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Evaluation of Energy Storage Providing Virtual Transmission Capacity

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***Abstract*—In this work, we introduce the concept of virtual transmission using large-scale energy storage systems. We also develop an optimization framework to maximize the monetized benefits of energy storage providing virtual transmission in wholesale markets. These benefits often come from relieving congestion for a transmission line, including both reduction in energy cost for the downstream loads and increase in production revenue for the upstream generators of the congested line. A case study is conducted using ISO-New England data to demonstrate the framework.**

***Index Terms*—Energy storage, virtual transmission, congestion relief, optimization, Mixed Integer Quadratic Programming (MIQP).**

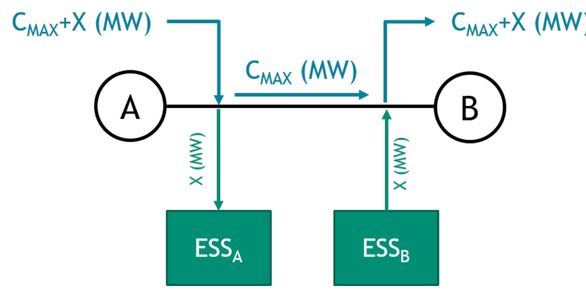

Fig. 1. Virtual Transmission Concept

I. Introduction

Over the last decade, renewable energy (e.g., wind and solar) has been rapidly growing, adding a large amount of clean generation to the electric grid in the U.S. This development is in line with the current policies of many states that target 100% renewable or 100% carbon-free electric grid in two or three decades. One challenge with this trend is that the current grid infrastructure is outdated and cannot keep up with the rapid development of renewable energy. This challenge is mostly related to the transmission system not having enough capacity to deliver all potential renewable energy generation to the loads, resulting in large amount of renewable curtailments. While transmission expansion are inevitable, it requires a lot of time and investment to upgrade and build new transmission lines. Therefore, non-wire alternatives, which include non-traditional transmission and distribution (T&D) solutions (e.g., demand response, distributed generation, and energy storage), are necessary to defer, reduce or even remove the need for transmission upgrades. Among the non-wire alternatives, energy storage systems (ESS) have proven to be very flexible and can provide multiple services. Previous works in this topic have shown the benefits of energy storage for transmission upgrade deferral and congestion relief [1–3], for reducing renewable energy curtailments [4, 5], for peak shaving [6, 7]. Other related works in the literature have assessed the potential revenues of ESSs for different applications such as for energy arbitrage and ancillary services in different markets [8–10], for behind-the-meter applications [11–13], and for enhancing generation fleet efficiency [14].

Although many studies have evaluated the potential revenue of ESSs for different applications as mentioned above, none of them have discovered the benefits of ESSs providing virtual transmission (VT) capacity (i.e., mimicking the line flow by simultaneously charge and discharge ESSs at both ends of a line). In wholesale markets, these benefits often include the reduction in energy cost for the downstream loads and the increase in production revenue for the upstream generators of congested lines after being relieved. In comparison with transmission upgrade, ESS deployments take much less time and smaller footprint and they can be relocatable. The only short coming of ESSs is that they have shorter life spans. For example, typical Li-ion battery systems last about 10 to 15 years in comparison with 50 to 60 years of a transmission line. Therefore, it is essential to evaluate the overall economic gain of ESSs in this application considering their limitations.

In this paper we propose an approach to evaluate the potential benefits of ESSs providing VT in wholesale markets. In the proposed approach, a Mixed Integer Quadratic Program (MIQP) is formulated to find the optimal charge/discharge operating scheme for ESSs that maximizes the targeted revenue for the storage owners. In the scope of this work, we assume ESSs are owned by the upstream generators. Therefore, the targeted revenue for ESSs is the increase in production revenue of the upstream generators that use virtual transmission capacity to sell more energy at higher energy price to the downstream loads during the congested times. The linear constraints of this optimization are based on the energy storage linear energy-flow model [15] and the static line ratings given by the system operators. A case study is conducted for a renewable energy export region in ISO-New England, in which the above optimization problem is solved using Gurobi solver in Pyomo environment [16]. Since perfect foresight data is used, the results show the maximum potential revenue of ESSs in this case study.

Specifically, the contributions of this paper include:

- An optimization framework for maximizing the revenue of ESSs providing virtual transmission capacity.
- A case study for a renewable energy export zone in ISO-New England. A few ESS sizes are investigated to see the sensitivity of overall benefit to ESS size.

II. Virtual Transmission using energy storage systems in wholesale markets

A. Virtual Transmission Concept

Virtual transmission refers to the non-wire solution that uses ESSs at both ends of a line to mimic the line flow. When the line is congested, simultaneously charging and discharging these ESSs allow sending more power to one end and receiving more power out of the other end of the line at the same time. This activity mimics an addition to the line capacity even though no more power than the line's rating is physically transmitted through the line. When the line is not congested, other operating schemes can be performed to manage the state of energy (SOE) and to maximize the benefits of the ESSs through other market activities. Fig. 1 shows an example of line AB with line rating C_{MAX} (MW). Two storage systems ESS-A and ESS-B are placed at the two ends of the line to provide virtual transmission capacity when needed. During a congested time, by simultaneously charging X (MW) to ESS-A and discharging X (MW) from ESS-B, the line capacity is virtually increased by X (MW).

B. Impact of Virtual Transmission on Local Marginal Price (LMP) in Wholesale Markets

To illustrate how virtual transmission can impact LMPs in wholesale markets, we use an example of two zones A and B connected through interface A-B. It should be noted that zone A and B can include a few generators and loads and interface A-B can include one or multiple transmission lines. Assuming at hour h, the loads of A and B are both 600 MW; the supply curves of the two zones are given in Fig. 2. Since the load in zone B is willing to pay as much as the generators in zone B offer, the supply curve of zone B can act as the demand curve for zone A, and vice versa.

If the interface is not congested, the marginal energy price (MEP) is cleared at the intersect of the two curves. Therefore, in this example, zone A's generation is cleared for 900 MW and zone B's generation is cleared for 300 MW. It means the power flow through interface A-B is 300 MW. However, if the interface is congested at hour h and only allows 200 MW to be delivered then Zone A's generation will be cleared for 800 MW at LMP^A while zone B's generation is cleared for 400 MW at LMP^B. Since Zone A's generation is cleared for 100 MW less than it is in the non-congested case, LMP^A is less than the MEP. On the other side, Zone B's generation is cleared for 100 MW more than it is in the non-congested case making LMP^B greater than the MEP (see Fig. 3). In other words, the congestion makes LMP^A and LMP^B deviate from the MEP in the opposite directions. In wholesale markets, this phenomenon is not desirable because it increases the overall system cost and also makes the loads pay more than the total amount that is paid to the generators.

In the congested case, if ESSs are placed at both ends of the interface and simultaneously charge and discharge X (MW) (less than 100 MW) during hour h, zone A can virtually send additional X MW to zone B. Therefore, the new LMP^A and LMP^B will be closer to the MEP. In other words, the virtual transmission capacity provided by ESSs can make the LMPs converge back to the MEP. The direct beneficiaries of adding X (MW) virtual transmission capacity are the upstream generators (zone A's generators) who can sell more energy at higher LMPs and the downstream loads (zone B's loads) who can buy energy at lower LMPs during congested times. From the perspective of the system operators, this reduces the overall system cost of the market since more energy from the cheaper generators can be delivered to the loads. It should be noted that ESSs only need to provide virtual transmission capacity during congested times. Furthermore, the value of virtual transmission capacity can vary depending on the needed

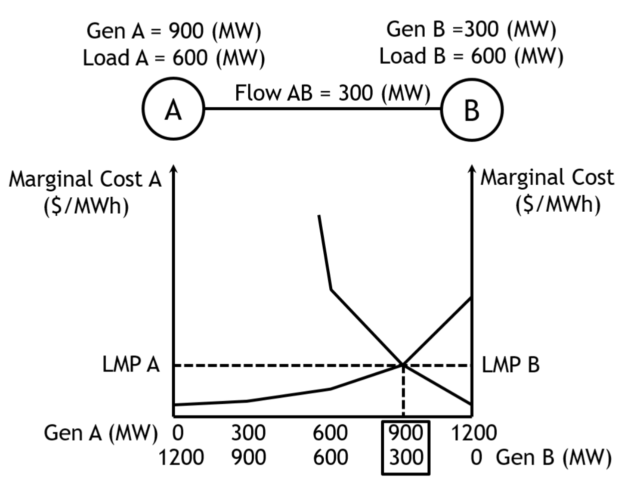

Fig. 2. LMPs - Non-congested Case

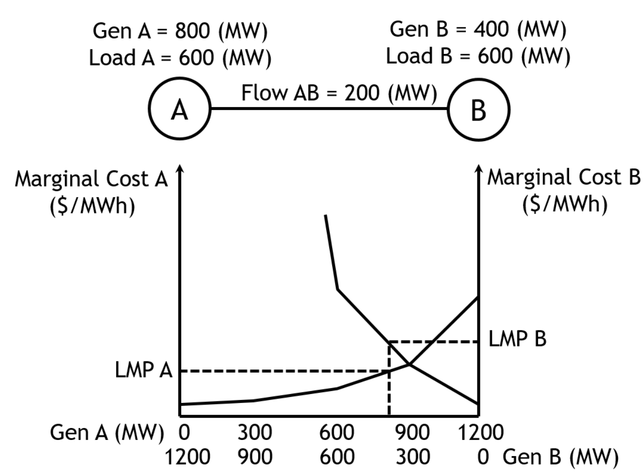

Fig. 3. LMPs - Congested Case

capacity to relieve congestion as well as the available capacity of the ESSs. Therefore, it is important to optimize ESSs' operation to maximize the targeted revenue for ESSs' owners.

III. Evaluation of energy storage providing virtual transmission

In this section, an optimization problem is formulated to find the optimal charge/discharge operating scheme of ESS-A and ESS-B at both ends of the transmission interface A-B (as described in Section II-B) for doing two activities: 1) providing virtual transmission capacity during congested times, and 2) doing energy arbitrage during non-congested times. The objective of this optimization is to maximize the total revenue from these activities for the upstream generators of the congested transmission interface. The objective function is given below where all variables and constants are declared in Table I.

$$\text{maximize } \mathrm{R_{virt}} + \mathrm{R_{arb}} \tag{1}$$

in which

$$\mathrm{R_{virt}} = \tau \sum_{i=1}^{\mathrm{H}} \alpha_i \left[\left(\mathrm{P}_i^{\mathrm{A}} + X_i\right) f_i^{\mathrm{A}}|_{\mathrm{P}_i^{\mathrm{A}}+X_i} - \mathrm{P}_i^{\mathrm{A}}\mathrm{LMP}_i^{\mathrm{A}} \right] \tag{2}$$

$$\mathrm{R_{arb}} = \tau \sum_{i=1}^{H} (1-\alpha_i)\mathrm{LMP}_i^{\mathrm{A}} \left(P_i^{A,d} + P^{B,d} - P_i^{A,c} - P_i^{B,c} \right) \tag{3}$$

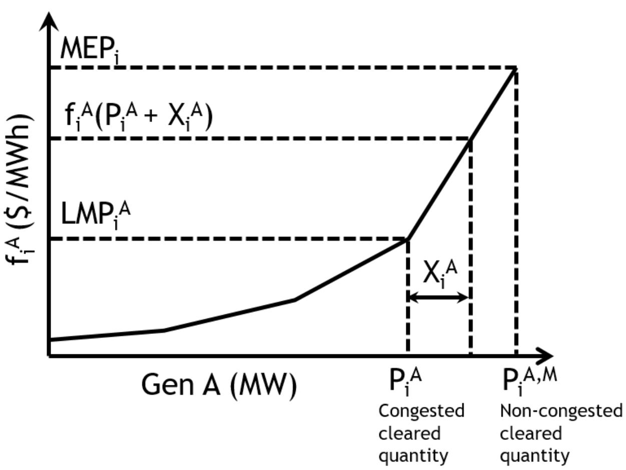

Fig. 4. Production cost function of zone A during a congested time

In (2), $\mathrm{R_{virt}}$ is the increase in total production revenue of zone A's generators by adding VT capacity during congested times and f_i^{A} (in \$/MWh) is the production cost function of zone A during a congested time. Assuming f_i^{A} is piece-wise linear (see Fig. 4), the last section of f_i^{A}, denoted as g_i, can be expressed as a linear function of X_i as in (4).

$$g_i(X_i) = \mathrm{m}_i X_i + \mathrm{LMP}_i^{\mathrm{A}} \tag{4}$$

$$\mathrm{m}_i = \frac{\mathrm{MEP}_i - \mathrm{LMP}_i^{\mathrm{A}}}{\mathrm{P}_i^{\mathrm{A,M}} - \mathrm{P}_i^{\mathrm{A}}} \tag{5}$$

TABLE I
NOMENCLATURE

Constants	Description	Unit
τ	Time step duration	hour
i	Time step index	-
H	Time horizon	-
$\overline{S}$	ESS's energy capacity	MWh
$\overline{P}$	ESS's power rating	MW
η_{s}	ESS's self-discharge efficiency $\in [0,1]$	-
η_{c}	ESS's round-trip efficiency $\in [0,1]$	-
α_i	1 if A-B is congested at i and 0 o.w.	-
$\mathrm{P}_i^{\mathrm{A}}$	Cleared generation of zone A at i	MW
$\mathrm{P}_i^{\mathrm{A,l}}$	Load of zone A at i	MW
$\mathrm{P}_i^{\mathrm{A,M}}$	Non-congested generation of zone A at i	MW
$\mathrm{P}_i^{\mathrm{A\text{-}B,\,max}}$	Line rating of interface A-B at i	MW
$\mathrm{LMP}_i^{\mathrm{A}}$	Cleared LMP of zone A at i	\$/MWh
MEP_i	Non-congested marginal energy price at i	\$/MWh
Variables	**Description**	**Unit**
X_i	VT capacity provided by ESSs at i	MW
$P_i^{\mathrm{A,c}}$	Charge power of ESS-A at i	MW
$P_i^{\mathrm{B,c}}$	Charge power of ESS-B at i	MW
$P_i^{\mathrm{A,d}}$	Discharge power of ESS-A at i	MW
$P_i^{\mathrm{B,d}}$	Discharge power of ESS-B at i	MW
$\beta_i^{\mathrm{A,c}}$	Binary charge status of ESS-A at i	-
$\beta_i^{\mathrm{B,c}}$	Binary charge status of ESS-B at i	-
S_i^{A}	ESS-A's state of energy at the end of i	MWh
S_i^{B}	ESS-B's state of energy at the end of i	MWh

Therefore, $\mathrm{R_{virt}}$ can be re-written as in (6)(7).

$$\mathrm{R_{virt}} = \tau \sum_{i=1}^{\mathrm{H}} \alpha_i \left[\left(\mathrm{P}_i^{\mathrm{A}} + X_i\right)\left(\mathrm{m}_i X_i + \mathrm{LMP}_i^{\mathrm{A}}\right) - \mathrm{P}_i^{\mathrm{A}}\mathrm{LMP}_i^{\mathrm{A}} \right] \tag{6}$$

$$\mathrm{R_{virt}} = \tau \sum_{i=1}^{\mathrm{H}} \alpha_i \left[m_i X_i^2 + \left(P_i^A m_i + LMP_i^A\right) X_i \right] \tag{7}$$

In (3), $\mathrm{R_{arb}}$ is the total revenue for doing energy arbitrage during non-congested times. We assume that charge and discharge activities of ESSs during those times do not impact the LMPs as long as the transmission interface constraint (as formulated in (16)) is not violated. Note that when interface A-B is not congested, $\mathrm{LMP^B}$ is equal $\mathrm{LMP^A}$. Therefore, arbitrage revenue can be simplified as in (3).

The constraints of the optimization are formulated as follows:

- **State of energy constraints:**

$$S_i^{\mathrm{A/B}} = \eta_s S_{i-1}^{\mathrm{A/B}} + \tau \left(\eta_c P_i^{\mathrm{A/B,c}} - P_i^{\mathrm{A/B,d}} \right) \tag{8}$$

$$0 \le S_i^{\mathrm{A/B}} \le \overline{S} \tag{9}$$

$$S_0^{\mathrm{A/B}} = S_{\mathrm{H}}^{\mathrm{A/B}} = 0.5 \tag{10}$$

These constraints calculate and make sure the SOEs of ESSs are in within their energy capacity limits.

- **Charge-discharge constraints:**

$$0 \le P_i^{\text{A/B,c}} \le \beta_i^{\text{A/B,c}} \overline{P} \tag{11}$$

$$0 \le P_i^{\text{A/B,d}} \le \left(1 - \beta_i^{\text{A/B,c}}\right) \overline{P} \tag{12}$$

The above constraints are for keeping charge and discharge powers of the ESSs within their power ratings. Even though charge and discharge activities can occur together within one time step (i.e, alternatively charge and discharge within one time step), doing such operating scheme can eliminate the capability of providing virtual transmission capacity. Therefore, binaries variables are used to avoid such activities.

- **Virtual transmission constraints:**

$$0 \le X_i \le P_i^{\text{A,M}} - P_i^{\text{A}} \tag{13}$$

$$X_i = \alpha_i P_i^{\text{A,c}} \tag{14}$$

$$X_i = \alpha_i P_i^{\text{B,d}} \tag{15}$$

Constraint (13) is for limiting the amount of VT capacity provided by the ESSs less than the needed amount. Constraints (14) and (15) are for making the charge power of ESS-A and discharge power of ESS-B equal to the VT capacity needed during congested times.

- **Transmission interface constraints:**

$$0 \le (\text{P}_i^{\text{A}} + X_i) - \text{P}_i^{\text{A,l}} + P_i^{\text{A,d}} - P_i^{\text{A,c}} \le \text{P}_i^{\text{A-B,max}} \tag{16}$$

These constraints make sure the power flow from zone A to zone B is less than the limit of the transmission interface. Since we assume zone A is an energy exporter, this power flow also needs to be greater than zero.

IV. A Case study in ISO - New England

In this case study, we investigate a real region, denoted as region A, in ISO-NE. This region has a few generators including a few hydro power plants and two wind plants. It exports its energy to region B, which is a load zone in ISO-NE, through an interface that includes a few transmission lines. Due to the congestions that often occur in one of the lines, the marginal wind plant in region A has to frequently curtail its output. Therefore, the congestion components of LMP^{A} are often negative.

Solving the above optimization, we valuate the revenue of ESSs providing VT capacity and doing energy arbitrage. ESSs of different power and energy ratings are investigated to characterize the sensitivity of the total revenue to ESS sizes. We also compare those with the benefit of using the same energy storage for wind curtailment utilization (i.e., save the curtailment during congested times and discharge that energy during non-congested times). Results show the LMP improvement in this case can be significant (see Fig. 7). For example, with 10 MW/10 MWh ESS at each end of the line or the total of 20 MWh storage can help increase revenue for region A $850,000 a year that is approximately 2.5 times higher than that of wind curtailment utilization. Fig. 5 shows an example of 24-hour charge/discharge profile of the ESSs. We can see that during hour 18, ESS-A and ESS-B respectively charge and discharge 10 MW to add 10MW VT capacity thereby reducing 10 MWh of wind curtailment and increasing the LMP by $5/MWh. This is important to note that in this case the revenue from doing energy arbitrage during non-congested times is negative (approx. -$3200). This is mainly because the money earned by doing energy arbitrage is still less than the money loss due to the energy losses by cycling the ESSs. However, energy arbitrage is still necessary to maintain the SOEs of the ESSs.

Fig. 6 shows the sensitivity of total revenue to ESSs' sizes. In this figure, x-axis represents the energy rating of each ESS and y-axis represents the total revenue while each line corresponds to a power rating. We can see that the revenue increases as the energy rating increases. The revenue also tends to increase with the larger power ratings, however, it is saturated at the power rating of 40 MW. This is because the maximum size of wind curtailment is 40 MW. In this case the maximum potential revenue for providing virtual transmission is about $3.25 millions a year.

V. Conclusions

In this paper, the concept of virtual transmission is introduced. We develop an optimization framework to maximize the total revenue of ESSs providing VT capacity during congested times together with energy arbitrage during non-congested times. In the proposed approach, an MIQP is formulated to find the optimal operating scheme of the ESSs at both ends of a transmission interface that maximize the total revenue. The results in the case study show VT capacity from ESSs can significantly improve the LMPs for the upstream region of the congested interface thereby increase the revenue for the generators in this region. Revenue form energy arbitrage activity in this case is negative, however, it is still a necessary activity for maintaining the SOEs. Future work in this area would consider the combination of VT with other market-based ancillary services such as frequency regulation.

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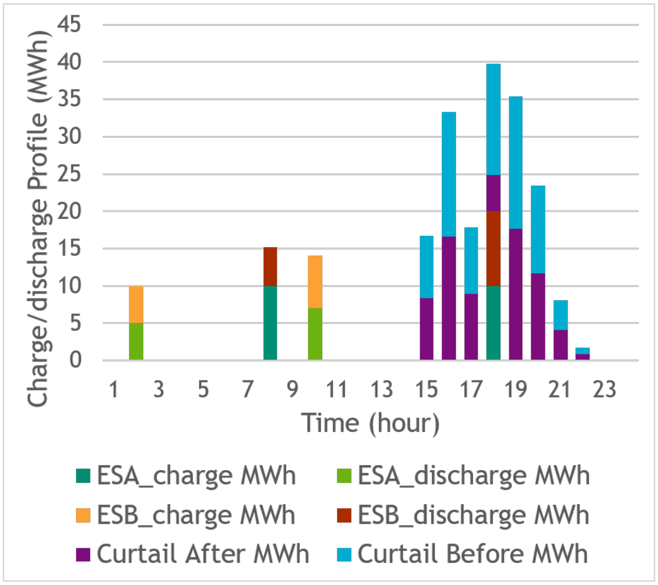

Fig. 5. 2 x (10 MW/ 10 MWh) Case: 24-hour charge/discharge profile example

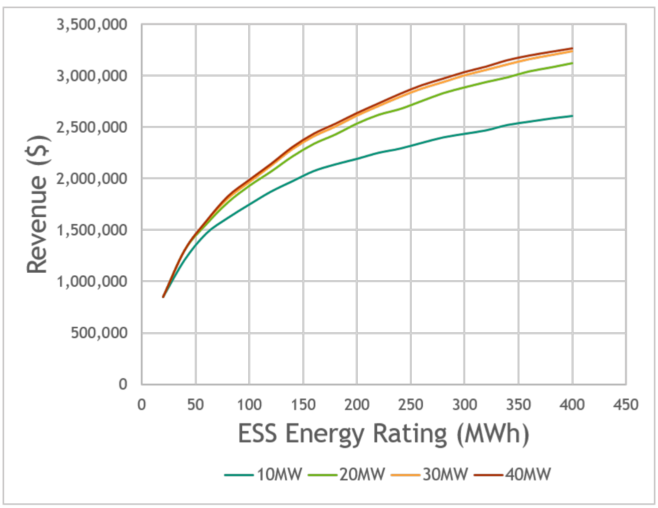

Fig. 6. Revenue vs. ESS sizes

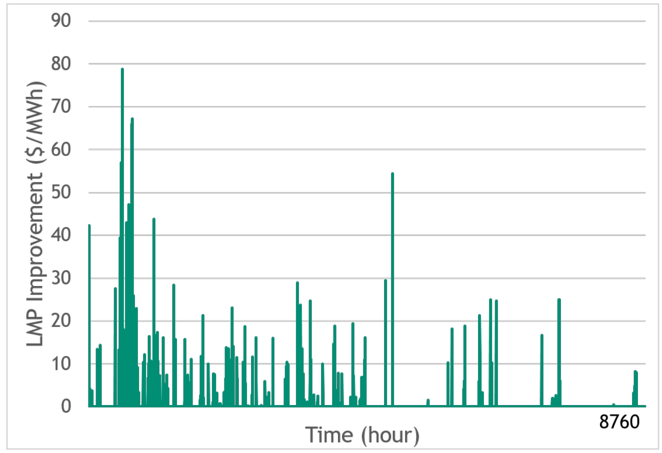

Fig. 7. 2 x (10 MW/ 10 MWh) Case: LMP improvement

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