Received 19 June 2020; revised 1 September 2020; accepted 7 October 2020.
Date of publication 15 October 2020; date of current version 19 November 2020.

Digital Object Identifier 10.1109/OAJPE.2020.3031526

Energy Storage as a Service: Optimal Pricing for Transmission Congestion Relief

JUAN ARTEAGA [1,3] (Student Member, IEEE), HAMIDREZA ZAREIPOUR [1] (Senior Member, IEEE), AND NIMA AMJADY [2] (Senior Member, IEEE)

[1] University of Calgary, Calgary, AB T2N 1N4, Canada
[2] Electrical Engineering Department, Semnan University, Semnan, Iran
[3] Facultad de Ingenieria, Universidad Panamericana, Zapopan 45010, Mexico
CORRESPONDING AUTHOR: J. ARTEAGA (juan.arteaga2@ucalgary.ca)

ABSTRACT This paper focuses on pricing Energy Storage as a Service (ESaaS) for Transmission congestion relief (TCR). We consider a merchant storage facility that competes in an electricity market to trade energy and ancillary services on a day-to-day basis. The facility also has the opportunity to provide a firm TCR service to a regional network operator under a long-term contract. Providing the additional TCR service would impose limitations on the facility's ability to fully harvest daily market trade opportunities. Thus, we model the opportunity costs associated with the TCR service and use it in a hybrid cost-value customized pricing technique to determine the risk-constrained optimal price of ESaaS for TCR. Given the long-term nature of the commitment to provide the TCR service, we use the Conditional Value at Risk (CVaR) metric to mitigate the long-term financial risks faced by the facility. The proposed pricing strategy enables the storage owner to estimate the additional financial gains and the associated risks that would likely result from adding the new service to its operation. Numerical simulations are provided to support the proposed methodology.

INDEX TERMS Energy storage as a service (ESaaS), transmission congestion relief, storage as transmission asset (SATA).

NOMENCLATURE

PARAMETERS

β	Confidence interval for CVaR calculation.
η	ESS's round trip efficiency.
ω	Weighted correction factor for risk profile.
π_s	Probability of occurrence of scenario s.
ρ	Percentage of SOC to be held at the end of optimization period.
$\mathrm{C}^{\mathrm{limit}}$	ESS's cycling limit.
$\mathrm{D}_k^{\mathrm{RD}}$	Regulation down energy deployment in scenario k.
$\mathrm{D}_k^{\mathrm{RU}}$	Regulation up energy deployment in scenario k.
$\mathrm{P}^{\mathrm{max}}$	ESS's maximum power capacity.
$\mathrm{P}_{chr}^{\mathrm{TCR}}$	Contracted power to be charged for TCR service.
$\mathrm{P}_{dis}^{\mathrm{TCR}}$	Contracted power to be discharged for TCR service.
$\mathrm{SOC}^{\mathrm{max}}$	ESS's maximum state of charge.
$\mathrm{SOC}^{\mathrm{min}}$	ESS's minimum state of charge.
ξ_k	Probability of occurrence of scenario k.
HEC	Highest estimated cost of alternative solutions.
LEC	Lowest estimated cost of alternative solutions.
VOM	ESS's variable operation and maintenance cost.

SETS

$\mathcal{C}$	Set of contracted hours for charging TCR service.
$\mathcal{D}$	Set of contracted hours for discharging TCR service.
$\mathcal{J}$	Set of quota curve steps indexed by j.
$\mathcal{K}$	Set of regulation deployment scenarios indexed by k.
$\mathcal{S}$	Set of opportunity cost scenarios indexed by s.
$\mathcal{T}$	ESS's market operation time horizon indexed by t.

VARIABLES

γ	Daily opportunity cost for providing TCR service.
λ_t^{E}	Energy price at time t.
$\lambda_t^{\mathrm{N}}(\Xi_t^{\mathrm{N}})$	Non-spinning reserve price as a function of ESS's offer at time t.
$\lambda_t^{\mathrm{RD}}(\Xi_t^{\mathrm{RD}})$	Regulation down price as a function of ESS's offer at time t.

$\lambda_t^{\mathrm{RU}}(\Xi_t^{\mathrm{RU}})$	Regulation up price as a function of ESS's offer at time t.
$\lambda_t^{\mathrm{S}}(\Xi_t^{\mathrm{S}})$	Spinning reserve price as a function of ESS's offer at time t.
λ^{TCR}	ESS's offer price for the TCR service.
$\mu_{t,j}^{\mathrm{N}}$	Non-spinning price bid by competitor in step j at time t.
$\mu_{t,j}^{\mathrm{RD}}$	Regulation down price bid by competitor in step j at time t.
$\mu_{t,j}^{\mathrm{RU}}$	Regulation up price bid by competitor in step j at time t.
$\mu_{t,j}^{\mathrm{S}}$	Spinning reserve price bid by competitor in step j at time t.
$\mathrm{D}_t^{\mathrm{N}}$	Non-spinning reserve energy deployment at time t.
$\mathrm{D}_t^{\mathrm{S}}$	Spinning reserve energy deployment at time t.
$\mathrm{P}_t^{\mathrm{Echr}}$	Energy charged by the ESS from the energy market at time t.
$\mathrm{P}_t^{\mathrm{Edis}}$	Energy discharged by the ESS to the energy market at time t.
$\mathrm{P}_t^{\mathrm{N}}$	ESS's capacity committed to non-spinning reserve at time t.
$\mathrm{P}_t^{\mathrm{RU/RD}}$	ESS's capacity committed to regulation up/regulation down at time t.
$\mathrm{P}_t^{\mathrm{S}}$	ESS's capacity committed to spinning reserve at time t.
SOC_t	ESS's state of charge at the end of time t.
ε	Threshold for VaR calculation.
ζ	Probability of being contracted in TCR auction.
$U_t^{\mathrm{dis/chr}}$	Discharging/Charging status binary variable at time t.
z_s	Auxiliary variable for CVaR linearization.

I. INTRODUCTION

APPLYING large-scale energy storage systems (ESSs) in the electrical power sector is not a new concept [1]. The resurgence of energy storage for grid applications is mainly owed to the exponential growth of variable renewable electricity generation [2] and the move towards 100% renewable grids [3]. According to the latest data from the US Department of Energy, as of early 2020, more than 87% of existing energy storage projects in the world are somehow directly linked to renewable energy integration [4].

The same source also reveals that close to 99% of the existing ESS projects are employed within the supply-side of interconnected power grids to provide energy or ancillary services [4]. Nevertheless, ESSs are also technically capable of supporting the transmission and distribution (T&D) networks [5]. Eyer and Corey [6] argue that in certain cases, a storage system with a relatively small capacity could be used to provide enough incremental capacity to defer the need for a large investment in T&D systems. A good example of this is found in Texas Public Utility Commission Docket 46368 [7], where American Electric Power, a local utility company, requested to install battery storage systems as a lower cost alternative to adding distribution capacity. In this request, the company argues that using storage to relieve congestion would require 9.3% of the investment needed to increase the line capacity. Furthermore, a single storage system asset has the technical capabilities of providing both supply services and transmission services [8].

When it comes to financial compensations for grid services, system assets in restructured electricity markets are traditionally allowed to receive only one kind of compensation, either through participating in the market (market-based) or through a cost-recovery rate (rate-based) [9]. Typically, supply-side resources are compensated through market-based mechanisms, whereas transmission and distribution assets are paid for through regulated rate-based processes. Some of the reasons behind the functional classification for power systems assets are the possibility of redundant compensation, the possibility of suppressing competitive prices in the market by allowing cost-recovery through rate-based compensation and jeopardizing independence of the system operator by controlling a resource that acts on the market and on the transmission network [10]. However, it has been noted that limiting the functions of storage facilities to one revenue stream can make them inefficiently used, thus their full value to the system can not be harvested [11].

Despite the long history of energy storage applications in the electricity sector, policy and regulatory frameworks for the seamless integration of ESSs into modern power grids are still evolving. In particular, mandated by the U.S. Federal Energy Regulatory Commission (FERC) Order 841 [12], some of the independent system operators (ISOs) in the USA have a framework to enable energy storage facilities to provide competitive energy and ancillary services (e.g., Southwest Power Pool and PJM Interconnection [13]). The policies and regulations around storage as a transmission asset (SATA) are also being explored by grid operators. For instance, in PJM [14], ERCOT [15] and MISO [16] discussions are taking place for allowing storage as transmission-only asset (SATOA) and its concurrent market participation is envisioned for the near future. However, currently no system operator allows storage to concurrently collect revenues from both streams. Nevertheless, there are discussions taking place in the utility sector to design policy and regulations to define how a storage facility can provide and get compensated for both market-based and rate-based services concurrently [10], [17]–[19].

There have been some proposals to overcome the functional classification barrier. Taylor [20] presents the concept of financial storage rights. In this proposal, the ISO dispatches the storage facility and financial storage rights would be traded with market participants similar to financial transmission rights. He [21] proposes an auction where the battery owner sells the power capacity. The charge and discharge capacities of the battery are sold to third parties with different purposes, allowing the storage facility to harvest revenue from both market-based and rate-based streams. Sioshansi in [9] proposes a mechanism to auction three energy storage products, namely, power discharged, power charged, and energy stored. He argues that under this mechanism, and by separating the facility's ownership from its operation, it neither relies on the ISO dispatches nor disturbs market price clearing process.

In this paper, we propose to apply the concept of Energy Storage as a Service (ESaaS) for Transmission Congestion Relief (TCR). ESaaS [22] has its roots in the Sharing Economy model [23] that has grown over the past decade in service sectors [24]. The Sharing Economy model is built on the principle of utilizing an idle capacity by someone other than the owner for a fee. The sharing economy principle has been applied for demand-side management [25] and smart homes [26]. The potential advantage of ESaaS for removing network overloads over building long-lasting new infrastructure is that network operators could avoid the risks of stranded assets when the future is highly uncertain.

We assume that a regional transmission or distribution network operator has conducted the required power flow studies, expecting occasional and predictable congestion on transmission/distribution corridors, and it has decided to remove the congestion by soliciting third-party solutions. Technically acceptable solution alternatives may include demand curtailment services [27], a new merchant transmission corridor, or energy storage systems [28]. We also assume that the interested parties will compete in an auction to win the TCR service contract. The storage facility is privately owned, and its main source of revenue is selling energy and ancillary services in a competitive market. However, it is also considering to participate in the network operator's auction and bid to provide ESaaS for TCR. The facility is exposed to day-to-day financial uncertainties of the energy and ancillary services markets. Provision of a firm TCR service may lead to losing some favorable trade opportunities in the market. We propose a methodology that estimates and models the opportunity costs associated with providing the TCR service. We also propose to use the opportunity costs model in a risk-constrained hybrid cost-value customized technique to optimally price the facility's TCR service such that (i) it has a chance of getting accepted in the auction, and (ii), if accepted, it is predictably likely that the associated financial compensations not only cover the aforementioned opportunity costs but also yield additional profits. We use CVaR to manage the risks of getting accepted in the auction versus the profitability of the TCR contract for the storage facility.

The significance of the proposed methodology is that it provides storage operators, network operators and policy makers insights into the financial costs, benefits and risks associated with ESaaS for TCR.

The rest of the paper is structured as follows. Section II presents the details on the proposed pricing procedure. Section III shows the results from simulations with real market data and section IV concludes the paper.

II. METHODOLOGY

In this paper, we consider a transmission (or could be a distribution) corridor that is at the risk of future congestion either in the normal or N-1 operation condition. This congestion may occur on either power flow directions, depending on system operation conditions [29]. Alternative solutions that could remove the corridor's congestion include building additional transmission capacity, curtailing load and generation, or using an ESS to provide or absorb energy. We focus on the latter and assume the storage facility is located at one end of the corridor and has the power and energy capacity that would be needed to remove the transmission congestion.

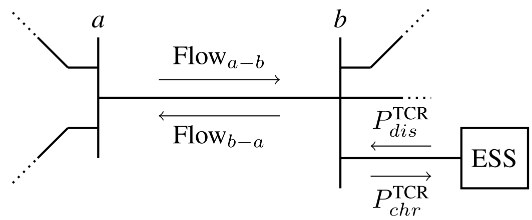


FIGURE 1. Example of a line with bi-directional flow and charging/discharging service according to ESS location.

An ESS could be used to relief congestion regardless of the direction of the flow [30]. To clarify, let us use the line depicted in Fig. 1 as an example. When power flows from *Bus a* to *Bus b* and surpasses the line limit, the ESS could remove this congestion by supplying energy at *Bus b* acting as a bridge to that congested corridor. Thus, the ESS would provide a discharge service, denoted by P_{dis}^{TCR}. Alternatively, if the power flows from *Bus b* to *Bus a* and the corridor is overloaded, the ESS could relive congestion by providing a charging service, denoted by P_{chr}^{TCR}. We also assume the congestion periods and volumes are specified by the network operator and that they do not change over the life of the TCR contract. For example, in a system with a large percentage of distributed solar generation, the charging service may be needed from 3 pm to 5 pm for 5 MW, and the discharging service from 7 pm to 9 pm for 8 MW. Considering the uncertainty in the time and volume of congestion as well as in the daily/seasonal variations of transmission congestion, and their associated impacts on the proposed approach is left for future research. Nevertheless, this model could be run on different stages depending on the transmission commitment for the day or season of the year in order to accurately calculate the opportunity costs in accordance with each transmission commitment.

If accepted by the network operator to provide this service, the storage facility must charge or discharge the required power for the required time period, specified by the TCR contract. We assume that the TCR service is firm, and takes priority over any other market operations, thus, during the contracted hours the facility is not allowed to provide any other services. During the non-contracted hours, however, it is allowed to participate in any energy and ancillary services markets provided: (i) its operations in those markets does not jeopardize its ability to deliver the TCR service as required, and (ii) its charge and discharge operations are managed such that the corridor's flow is always below its maximum allowed capacity. Any loss of revenue resulting from price differentials during charging and discharging hours must be born by the storage facility.

Providing the transmission service will likely result in financial losses for the ESS from its market operation, simply because the new service adds hard constraints to the ESS market operations. Hence, the TCR service should be priced in a way that it not only covers the lost revenues, but also leads to additional profits. Since we assume the TCR service contract to be long-term (e.g., one year), and the ESS would be exposed to the volatility of the hourly energy and ancillary services prices, there is market operation uncertainty that must be mitigated. Furthermore, the ESS is not guaranteed to win the contract in the auction and must compete with other alternatives. Therefore, the ESS must bid into the auction such that the expected profit from providing the TCR service is balanced against the risk of losing the auction.

We propose a hybrid cost-value customized pricing technique [31] to find the optimal offer price for the storage facility's TCR service when participating in the public auction. This offered price is determined such that it maximizes the total expected profit that the storage system could gain from providing market and TCR services. In the following sections, the components of the proposed method are discussed in detail.

A. OPPORTUNITY COSTS OF PROVIDING THE TCR SERVICE

Let define a *Expected Daily Constrained Profit* as the maximum profit the ESS would earn in a given day from market operations if the ESS were committed to provide the TCR service. Further, let define the *Expected Daily Benchmark Profit* as the maximum profit that the ESS would earn on the same day from market operations when the ESS does not provide the transmission service. The operation models to optimize market participation of the ESS to maximize those profits is not the focus of this paper; thus, any market operation model available in the literature could be used i.e. [32], [33]. Nevertheless, in this paper we use a price-taker approach in the energy market and a price-maker approach in the ancillary services markets as presented in [34]. This is done to capture the impact that an ESS could have on the prices of different products, given its size relative to that of the market of each product. This combined modelling approach allows for an accurate estimation of the market profits without adding unnecessary complexities. Also, in line with [34], we use three uncertainty mitigation techniques depending on the nature of the uncertain variable. More specifically, robust optimization [35] is used for the energy prices and price offers from competitors in the ancillary services markets, since forecast with an uncertainty range are usually available for these uncertain variables. An adaptive robust formulation [36] is used for the contingency reserves, given their rare deployment and binary behaviour. Also, a scenario-based stochastic approach [37] is applied for the frequency regulation deployment, since it has a continuous nature and it can not be forecast.

To build the optimal market participation models to calculate the constrained and benchmark profits, let us define the set of decision variables $\Phi = \{P_t^{\mathrm{Edis}}, P_t^{\mathrm{Echr}}, P_t^{\mathrm{RU}}, P_t^{\mathrm{RD}}, P_t^{\mathrm{S}}, P_t^{\mathrm{N}}\}$, which defines the amount of power the ESS bids to the energy market for discharging and charging, regulation up, regulation down, spinning and non-spinning reserves markets respectively for every hour t. Also let us define the set of uncertain variables as $\Psi = \{\lambda_t^{\mathrm{E}}, \mu_{t,j}^{\mathrm{RU}}, \mu_{t,j}^{\mathrm{RD}}, \mu_{t,j}^{\mathrm{S}}, \mu_{t,j}^{\mathrm{N}}, D_t^{\mathrm{S}}, D_t^{\mathrm{N}}\}$, which represent the price for energy, the price offers from other ancillary services suppliers and the energy deployment from spinning and non-spinning reserves. We also define the set of hours that the charge and discharge services are needed as $\mathcal{C}$ and $\mathcal{D}$, respectively, and the amount of power needed for TCR for charging and discharging as P_{chr}^{TCR} and P_{dis}^{TCR}. Unpredictable ancillary services deployments add uncertainty to the ESS's state of charge and could hinder its ability to provide a firm TCR service. Thus, we limit the ESS operation to only charging/discharging energy during the contracted TCR service hours $\mathcal{C}$ and $\mathcal{D}$, and do not allow it to offer any ancillary services.

The optimal market participation model to calculate the *Expected Daily Constrained Profit* (EDCP) can be formulated as follows:

$$
\begin{aligned}
\mathrm{EDCP} = \; & \max_{\Phi=\{P_t^{\mathrm{Edis}},P_t^{\mathrm{Echr}},P_t^{\mathrm{RU}},P_t^{\mathrm{RD}},P_t^{\mathrm{S}},P_t^{\mathrm{N}}\}} \; \min_{\Psi=\{\lambda_t^{\mathrm{E}},\mu_{t,j}^{\mathrm{RU}},\mu_{t,j}^{\mathrm{RD}},\mu_{t,j}^{\mathrm{S}},\mu_{t,j}^{\mathrm{N}},D_t^{\mathrm{S}},D_t^{\mathrm{N}}\}} \\
& \sum_{t=1}^{\mathcal{T}} P_t^{\mathrm{Edis}}(\lambda_t^{\mathrm{E}} - VOM) - P_t^{\mathrm{Echr}}(\lambda_t^{\mathrm{E}} + VOM) \\
& + P_t^{\mathrm{RU}} \cdot \lambda_t^{\mathrm{RU}}(\Xi_t^{\mathrm{RU}}) + P_t^{\mathrm{RD}} \cdot \lambda_t^{\mathrm{RD}}(\Xi_t^{\mathrm{RD}}) + P_t^{\mathrm{S}} \cdot \lambda_t^{\mathrm{S}}(\Xi_t^{\mathrm{S}}) \\
& + P_t^{\mathrm{N}} \cdot \lambda_t^{\mathrm{N}}(\Xi_t^{\mathrm{N}}) + (\lambda_t^{\mathrm{E}} - VOM)\Big[\sum_{k=1}^{\mathcal{K}} \big(P_t^{\mathrm{RU}} D_k^{\mathrm{RU}} \xi_k\big) \\
& + P_t^{\mathrm{S}} D_t^{\mathrm{S}} + P_t^{\mathrm{N}} D_t^{\mathrm{N}}\Big] - (\lambda_t^{\mathrm{E}} + VOM) \sum_{k=1}^{\mathcal{K}} P_t^{\mathrm{RD}} D_k^{\mathrm{RD}} \xi_k \qquad (1)
\end{aligned}
$$

subject to:

$$
\begin{aligned}
SOC_t = \; & SOC_{t-1} + \eta\big(P_t^{\mathrm{Echr}} + \sum_{k=1}^{\mathcal{K}} P_t^{\mathrm{RD}} D_k^{\mathrm{RD}} \xi_k\big) - P_t^{\mathrm{Edis}} \\
& - \sum_{k=1}^{\mathcal{K}} P_t^{\mathrm{RU}} D_k^{\mathrm{RU}} \xi_k - P_t^{\mathrm{S}} D_t^{\mathrm{S}} - P_t^{\mathrm{N}} D_t^{\mathrm{N}} \quad \forall\, t \in \mathcal{T} \qquad (2)
\end{aligned}
$$

$$SOC^{\min} \le SOC_t \le SOC^{\max} \quad \forall\, t \in \mathcal{T} \qquad (3)$$

$$SOC_{t-1} - SOC^{\min} \ge P_t^{\mathrm{Edis}} + P_t^{\mathrm{RU}} + P_t^{\mathrm{S}} + P_t^{\mathrm{N}} \quad \forall\, t \in \mathcal{T} \qquad (4)$$

$$SOC^{\max} - SOC_{t-1} \ge P_t^{\mathrm{Echr}} + P_t^{\mathrm{RD}} \quad \forall\, t \in \mathcal{T} \qquad (5)$$

$$SOC_{24} \geq \rho \cdot SOC^{\max} \tag{6}$$

$$(\frac{1}{2})\sum_{t=1}^{\mathcal{T}} \big(P_t^{\text{Echr}} + P_t^{\text{Edis}} + P_t^{\text{S}}D_t^{\text{S}} + P_t^{\text{N}}D_t^{\text{N}} + \sum_{k=1}^{\mathcal{K}} P_t^{\text{RU}}D_k^{\text{RU}}\xi_k + P_t^{\text{RD}}D_k^{\text{RD}}\xi_k\big) \leq C^{\text{limit}}SOC^{\max} \tag{7}$$

$$P_t^{\text{Echr}} + P_t^{\text{RD}} \leq P^{\max}U_t^{\text{chr}} \quad \forall\, t \in \mathcal{T} \tag{8}$$

$$P_t^{\text{Edis}} + P_t^{\text{S}} + P_t^{\text{N}} + P_t^{\text{RU}} \leq P^{\max}U_t^{\text{dis}} \quad \forall\, t \in \mathcal{T} \tag{9}$$

$$U_t^{\text{chr}} + U_t^{\text{dis}} \leq 1 \quad \forall\, t \in \mathcal{T} \tag{10}$$

$$P_t^{\text{Edis}} = P_{dis}^{\text{TCR}} \quad \forall\, t \in \mathcal{D} \tag{11}$$

$$P_t^{\text{Echr}} = P_{chr}^{\text{TCR}} \quad \forall\, t \in \mathcal{C} \tag{12}$$

$$P_t^{\text{RU}},\ P_t^{\text{RD}},\ P_t^{\text{S}},\ P_t^{\text{N}} = 0 \quad \forall\, t \in \mathcal{C}, \mathcal{D} \tag{13}$$

here, the max min formulation is used to capture the robust nature of the uncertainty mitigation. The objective function (1) maximizes the profit that would be earned under the worst-case realization of the uncertain variables, by determining the optimal power quantities that should be offered for each service. Note that in this formulation the energy price is considered independent of the actions of the storage facility. However, for the ancillary services, the prices are a function of the offered quantity by the ESS and the predicted price offers from competitors i.e., $\Xi_{\mathbf{t}}^{(\cdot)} = \{P_t^{(\cdot)}, \mu_{t,j}^{(\cdot)}\}$. It is assumed that the ESS will offer with a price of zero to be certainly cleared in the market. However, the offered quantities change the supply curves of the markets; thus, the ESS is a price-maker on the ancillary services markets [34]. Also note that the energy deployment in the regulation markets is modelled with a stochastic approach while the deployment from spinning and non-spinning reserves use a robust approach. In this formulation the frequency regulation service is divided into regulation up and down to provide clarity on the formulation. However, this may vary depending on the rules of the local market. Constraint (2) computes the state of charge of the ESS at the end of every hour t. Round trip efficiency is used to account for internal losses, which only affect the energy component of an ESS but not its power component. (3) limits the expected state of charge of the ESS between its lower and upper ratings in every hour. (4) states that the sum of services offered in any hour can not be greater than the expected energy on storage at the end of the previous hour. Likewise, (5) limits the quantity of the charging services to the expected available storage capacity. (6) is used to replenish the stored energy to some percentage of the maximum energy capacity of the ESS at the end of every operation day. (7) is added to establish the limit on the number of daily cycles. (8) and (9) make sure the power rating of the ESS is not violated and (10) defines the status of the ESS to charging or discharging, but not both at any given hour. (11) and (12) force the ESS to discharge and charge respectively during the corresponding contracted hours. The equations in (13) make sure that no ancillary services are offered during the TCR service contract hours. Note that equations (11) to (13) are equality constraints; this is set with the purpose of exactly providing the contracted energy and also to find the most restrictive schedule that could affect profits from the market. The model in (1) to (13) yields an operation schedule that maximizes the market profits of the storage during non-contracted hours while providing the TCR service requirements during the contracted hours. For this model to be solvable by commercial solvers some modifications are needed, such as, a linearization on the ancillary services price calculations and also to use the duality theorem on the inner minimization, to convert the max min formulation to a max max formulation. Given space limitations no further details are provided; the interested reader can refer to [34] for further details.

An optimization model to determine the *Expected Daily Benchmark Profit* (EDBP) can be built by removing the transmission commitment constraints from the *Expected Daily Constrained Profit* model in (1) to (13) as follows.

$$\text{EDBP} = \max_{\Psi} \min_{\Phi} \quad (1)$$
$$\text{subject to: (2) to (10)}$$

The difference between the *Expected Daily Benchmark Profit* and the *Expected Daily Constrained Profit* is considered as the daily opportunity cost, i.e.,

$$\gamma = \text{EDBP} - \text{EDCP} \tag{14}$$

which, is further referred to as γ. Observe that the daily opportunity cost γ depends on market conditions and price volatility of the particular operation day. These conditions change from one day to another, γ is thus a stochastic variable. In this paper, we find the values of γ for a large number of daily market operation conditions scenarios, and identify its associated empirical probability density function (PDF) by $p(\gamma)$ [38]. $p(\gamma)$ will be used later for market uncertainty and risk mitigation.

B. PROBABILITY OF WINING A TCR SERVICE CONTRACT

In pricing theory [31], adding a value component to the cost of a service is a way of reflecting how much the service is worth to the client, or how much the client is willing to pay for it. This value component is independent of the cost of producing the service. For this paper, the client is the network operator, and its willingness to pay for a TCR service can be estimated based on the costs of other technically acceptable alternative solutions to relive congestion. Examples of alternative solutions include adding more capacity to the existing line, building a new line, or offering a demand response compensation program. We assume the costs of alternative solutions would fall in a range bound by the Lowest Estimated Cost of alternative solutions (LEC) and the Highest Estimated Cost of alternative solutions (HEC). Like any competitive entity offering an alternative, the storage operator would use all the information available at the time to estimate the values of LEC and HEC. To keep consistency with the proposed opportunity cost calculations, these estimations should represent the daily cost of employing the alternative solutions by the

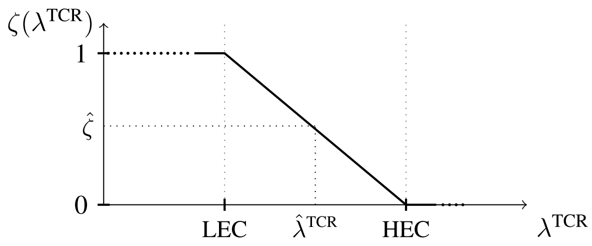


FIGURE 2. **Probability distribution of being awarded a transmission contract, bounded by LEC and HEC. Showing that for a given assigned price $\hat{\lambda}^{\mathrm{TCR}}$, there is a corresponding probability $\hat{\zeta}$ of obtaining the contract.**

network operator to relieve transmission congestion. Challenges and methods for finding the values of LEC and HEC are not the focus of this paper. The LEC to HEC range can be used to build the probability distribution of being awarded the contract to provide the transmission service. Fig. 2, shows a graphical representation of the probability distribution of being awarded the TCR contract. This distribution is usually used in similar pricing studies [31]; however, other distributions can be used if further knowledge on the contracting decision is available. The choice of this distribution and the representation of its uncertainty is not the focus of this paper. Fig. 2 shows that if the ESS's offered price is set at just below the LEC, it would most likely win the auction. On the other hand, if the offer price is set at the HEC or above it, it is unlikely that the ESS wins the auction.

C. EXPECTED PROFIT CONTRIBUTION OF THE TCR SERVICE

Assume that the ESS's offer price is set at λ^{TCR}. The opportunity cost of providing this service for a given day is described by γ. This service also adds λ^{TCR} to the daily revenues of the ESS operation. Thus, the expected profit contribution (EPC) of the TCR service to the daily ESS operation can be represented as follows:

$$\mathrm{EPC}(\lambda^{\mathrm{TCR}}) = \zeta(\lambda^{\mathrm{TCR}}) \times (\lambda^{\mathrm{TCR}} - \gamma) \tag{15}$$

where, $\zeta(\lambda^{\mathrm{TCR}})$ is described by the distribution shown in Fig. 2, λ^{TCR} represents the value of the TCR service and γ integrates the opportunity cost associated with the service in the expected profit in a given day.

The EPC function yields a concave quadratic function, where the EPC becomes negative when the offer price is set bellow the opportunity cost of the service, i.e. $\lambda^{\mathrm{TCR}} < \gamma$. The EPC becomes 0 when the price is set at the higher estimated cost for alternative solutions, i.e. $\lambda^{\mathrm{TCR}} \geq \mathrm{HEC}$. This would mean that the ESS's offer price for the TCR service is set too high and its offer is not accepted in the auction. Winning the TCR service is only profitable if the ESS's accepted offer price is set somewhere between these two limits, i.e. $\gamma < \lambda^{\mathrm{TCR}} < \mathrm{HEC}$. The objective of the ESS operator would be to determine the optimal value of λ^{TCR} that would maximize the $\mathrm{EPC}(\lambda^{\mathrm{TCR}})$ in (15). This is the focus of this paper and is explained next.

D. OPTIMIZING THE OFFER PRICE UNDER UNCERTAINTY

The value of EPC in (15) highly depends on both λ^{TCR} and γ. γ is an uncertain variable while λ^{TCR} is the decision variable. When the TCR contract is won, the value of λ^{TCR} is fixed for the life of the contract. The daily opportunity cost γ, on the other hand, will vary from one day to another depending on daily market conditions. A common, well-established risk measure that is widely used for practical applications in finance is the Conditional Value at Risk metric [39]. A risk-constrained formulation based on CVaR is proposed here for optimizing the value of λ^{TCR} considering the uncertainties in γ against the risk of losing the auction, which is reflected by $\zeta(\lambda^{\mathrm{TCR}})$.

CVaR is defined as the expected loss exceeding an upper percentile i.e. value at risk (VaR) of a loss function [40]. Let us define the loss function as $f(\lambda^{\mathrm{TCR}}, \gamma) = \gamma - \lambda^{\mathrm{TCR}}$, where λ^{TCR} is the decision variable bounded by LEC and HEC and γ is the uncertain variable. For each possible value of λ^{TCR}, the loss function is a random variable with a PDF induced by $p(\gamma)$ [40].

In line with [40], the mathematical definitions of VaR and CVaR can be characterized and discretized into the following risk function.

$$F_\beta(\lambda^{\mathrm{TCR}}, \varepsilon) = \varepsilon + (1-\beta)^{-1} \sum_{s\in\mathcal{S}} \pi_s [f(\lambda^{\mathrm{TCR}}, \gamma_s) - \varepsilon]^+ \tag{16}$$

where, β is the confidence interval established by the decision maker and ε sets the threshold for the value at risk calculation. $\mathcal{S}$ is the set of opportunity cost scenarios used to discretize the integration of the loss function, and π_s is the probability of occurrence for scenario s, which follows the same probability distribution as $p(\gamma)$. Minimizing the risk function $F_\beta(\lambda^{\mathrm{TCR}}, \varepsilon)$ is equivalent to minimizing $CVaR^\beta(\lambda^{\mathrm{TCR}})$, while obtaining a near optimal value for $VaR^\beta(\lambda^{\mathrm{TCR}})$ [40]. Equation (16) introduces a non-linearity to the problem with the term $[f(\lambda^{\mathrm{TCR}}, \gamma_s) - \varepsilon]^+$, which is equivalent to $\max\{f(\lambda^{\mathrm{TCR}}, \gamma_s) - \varepsilon, 0\}$. This non-linearity can be avoided by introducing the set of non-negative auxiliary variables $\mathbf{z}$ and adding the following constraint [40].

$$z_s \geq f(\lambda^{\mathrm{TCR}}, \gamma_s) - \varepsilon \quad \forall\, s \in \mathcal{S} \tag{17}$$

Using this methodology, the problem of setting the TCR service offer price to maximize its associated expected profit while minimizing the risk, can be formulated as follows:

$$\max_{\lambda^{\mathrm{TCR}},\varepsilon} (1-\omega)\big(\zeta(\lambda^{\mathrm{TCR}}) \times (\lambda^{\mathrm{TCR}} - \sum_{s\in\mathcal{S}} \pi_s\gamma_s)\big) - \omega\big(\varepsilon + (1-\beta)^{-1} \sum_{s\in\mathcal{S}} \pi_s z_s\big) \tag{18}$$

$$\text{subject to: } z_s \geq (\gamma_s - \lambda^{\mathrm{TCR}}) - \varepsilon \quad \forall\, s \in \mathcal{S} \tag{19}$$

$$z_s \geq 0 \quad \forall\, s \in \mathcal{S} \tag{20}$$

where, the first term of (18) maximizes the EPC of the TCR service. Note that this first term is the stochastic version of (15), where uncertainty on the opportunity cost is considered. The second term of (18) minimizes the linearized version of the risk function (16). ω is the weighted correction factor to balance between expected profit and risk allowance. The value of ω varies from 0 to 1 and is set by the decision maker. Assigning a value of 0 to ω would mean that the decision maker pretends to maximize the expected profit regardless of the risk; on the other hand, setting ω to 1 would mean that the decision maker is not willing to take any risk, ignoring the possible increase in profit. Constraint (19) is added to linearize the constraints of this problem and non-negativity is enforced on the auxiliary variables in (20). In this formulation, when adopting a low risk profile, the price for the transmission service will tend to be high, and it will decrease as more risk is allowed to be taken.

Solving the optimization problem (18)-(20) will provide the storage owner with a bid value to participate in the TCR service auction that balances the risks of not wining the contract and expected market opportunity costs against the additional profit from providing the transmission service.

III. NUMERICAL RESULTS

We consider a 10 MW, 20 MWh Lithium-ion battery storage facility with round trip efficiency of 85% that participates in energy and ancillary services markets. For these simulations, the daily market operation decision variables are the hourly commitments for energy, frequency regulation, spinning and non-spinning reserves. A cycle limit of one per day is enforced and the state of charge of the ESS most be replenished to at least half of its capacity at the end of the optimization period of 24 hours. Uncertainty is considered in future energy prices, offers by competitors and in energy deployment from ancillary services. Please note that the choice of different market products, market segments, operation policies and uncertainty considerations does not impact our methodology.

To determine $p(\gamma)$, we run the benchmark and constrained market models for each individual day of five representative years on historical data from the Alberta electricity market. The simulations provide 1,825 daily schedules that represent a wide range of operation conditions. The opportunity cost of each day is used to construct the cumulative distribution of the opportunity cost, $p(\gamma)$. For the TCR service, the battery is assumed to be committed to charge 5 MW from hour ending 15 to hour ending 17 and discharge 4 MW from hour ending 19 to hour ending 21 every day. The lowest estimated cost and highest estimated cost of alternative solutions are set to \$5,500/day and \$8,000/day respectively. To estimate this range, it is assumed that the low-cost alternative solution is a demand response program priced based on the value of lost load [41]. And that the high-cost alternative is the addition of transmission capacity, priced based on previous projects in the area, in this case information from the Alberta Electric System Operator is used [42]. For the risk formulation, a confidence level β of 95% is chosen. Simulations were run in pyomo [43] using gurobi [44] as an optimizer on an i5 intel processor with 8G of RAM taking 1.7 hours to run all 1,825 EDBP and EDCP daily calculations. This translates to an average of 1.6 seconds per daily profit calculation.

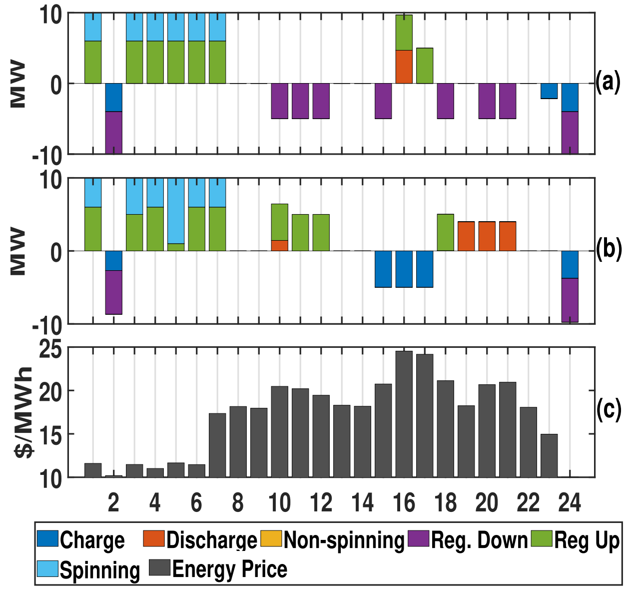


FIGURE 3. Battery Schedule for a typical day in (a) Market only operation and (b) Transmission constrained operation with (c) Price profile for the energy market.

Figure 3, presents an example of a daily schedule of market participation. Fig. 3 (a), shows the schedule for a typical day of operation using the *Daily Benchmark Profit* calculation model (1)-(10), and Fig. 3 (b), shows the schedule in the market for the same day for the *Daily Constrained Profit* calculation model (1)-(13), where the storage provides transmission services. Fig. 3 (c), shows the price forecast for the energy market on the same day. By comparing Fig. 3 (a), and Fig. 3 (b), it can be seen how the market participation of the ESS is affected by the commitment to supply energy for TCR. Specifically, in the benchmark schedule (3(a)) during hours 10 to 12 the ESS is charging in preparation for the price spike predicted for hour 16, where it discharges. However, in the constrained schedule an opposite behaviour can be observed, since the ESS is committed to discharging services during hours 10 to 12 in preparation to its TCR service commitment of charging during hours 15 to 17 as stated in constraint (12). By doing so, the ESS misses the opportunity to profit from the highest energy price on hour 16; instead, it is forced to charge for transmission purposes at a high energy price hour. From the comparisons on the schedules, it can be seen that the transmission constrained schedule does not follow an intuitive price signal to increase profit, alternatively it prepares to provide the transmission services, regardless of market profit loss. On this sample day, the market profit is 40% lower for the transmission-constrained model than that of the benchmark model.

For the 1,825 simulated days, $p(\gamma)$, shown in Fig. 4, presents a very skewed distribution where 80% of the daily

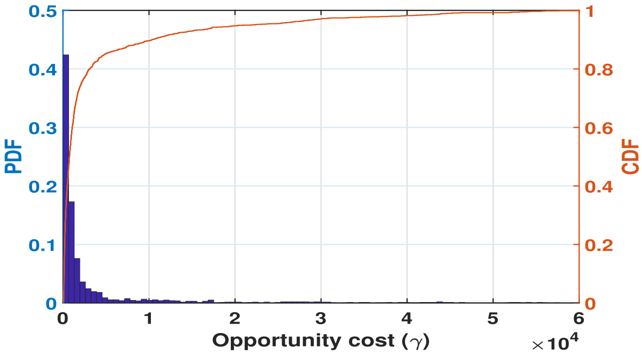


FIGURE 4. **Empirical PDF and CDF of the daily opportunity cost.**

opportunity cost occurrences are below \$3,095/day, and the remaining 20% is spread out from \$3,095/day up to a maximum opportunity cost of \$64,858/day, with a median of \$1,681/day. The average opportunity cost is of \$3,700/day.

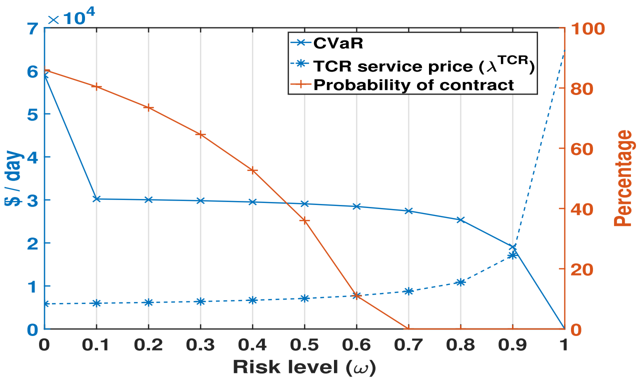


FIGURE 5. **Optimal price for transmission services, CVaR metric and probability of contract for different levels of risk.**

Figure 5, shows the optimal offer price for the TCR service, the probability of being contracted, and the CVaR at different risk levels. If a risk prone profile is adopted, i.e. $\omega = 0$, the offer price is only defined by the EPC function, i.e., (15); thus, the price is set at \$5,850, with a probability of being contracted of 86%; however, using this price, the CVaR is of \$59,008, meaning that there is a 5% probability that the expected daily profit loss could be as high as \$59,008. By slightly increasing ω from 0 to 0.1, the bid price goes up by \$139, which reduces the probability of being contracted by 5.6%. However, the reduction in the financial risk is significantly higher than the reduction in probability of being contracted, reducing the CVaR by 49% down to \$30,209.

As less risk is tolerated and the value of ω is increased, the offer price for the TCR service is increased and the probability of being contracted decreases and so does the CVaR. Note that the probability of being contracted decreases at a higher rate than the CVaR, until it reaches a point where in order to obtain a lower risk metric, the price needs to be higher than the higher estimated cost of alternative solutions, which results in not being awarded the contract to provide the service. In Fig. 5, this happens when ω is set higher than 0.6. Note that if a risk averse profile is adopted, i.e. $\omega = 1$, the optimal offer price for the service is set at the highest observed opportunity cost, and both the probability of being contracted and the risk decrease to zero.

Let us discuss some ad-hoc pricing strategies for the transmission service by the storage owner. One approach is to set the TCR service price at the highest estimated cost of alternative solutions, i.e., at HEC. Since this is a high price for the service, this strategy has little to no chance of getting accepted in the auction. On the other hand, the storage owner may set its offer price at the lowest estimated cost of alternative solutions, i.e., at LEC. As opposed to the previous one, this strategy has a very high chance of success. Alternatively, the price for the transmission service could be arbitrarily set at the average or median of historically observed daily opportunity costs. For the simulated data, these values are \$3,700/day and \$1,681/day, respectively. Considering these ad-hoc offer prices, and assuming the ESS wins the auction at the offered price, we calculate the annual net profit gain/loss from providing the service yielded by each of these strategies. We compare those profit changes to that associated with the price suggested by the proposed model. From Fig. 5, with a confidence level of $\beta = 0.95$ for the CVaR, and a risk profile of 0.1, i.e $\omega = 0.1$, the suggested price point by our model is $\lambda^{TCR} =$ \$5,989/day.

We use data from two individual out-of-sample years from Alberta's market for the comparisons. The two out-of-sample years are selected to represent both the high and low sides of the opportunity cost distributions. More specifically, the average (median) daily opportunity costs for the two sample years are \$3,580/day (\$913/day) and \$5,462/day (\$1,476/day).

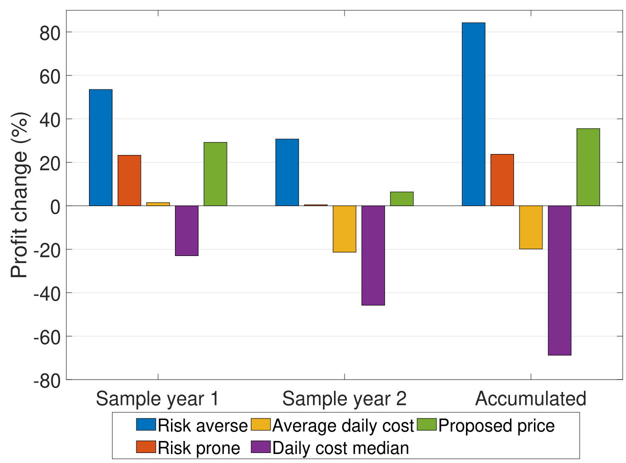


FIGURE 6. **Comparison of the effects of different pricing strategies on profit as a percentage of the benchmark profit for two sample years and the summation of the sample years.**

The results are presented in Fig. 6; as expected, setting the offer price of the TCR service very high, i.e., at $\lambda^{TCR} =$ HEC = \$8,000/day would result in high incremental profits in both years, up to 84% (blue bar). However, one can only wish for this offer to be accepted and in case any alternative solution is priced lower than this, the contract will not be obtained. Setting the price at $\lambda^{\text{TCR}} = \text{LEC} = \$5{,}500$/day results in mixed outcomes from year to year (orange bar), leading to a net profit in one year and to break even in another. Setting the price at the average historically observed opportunity cost, i.e., $\lambda^{\text{TCR}} = \$3{,}700$/day would result in similar mixed outcomes depending on the year (yellow bar). Even though this strategy has a very high chance of success in the auction, the outcomes are inconsistent. Setting the price at the median observed opportunity cost, i.e., $\lambda^{\text{TCR}} = \$1{,}681$/day would result in consistent losses in both years (purple bar); this is simply because this is a very low price to ask for a service that occasionally leads to very high opportunity costs. However, the net profit increment is positive for both years if the price suggested by the proposed model is used, i.e., $\lambda^{\text{TCR}} = \$5{,}989$/day, shown by the green bar. The key difference between this and the risky strategy of setting the price at HEC is that the proposed price has a 80% chance of actually being accepted in the auction.

Considering both years together, the strategy of setting the price at LEC shows a total profit increase of 24%, while using the average or the median show a net loss over the two sample years. The proposed model outperforms the other alternatives by obtaining a profit increase of 36% over the 2-year period.

IV. CONCLUSION

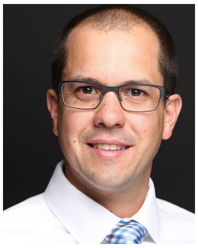
ESaaS is built on the principles of Sharing Economy where the idle capacity of a merchant ESS is used by others for a fee. In this paper, a risk-based, hybrid cost-value optimization technique to optimally price ESaaS for removing predictable overloads on a transmission corridor is proposed. The ESS owner has to compete with other solution providers for a TCR contract; thus, it should price its service considering the daily opportunity costs of providing this service as well as the price of other technically feasible solutions. The opportunity cost component of the pricing technique is obtained as the difference between the maximum possible profit in the market and the profit that can be obtained in the market with the operation schedule limited by the transmission commitment. The value component is obtained through an estimation of the lower and higher costs of alternative solutions to the transmission congestion problem. With that estimation, a probability distribution for the chance of winning the contract to provide the TCR service is computed. We employ CVaR metric to mitigate the risks of pricing ESaaS high and losing the contract, versus pricing it low and securing the contract but the TCR fees not turning an overall profit.

The simulation results show that the proposed procedure is able to provide insights into the financial gains and the associated risks of offering TCR as an ESaaS by a merchant ESS. In particular, depending on the price at which the service is compensated, extending the storage system's operation to provide both market-based and rate-based services could improve the ESS' business case. However, the extent of additional profit that the storage system can gain by providing transmission services depends on the prices of alternative solutions available to the network operator. If the ESS competes against low-cost solutions, it must bid its service at lower prices in order to win the contract. In that case, the storage facility runs the risks of occasional high opportunity costs against the additional profit from a firm TCR service.

REFERENCES

[1] J. L. Woodbridge, "Application of storage batteries to regulation of alternating-current systems," *Trans. Amer. Inst. Electr. Eng.*, vol. 27, no. 2, pp. 987–1021, Jun. 1908.
[2] P. Denholm, E. Ela, B. Kirby, and M. Milligan, "The role of energy storage with renewable electricity generation," NREL, Golden, CO, USA, Tech. Rep. NREL/TP-6A2-47187, 2010. [Online]. Available: http://www.osti.gov/bridge
[3] G. Krajačić, N. Duić, Z. Zmijarević, B. V. Mathiesen, A. A. Vučinić, and M. da Graça Carvalho, "Planning for a 100% independent energy system based on smart energy storage for integration of renewables and Co_2 emissions reduction," *Appl. Thermal Eng.*, vol. 31, no. 13, pp. 2073–2083, 2011.
[4] US Department of Energy (DOE). (2020). *Global Energy Storage Database | Energy Storage Systems*. [Online]. Available: https://www.sandia.gov/ess-ssl/global-energy-storage-database-home/
[5] A. D. Del Rosso and S. W. Eckroad, "Energy storage for relief of transmission congestion," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1138–1146, Mar. 2014.
[6] J. Eyer and G. Corey, "Energy storage for the electricity grid: Benefits and market potential assessment guide," *Sandia Nat. Laboratories*, vol. 20, no. 10, p. 5, 2010.
[7] AEP. (2016). *Application of American Electric Power Texas North Company for Regulatory Approvals Related to the Installation of Utility-Scale Battery Facilities*. [Online]. Available: https://interchange.puc.texas.gov/Documents/46368_2_910546.PDF
[8] H. Khani, M. R. Dadash Zadeh, and A. H. Hajimiragha, "Transmission congestion relief using privately owned large-scale energy storage systems in a competitive electricity market," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1449–1458, Mar. 2016.
[9] R. Sioshansi, "Using storage-capacity rights to overcome the cost-recovery hurdle for energy storage," *IEEE Trans. Power Syst.*, vol. 32, no. 3, pp. 2028–2040, May 2017.
[10] *Storage Policy Statement, Utilization of Electric Storage Resources for Multiple Services When Receiving Cost-Based Rate Recovery*, Federal Energy Regulatory Commission, Washington, DC, USA, 2017.
[11] D. Bhatnagar, A. Currier, J. Hernandez, and O. Ma, "Market and policy barriers to energy storage deployment: A study for the energy storage systems program," Sandia, Tech. Rep. SAND-2013-7606, Sep. 2013, p. 58. [Online]. Available: http://www.sandia.gov/ess/publications/SAND2013-7606.pdf
[12] *FERC Order 841*, Federal Energy Regulatory Commission, Washington, DC, USA, 2018.
[13] The Federal Energy Regulatory Commission. (2019). *FERC Approves First Compliance Filings on Landmark Storage Rule*. [Online]. Available: https://www.ferc.gov/media/news-releases/2019/2019-4/10-17-19-E-1.asp#.XrWGUBNKjUJ
[14] PJM. (2020). *Develop PJM Business Rule Proposals for Integrating Storage As a Transmission Asset*. [Online]. Available: https://www.shorturl.at/
[15] ERCOT. (2020). *Rulemaking to Address the Use of Non-Traditional Technologies in Electric Delivery Service*. [Online]. Available: http://interchange.puc.texas.gov/Documents/48023_70_1004288.PDF
[16] MISO. (2020). *Using Storage as Transmission Assets to Provide Market Services*. [Online]. Available: https://www.shorturl.at/
[17] *Decision on Multiple-Use Application Issues*, Proposed Decision, California Pubic Utilities Commission, San Francisco, CA, USA, 2018.
[18] NYISO. (2020). *Distributed Energy Resources Participation Model*. [Online]. Available: https://www.nyiso.com/distributed-energy-resources-der-
[19] CAISO. (Oct. 2018). *Second Revised Straw Proposal—Storage as Transmission Asset*. [Online]. Available: http://www.caiso.com/Documents/SecondRevisedStrawProposal-Storageas-TransmissionAsset.pdf
[20] J. A. Taylor, "Financial storage rights," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 997–1005, Mar. 2015.

[21] X. He, E. Delarue, W. D'haeseleer, and J.-M. Glachant, ''A novel business model for aggregating the values of electricity storage,'' *Energy Policy*, vol. 39, no. 3, pp. 1575–1585, Mar. 2011.
[22] K. Wazni, ''Energy storage as a service: Why renting can be better than buying,'' *Power*, vol. 163, no. 1, 2019.
[23] H. Heinrichs, ''Sharing economy: A potential new pathway to sustainability,'' *GAIA-Ecological Perspect. Sci. Soc.*, vol. 22, no. 4, pp. 228–231, Dec. 2013.
[24] S. K. Curtis and O. Mont, ''Sharing economy business models for sustainability,'' *J. Cleaner Prod.*, vol. 266, Sep. 2020, Art. no. 121519.
[25] P.-H. Cheng, T.-H. Huang, Y.-W. Chien, C.-L. Wu, C.-S. Tai, and L.-C. Fu, ''Demand-side management in residential community realizing sharing economy with bidirectional PEV while additionally considering commercial area,'' *Int. J. Electr. Power Energy Syst.*, vol. 116, Mar. 2020, Art. no. 105512.
[26] B. Celik, R. Roche, D. Bouquain, and A. Miraoui, ''Decentralized neighborhood energy management with coordinated smart home energy sharing,'' *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 6387–6397, Nov. 2018.
[27] F. Shen, Q. Wu, S. Huang, X. Chen, H. Liu, and Y. Xu, ''Two-tier demand response with flexible demand swap and transactive control for real-time congestion management in distribution networks,'' *Int. J. Electr. Power Energy Syst.*, vol. 114, Jan. 2020, Art. no. 105399.
[28] R. Khatami and M. Parvania, ''Spatio-temporal value of energy storage in transmission networks,'' *IEEE Syst. J.*, vol. 14, no. 3, pp. 3855–3864, Sep. 2020.
[29] N. Patel, D. Porwal, A. K. Bhoi, D. Kothari, and A. Kalam, ''An overview on structural advancements in conventional power system with renewable energy integration and role of smart grids in future power corridors,'' in *Advances in Greener Energy Technologies*. Springer, 2020, pp. 1–15.
[30] S. Wang, G. Geng, and Q. Jiang, ''Robust co-planning of energy storage and transmission line with mixed integer recourse,'' *IEEE Trans. Power Syst.*, vol. 34, no. 6, pp. 4728–4738, Nov. 2019.
[31] R. Phillips, *Pricing and Revenue Optimization*. Stanford, CA, USA: Stanford Business Books, 2005.
[32] B. Cheng and W. Powell, ''Co-optimizing battery storage for the frequency regulation and energy arbitrage using multi-scale dynamic programming,'' *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 1997–2005, May 2016.
[33] Y. Shi, B. Xu, D. Wang, and B. Zhang, ''Using battery storage for peak shaving and frequency regulation: Joint optimization for superlinear gains,'' *IEEE Trans. Power Syst.*, vol. 33, no. 3, pp. 2882–2894, May 2018.
[34] J. Arteaga and H. Zareipour, ''A price-maker/price-taker model for the operation of battery storage systems in electricity markets,'' *IEEE Trans. Smart Grid*, vol. 10, no. 6, pp. 6912–6920, Nov. 2019.
[35] S. Nojavan, A. Najafi-Ghalelou, M. Majidi, and K. Zare, ''Optimal bidding and offering strategies of merchant compressed air energy storage in deregulated electricity market using robust optimization approach,'' *Energy*, vol. 142, pp. 250–257, Jan. 2018.
[36] A. Baringo and L. Baringo, ''A stochastic adaptive robust optimization approach for the offering strategy of a virtual power plant,'' *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3492–3504, Sep. 2017.
[37] N. Yu and B. Foggo, ''Stochastic valuation of energy storage in wholesale power markets,'' *Energy Econ.*, vol. 64, pp. 177–185, May 2017.
[38] H. Akhavan-Hejazi and H. Mohsenian-Rad, ''Energy storage planning in active distribution grids: A chance-constrained optimization with non-parametric probability functions,'' *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 1972–1985, Aug. 2016.
[39] M. Asensio and J. Contreras, ''Risk-constrained optimal bidding strategy for pairing of wind and demand response resources,'' *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 200–208, Jan. 2017.
[40] P. Krokhmal, T. Uryasev, and J. Palmquist, ''Portfolio optimization with conditional value-at-risk objective and constraints,'' *J. Risk*, vol. 4, no. 2, pp. 43–68, Mar. 2001.
[41] T. Schröder and W. Kuckshinrichs, ''Value of lost load: An efficient economic indicator for power supply security? A literature review,'' *Frontiers Energy Res.*, vol. 3, p. 55, Dec. 2015.
[42] AESO. (2020). *Transmission Cost Report*. [Online]. Available: https://public.tableau.com/profile/transmissioncost#/
[43] W. E. Hart, J.-P. Watson, and D. L. Woodruff, ''Pyomo: Modeling and solving mathematical programs in Python,'' *Math. Program. Comput.*, vol. 3, no. 3, pp. 219–260, Sep. 2011.
[44] Gurobi Optimization. (2020). *Gurobi Optimizer Reference Manual*. [Online]. Available: http://www.gurobi.com



JUAN ARTEAGA (Student Member, IEEE) received the B.E. and M.Eng. degrees in industrial engineering from the Universidad Panamericana, Guadalajara, Mexico, in 2006 and 2008, respectively, and the Ph.D. degree from the Department of Electrical Engineering, University of Calgary, in 2020. His research interests include energy storage economic feasibility, electricity markets modeling, energy efficiency and energy optimization techniques. He has publication in topics related to grid-scale energy storage, ranging from applications of lithium-ion batteries in the grid, to monetizing strategies for energy storage providing multiple services, including planning and operation algorithms, as well as a policy proposal to encourage investment in energy storage.

HAMIDREZA ZAREIPOUR (Senior Member, IEEE) received the Ph.D. degree in electrical and computer engineering from the University of Waterloo, Ontario, Canada, in 2006. He is currently a Professor with the University of Calgary, Canada. He leads a research team focused on modeling and integration of bulk energy storage systems into optimal operation and planning practices of electrical grids. He is the past Chair of the IEEE PES Working Group on Business Models for Energy Storage Systems.

NIMA AMJADY (Senior Member, IEEE) received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from the Sharif University of Technology, Tehran, Iran, in 1992, 1994, and 1997, respectively. He is currently a Full Professor with the Electrical Engineering Department, Semnan University, Iran. He is also a Consultant of the Iran Grid Management Company (IGMC) and the Consultant of Semnan University President. He was selected as the Iran's youngest professor in 2007. His research interests include forecast processes as well as operation and planning of power systems.