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Liquid Air Energy Storage: Price Arbitrage Operations and Sizing Optimization in the GB Real-Time Electricity Market

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Keywords: Liquid Air Energy Storage (LAES); Real-time electricity market; Operation strategy; Price arbitrage; Sizing optimization

Nomenclature

CAES	Compressed Air Energy Storage
EES	Electrical Energy Storage
GA	Genetic Algorithm
IRR	Internal Rate of Return
LAES	Liquid Air Energy Storage
NCI	Net Cash Inflow
NPV	Net Present Value
NPVR	Net Present Value Rate
PHES	Pumped Hydroelectric Energy Storage
C_{NCI}	Net Cash Inflow (£)
C_{inv}	Initial Investment (£)
r	Discount Rate (%)
C_L	Cost for the Liquefaction Unit (£)
C_T	Cost for Cryogenic Tanks (£)
C_D	Cost for the Discharging Unit (£)
$\dot{m}$	Liquefaction Capacity (tonnes/day or MWh/day)
V	Storage Capacity (tonnes or MWh)
PR	Discharge Power Rating (MW)
$R_{arbitrage}$	Revenue Achieve by Electricity Price Arbitrage (£)
$C_{purchase}$	Electricity Purchasing Cost (£)
$C_{O\&M}$	Operation and Maintenance Costs (£)
L	Level of Stored Air (tonnes)
L_{min}	Minimum Level of Stored Liquid Air (tonnes)
L_{max}	Maximum Level of Stored Liquid Air (tonnes)
P	Electricity Price ((£/kWh)
P_{h_ths}	Upper Threshold of Electricity Price (£/kWh)
P_{l_ths}	Lower Threshold of Electricity Price (£/kWh)
P_t	Spot Price at Time t (£/kWh)
η	Round-trip Efficiency (%)
T_D	Discharging Time (hour)
T_C	Charging Time (hour)
MP_D	Marginal Price for Discharging (£/kWh)
MP_C	Marginal Price for Charging (£/kWh)

1 Introduction

Electricity generation from renewable sources has grown rapidly due to the promotion of clean energy policies in many countries. This presents challenges to national grid when the supply is from variable sources, such as wind and solar (Ren et al., 2017). In order to integrate large amounts of intermittent generation into the grid, (Barton and Infield, 2004), (Arani et al., 2017) and many others have suggested that Electrical Energy Storage (EES) system is a potential solution for increasing the penetration of renewable on the power network.

Large-capacity energy storage is now widely recognised as one of the technologies with most potential for the successful integration of renewable electricity generation, argued by (Bird et al., 2013), (Luo et al., 2015) and (Weitemeyer et al., 2015). Many studies focus on a variety of EES technologies and their uses with intermittent renewable sources, such as (Rehman et al., 2015) and (Larcher and Tarascon, 2015). An ideal EES technology to cope with the increasing deployment of renewable electricity generation on electricity grids should have a high power rating, a large storage capacity, high efficiency, low costs and no geographic constraints (Antonelli et al., 2016). Currently, only two technologies are considered mature for grid-scale energy storage, according to (Evans et al., 2012), (Rodrigues et al., 2014) and (Guizzi et al., 2015): PHES and CAES. Traditionally, PHES is used for large capacity storage due to its low cost per stored MWh (Rastler, 2010) and many other factors such as the lack of other proven technologies. However, the capacity for using large-scale water reservoirs has reached its limit in many developed countries due to geographic constraints (Ameel et al., 2013). Similarly, specific geographical conditions are also required for the application of large-scale underground CAES, and to date, there are only two such grid-scale CAES plants that have been demonstrated in operation: a 110 MW plant in McIntosh, Alabama and a 290 MW plant in Huntorf, Germany (IRENA, 2017). Due to the drawback that their application is constrained by geological features, considerable effort has been made in order to find different EES approaches that can provide large scale, cost-efficient solutions without such constraints.

Compared to CAES, which stores air as a gaseous phase, a much higher energy density can be achieved by liquid air energy storage (LAES) that stores air in its liquid phase (for more details, please refer to (Ameel et al., 2013) and (Ding et al., 2016)). LAES uses liquid air as a storage medium and includes three distinct processes: charging, storing and discharging (see Figure 1).

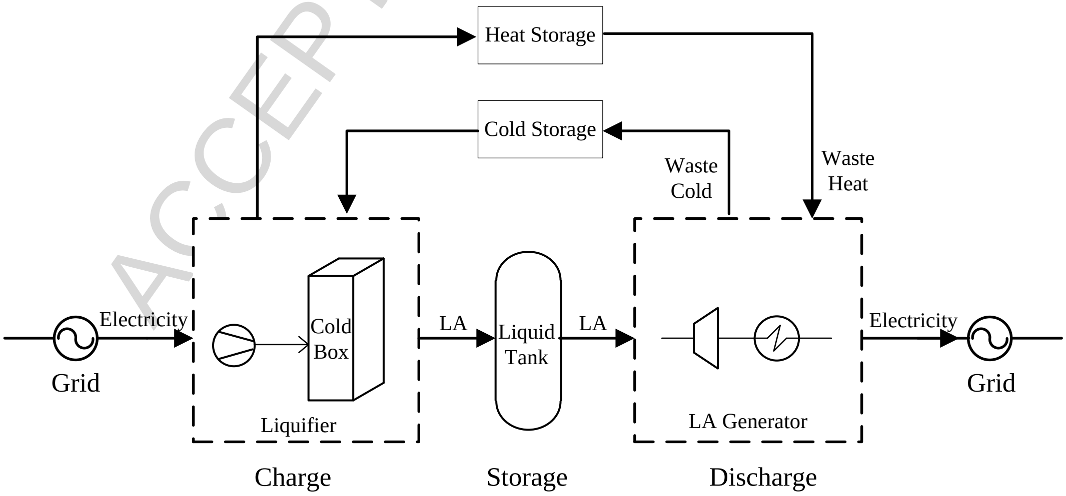

Figure 1: Schematic diagram of a LAES system.

To charge the store, air is liquefied through standard industrial gas processes by compression and cooling to an extremely low temperature. According to (Ding et al., 2016), the volumetric exergy density of liquid air is at least 10 times that of compressed air when the storage pressure is lower than 10 MPa, which enables liquid air to be highly competitive in terms of volumetric energy density even compared with battery technologies (Chen et al., 2009). In the storing process, the liquefied air is stored in insulated tanks at around -196 °C at near atmospheric pressure, and thus the off-peak electricity consumed during the liquefaction process is converted into cryogenic energy (Chen et al., 2016). In the discharging process, the stored liquid air is pumped and evaporated, and its expansion turns turbines to generate electricity when needed. The LAES system is able to enhance its round trip efficiency by capturing and recycling the heat of compression, and coolth of expansion. The features of LAES include: 1) it is a grid-scale energy storage system using established technology with no geographic constraints; 2) the effective round trip efficiency of the LAES system can be improved significantly by the utilization of external heat/cold through integration with other systems such as thermal power plants or a LNG regasification facilities; 3) there are three physically different components which can be independently sized, making it possible and also essential to optimize the LAES system for different applications (Xie et al., 2018).

LAES has drawn increasing attention in the UK since the 300 kW/2.5 MWh pilot scale demonstration plant, built by Highview Power Storage, started operations in 2010 (Brett, 2011), now in use at the University of Birmingham (Sciacovelli et al., 2017). In April 2018, Highview's pre-commercial demonstrating plant started operation[1]. It is located alongside the Pilsworth landfill gas generation site in Bury, UK, to obtain low grade waste heat from the gas engines and therefore increase the round-trip efficiency of the system.

Existing literature regarding LAES are mostly focusing on its technical performance. (Krawczyk et al., 2018) presented a thermodynamic analysis of a LAES system and a CAES system, and argued that one advantage of the LAES over the CAES is the significantly lower volume needed for energy storage. (Peng et al., 2018b) conducted a thermodynamic study on the effect of cold and heat recovery on the performance of LAES and found that the cold energy has a much significant effect on the round-trip efficiency of LAES than the heat energy. (She et al., 2017b) studied the possibilities of improving the round trip efficiency of LAES through effective utilization of heat of compression and their thermodynamic analyses showed that the round-trip efficiency could be enhanced 9-12% by using the excess heat of compression as a heat source to power an organic Rankine cycle. (Peng et al., 2018a) analysed the performance of a LAES system with packed bed units and according to their results, a LAES system may probably be considered as a viable option for grid-scale (>100 MW) electric energy storage. Similar studies include (She et al., 2017a), (Borri et al., 2017), (Hüttermann and Span, 2017) and many others.

However, techno-economic analysis on LAES are very limited. (Tafone et al., 2017) evaluated the technical and economic feasibility of a LAES system for building demand management applications. (Pimm et al., 2015) proposed a realistic control strategy for a hybrid energy storage system based on LAES and CAES to achieve the maximum arbitrage profit. Although there are many techno-economic analysis focusing on other energy storage technologies, (Kapila et al., 2017) argued that the economic assessment remains obscure in most of the studies, and many techno-economic ESS studies only give information on the unit capacity capital cost (how much per kW or per kWh) for the energy storage plant without any detailed economic feasibility analysis. For example, (Bayon et al., 2018) provided a cost assessment of thermochemical energy storage (TCES) systems, and (Kalinci et al., 2015) calculated the net present cost for hydrogen energy storage, while other techno-economic analysis include (Yu and Foggo, 2017), (Després et al., 2017) and (Bistline, 2017).

To fill these gaps, this study assesses the economic feasibility of adopting LAES in the UK, and optimizes the size of individual components for charging, storing and discharging energy, taking into consideration profits from energy arbitrage markets. The arbitrage optimization problem has been successfully applied in many studies, with the aim of identifying the optimal scheduling strategy to maximize the value of arbitrage in different electricity markets, for example, (Pimm et al., 2015), (Zafirakis et al., 2016) and (Babacan et al., 2017). Different from previous studies, the methodology developed in this paper is not to conduct an arbitrage optimization for a LAES plant of a certain size similar to (Sioshansi et al., 2009), (Bradbury et al., 2014) and (Wilson et al., 2018),

[1] Highview Power website: https://www.highviewpower.com/plants/[accessed on 26/04/2018]

but to find the optimal arbitrage operations for LAES systems of different sizes and to identify the optimal size for each component, considering both profit from the energy arbitrage markets and the total cost of the plant. In other words, this research is trying to suggest the optimal arbitrage operations and the sizes of system components so as to assess the economic viability for building a LAES plant, which has not been analysed before and is significant for the future application of LAES technology.

This article is organized as follows: Section 2 describes the methodologies of arbitrage optimization and sizing optimization and some relevant data; Section 3 presents the simulation results and discusses key influencing factors; Section 4 presents the conclusions and discusses the implications of the results.

2 Methodology and Data

2.1 Optimization model and data

The model for maximizing the arbitrage revenue is defined by Equation (1) and Equation (2), to identify the optimal size for each component and the optimal operation strategy considering both profit from the energy arbitrage markets and the total cost of the plant.

$$max\ NPV \tag{1}$$

Where NPV is the net present value of the liquid air energy storage investment project, and is determined by the lifetime earnings before interest depreciation and the total capital cost in the initial year. Residual value is not considered in this model due to the lack of data, as a result, the results obtained would represent a conservative estimation.

$$NPV = \sum_{i=1}^{lifetime} \frac{C_{NCI}}{(1+r)^i} - C_{inv} \tag{2}$$

Where, C_{NCI} is the net cash inflow during time period i, C_{inv} is the total initial capital cost, and r is the discount rate (assumed to be 6% in this analysis). Lifetime of the liquid air energy storage plant is assumed to be 30 years.

The calculation of C_{NCI} will be discussed in the following section 2.2: Arbitrage optimisation. Total initial capital cost is consist of three parts: liquid faction unit, storage tanks and discharging unit, as given in Equation (3).

$$C_{inv} = C_L + C_T + C_D \tag{3}$$

Based on Highview Power Storage Technology and Performance Review 2012, cost function for each unit can be written as Equation (4)-(6).

Cost for liquefaction unit: *(Thousand \$ in 2012):* $C_L = \left(\frac{\dot{m}}{4}\right)^{0.6} * 11406$ (4)

Cost for storage tanks: *(Thousand \$ in 2012):* $C_T = \left(\frac{V}{85.7}\right)^{0.6} * 1778$ (5)

Cost for discharging unit (Thousand \$ in 2012): $C_D = \left(\frac{PR}{10}\right)^{0.6} * 5653$ (6)

Where, $\dot{m}$ is the liquefaction capacity, V denotes storage capacity, and PR is discharge power rating. The results obtained (\$ in 2012) are then converted to the British Pound of today (£ in 2017). The average exchange rate for the GBP against the USD in the year 2012 is 1.58.[2] Inflation rate of each year over 2012-2017 is obtained from the Office for National Statistics.[3] Based on the above cost functions, the capital cost for Highview's newly built 5MW/15MWh demonstrating plant is

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[2] Her Majesty's Revenue and Customs (HMRC), https://www.gov.uk/government/publications/exchange-rates-for-customs-and-vat-yearly

[3] Office for National Statistics, https://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/l522/mm23

estimated to be 4.35 million $ in 2012, which is about 2.97 million £ in 2017. After verifying with Highview Power, this number is confirmed to be much closed to the actual capital cost of the demonstrating plant. As a result, the above cost functions are considered to be reliable and used in the optimization model.

2.2 Arbitrage optimisation

This section will evaluate the net cash inflow C_{NCI} in Equation (2), using an arbitrage algorithm described in Figure 2. The calculation of C_{NCI} can be written as the difference of cash outflows and cash inflows:

$$C_{NCI} = R_{arbitrage} - C_{purchase} - C_{O\&M} \tag{7}$$

Where, $R_{arbitrage}$ represents revenue achieved by electricity price arbitrage, $C_{purchase}$ denotes the annual cost of purchasing electricity from the grid and $C_{O\&M}$ denotes the operation and maintenance costs per annum. According to (Strahan et al., 2013), the operation and maintenance costs typically amount to between 1.5% and 3% of the capital cost of the plant per annum. In this paper, O&M costs are assumed to take up 1.5% of the plant purchase price per annum. For the electricity price, the UK's half-hourly electricity spot prices in 2015 are used.

As shown in Figure 2, the main purpose of this arbitrage optimisation algorithm is to determine a high price (upper threshold) P_{h_ths} and a low price (lower threshold) P_{l_ths} within a certain time period, which enables a maximum potential arbitrage revenue when selling electricity at price P_{h_ths} and buying electricity at price P_{l_ths}. Detailed processes of the arbitrage optimisation are described as follows:

a) For all prices within the selected time period, sorting from the lowest price to the highest price, thus an increasing sequence is obtained as:

$$P=[p_1, p_2, \ldots\ldots p_n] \tag{8}$$

b) For the discharging time, giving it the initial value 1:

$$T_D=1 \tag{9}$$

c) Finding the corresponding marginal price for discharging:

$$MP_D=P(n-T_D+1) \tag{10}$$

For example, when $T_D=1$, then $MP_D=P(n)$, suggesting the system will only discharge during the time period with the highest electricity price).

d) To maintain a balanced level of stored liquid air, the charging time T_C is determined by the amount of liquid air needed for discharging:

$$T_C * \eta * Pow_{charge} = T_D * Pow_{discharge} \tag{11}$$

Where, η denotes the round-trip efficiency of the LAES plant and in this paper, it is assumed to be 60%. Pow_{charge} and $Pow_{discharge}$ represent the power rating for charging unit and discharging unit, respectively.

e) Finding the corresponding marginal price for charging:

$$MP_C=P(T_C) \tag{12}$$

f) Examining whether there is room for arbitraging, based on Equation (13):

$$MP_D \geq MP_C / \eta \tag{13}$$

If the above inequality holds, which means there is still further room for arbitraging, then set the charging time to $T_D=T_D+1$ and repeat steps c) to f).

Otherwise the price thresholds are determined by:

$$P_{h\_ths}= P(n-T_D);\ P_{l\_ths}=MP_C \tag{14}$$

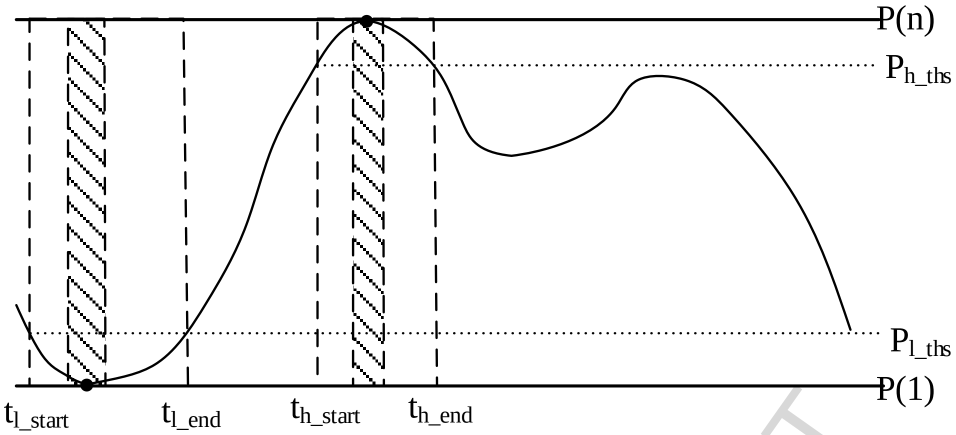


Figure 2: An illustration describing the arbitrage optimisation algorithm.

It is worth mentioning that, the algorithm described above is to find the theoretically maximum value for arbitraging; however, this maximum value may not be achieved due to other constraints while operating. For example, when the electricity price rises in excess of the upper threshold P_{h_ths}, there is chance that the system cannot discharge due to the low level of stored liquid air. This situation is defined as deviation from the theoretical optimization. The time periods during which the system not being able to follow operation strategies given by the algorithm are recorded, to evaluate the degree of deviation and show how effective the model works.

2.3 Sizing Optimisation

As the liquefaction unit, cryogenic tank and recovery unit can be fully decoupled, it is possible to find the optimal design of the size/capacity of different components to maximise the economic competitiveness for the LAES system.

Based on the UK's half-hourly electricity spot price in 2015, the revenue stream from price arbitrage is calculated every half hour. The optimisation algorithm (see Figure 3) in our model is to find the optimal design of the size/capacity of different components using the method of Genetic Algorithm (GA). As a computational model, GA searches the solution space of an objective function by simulated evolution (Whitley, 1994), and is widely used for solving optimization problems, such as (Arabali et al., 2013), (Qiu et al., 2015), (Asadi et al., 2014), etc.

Figure 3 describes the processes of the sizing optimisation, which are designed as:

a) Select a certain period of time, based on which the price thresholds are calculated. Different strategies are created for a practical use in reality.

Table 1: Different operating strategies for deciding the price thresholds.

Service mode	Operating Strategy
12 prognostic strategy	Due to the limited knowledge of future prices, decisions on buying and selling electricity are made using 12 historical prices and 12 future prices.
6 prognostic strategy	Future prices can be obtained 6 hours in advance, decisions on buying and selling electricity are made using 18 historical prices and 6 future prices.
24 historical strategy	Future prices are not known, and historical prices for the past 24 hours are used to determine the price thresholds.

b) When the current electricity price is higher than the high price decided in Section 2.3, check the level of stored liquid air and decision can be made whether to discharge or stand by.
c) Similarly when the current electricity price is lower than the low price decided in Section 2.3, check if there is room for storing more liquid air and decision can be made whether to charge or stand by.
d) Otherwise, stand by and examine the next time step.

e) For the given discharge power rating P (for example, 50 MW), find the optimal set of storage capacity V and liquefaction capacity $\dot{m}$ to maximize the NPV, based on GA algorithm.

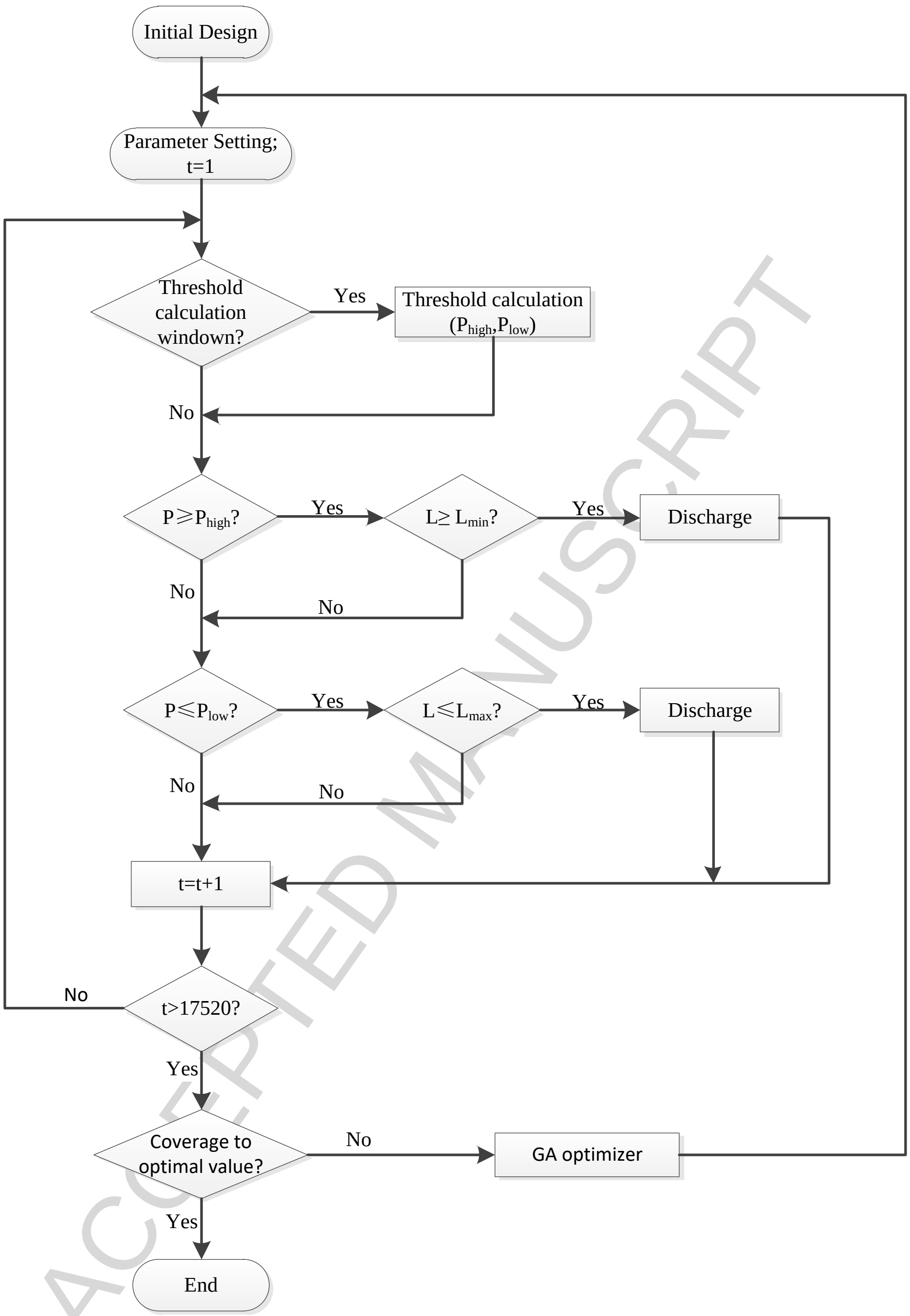


Figure 3: A flowchart describing the sizing optimisation algorithm.

3 Results and discussion

To illustrate the functioning of the algorithm, Figure 4 shows the simulation results provided by Matlab for a week (336 half-hours) in 2015, which describes arbitrage possibilities according to the UK's real-time spot price in 2015, based on a 200MW system with waste heat of 150^{o}C. It can be observed that when electricity price drops below the low price threshold (the upper figure), a charging decision will be made, thus will lead to an increase in the level of liquid air stored (the middle figure) and operation of the liquefier (the bottom figure). Similarly, when electricity rises in excess of the high price threshold, a discharging decision will be made, which will result in a decrease in the level of liquid air stored and operation of the generator. Otherwise, the level of liquid air stored will remain unchanged, as there is no room for arbitraging.

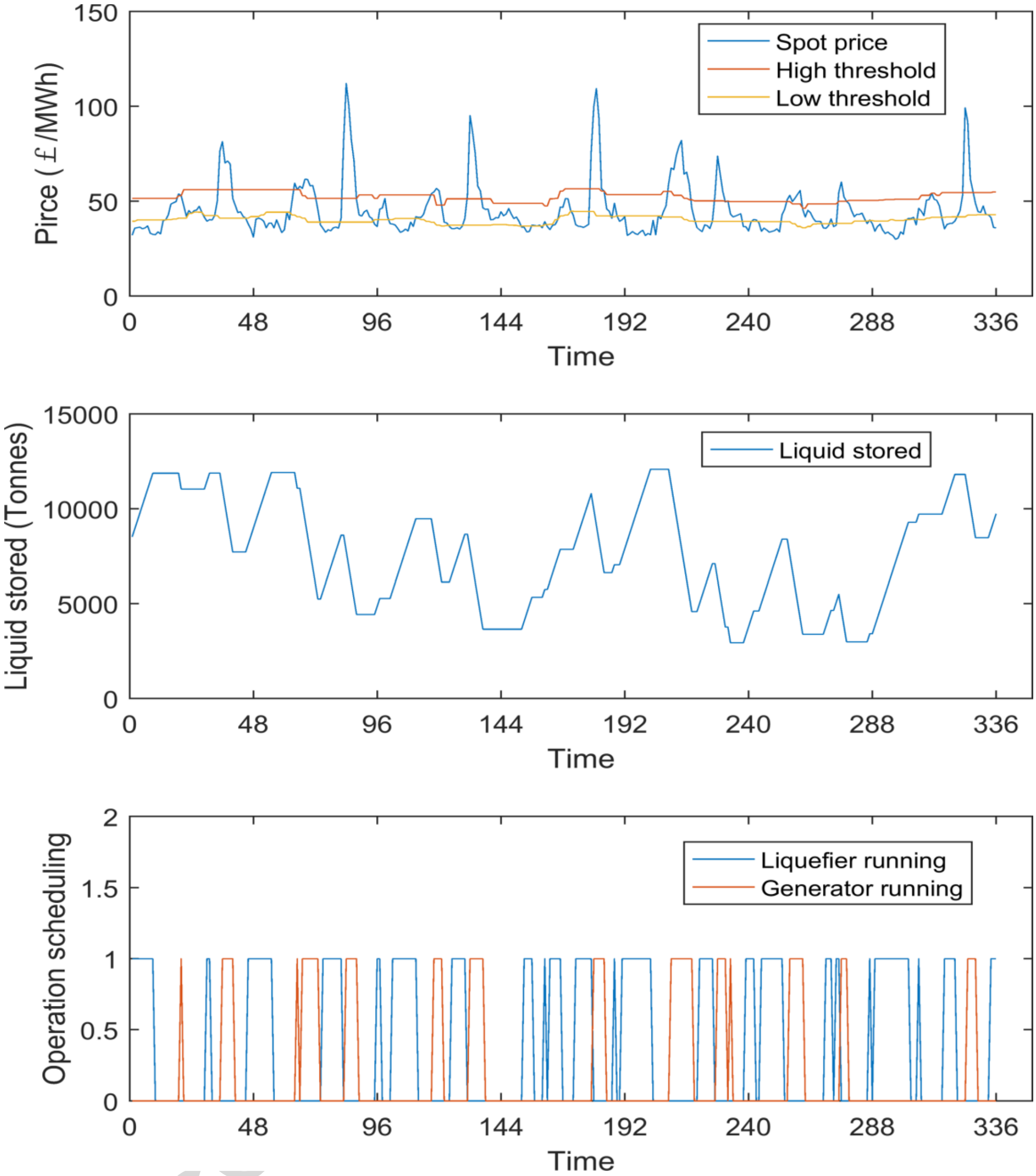


Figure 4: Operation results for a week showing how the arbitrage algorithm works.

Based on the results obtained, it is found that the economic viability of the LAES plant is affected by both the system scale (the size of each component) and the utilization of waste heat. Figure 5 indicates the internal rate of return (IRR) for a LAES system ranging from 50MW to 200MW, using waste heat between 0^{o}C and 150^{o}C. It is observed that in order to be profitable (given the interest rate of 6%), the scale of the system should be at least 100MW and using waste heat of no less than 150^{o}C.

There is considerable waste heat or surplus heat generated from industrial processes. Connective Energy estimated that 40 TWh/y of waste heat associated with industrial process can be captured in the UK (McKenna and Norman, 2010), while (Strahan et al., 2013) suggests it is sensible to assume this number to be within 10-40 TWh/y. However, due to the inconsistency of the heat sources and heat demands, technologies converting waste heat into more easily usable forms of energy are needed. LAES is a possible solution for heat recovery, by converting low grade heat into power. By integrating waste heat into the discharging process, it can help the vaporization of liquid air and make more work available to the generator, which then creates more discharging power from a given amount of liquid air and improves the round trip efficiency of the LAES system significantly. A greater degree of waste heat adopted means a better performance of the system.[4]

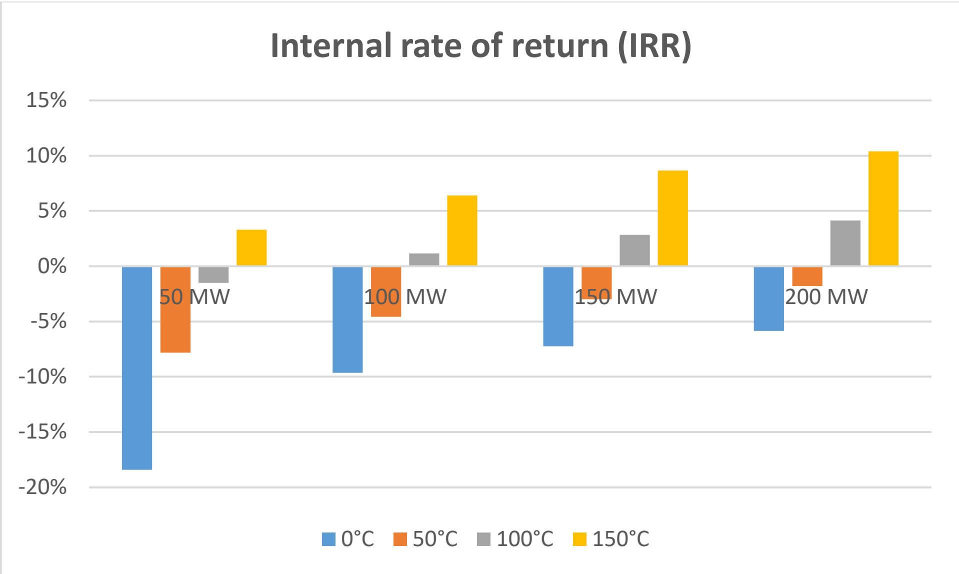


Figure 5: Internal rate of return: the influence of system size and waste heat.

Besides system scale and waste heat, arbitrage operating strategy also has an impact on the profitability of a LAES system. Table 2 shows the value of IRR for the system under different operating strategies, suggesting that the 12 prognostic (price thresholds for arbitraging are determined using 12 historical prices and 12 future prices) is the best operating strategy; while the 24 historical (no future prices are available) is the worst strategy. When prices are known for the upcoming 12 hours in an electricity spot market, the 12 prognostic strategy can be adopted, and that would enable an IRR of 10.4% for a 200MW LAES system using waste heat of 150^{o}C. If the electricity future prices are known only 6 hours in advance, the system can run under the 6 prognostic strategy and secure an IRR of 9.52%. When no future prices are available, the arbitrage algorithm is based solely on historical electricity price data, which would result in a significant drop in the IRR.

Table 2: The Internal Rate of Return (IRR) under different operating strategies.

	Operating strategy	0^{o}C waste heat	50^{o}C waste heat	100^{o}C waste heat	150^{o}C waste heat
50MW	12 prognostic	-18.41%	-7.83%	-1.50%	3.29%
	6 prognostic	-21.23%	-8.56%	-1.91%	2.83%
	24 historical	-	-8.78%	-2.19%	2.44%
100MW	12 prognostic	-9.65%	-4.58%	1.16%	6.39%
	6 prognostic	-10.03%	-5.11%	0.71%	5.83%
	24 historical	-10.49%	-5.58%	0.41%	5.29%
150MW	12 prognostic	-7.24%	-2.97%	2.85%	8.67%
	6 prognostic	-7.78%	-3.46%	2.30%	7.91%
	24 historical	-8.06%	-3.96%	2.00%	7.28%
200MW	12 prognostic	-5.86%	-1.79%	4.14%	10.40%
	6 prognostic	-6.36%	-2.27%	3.59%	9.52%
	24 historical	-6.64%	-2.83%	3.17%	8.74%

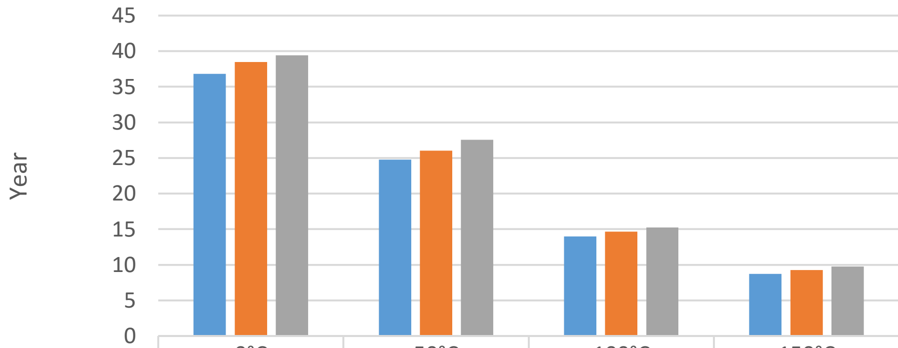
[4] Liquid Air Energy Storage (LAES) 2015, http://www.highview-power.com/wp-content/uploads/Highview-Brochure-2015.pdf [accessed 20/03/2017].

Furthermore, through providing the optimal size for each component and the corresponding net present value (NPV), Table 3 implies economic viability for a 200MW LAES system under different operating strategies (with waste heat of 150 ^{o}C). It can be observed that for a given size of generator (for example, 200MW), the optimal sizes of a liquefier are quite similar for all the three strategies. However, significant differences are found in the optimal sizes for storage tanks. Under the 12 prognostic strategy, as for each time step, prices are known for the following 12 hours, arbitrage decisions are more sensible and justified, and therefore the demands for storage capacity are comparatively less. As a result, in order to obtain a maximum potential arbitrage revenue, a higher initial investment is needed for the 24 historical strategy, as a much larger storage capacity is required. In the best case scenario that the 12 prognostic strategy can be applied, a 200MW LAES system is able to achieve a positive NPV of £43.8 M.

Table 3: Economic viability for a 200MW system under different operating strategies.

	Reserve revenue p.a.(£M)	Liquefaction capacity (thousand tonnes/day)	Tank size (thousand tonnes)	Initial investment (£M)	NPV (£M)
12 prognostic	11.1	20.5	9.7	97.4	43.8
6 prognostic	11.3	22.3	13.6	104.2	37.2
24 historical	11.1	21.2	21.1	108.4	29.9

Figure 6 shows payback period for a 200MW LAES system under the three above-mentioned operating strategies, using waste heat ranging from 0 ^{o}C to 150 ^{o}C. It is noticed that, without using waste heat, the payback period for a 200MW system can be as long as 36.9 to 39.4 years, depending on which arbitrage strategy is applied. However, with waste heat of 150 ^{o}C adopted, the payback period can be shortened to 8.7-9.8 years.



	0°C	50°C	100°C	150°C
12 prognostic	36.82554463	24.78293874	13.98759805	8.74683351
6 prognostic	38.47763408	26.01195454	14.68242375	9.259495229
24 historical	39.4006026	27.54168454	15.25574742	9.761910236

Figure 6: Payback period for a 200MW LAES system under different operating strategies.[5]

As the selection of interest rate may have an impact on the economic viability of the investment project, a sensitivity study on interest rate has been carried out. Table 3 shows the Net Present Value Rate (NPVR) of the LAES project, which is measured by the ratio of NPV to the initial investment. NPVR evaluates the cost-efficiency of the investment, and a higher NPVR means a higher return for a certain level of investment. It can be observed from Table 3 that, as the LAES system scales up, the profitability increases, from 0.06 for a 50MW LAES system to 1.08 for a 200MW LAES system, with discount rate of 2%. Moreover, as interest rate increases, the profitability of the project could be restrained significantly. Even for a 200MW LAES using waste

[5] Ambient temperature is assumed to be 20 ^{o}C.

heat of 150°C and under the 12 prognostic operating strategy (the optimal operating strategy), the project is not economic viable when the discount rate is 10%.

Table 3: The Net Present Value Rate (NPVR) with different discount rates (150°C waste heat).

	Selection of interest rate				
	2%	4%	6%	8%	10%
50MW	0.06	-0.17	-0.32	-0.44	-0.52
100MW	0.49	0.17	-0.05	-0.21	-0.32
150MW	0.81	0.43	0.16	-0.04	-0.18
200MW	1.08	0.64	0.33	0.11	-0.06

In order to validate the effectiveness of the model built in this paper, Figure 7 indicates the percentage that the system does not charge (or discharge) as instructed by the arbitrage algorithm due to the constraint of liquid air storage, which is defined as the degree of deviation from the theoretical arbitrage optimization. The largest deviation is recorded as 4.4%, which means even in the worst case scenario using the 24 historical strategy with no access to external heat, 95.6% of buying and selling decisions made by the arbitrage algorithm are actually performed. This deviation can be as low as 0.8% when using the 12 prognostic strategy.

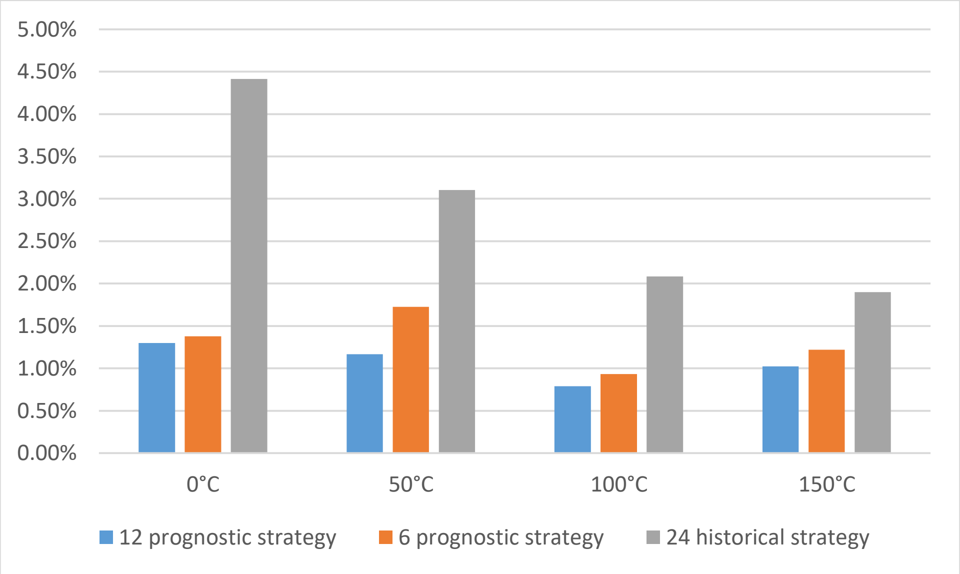


Figure 7: Deviation from the theoretical arbitrage optimization.

4 Conclusions

This paper proposes a methodology to evaluate the economic viability of liquid air energy storage based on price arbitrage operations in the GB real-time electricity market. Based on the UK's half-hourly electricity spot price in 2015, the arbitrage algorithm designed in this article determines price thresholds every half hour under different operation strategies and according to which, decisions are made for the system to charge, discharge or stand by. In addition, by using a genetic algorithm, our model also provides the optimal design of the size of different components for the system, taking into consideration both the corresponding capital expenditure and the potential arbitrage revenue.

Results suggest that:

(1) The economic viability of a LAES plant is affected by both the system scale (the size of each component) and the utilization of waste heat. It is unlikely to be economically feasible without using waste heat, even for a 200MW plant. In order to be profitable (given the interest rate of 6%), the scale of the system should be at least 100MW and using waste heat of no less than 150°C. This implies great potential for liquid air energy storage plants

to improve their economic feasibility through integrating with energy intensive industries to get access to waste heat.

(2) For a comparison among the three arbitrage strategies, the 12 prognostic (price thresholds for arbitraging are determined using 12 historical prices and 12 future prices) is the best operating strategy; while the 24 historical (no future prices are available) is the worst strategy. Due to the diversity of electricity spot markets, three arbitrage strategies are proposed in this paper, and the knowledge of future prices has a significant impact on the economic viability of a LAES system.

(3) For the scaling of a liquid air energy storage plant, a larger capacity of storage tanks is needed under 24 historical strategy, to maximum potential revenue from arbitraging. As a result, a higher initial investment and a lower NPV is found for the 24 historical strategy. In the best case scenario that the 12 prognostic strategy can be applied, a 200MW LAES system is able to achieve a positive NPV of £43.8 M.

(4) Without using waste heat, the payback period for a 200MW system can be as long as 36.9 to 39.4 years, depending on which arbitrage strategy is applied. However, with waste heat of 150 ^{o}C adopted, the payback period can be shortened to 8.7- 9.8 years.

(5) With regard to the validation of the model, the degree of deviation from the theoretical arbitrage optimization is calculated. Results suggest that the largest deviation is recorded as 4.4% under the 24 historical strategy; while it can be as low as 0.8% when using the 12 prognostic strategy.

Compared with a payback period of more than 40 years for a 300 MW/1800 MWh pumped hydro energy storage plant (Barbour et al., 2016), the application of liquid air energy storage seems very promising, as its payback period can be shortened by employing waste heat. For example, with waste heat of 150 ^{o}C adopted, the payback period can be as short as 8.7-9.8 years.

Our future study will be trying to evaluate the optimal arbitrage operations and the sizes of system components to achieve the maximum potential revenue from arbitraging in the UK over the past decade, and to understand the impact of price volatility on the potential revenue that a LAES plant could theoretically capture. Our model will also be further developed to include additional potential revenue streams from ancillary markets.

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Abstract

Liquid air energy storage is a novel proven technology that has the potential to increase the penetration of renewable on the power network and in the meanwhile to obtain revenues through energy price arbitrage. This paper proposes a methodology to evaluate the economic viability of liquid air energy storage based on price arbitrage operations in the GB real-time electricity market. The arbitrage algorithm designed in this article determines price thresholds every half hour under different operation strategies and according to which, decisions are made for the system to charge, discharge or stand by, and the optimal design of the size of different components for the system are also evaluated. Results suggest that the 12 prognostic is the best operating strategy, and under which a 200MW LAES system is able to achieve a positive net present value of £43.8 M. Without using waste heat, the payback period for a 200MW system can be as long as 36.9 to 39.4 years, depending on which arbitrage strategy is applied. However, with waste heat of 150 ^{o}C adopted, the payback period can be shortened to 8.7-9.8 years.

Highlights

- It evaluates the economic viability of Liquid Air Energy Storage in the UK.
- Operation strategies to achieve maximum potential arbitrage revenue are discussed.
- Optimal sizes for the charging, storing and discharging unit are obtained.
- A 200MW LAES system could achieve a positive NPV of £43.8 M.
- Under the optimal design, payback period can be shortened to 8.7-9.8 years.

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