATSI
Bus 2	BGE, PEPCO
Bus 3	METED, PPL
Bus 4	JCPL, PECO, PSEG, AECO, DPL, RECO
Bus 5	DOM
Line	**PJM Interface**
Line 1	¼ of Western Interface capacity
Line 2	½ of Western Interface capacity
Line 5	¼ of Western Interface capacity
Line 3	Bedington-Black Oak, AP South, AEP-DOM
Line 4	Central Interface
Line 6	Eastern Interface
Not modeled	500X(5004+5005)

		COMED	AEP	DAY	DUQ	APS	PENELEC	BGE	PEPCO	PPL	METED	PSEG	PECO	JCPL	RECO	DPL	AECO	DOM
Bus 1	COMED	1.00	1.00	1.00	0.99	0.96	0.94	0.81	0.77	0.96	0.88	0.89	0.88	0.89	0.89	0.87	0.88	1.00
	AEP	1.00	1.00	1.00	0.99	0.95	0.94	0.80	0.76	0.96	0.87	0.88	0.88	0.89	0.89	0.87	0.88	1.00
	DAY	1.00	1.00	1.00	0.99	0.97	0.95	0.83	0.79	0.97	0.89	0.90	0.89	0.90	0.90	0.89	0.90	1.00
	DUQ	0.99	0.99	0.99	1.00	0.99	0.98	0.89	0.86	0.99	0.94	0.95	0.94	0.95	0.95	0.94	0.94	0.99
	APS	0.96	0.95	0.97	0.99	1.00	1.00	0.94	0.92	1.00	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.97
	PENELEC	0.94	0.94	0.95	0.98	1.00	1.00	0.96	0.94	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.95
Bus 2	BGE	0.81	0.80	0.83	0.89	0.94	0.96	1.00	1.00	0.94	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.83
	PEPCO	0.77	0.76	0.79	0.86	0.92	0.94	1.00	1.00	0.92	0.98	0.98	0.98	0.97	0.97	0.98	0.98	0.79
Bus 3	PPL	0.96	0.96	0.97	0.99	1.00	1.00	0.94	0.92	1.00	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.97
	METED	0.88	0.87	0.89	0.94	0.98	0.99	0.99	0.98	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.89
Bus 4	PSEG	0.89	0.88	0.90	0.95	0.98	0.99	0.99	0.98	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.90
	PECO	0.88	0.88	0.89	0.94	0.98	0.99	0.99	0.98	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.90
	JCPL	0.89	0.89	0.90	0.95	0.98	0.99	0.99	0.97	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.91
	RECO	0.89	0.89	0.90	0.95	0.98	0.99	0.99	0.97	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.91
	DPL	0.87	0.87	0.89	0.94	0.98	0.99	0.99	0.98	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.89
	AECO	0.88	0.88	0.90	0.94	0.98	0.99	0.99	0.98	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.90
Bus 5	DOM	1.00	1.00	1.00	0.99	0.97	0.95	0.83	0.79	0.97	0.89	0.90	0.90	0.91	0.91	0.89	0.90	1.00

Fig. 11 Correlation coefficients between zones for 2010 hourly day-ahead LMPs. High correlation within a bus supports the model's simplifying assumption that transmission is unconstrained within the bus

PJM operates several electricity markets, the largest of which are the day-ahead (DAH) and real-time energy markets. We modeled the DAH market instead of the real-time market for two reasons. First, the DAH market is larger, with generally lower and less volatile prices, serving as a conservative lower bound on storage profits [4]. Secondly, prices in the real-time market are highly influenced by factors outside the capability of PHORUM, such as sudden changes in the weather, forced generator outages, transmission outages, and strategic behavior. According to PJM, "The price difference between the Real-Time and the Day-Ahead Energy Markets results, in part, from volatility in the Real-Time Energy Market that is difficult, or impossible, to anticipate in the Day-Ahead Energy Market" [4]. We assumed all available generators participate in the DAH market. In reality, 2010 PJM DAH load was met by a combination of bilateral contracts (4.9%), self-supply from the load-serving entity's own generation (75.8%), and spot purchases on the DAH market (19.3%) [4]. This assumption is equivalent to assuming that bilateral contracts and self-supply do not cause out-of-merit-order dispatch.

We ran 365 optimizations, each minimizing costs over 48 hours. Each 48-hour optimization was initialized with four variables from the last hour of the previous day's optimization:

- The on/off state of each generator
- How much longer each generator must remain on/off
- The power output of each generator
- The state of charge for each storage unit

Fig. 12 illustrates how cross-day variables are handled by PHORUM. In addition, the state of charge of each storage device at hour 48 is constrained to be the same as the each 48-hour optimization constraints.

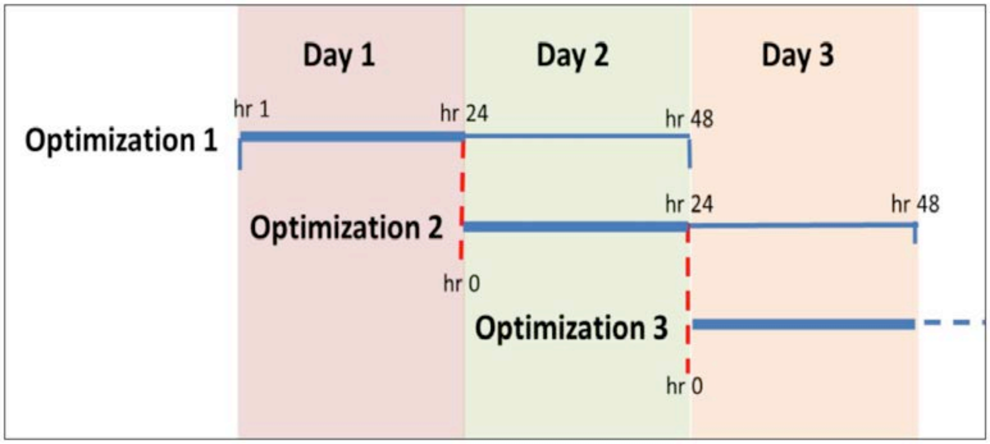

Fig. 12 Illustration of how PHORUM handles day boundaries. Each optimization runs for a full 48 hours, but only the first 24 hours of results are retained. Variables are passed from the 24^{th} hour of the first optimization to hour 0 of the second.

Table 13 details each data element used in PHORUM. We made several modifications to the generator data in order to improve accuracy. First, for generators in the PJM EIA-411 generator database but not in the NEEDS database, we assumed values for NEEDS and eGRID data elements. These assumptions are based on values for similar plants. Similarly, the PJM database occasionally combines two generators that NEEDS calls out separately. In these cases, we combined the generators as in the PJM database and assume values based on the constituent generators. We assumed generators have linear heat rates, variable O&M costs, ramp rates, and emission factors over their operating range. Better data could further improve accuracy. In particular, better information on when generators are offline for maintenance, more detailed transmission constraints, and more refined buses would improve the model.

Table 13 PHORUM data sources

Data Element	Source
Generator Data	
Plant type	[42]
State & county[1]	[42]
Heat Rate [Btu/kWh]	[42]
Fuel	[42]
Capacity [MW] (Summer & winter)[2]	[43]
Variable O&M Cost [$/MWh][3]	[44]
Monthly Fuel Price: Jan – Dec 2010 [$/MMBtu][4]	[45, 46]
Ramp Rate [MW/hr][5]	[47]
Min uptime & downtime [hrs][6]	[48]
Startup cost adder [$][7]	[49, 50]
Minimum Generation [% of maximum generation]	[51]
Monthly Equivalent Availability Factor: Jan – Dec 2010[8]	[52, 53]
Stack Height [ft]	[54]
CO_2 emission rate [lb/MMBtu]	[12]

NO_x & SO_2 emission rates [lb/MWh]	[12]
Hourly Data	
Load[10]	[55]
Imports/Exports [MW][11]	[56]
Zonal Locational Marginal Prices (LMPs) [$/MWh]	[57]
Transmission Capacity [MW]	[58]
Wind Generation [MW][12]	[59]
Reserve Requirement [MW][13]	[16]

[1] Plants are assigned to zones by state and county codes.

[2] Generator capacities listed for different databases (PJM EIA-411, eGRID, and NEEDS) vary widely. We use data listed in the PJM EIA 4-11 report. Hydro generator capacities are derated by their annual capacity factor.

[3] Variable O&M costs are 2010 values. LFG and MSW costs are based on [60].

[4] Fuel prices are aggregated by state and by month for each fuel. This aggregation captures both location and seasonal variation in fuel price. Prices are primarily based on the EIA's Electric Power Monthly data for coal, petroleum liquids, and natural gas delivered price. These databases intentionally exclude some entries in order to maintain anonymity for data providers. Excluded prices are assumed to be the Census Division average, with the exception of West Virginia coal prices, which are derived from the EIA-423 reporting. Prices are assumed to be the same for all types of coal (BIT, SUB, waste coal, etc) and liquid petroleum (DFO, RFO). Fuel price for LFG, MSW, and NUC are assumed to be zero.

[5] Ramp rates are derived from the GADS database [47]. Ramp rates are assumed to be equal for up-ramping and down-ramping. The GADS data was used to identify how the ramp rate of each plant type was correlated to the plant's capacity. We used an OLS regression of ramp rate against generator capacity. Results are as follows:

- Combined cycle: 0.22 MW h ramp / MW capacity
- Steam Turbine: 0.14 MW/h ramp / MW capacity
- Gas Turbine: 0.34 MW/h ramp / MW capacity
- Combustion Turbine: 0.33 MW/h ramp / MW capacity

[6] Minimum runtime for small (<150MW) coal plants have been adjusted to account for the fact that these plants are used within PJM as shoulder plants. Runtimes for LFG and MSW plants are assumed to be equal to combined cycle plants.

[7] Based on InterTek and CAISO data, startup costs are assumed at $25/MW for combustion turbine, $50/MW for combined cycle, $100/MW for coal, and $500/MW for nuclear

[8] PJM provided monthly 2010 EAF data, aggregated by generator type (coal 0-249 MW, coal 250-499 MW, coal 500+MW, gas CC, and gas CT). PJM-provided estimates were divided in half to roughly account for the effect of monthly averaging. Nuclear EAF was derived from NRC data, using generators in PJM. EAF for LFG and MSW was assumed to be equal to natural gas combustion turbine plants.

[9] NEI contains data on total pollutant emissions from each generator. Data was cross-referenced with total annual power output numbers from eGRID to find pollutant emission rates in units of tons/MWh.

[10] PJM sums the DAH load for all zones within the MIDATL region (PENELEC, BGE, PEPCO, METED, PPL, JCPL, PECO, PSEG, AECO, DPL, and RECO) into one entry. Therefore, we divide MIDATL load into its constituent zones. We do this by analyzing the Real Time load data, which is provided separately for all MIDATL zones. For each MIDATL zone, we find the percentage of MIDATL total its load contributes. We then assume that this percentage is the same for DAH and RT loads. Finally, we use that percentage to find the DAH load for each MIDATL zone.

[11] Imports and export data is provided for each interface. We assign these interfaces to the appropriate zones as follows. We assume imports and exports do not change based on PJM prices.

Zone	Interfaces
AEP	ALTE, ALTW, CPLW, CWLP, DUK, EKPC, IPL, LGEE, MEC, MECS, NIPS, OVEC, TVA, WEC
PENELEC	FE
PSEG	NEPT, NYIS, LIND
DOM	CPLE
DAY	CIN

[12] PJM provides hourly wind generation for WEST & MIDATL PJM regions. All WEST wind generation is assigned to bus 1, all MIDATL wind is assigned to bus 3, which is the location of most Mid-Atlantic wind capacity [61]. We assume wind generation is must take, and subtract it from load.

[13] For RFC (bus 1), DOM (bus 5) and Mid-Atlantic (buses 2-4), the synchronized reserve requirement is the single largest unit. This is 1300 MW for bus 1, 1170 MW for buses 2-4, and 1170 MW for bus 5. The 1170 MW reserve for buses 2-4 is apportioned among the buses based on their loads. Reserve requirements are added to zonal loads.

To investigate the accuracy with which the model dispatches generators, we compared the simulated capacity factors of several PJM generators to their actual 2010 capacity factors. To find the generation and of PJM plants in 2010, we used data from the EPA's Air Market Program Database (AMPD), which tracks generation and emissions from all plants regulated by the Clean Air Interstate Rule [62]. Because AMPD tracks generation at the plant level, we summed the power generation from all generators at the same plant in our simulation. In total, we compared the generation from 196 plants in PJM. Fig. 13 shows the simulated and actual generation from all plants. The mean error in capacity factor, weighted by plant capacity, was 3.6%. The root mean squared error in capacity factor, weighted by plant capacity, was 15.9%.

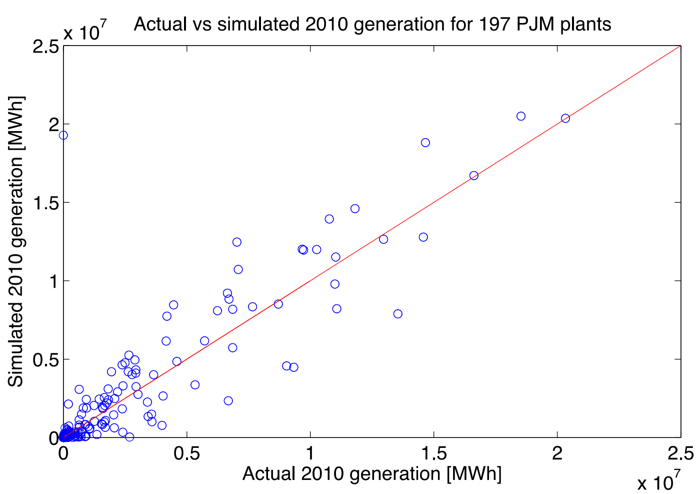

Fig. 13 Actual vs simulated 2010 generation for 197 PJM plants

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