Impact of Energy Storage on Market-Based Generation Investment Planning

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***Abstract*—Previous work has analyzed the role of energy storage (ES) on generation investment planning through centralised cost-minimization models which are inherited from the era of regulated electricity utilities. This paper investigates this issue in the context of the deregulated market environment by proposing a new strategic generation investment planning model. The decision making of a strategic generation company is modeled through a multi-period bi-level optimization problem, where the upper level determines the profit-maximizing investment decisions of the generation company and the lower level represents the market clearing process, accounting for the time-coupling operational characteristics of ES. This bi-level problem is solved after converting it to a single-level mixed-integer linear problem (MILP). Case studies demonstrate that the introduction of ES reduces the total generation capacity investment and enhances investments in "must-run" baseload generation over flexible peaking generation, yielding significant system cost savings.**

***Index Terms*-- Bi-level optimization, electricity markets, energy storage, generation investment planning.**

NOMENCLATURE

A. *Indices and Sets*

$t \in T$	Index and set of hours
$d \in D$	Index and set of representative days
$i \in I$	Index and set of generation technologies
$I^{MR} \subseteq I$	Subset of must-run generation technologies
V^{LL}	Set of decision variables of lower level problem
V	Set of decision variables of MPEC model

B. *Parameters*

τ, N_T	Temporal resolution and length of market horizon
w_d	Weighting factor of day d
IC_i	Investment cost of generation technology i (£/kW/year)
c_i	Marginal operation cost of generation technology i (£/MWh)
$b_{d,t}$	Marginal benefit of demand at day d and hour t (£/MWh)
$d_{d,t}^{max}$	Maximum demand at day d and hour t (MW)
s^{max}	Power capacity of ES (MW)
E^{cap}	Energy capacity of ES (MWh)
E^{max}	Maximum energy limit of ES (MWh)
E^{min}	Minimum energy limit of ES (MWh)
E_o	Initial energy level of ES (MWh)
η^c, η^d	Charging and discharging efficiency of ES
Υ	System adequacy coefficient

C. *Variables*

X_i	Invested capacity of technology i (MW)
$g_{i,d,t}$	Power output of technology i at day d and hour t (MW)
$d_{d,t}$	Power input of demand at day d and hour t (MW)
$s_{d,t}^c$	Charging power of ES at day d and hour t *(MW)*
$s_{d,t}^d$	Discharging power of ES at day d and hour t *(MW)*
$E_{d,t}$	Energy level of ES at day d at the end of hour t (MWh)
$\lambda_{d,t}$	Market clearing price at day d and hour t (£/MWh)

I. INTRODUCTION

Growing environmental and energy security concerns have paved the way for the decarbonization of energy systems through the large-scale integration of renewable generation and the electrification of transport and heat sectors. However, these paradigm changes introduce great techno-economic challenges, associated with the high variability and limited controllability of renewable generation as well as the increasing demand peaks, respectively.

In this setting, energy storage (ES) technologies have attracted special interest by governments, industry and academia, as their flexibility can support system balancing and limit peak demand levels, improving the cost efficiency of low-carbon electricity systems [1]-[2]. A particularly interesting area of research lies in investigating the role and

The work of Temitayo Oderinwale is sponsored under the Presidential Special Scholarship Scheme for Innovation and Development (PRESSID) of the Federal Government of Nigeria coordinated by the National Universities Commission (NUC) and funded by the Petroleum Technology Development Fund (PTDF).

value of ES in long-term generation investment planning decisions. However, previous studies in this area, [3]-[7], have employed centralised planning models inherited from the era of vertically integrated electricity utilities, optimising system objectives (i.e. minimising the long-term system cost) and assuming perfectly competitive behaviour by market participants.

The recent deregulation of the electricity industry has driven unbundling of vertically integrated monopoly utilities and the introduction of competition in the generation and supply sectors. This means that such centralised models are not able to provide accurate and meaningful insights anymore, since they neglect the fact that self-interested generators' actions are not generally aligned with system cost minimization but rather rely on profit-driven decisions. In this setting, generation companies need suitable models to optimize their investment strategies, accounting for the impact of these strategies on the competitive market.

A few recent papers, [8]-[12], have modeled this strategic generation investment planning framework under different assumptions and conditions. All these studies employ the same fundamental methodology to model strategic generation planning, namely *bi-level optimization*. The strength of this modeling approach lies in its capacity to comprehensively capture the interactions between the strategic investment decisions of the generation companies and the competitive clearing of the electricity market at the operational timescale.

However, all these previous works on strategic generation investment planning exhibit a fundamental shortcoming. Time-coupling at the operational timescale is not considered, implying that the optimal market clearing is independently carried out for each time period. This means that they are inherently unable to represent the operation of ES which is naturally associated with time-coupling effects, as its charging and discharging cycles are interrelated.

This paper makes the first attempt to fill this knowledge gap by incorporating the operation of ES in a strategic generation investment planning modeling framework. The decision making of a strategic generation company is modeled through a *multi-period bi-level optimization problem*. The upper level (UL) problem determines the optimal investment decisions of the generation company so as to maximize its profit, given by the difference between its profit in the electricity market and its investment cost for procuring generation capacity. This UL problem is subject to the lower level (LL) problem which represents endogenously the electricity market clearing process on a daily basis, accounting for the time-coupling operational characteristics of ES through a generic, technology-agnostic model. This bi-level problem is solved after converting it to a *Mathematical Program with Equilibrium Constraints* (MPEC), and linearizing the latter through suitable techniques.

Case studies with the developed model are carried out on a test system with a yearly operation horizon and hourly resolution. The results indicate that ES reduces the total generation capacity investment and enhances investments in "must-run" baseload generation over flexible peaking generation. Furthermore, this reduction of the total capacity investment and the reduced need to run mid-merit and peaking generation with high operating costs results in significant system cost savings. These impacts are enhanced for higher values of the power-to-energy ratio and the energy efficiency of ES.

The rest of this paper is organized as follows. Section II details the proposed modeling framework. Section III presents the case studies and quantitative results. Finally, Section IV discusses conclusions and future extensions of this work.

II. Proposed Modeling Framework

A. Modeling Assumptions

For clarity reasons, the main assumptions behind the proposed model are outlined below:

- The model assumes a static planning approach and a yearly operation horizon. In other words, the strategic generation company determines its optimal investment decisions considering a single, future target year. Both investment and operating costs and revenues are calculated at the same yearly basis.
- The strategic generation company can invest in generation capacity of different technologies. Each generation technology is characterized by different investment and operating costs and a subset of the technologies are assumed "must-run" i.e. they must be operating at their full capacity during all times.
- The considered electricity market is a pool-based energy-only market with a day-ahead horizon and hourly resolution and is cleared by the market operator through the solution of a short-term social welfare maximization problem.
- The strategic generation company submits to the market a linear offer curve for each of the different technologies within its generation portfolio. This curve represents the actual operating cost function of the respective technology, since strategic offering effects are neglected in this paper.
- The demand side submits to the market a linear bid curve. In order to capture the temporal variability of demand characteristics, a set of representative days is examined.
- The considered ES is assumed to be already built and does not belong to the strategic generation company.
- Following the approach adopted in [13], a generic, technology-agnostic model is employed for the representation of the technical characteristics of ES, which includes charging and discharging efficiencies, energy balance constraints as well as minimum and maximum energy and power limits. The operation and maintenance costs of ES are assumed negligible, so it does not submit a price offer or bid to the market.

B. Bi-Level Optimization Fomulation

The proposed bi-level optimization formulation models the decision making process of the strategic generation company and is formulated as follows:

(Upper level)

$$\max_{\{X_i\}} \sum_d w_d \left(\sum_{i,t}(\lambda_{d,t} g_{i,d,t} - c_i g_{i,d,t})\right) - \sum_i IC_i X_i \quad (1)$$

subject to:

$$X_i \geq 0, \forall i \quad (2)$$

$$\sum_i X_i \geq \Upsilon * \left(d_{d,t} + s^c_{d,t} - s^d_{d,t}\right), \forall d, \forall t \quad (3)$$

(Lower level)

$$\min_{V^{LL}} \left(\sum_{d,t,i} c_i g_{i,d,t} - \sum_{d,t} b_{d,t} d_{d,t}\right) \quad (4)$$

where:

$$V^{LL} = \{g_{i,d,t}, d_{d,t}, s^c_{d,t}, s^d_{d,t}, E_{d,t}\} \quad (5)$$

subject to:

$$d_{d,t} + s^c_{d,t} - s^d_{d,t} - \sum_i g_{i,d,t} = 0 : \lambda_{d,t}; \forall d, \forall t \quad (6)$$

$$0 \leq g_{i,d,t} \leq X_i : \mu^-_{i,d,t}, \mu^+_{i,d,t}; \forall i \notin I^{MR}, \forall d, \forall t \quad (7)$$

$$g_{i,d,t} = X_i : \xi_{i,d,t}, \forall i \in I^{MR}, \forall d, \forall t \quad (8)$$

$$0 \leq d_{d,t} \leq d^{max}_{d,t} \; v^-_{d,t}, v^+_{d,t}; \; \forall d, \forall t \quad (9)$$

$$E_{d,t} = E_{d,t-1} + \tau \eta^c s^c_{d,t} - \frac{\tau s^d_{d,t}}{\eta^d} : \pi_{d,t}; \forall d, \forall t \quad (10)$$

$$E_0 = E_{d,t} : \rho_d; \forall d, \forall t = N_T \quad (11)$$

$$E^{min} \leq E_{d,t} \leq E^{max} : \; \sigma^-_{d,t}, \sigma^+_{d,t}; \forall d, \forall t \quad (12)$$

$$0 \leq s^c_{d,t} \leq s^{max} : \varphi^-_{d,t}, \varphi^+_{d,t}; \forall d, \forall t \quad (13)$$

$$0 \leq s^d_{d,t} \leq s^{max} : \chi^-_{d,t}, \chi^+_{d,t}; \; \forall d, \forall t \quad (14)$$

The upper level (UL) problem maximizes the profit of the strategic generation company across the yearly planning horizon (1), given by the difference between its yearly operational profit in the electricity market (first term) and its annuitized investment cost for procuring generation capacity (second term). This problem is subject to the positivity limits of the investment decisions (2), the adequacy constraint (3) which is enforced by the regulator to preserve security of supply requirements, as well as the lower level (LL) problem (4)-(14). The latter represents the market clearing process at each representative day, minimising the negative social welfare (4), subject to demand-supply balance constraints (6) (the Lagrangian multipliers of which constitute the market clearing prices), and the operating constraints of the generation side (7)-(8), the demand side (9), and the ES. The latter include energy balance constraints (10), the assumption of energy neutrality over the daily market horizon (11), and minimum and maximum energy and power limits (12)-(14).

C. MPEC Formulation

In order to solve this bi-level optimization problem, the LL problem is replaced by its *Karush-Kuhn-Tucker* (KKT) optimality conditions, a replacement enabled by the fact that the LL problem is continuous and convex. This converts the bi-level problem to a single-level MPEC which is formulated as:

$$\max_{V} \sum_d w_d \left(\sum_{i,t}(\lambda_{d,t} g_{i,d,t} - c_i g_{i,d,t})\right) - \sum_i IC_i X_i \quad (15)$$

where:

$$V = \begin{Bmatrix} X_i, g_{i,d,t}, d_{d,t}, s^c_{d,t}, s^d_{d,t}, E_{d,t}, \lambda_{d,t}, \mu^-_{i,d,t}, \mu^+_{i,d,t}, \xi_{i,d,t}, \\ v^-_{d,t}, v^+_{d,t}, \pi_{d,t}, \rho_d, \sigma^-_{d,t}, \sigma^+_{d,t}, \varphi^-_{d,t}, \varphi^+_{d,t}, \chi^-_{d,t}, \chi^+_{d,t} \end{Bmatrix} \quad (16)$$

subject to:

(2)-(3), (6), (8), (10)-(11)

$$c_i - \lambda_{d,t} - \mu^-_{i,d,t} + \mu^+_{i,d,t} = 0, \forall i \notin I^{MR}, \forall d, \forall t \quad (17)$$

$$c_i - \lambda_{d,t} + \xi_{i,d,t} = 0, \forall i \in I^{MR}, \forall d, \forall t \quad (18)$$

$$\lambda_{d,t} - b_{d,t} - v^-_{d,t} + v^+_{d,t} = 0, \forall d, \forall t \quad (19)$$

$$\lambda_{d,t} - \tau \eta^c \pi_{d,t} - \varphi^-_{d,t} + \varphi^+_{d,t} = 0, \forall d, \forall t \quad (20)$$

$$-\lambda_{d,t} + \frac{\tau \pi_{d,t}}{\eta^d} - \chi^-_{d,t} + \chi^+_{d,t} = 0, \forall d, \forall t \quad (21)$$

$$-\sigma^-_{d,t} + \sigma^+_{d,t} + \pi_{d,t} - \pi_{d,(t+1)} = 0, \forall d, \forall t < N_T \quad (22)$$

$$-\sigma^-_{d,t} + \sigma^+_{d,t} + \pi_{d,t} - \rho_d = 0, \forall d, \forall t = N_T \quad (23)$$

$$0 \leq g_{i,d,t} \perp \mu^-_{i,d,t} \geq 0 : \forall i \notin I^{MR}, \forall d, \forall t \quad (24)$$

$$0 \leq \left(X_i - \; g_{i,d,t}\right) \perp \mu^+_{i,d,t} \geq 0, \forall i \notin I^{MR}, \forall d, \forall t \quad (25)$$

$$0 \leq d_{d,t} \perp v^-_{d,t} \geq 0, \forall d, \forall t \quad (26)$$

$$0 \leq \left(d^{max}_{d,t} - \; d_{d,t}\right) \perp v^+_{d,t} \geq 0, \forall d, \forall t \quad (27)$$

$$0 \leq \left(E_{d,t} - E^{min}\right) \perp \sigma^-_{d,t} \geq 0, \forall d, \forall t \quad (28)$$

$$0 \leq \left(E^{max} - \; E_{d,t}\right) \perp \sigma^+_{d,t} \geq 0, \forall d, \forall t \quad (29)$$

$$0 \leq s^c_{d,t} \perp \varphi^-_{d,t} \geq 0, \forall d, \forall t \quad (30)$$

$$0 \leq \left(s^{max} - s^c_{d,t}\right) \perp \varphi^+_{d,t} \geq 0, \forall d, \forall t \quad (31)$$

$$0 \leq s^d_{d,t} \perp \chi^-_{d,t} \geq 0, \forall d, \forall t \quad (32)$$

$$0 \leq \left(s^{max} - \; s^d_{d,t}\right) \perp \chi^+_{d,t} \geq 0, \forall d, \forall t \quad (33)$$

The set of decision variables of the MPEC formulation (16) includes i) the decision variables of the UL problem, ii) the decision variables of the LL problem, and iii) the

Lagrangian multipliers associated with the constraints of the LL problem. The KKT optimality conditions of the LL problem correspond to equations (17)-(33).

This MPEC formulation is characterized by several non-linearities, including bilinear terms in the objective function (15) and the complementarity slackness conditions (24)-(33). In order to avoid global optimality issues associated with non-linear formulations, this MPEC is transformed to a *mixed-integer linear problem* (MILP), which can be efficiently solved to global optimality using commercial branch-and-cut solvers. For space limitation reasons, this transformation is not presented here, but adopts the linearization approaches presented in previous relevant works [13].

III. Case Studies

A. Test System and Implementation

The strategic generation company can invest in three different technologies, namely nuclear, combined cycle gas turbines (CCGT) and open cycle gas turbines (OCGT). Nuclear generation is assumed "must-run". The assumed values of the investment and operating costs of these technologies are presented in Table I. Four typical days representing the four seasons of the year are used, and the respective maximum demand profiles are obtained from [14].

TABLE I. Investment and Operating Costs of Generation Technologies

Technology	Nuclear	CCGT	OCGT
IC_i (£/kW/year)	328.21	52.12	26.46
c_i (£/MWh)	4.72	37.68	56.98

The developed MILP model has been implemented and solved using the optimization software FICO™ Xpress [15] on a computer with a 6-core 3.50 GHz Intel(R) Xeon(R) E5-1650 processor and 32 GB of RAM. The average computational time required for solving this MILP across all the examined scenarios was approximately 15 minutes.

B. Results

The scope of the case studies lies in quantitatively analyzing the impacts of ES on the investment decisions of the considered strategic generation company. For this reason, we run the developed model for different scenarios regarding the operating parameters of ES. For ease of reference a baseline scenario is defined, characterized by the ES parameters presented in Table II.

TABLE II. ES Parameters in Baseline Scenario

Parameter	$E^{cap} = E^{max}$	E^{min}	E_0	s^{max}	$\eta^c = \eta^d$
Value	16GWh	$20\%E^{cap}$	$25\%E^{cap}$	$50\%E^{cap}/1\text{h}$	0.9

In the first study, we examine different scenarios regarding the energy capacity of ES while keeping the rest of the parameters equal to their baseline values (Table II). Fig. 1 presents the net demand of the system (accounting for the charging and discharging power of ES) corresponding to one of the considered representative days, for the different examined scenarios along with a scenario without ES in the system (No ES). The introduction of ES flattens the demand profile by charging during off-peak periods and discharging during peak periods, with this effect being enhanced as the energy capacity of the ES is increased.

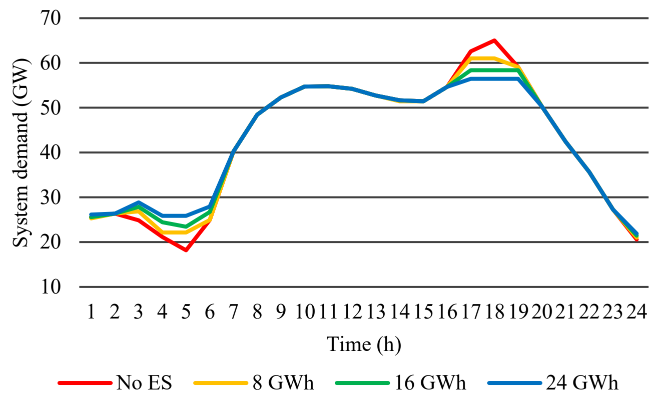

Figure 1: Net system demand for different ES energy capacity scenarios.

Fig. 2 presents the optimal investment decisions of the generation company for the examined scenarios. Since ES reduces the peak demand levels (Fig. 1), it drives a reduction in the total capacity investment. Furthermore, since it flattens the demand profile, it enhances the competitiveness of "must-run" nuclear generation. As a result, the invested nuclear capacity is increased, while the invested CCGT and OCGT capacity is reduced.

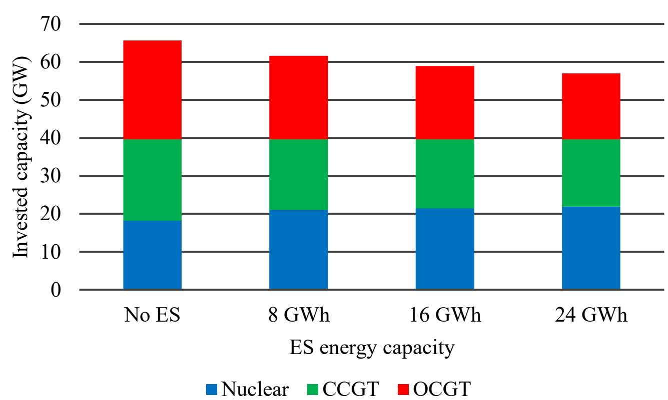

Figure 2: Investment decisions of strategic generation company for different ES energy capacity scenarios.

Fig. 3 presents the total system cost savings brought by ES with respect to the case without ES. The results demonstrate that the total system cost (sum of investment and operating costs) is reduced by the introduction of ES. This positive impact of ES is driven by the combination of two effects: a) the reduction of the total capacity investment and b) the reduced need to run CCGT and OCGT generation which is characterized by high operating costs.

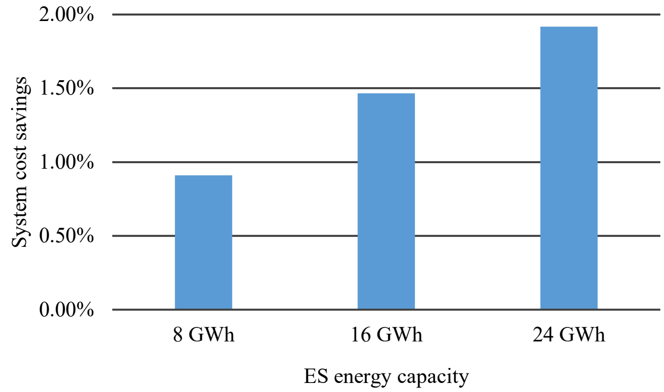

Figure 3: System cost savings for different ES energy capacity scenarios.

In the second study, we examine different scenarios regarding the ratio between the power capacity and the energy capacity of ES (known as power-to-energy ratio) while keeping the rest of the parameters equal to their baseline values (Table II). A higher power-to-energy ratio enhances the ability of ES to charge / discharge during critical off-peak / peak periods, enhancing the two effects discussed above with the effect of reduced total capacity investment being more prominent (Fig. 4). As a result, a higher power-to-energy ratio enhances the positive impact of ES on total system cost (Fig. 5).

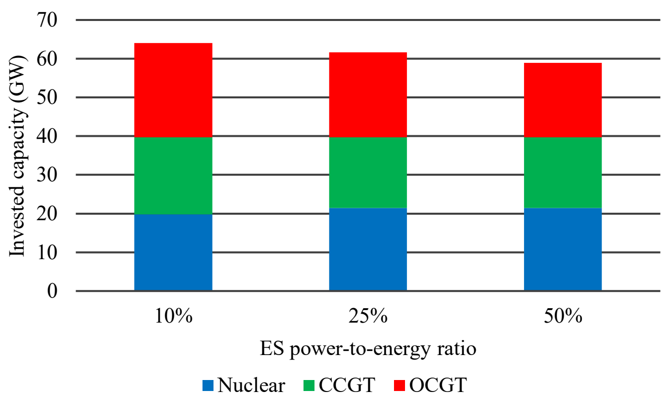

Figure 4: Investment decisions of strategic generation company for different ES power-to-energy ratio scenarios.

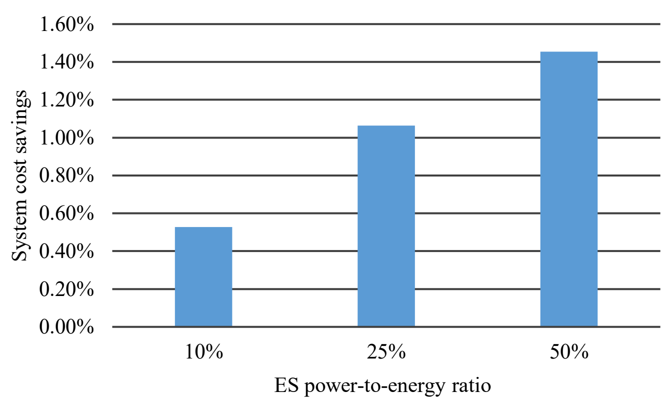

Figure 5: System cost savings for different ES power-to-energy ratio scenarios.

In the last study, we examine different scenarios regarding the efficiency of ES (assuming equal charging and discharging efficiencies in every scenario) while keeping the rest of the parameters equal to their baseline values (Table II). A higher efficiency reduces its energy losses and enables it to further flatten the demand profile, enhancing the two effects discussed above with the effect of reduced total capacity investment being again more prominent (Fig. 6). As a result, a higher efficiency enhances the positive impact of ES on total system cost (Fig. 7).

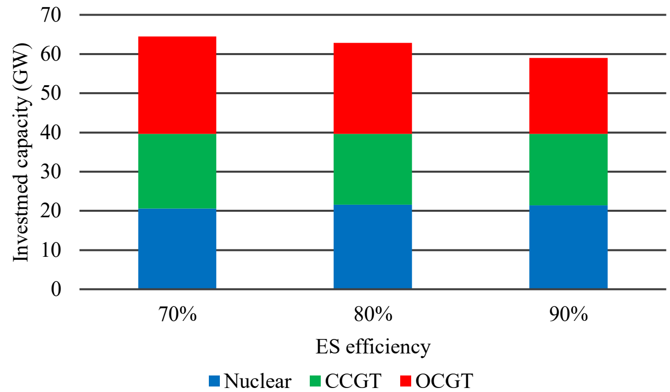

Figure 6: Investment decisions of strategic generation company for different ES efficiency scenarios.

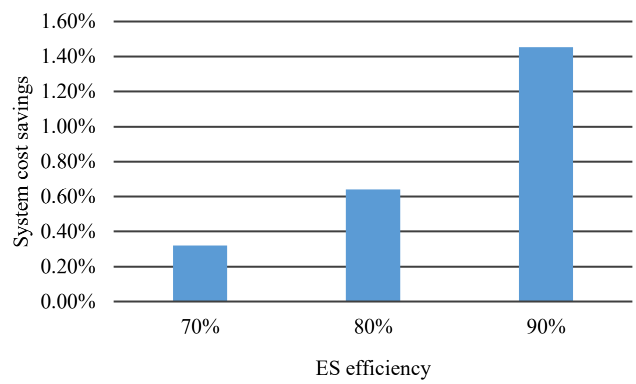

Figure 7: System cost savings for different ES efficiency scenarios.

IV. Conclusions

Energy storage is considered one of the key technologies for addressing the techno-economic challenges of future electricity systems. However, their role and value in long-term generation investment planning has been only analyzed through centralised cost-minimization models inherited from the era of vertically integrated electricity utilities. On the other hand, although existing strategic generation investment planning models capture more accurately the deregulated market environment, they do not consider time-coupling in their operational timescale and thus they are inherently unable to analyze the impacts of ES.

In order to fill this knowledge gap, this paper has proposed a new strategic generation investment planning model incorporating the operation of ES. Specifically, the decision making of a strategic generation company is modeled through a multi-period bi-level optimization problem, where the upper level determines the optimal investment decisions of the generation company so as to maximize its profit, and the lower level represents the market clearing process, accounting for the time-coupling operational characteristics of ES. This bi-level problem is solved after converting it to a single-level MILP.

Case studies have demonstrated that the introduction of ES reduces the total generation capacity investment and enhances investments in "must-run" baseload generation over flexible peaking generation. Furthermore, this reduction of the total capacity investment and the reduced need to run mid-merit and peaking generation with high operating costs results in significant system cost savings. These impacts are enhanced for higher values of the power-to-energy ratio and the energy efficiency of ES.

REFERENCES

[1] B. P. Roberts, and C. Sandberg, "The role of energy storage in development of smart grids," *IEEE Proc.*, vol. 99, no. 6, pp. 1139–1144, Jun. 2011.

[2] G. Strbac, et al., "Opportunities for Energy Storage: Assessing Whole-System Economic Benefits of Energy Storage in Future Electricity Systems," *IEEE Power Energy Mag.*, vol. 15, no. 5, pp. 32–41, Sep. 2017.

[3] P. Yang and A. Nehorai, "Joint Optimization of Hybrid Energy Storage and Generation Capacity with Renewable Energy," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1566–1574, Jul. 2014.

[4] D. Pudjianto, M. Aunedi, P. Djapic, and G. Strbac, "Whole-systems assessment of the value of energy storage in low-carbon electricity systems," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1098–1109, 2014.

[5] F. J. de Sisternes, J. D. Jenkins, and A. Botterud, "The value of energy storage in decarbonizing the electricity sector," *Appl. Energy*, vol. 175, pp. 368–379, 2016.

[6] F. Liu, M. Giulietti, and B. Chen, "Joint optimisation of generation and storage in the presence of wind," *IET Renew. Power Gener.*, vol. 10, no. 10, pp. 1477–1487, 2016.

[7] Salvador Pineda, Juan M. Morales, "Chronological Time-Period Clustering for Optimal Capacity Expansion Planning With Storage", Power Systems IEEE Transactions on, vol. 33, no. 6, pp. 7162-7170, 2018.

[8] F. H. Murphy and Y. Smeers, "Generation Capacity Expansion in Imperfectly Competitive Restructured Electricity Markets," *Oper. Res.*, vol. 53, no. 4, pp. 646–661, 2005.

[9] E. Centeno, S. Wogrin, A. López-Peña, and M. Vázquez, "Analysis of investments in generation capacity: a bilevel approach," *IET Gener. Transm. Distrib.*, vol. 5, no. 8, p. 842–849, 2011.

[10] S. Wogrin, E. Centeno, and J. Barquin, "Generation Capacity Expansion in Liberalized Electricity Markets: A Stochastic MPEC Approach," *IEEE Trans. Power Syst.*, vol. 26, no. 4, pp. 2526–2532, Nov. 2011.

[11] S. J. Kazempour, A. J. Conejo, and C. Ruiz, "Strategic generation investment using a complementarity approach," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 940–948, 2011.

[12] S. J. Kazempour and A. J. Conejo, "Strategic generation investment under uncertainty via Benders decomposition," *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 424–432, 2012.

[13] Y. Ye, D. Papadaskalopoulos, R. Moreira and G. Strbac, "Investigating the Impacts of Price-Taking and Price-Making Energy Storage in Electricity Markets through an Equilibrium Programming Model", IET Generation, Transmission & Distribution, vol. 13, no. 2, pp. 305-315, 2019.

[14] P. J. Ramirez, D. Papadaskalopoulos, and G. Strbac, "Co-Optimization of Generation Expansion Planning and Electric Vehicles Flexibility," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1609–1619, May 2016.

[15] FICO XPRESS website, http://www.fico.com/en/Products/DMTools/Pages/FICO-Xpress-Optimization-Suite.aspx.