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A methodology for techno-economic evaluation of asymmetric energy storage systems: A nuclear energy case study

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ABSTRACT

This paper discusses a novel methodology for the analysis of energy storage system. This methodology combines engineering and economic modelling to assess the relative economic performance of plant designs within a simulated UK electricity market. It presents a case study that explores whether a nuclear power plant can be combined with a liquid air energy storage plant to allow the resultant hybrid plant to provide a load-following electricity supply. The approach adopted is distinct from much of the work on conventional load following nuclear power plant operations, as in our case the underlying nuclear energy production does not vary. The methodology expands the previous literature on energy storage systems.

1. Introduction

Energy storage is becoming an increasingly important topic in the drive towards decarbonisation of electricity generation. Nuclear, whilst perhaps less of a hot topic, is also seeing something of a renaissance with new power plants planned around the world. As renewables become a more prominent source of electricity, there will come a greater need for the provision of grid-scale electricity storage, load-following electricity generation, or some degree of demand-side management. The enormous challenge of decarbonisation will likely require a combination all of these options.

The role of nuclear fission energy in a whole electricity system of the future with greater variability between generation supply and demand has prompted a range of academic assessments in recent years. One such consideration is the possibility of nuclear electrical load-following. It is an important technological option going forward. Some nuclear reactor developers are incorporating load-following capabilities into their designs. NuScale, for example, can reduce power output by bypassing the steam turbine. The economic basis for such an operational model still remains somewhat uncertain (Loiselet al., 2018). This paper is not focussed on assessing the merits, or otherwise, of such a case and takes a different approach to flexibility.

The possibility that nuclear energy might be produced by baseload technologies for an electricity system that is at times replete with low-carbon renewable power takes one to the idea that nuclear energy might be diverted to non-electrical purposes such as industrial process heat applications and co-generation as reviewed by (Locatelliet al., 2017) and as addressed by the Royal Society in a policy briefing published in 2020. Such ideas are not the focus of this paper.

Finally, the option of mitigating economic problems arising from supply-demand mismatch via energy storage is prompting attention. There has been consideration of a range of storage options such as via hydrogen (Cany et al., 2017) or high temperature heat storage (Alameriet al., 2020; Stack and Forsberg, 2015; Forsberg, 2019) by a small number of researchers. In this paper we will focus on energy storage and consider specifically the potential of cryogenic liquid air energy storage, a case study for which only a small literature exists (Liet al., 2014).

Standalone nuclear power plants have some potential to fulfil a load-following role, as they have historically done in France (Malischek and Trüby, 2016; Pouret et al., 2009), and to a lesser extent in Germany (Ingersollet al., 2016). They cannot, however, be ramped as fast as

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natural gas plants (Luan et al., 2011). In addition, the best way to recoup investment costs from a high capital cost plant with minimal fuel costs, such as a nuclear plant, is to run it at full capacity throughout its lifetime. This has long been a characteristic of nuclear power in the UK, and no less so today with the availability of guaranteed long-term electricity prices in the form of CFD (contract for difference) pricing.

This study sought to determine whether an NPP (nuclear power plant) might feasibly be coupled with an ESS (energy storage system). The benefits of doing so would be twofold. Firstly, the coupling of an ESS would allow the NPP-ESS hybrid to operate as a load-following power plant. In this work we assume the underlying NPP to produce nuclear heat continuously at full capacity between scheduled refuel and maintenance shutdowns which might occur every 18 months. The proposed NPP-ESS hybrid would contribute valuable flexibility services to the electricity grid beyond nuclear power’s traditional baseload role. It would not waste energy or cause the nuclear reactor to have to deviate from a stable operating condition. Secondly, targeting price peaks in the electricity spot market could allow an NPP’s operators to increase revenues. This is important in the context of nuclear power’s reliance in the face of the falling CFD prices of renewable generators.

The approach to this problem was the development of two complementary models. The first, an engineering process model, was used to design the coupled NPP and ESS plant. This allowed components to be sized and costs to be estimated. The second, a Monte Carlo model, allowed the economic performance of proposed plant designs to be explored in a variety of hypothetical market scenarios.

The remainder of the paper is split into sections. Section II provides a review of existing literature on ESSs, and on the coupling of NPPs to them. Section III discussed the nature of the UK electricity market. Section IV presents the modelling approach. Section V details the case study of the coupled NPP and ESS plant. Section VI discusses its conclusions and section VII its wider implications.

This work builds on existing work presented in a peer-reviewed working paper (Wilson et al., 2020). This work is a significant development on the two models described in that paper. The major changes are discussed in detail in section IV.

2. Literature review

The case study presented herein was, in part, inspired by Charles Forsberg of MIT (the Massachusetts Institute of Technology). He has opined that the challenge for the future of nuclear power is not simply to reduce costs – it is to increase revenues (Stack and Forsberg, 2015). The reason the methodology described in this study was developed was to assess whether nuclear power might be coupled with energy storage to enable it to fulfil more of a load-following role and to generate additional revenue by capitalising on peaks in the spot market. The MIT team propose a thermal storage system coupled to a novel high-temperature nuclear reactor design. An important feature is its use of a VHTR (very high temperature reactor), a next-generation reactor technology. This study is concerned with whether a viable system might be achieved with current-generation nuclear technology and an alternative ESS.

There remains a plethora of energy storage options available (Strbac et al., 2012). One of the most developed of these is LAES (liquid air energy storage) which has an operating pilot plant in the UK (Morgan et al., 2015) owned by Highview Power, and has been extensively studied by a group at Birmingham University (Sciacci et al., 2017). LAES involves using excess electricity to run air liquefaction equipment, liquefying ambient air and storing it in an insulated tank. When power is in demand, this air is released, vapourised, and expanded through turbomachinery to generate electricity. By cooling a thermal storage medium as the system is discharging and using it as a heat sink when charging the system, this has a potential round-trip efficiency of around 50% (Morgan et al., 2015). Further, by storing the heat of compression and using this to heat discharge air, further efficiency improvements approaching 70% can be attained (Penget al., 2018; Sheet et al., 2017).

The use of thermal storage media as a heat sink during charge of an LAES system is of critical importance; the Highview pilot plant achieved round-trip efficiencies of only 9% owed in no small part to its limited use of this approach. It is known in the broader literature as ‘cold storage’ or ‘cold recycle’. Whilst this is perhaps a misnomer from a thermodynamic perspective, given cold is an absence of energy, the decision has been made to utilise this nomenclature for simplicity and to stay in line with the wider literature.

Many options for coupling LAES with other systems have been suggested in literature. Some of these suggest coupling with other types of plant to improve efficiency. Coupling with potential heat sinks in LNG regassification plants can significantly reduce the energy cost of charging the system (Penget al., 2019; Kim et al., 2018). Some studies have also suggested the use of waste heat sources or combustion of natural gas as a means to improve the power yield of the discharge cycle (Kim et al., 2018; Antonelli et al., 2017).

Of the current literature, the authors are aware of only a single detailed study into the coupling of an LAES plant to an NPP (Liet al., 2014). This is surprising given that one of the hallmarks of LAES plants is that parts of their discharge power cycles operate at very low temperatures. This means that they are especially well-suited to utilising low-grade heat. This is something that current generation LWRs (light water reactor) have in abundance.

Whilst (Liet al., 2014) provides some interesting conclusions related to such an approach, it also has some important issues. Perhaps most importantly, compression is approximated to isothermal rather than isentropic processes. This is somewhat unrealistic for a grid-scale LAES plant that will rely on axial compressors where heat is not rapidly dissipated and that would be better approximated as being isentropic. Isothermal treatment is representative of an energy saving of around a third when charging the system and is a contributing factor for the fact that the modelling in (Liet al., 2014) achieved round-trip efficiencies exceeding 70% rather than the more modest efficiencies achieved in this study. This gap in the literature for LAES was one of the key motivations for the revisiting this system for a detailed engineering examination as part of the case study in section V. In section V we shall also return to the issue of round-trip efficiency and assess whether it should be a major consideration when assessing the merits of real ESS systems in the UK electricity market.

3. Electricity markets in the UK

Engineering design and physical plant performance are only part of the story in the real world. The other part, a plant’s economic performance, is arguably of greater importance if a plant is to be built. Analysis of electricity price data (Smith and Halliday, 2016), and an early version of this work (Wilson et al., 2020), shows that the electricity market exhibits a daily price profile that makes it difficult to achieve sufficiently large price differences to make a simple arbitrage approach profitable at efficiencies of 50%. Higher efficiencies can increase the potential opportunities for arbitrage by demanding a smaller price swing. Such improvements, however, require additional plant and come at a real capital cost.

The ability to understand the effects of additional capital cost are one of the core considerations of this study. A cornerstone of contemporary project economic analysis is DCF (discounted cash flow) analysis, whereby future revenues are discounted to account for the fact that a given amount of money is worth less in the future than it is today. An important metric of DCF is NPV (net present value). This is calculated by:

$$NPV = \sum_{t=0}^{T} \frac{R(Y)}{(1 + i_{DCF})^t},$$

where $N$ is the total number of periods over which the project is assessed,
$R(Y)$ is the cash flow for a given year, $Y$ is that year and $i_{\text{disc}}$ is the discount rate.

The implications of the use of NPV as a metric of plant performance can be seen by considering this formula. Consider a plant that takes 5 years to build and a modest project discount rate of 8%. In its first year of operation (year 5), the plant’s cash flow is discounted by a factor of nearly 1.5, a factor that increases exponentially with the plant’s life. The capital investments costs, then, become a key driver of the NPV.

The importance of capital cost in modern economic analysis was a core motivation of this study. In considering that capital cost is a paramount driver of economic performance comes the hypothesis that a more efficient but costlier plant might not be the best investment proposal. This study takes this a step further, however. Many ESSs, including LAES, are asymmetric. That is, from an engineering design perspective, their charge and discharge rates are essentially independent of one another. This study speculates that by analysis of the economic performance of competing designs of ESSs, their charge/discharge profile can be optimised for the market in which they are to operate.

UK electricity spot market prices exhibit complex seasonal, weekly and diurnal patterns, as shown in Fig. 1. The diurnal pattern is characterised by a long trough at night (when demand is at its lowest) and a peak in the evening (when people are returning home, but shops and offices are still lit). Seasonal variation is characterised by a greater daily variation in colder months with shorter days compared to the summer months.

The discussion of the previous paragraph is, of course, somewhat superficial. Whilst such behaviour can be considered to be driven by consumer behaviour to a degree, the actual price of a given balancing period will be a product of the complex interplay of both supply and demand. This can be seen in the substantial differences between the January and October evening peaks in the figure, as well as the highly stochastic and unpredictable period-to-period variation the data exhibits. Capturing both the stochastic and the more predictable behaviour would go to form a core part of the financial model, as discussed in section IV.

4. Methodology

An early version of the methodology used in this study was published in the peer-reviewed Energy Policy Research Group working paper series (Wilson et al., 2020). The referenced working paper details the economic performance assessment of a hybrid NPP-LAES plant in the UK electricity market. Whilst the minutiae of the modelling approach has since seen significant development, as will be discussed in section V, the fundamental methodology presented shares similarities with the early draft work (Wilson et al., 2020).

From a modelling perspective, the approach requires two models: an engineering and a financial model. The engineering model is used to assess the performance of a proposed plant design when acting as an ESS in terms of its power ratings when charging or discharging. This allows sizing of the required components and, in turn, cost estimation of the plant capital investment via the methodology described in literature (Peterset al., 1968).

The economic model uses a Monte Carlo approach to assess the potential commercial performance of the given plant design in the face of uncertainty, given its performance parameters and capital cost. It combines simulation of electricity prices and of operational decision-making to model electricity sales into the spot market and thus the economic performance of plant design. This model is run for thousands of iterations, yielding an NPV probability distribution. By assessing multiple competing plant designs in this way, their relative economic viabilities can be assessed, and this can provide insights into which might be best suited to the given market.

The detail of the engineering model is discussed in the preliminary work (Wilson et al., 2020) and it does not make sense to repeat this information in this paper, since the model itself has not changed; only its parameters have been refined in this study, as will be discussed in section V. The financial model, on the other hand, has changed significantly and will be outlined in more detail in this section. The core difference between this and the preliminary work (Wilson et al., 2020) is that the financial model is now able to simulate electricity price arbitrage for the LAES plant.

The engineering model is a dynamic process model written using Modelica code and simulated within the Dymola environment. Models are built up in a modular sense with each key process component (compressor, turbine, heat exchanger, etc.) having its own sub-model. The ThermoPower Modelica library (Casella and Leva, 2009) formed the basis for many of the components used, however the nature of the LAES system necessitated many components be built from scratch and these comprise their own library, which has been made publicly available (Wilson, 2020a). Thermophysical properties for air and water also form a key component of the model and are sourced from the open-source CoolProp program (Bellet al., 2014) integrated into the simulation using the ExternalMedia Modelica library (Casella and
The financial model has also been made publicly available (Wilson, 2020b) and is built in Excel using the Palisade @RISK plugin (Palisade), which facilitates Monte Carlo simulations. A cornerstone of the approach described herein is the UK spot market simulation model which forms a core component of the financial model. This simulation uses a set of time series to predict electricity prices. These prices themselves are formed of three components; the average electricity price uses a set of time series to predict electricity prices. These prices are formed of three components; the average electricity price for a given day, \( A(D) \), the ratio of a given period’s price to that day’s average, \( \phi(P) \), and an error value in that ratio \( \varepsilon(P) \). Each of these is modelled using its own time series and the composite price for each period \( S(P) \) is calculated as:

\[
S(P) = (\phi(P) + \varepsilon(P)) \times A(D)
\]

Time series have a considerable history of use in modelling electricity prices (Weron, 2014), however the stochastic nature of a single time series means that diurnal variation in electricity price is lost. The series \( \phi(P) \) captures this diurnal variation in the form of a daily profile, based on mean averages taken from the electricity price dataset (Smith and Halliday, 2016). Whilst this will of course fall victim to the flaw of averages, the combination of this profile with stochastic time series for \( \varepsilon(P) \) means that the more unpredictable nature of real-world electricity prices is still captured while still retaining the behaviourally-driven diurnal profile that spot market prices exhibit. The amplitude of the daily profile is adjusted using a parameter, \( \alpha \), allowing different day profiles to be studied.

All series were defined using historical UK electricity price data (Smith and Halliday, 2016). These data were initially processed by calculating the mean average price for each day, followed by the ratio of electricity price to those daily average prices over the 8 years of the dataset. The dataset for the mean ratios were split by month, and then into weekend and weekday subsets. These mean ratios were used for the series values of \( \phi(P) \). The difference between actual prices and those predicted by the product of \( A(D) \) and \( \phi(P) \), essentially providing a dataset of error values. This provided both a measure of the prediction accuracy of the average \( \phi(P) \) curves, but also a dataset to which a time series for \( \varepsilon(P) \) could be fit using @RISK’s fitting algorithms. @RISK provides a variety of time series and rates the quality of fit according to their AIC (Akaike information criterion), which estimates the quality of the statistical model fit to the available data.

The error values time series for \( \varepsilon(P) \) was most accurately modelled using an AR (auto-regressive) model. Such a model has a moderate but long-lasting response to shocks in values and successive values tend to occur on one side of the mean. This is typically what occurs in the error data; when the value of \( \varepsilon(P) \) is large, successive values tend to occur on one side of the mean. In reality, this means that when the expected day profile underestimates or overestimates the data, it tends to do so for a whole day, or even a few days.

The day average time series for \( A(D) \) was best modelled using an ARMA (auto-regressive moving average) model. This combines an AR model with an MA (moving average) model, where shocks have a substantial but short-lived effect on the values of the series. The resultant time series tends to oscillate around its mean rather than spending long periods on one side of the mean or the other. Again, this is exactly what occurs in the historical electricity price data.

The compound prices, \( S(P) \), calculated from these time series are used to populate a set of 30 Excel sheets, each of which represents a single year of the financial model. Each row of these sheets represents a half-hour balancing period for selling electricity into the spot market, tracking the variables shown in Table 1. Fixed output sales from the NPP are sold at a CFD price defined by parameter and adjusted using CPI. Costs to charge the system are taken either the current spot market price, or the current CDF price, whichever is cheaper.

The hybrid NPP-LAES plant has five modes of operation:

- **Baseload**: the plant is operating as a baseload NPP. The LAES plays no role.
- **Charge**: the plant is charging the LAES system.
- **Discharge**: the plant is discharging the LAES system.
- **Offline**: the plant is refuelling or in maintenance; neither the NPP nor the LAES system are operating.
- **Restart**: the nuclear plant is refuelled and ready to restart.

The model makes the decision on how the nuclear plant is to operate within each row of the model according to the flow chart in Fig. 2. The first two rows of the flowchart relate to the fuelling of the NPP and represent when the plant will be offline when its uptime, \( t_U(P) \), is equal to how long that fuel load lasts, \( t_{FUEL} \), or will restart when its downtime \( t_{DOWN}(P) \), is equal to the time it takes to refuel \( t_{REFUEL} \).

The two next rows relate to making the decision to charge the LAES plant. Where the mass of air in the tank, \( M_{TANK}(P) \) is zero and the current time is within the charging window defined by the model parameters, or when the tank is part full, the decision is made to charge the LAES plant. When the current electricity spot market price, \( S(P) \), is greater than the cost to charge the system, \( \mu(P) \), or when the system was discharging in the previous period and the tank in not yet empty, the decision is made to discharge the LAES plant. If none of these conditions are present, then the hybrid plant simply operates as a baseload NPP.

The most novel part of the approach to financial modelling is that this decision-making process allows the model to mimic the way a real plant might be operated without its operators having perfect prediction of future electricity prices. The model’s decision-making algorithm for the discharge condition is only aware of the mean cost to charge the plant during the previous charging cycle. This is analogous to a real plant where the operators would know the cost to charge their plant and would be able to bid into the spot market at a sufficiently high level to ensure they make a profit.

The remainder of the financial model operates in much the same way as a traditional Monte Carlo model. Uncertain initial parameters are treated as probability distributions rather than the fixed inputs that would be used in a deterministic model. The model is then run for multiple iterations. Each iteration samples the probability distributions to determine the input parameters and produces a new set of electricity prices from the time series. From this, it calculates the NPV and payback period (the amount of time taken to pay back its initial investment) outputs.

The uncertain input parameters are denoted \( (I) \) in Table 2 to indicate that they change with each iteration, I. PERT (program evaluation and review technique) distributions were used for the majority of uncertain input parameters. Binomial distributions were used for construction times, which must take integer values for the purposes of the model. A four-parameter beta distribution was used to model the LAES plant capital cost from the outcome of the cost estimation exercise. The values used for fixed inputs, and the parameters of the probability distributions are listed in the appendix.

### Table 1: Financial model variables.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S_{set}(P) )</td>
<td>Strike price for a given year</td>
</tr>
<tr>
<td>( t(P) )</td>
<td>Time of day for a given period</td>
</tr>
<tr>
<td>( S(P) )</td>
<td>Spot market price for a given period</td>
</tr>
<tr>
<td>( W_{fix}(P) )</td>
<td>Fixed power output for a given half-hour period</td>
</tr>
<tr>
<td>( W_{var}(P) )</td>
<td>Variable power output for a given half-hour period</td>
</tr>
<tr>
<td>( R_{total}(P) )</td>
<td>Total revenue for a given half-hour period</td>
</tr>
<tr>
<td>( R_{NPP}(P) )</td>
<td>NPP revenue for a given half-hour period</td>
</tr>
<tr>
<td>( R_{LAES}(P) )</td>
<td>LAES revenue for a given half-hour period</td>
</tr>
<tr>
<td>( t_{UP}(P) )</td>
<td>Length of time the plant has been up for during a given period</td>
</tr>
<tr>
<td>( t_{DOWN}(P) )</td>
<td>Length of time the plant has been down for during a given period</td>
</tr>
<tr>
<td>( M_{TANK}(P) )</td>
<td>Mass currently stored in the tank</td>
</tr>
<tr>
<td>( \Delta M_{TANK} )</td>
<td>Change in mass in the tank</td>
</tr>
<tr>
<td>( \mu(P) )</td>
<td>Mean average cost to charge the system</td>
</tr>
</tbody>
</table>
Fig. 2. Plant operating decision.
It is important to note that only the LAES part of the plant is treated with a detailed engineering cost analysis. The NPP base asset cost is treated as having a fixed value, and potential over spend is treated using a spending factor, $\phi_{\text{cost,NPP}}(I)$, by which this base cost is multiplied. NPP base capital cost parameters are taken from NuScale literature (NuScale, 2018). Arguably, this base cost is optimistic and this is compensated for by the NPP spending factor, $\phi_{\text{cost,NPP}}(I)$.

### 5. Case study

This engineering model was used to study the performance of an LAES plant linked to a light water SMR (Small Modular Reactor). The SMR chosen was the PWR (Pressurised Water Reactor) developed by NuScale. The preliminary work (Wilson et al., 2020) details the bulk of this engineering modelling. This preliminary work trialled a variety of hybrid plant configurations, but ultimately the charge section of the plant would share its major design characteristics with Highview Power’s vision for their commercial LAES plant.

The engineering model itself focused on modelling the LAES charge and discharge power cycles. Only the secondary loop of the NPP was modelled, with heat exchange with the primary loop taken as a steady-state heat source. Key technical parameters for plant characteristics were taken from NuScale’s Nuclear Regulatory Commission certification documentation (NuScale Power, 2018b).

One of the core conclusions of the preliminary work was that the hybrid plant discharge cycle operates best when steam is diverted from the NPP’s secondary loop to heat the LAES plant’s working fluid before expansion. Much as with the preliminary work, multiple configurations of hybrid plant were optimised and their components sized to be used as a basis for capital cost estimation for the financial model. In this case, the focus was on varying the number of compression and expansion stages, with an eye to optimising the flow rate of steam diverted from the secondary loop to the LAES discharge cycle. This diversion entails ramping down the NPP’s steam turbine to part load. Steam turbines are typically allowed to operate at loads of 50–100% of full power when load following (Kumaret al., 2012; Lokhov, 2011). This was the range in which plant performance was studied in the engineering model.

An important simplification of this preliminary work is that it treated the NPP’s steam turbine as having a continuous isentropic efficiency throughout its operating range. Based on published data (Karakurt and Gunes, 2017), this would not be the case and it can be reasonably expected that isentropic efficiency would fall with the turbine operating at part load. It was treated as such in this study. The results of engineering investigations showed that the additional power generated by the LAES plant’s turbines operating at higher temperatures more than offset this energy cost, but that this nevertheless caused some additional complications.

The steam turbine’s isentropic efficiency is varied depending on its load by parameter defined by the values in Fig. 4 (Karakurt and Gunes, 2017). The consequences of this are significant. One of these can be seen in Fig. 5. Because the steam turbines efficiency drops off most sharply as it moves away from its design flow rate, the specific energy yield of the hybrid plant improves as discharge flow rates increase, up to the defined minimum load for the NPP steam turbine. This is a consequence of the fact that the first 10% of the steam taken from the NPP’s secondary loop comes at the highest energy cost, with this cost falling as more is taken.

The significance of this should not be dismissed. As can be seen in Fig. 5, a given peak discharge pressure for the LAES has a marked peak specific energy yield where the NPP steam turbine is running at half load. The difference between the best and the worst specific energy yields on this curve is over 20%. As mentioned previously, the LAES plant is highly flexible in terms of its charge and discharge power profiles. Coupling with an NPP is problematic, as doing so either locks the system into a specific power rating or means running it in a sub-optimal condition.

There are, however, some advantages in the ability to utilise nuclear heat, particularly the waste heat from the condenser. One of the most important parts of an LAES system is its cold store. Highview’s commercial design posits that this cold store will be a gravel bed (Sciacovelli et al., 2017), but more complex designs have been proposed that utilise liquid hydrocarbon fluid loops (Liet al., 2014; Guzziet al., 2015). The trade-off between these options is potentially significant. From a thermodynamic design perspective, solid media cold stores have transient behaviour as they are heated or cooled. This is particularly true at the end of charge or discharge cycles.

Fig. 6 shows the dynamics of a cold store during a single discharge cycle. The lines that begin at the upper left show the temperature of the air in the cold store loop and the average temperature of the cold store’s gravel bed on the left-hand axis. As the discharge cycle approaches its end and the temperature of the cold store is reduced, the air’s outlet temperature falls. This has two important consequences.

Firstly, the cold store becomes less efficient at storing cold in the discharge air stream, as can be seen from the lines that begin at the lower left. The topmost of these lines shows the amount of cold that could ideally be extracted from the discharge air stream; the lower one shows the amount that is actually extracted. The hydrocarbon loops that have been proposed would be better able to maintain steady-state temperature gradients and extract this cold more efficiently, however such systems are still to be successfully demonstrated.

The second consequence of this is that the temperature of the discharge cycle’s air following heat exchange with the cold store will fall towards the end of the discharge cycle. Here, the abundance of waste heat available at the NPP’s condenser becomes useful, and as can be seen...
in Fig. 3, this study suggests its use for preheating the discharge air before it enters the expansion train. This heat is sufficiently abundant that it enables the expansion train to operate in a steady-state condition throughout a discharge cycle.

The peak temperature of the discharge cycle is limited by the temperature profile along the superheater heat exchangers. Essentially, that means it is limited by the saturation point, and hence pressure, of water supplied by the NPP. As has been mentioned, this study has used NuScale’s PWR SMR as the basis for its engineering model parameters (NuScale Power, 2018a; NuScale Power, 2018b), an NPP whose secondary loop operates at 3.5 MPa. By contrast, the preceding study of a comparable hybrid plant (Liet al., 2014) treats the NPP steam as being supplied at 7 MPa. This means that its saturation point is higher, and in turn the peak discharge temperature and the power yield are also higher. This speaks to an important consideration in the compatibility of an NPP with an LAES plant and that the higher pressures offered by some plant designs offer non-negligible gains in LAES discharge output power and round-trip efficiency.

With the most important engineering design considerations laid out in the preceding text, this paper will now move on to more top-level results and the interplay between the engineering and financial analyses. The starting point for the combined modelling was to determine the implications of compression and expansion staging for plant economics. Twelve designs were studied with 2-, 4-, 6- and 8-stage compression and with 2-, 3- and 4-stage expansion.

Fig. 7 shows the effect of staging on hybrid plant round-trip efficiency. As might be expected, a greater number of stages results in a higher round-trip efficiency. Equally, turbomachinery, and its associated heat exchange equipment makes up the lion’s share of plant equipment costs. It is a core assertion of this study that plant efficiency is a less important consideration to investors than profitability. The real capital cost of improvements in efficiency is thus central to this study.

To contextualise this, consider the equation used to scale equipment costs (Smith, 2005):

$$C(A) = C(B) \left( \frac{S(A)}{S(B)} \right)^x$$

(3)

where $C(A)$ is the unknown cost of piece of equipment A, $C(B)$ is the known cost of piece of equipment B, $S(A)$ and $S(B)$ are the sizes of pieces

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**Fig. 3.** Hybrid plant layout for maximum number of compression/expansion stages (NPP secondary loop section in grey hatched box). Figure adapted from preliminary work (Stack and Forsberg, 2015).

**Fig. 4.** Isentropic efficiency of steam turbine at part load.
of equipment A and B respectively and $X$ is a cost exponent for the type of equipment.

The data used for estimation was taken from a variety of sources (Peters et al., 1968; Smith, 2005; Couper, 2012; Wu et al., 2020; Kerry, 2007; Hue et al., 2013). Where multiple sources were available, the costliest option was chosen to ensure a conservative financial model. Historical data was adjusted to 2018 GB£ using CEPCI (chemical engineering plant cost indices) (Jenkins, 2018; Chemical Engineering Plan, 2008, 2010, 2015). Exponents for the difference pieces of equipment were taken from (Smith, 2005). This data is summarised in Table 3. As shown, exponents for the value of $X$ are typically less than 1. A consequence of this is that several small pieces of equipment will cost more than a single large piece of equipment for a given total size. Thus, staging has a significant effect on plant cost.

The overall LAES plant capital investment was estimated from the total equipment capital costs using the technique described in (Peters et al., 1968) and refined by a group at Worcester Polytechnic Institute (Koc et al., 2012; Koc et al., 2013). This essentially uses a set of scaling factors to estimate the components of overall plant cost. The nature of these scaling factors lends itself to the creating of PERT probability distributions which utilise the same minimum, maximum and most likely parameters. Estimating plant costs using the resulting distributions yielded distributions of plant capital cost best modelled via beta distributions. Thus, one distribution was created for plant cost, $C_{\text{LAES}}(I)$, for each of the 12 modelled plant designs shown in Fig. 7.

Each plant design was then simulated in the financial model. The parameters for the model are shown in Tables 4–7 in the appendix. Economic modelling was performed first in two hypothetical market
scenarios; one with a modest parameter for the mean of the day average time series (the ‘A’ set of simulations), and one with a more extreme parameter (the ‘B’ set).

Before embarking on discussion of the economic model results, it is worth noting how these results are expressed for readers who might perhaps be unfamiliar with their visualisation. Results are visualised using box-and-whisker plots which offer a way of expressing results with a probabilistic spread. The limits of the box part of the plot express the upper and lower quartiles of the dataset in question, with its bar representing the mean. Typically, the whiskers would represent maximum and minimum values but, in this case, represent 10th and 90th percentiles for the sake of space.

The results of the first round of modelling can be seen in Fig. 8, and are broadly what was expected based on the results of the preliminary work (Wilson et al., 2020). Where market prices were modest, the proposed plant performs poorly, with all of the A simulations having NPV distributions lower than, and payback periods longer than, an NPP-only configuration, denoted configuration ‘0’. Such a result portrays an unequivocally weak case for the proposed hybrid plant; ultimately the LAES does not generate sufficient revenue to cover its capital investment. Where spot market prices are higher, the hybrid plant generally performs well.

There are some additional conclusions that might be gleaned from this round of modelling. The preliminary work (Wilson et al., 2020) drew the conclusion that the larger the discharge power of the LAES plant, the more it would capitalise on high market prices and the more profitable the hybrid plant would be. Essentially it concluded that discharge power was a key driver of profitability. The configurational comparison described here provides additional context to this. Whilst round-trip efficiency is without a doubt of significant importance, some plant designs of higher efficiency actually perform worse than some of their less efficient alternatives due to their increased capital cost. In addition, the effect of efficiency improvements is readily apparent in terms of the diminishing returns seen when increasing numbers of compression/expansion staging. This is due to the way equipment costs are scaled and the fact that larger machinery offers the advantage of a

Table 3
Cost estimation data.

<table>
<thead>
<tr>
<th>Equipment</th>
<th>C(B)</th>
<th>S(B)</th>
<th>X</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compressor</td>
<td>7022</td>
<td>0.746</td>
<td>0.62</td>
<td>kW</td>
</tr>
<tr>
<td>Turbine</td>
<td>978</td>
<td>0.746</td>
<td>0.81</td>
<td>kW</td>
</tr>
<tr>
<td>Pump</td>
<td>0.483</td>
<td>1</td>
<td>1</td>
<td>kW</td>
</tr>
<tr>
<td>Heat exchanger (rated to 2 MPa)</td>
<td>151,879</td>
<td>140</td>
<td>0.44</td>
<td>m²</td>
</tr>
<tr>
<td>Heat exchanger (rated to 3 MPa)</td>
<td>190,203</td>
<td>140</td>
<td>0.44</td>
<td>m²</td>
</tr>
<tr>
<td>Heat exchanger (rated to 7 MPa)</td>
<td>227,109</td>
<td>140</td>
<td>0.44</td>
<td>m²</td>
</tr>
<tr>
<td>Heat exchanger (rated to 10 MPa)</td>
<td>287,434</td>
<td>140</td>
<td>0.44</td>
<td>m²</td>
</tr>
<tr>
<td>Heat exchanger (rated to 20 MPa)</td>
<td>359,399</td>
<td>140</td>
<td>0.44</td>
<td>m²</td>
</tr>
<tr>
<td>Storage tank</td>
<td>654,210</td>
<td>2500</td>
<td>0.57</td>
<td>m³</td>
</tr>
<tr>
<td>Cold store</td>
<td>834,211</td>
<td>2500</td>
<td>0.57</td>
<td>m³</td>
</tr>
</tbody>
</table>

Fig. 7. A/B simulation results for configurational modelling.

Fig. 8. Round-trip efficiency dependency on staging.
smaller per-megawatt cost. Whilst an industrial plant design cost analysis would without a doubt be more detailed than the one conducted herein, the economies of scale at the equipment level are well documented and lend credence to the idea that chasing efficiency is not necessarily the best approach to improving plant profitability.

The final rounds of simulation took the best-performing plant design from the A/B simulations. That was configuration 12, with eight compression stages and four turbine stages. These simulations were intended to test the market conditions required for hybrid plant profitability.

The C set of simulations, shown in Fig. 9 were focused on sensitivity testing the day average parameters, $A(D)$, and the amplitude of the daily price curves. Day curve amplitudes are a numerical scaling factor by which the values of $\varphi(P)$ are multiplied. These amplitudes allow the financial model to simulate greater diurnal variability. All parameters studied for the C set of simulations were maintained throughout the duration of the model.

In Fig. 9, the differently-shaded groups of 3 bars represent a given day average parameter as defined by the legend. Plants operating in conditions of higher average prices perform better. Within each day average price group, day curve amplitudes are given values of 2, 2.5 and 3. To put this into context, an amplitude of 2.5 is analogous to day profiles in 2008, the year of the dataset (Smith and Halliday, 2016) with the greatest diurnal variation.

These results provide an important insight into the proposed hybrid plant. Increasing the day average value by 25% from C15 to C3 results in an increase in mean NPV of around £50m (around 12.5%). A comparable increase is seen in comparing C13 with C15, where the amplitude is increased some 50%. Despite the additional arbitrage opportunities available with higher diurnal variation, sustained higher prices are a more important driver to NPV than diurnal volatility.

The reason for this can be seen when examining detailed simulation variables. At high day averages, the electricity used to charge the system is typically purchased from the NPP, as the CfD price is lower than the spot market price. High amplitudes are not sufficient to change this, as might be expected looking back at Fig. 1. This shows that in the colder months when the hybrid plant is inevitably most profitable, troughs are significantly shallower than peaks are tall. This is a major redeeming feature of the proposed plant: the availability of electricity at a guaranteed price from the NPP places a price ceiling on the cost to charge the LAES plant and mitigates the risk of high spot market prices to system charging costs.

The final round of simulations was interested in determining how long market conditions must be sustained for the hybrid plant to remain profitable. The results are shown as the D set of simulations in Fig. 10. D1-D4 begin with the same set of parameters as simulation C15. D5-D8 begin with the same parameters as simulation C3. The first simulation of each set maintains those parameters for 25 years before reducing them to levels commensurate with market conditions today. Each successive simulation in each set maintains the parameters for a duration of five fewer years.

As expected, the shorter the period for which high market prices are maintained, the lower the resultant NPV distribution. At lower day averages, market conditions must be maintained for a period of at least 25 years for the hybrid plant to perform better than an NPP-only plant. The higher day averages are somewhat more favourable, only necessitating a period of high prices for 15 years.

It should be noted, however, that in both cases prices are high compared to those today. Whilst this is not entirely unprecedented - periods of sustained high prices do occur in the UK electricity spot market – these periods are comparatively transient and are better measured in months or years than decades.

6. Conclusions

This study provides significant insight into the synergies of NPP and LAES systems, particularly around opportunities associated with the substantial waste heat available from a NPP’s secondary loop. This study clearly demonstrates that there is plenty of heat available at the NPP’s condenser to vaporise the discharge air stream from an LAES store. Were this system to be explored further with use of waste heat from the LAES charge compression train to heat the discharge power cycle, efficiency improvements might be possible over the standalone LAES systems. Literature on these systems often suggests reliance on zero-cost waste heat, but fail to present options for sources (Sciavovelli et al., 2017; Sciavovelli et al., 2017). NPPs present a credible option in this regard.

This study also examines the challenges associated with using secondary loop steam from an NPP in an LAES system. As section V notes, the nature of diverting steam from the NPP essentially locks the otherwise flexible LAES plant into a specific rate of discharge. Whilst this
paper presents a plant configuration where an NPP could provide waste heat to the discharge LAES cycle, this reduction of system operating flexibility is an important consideration. Were the proposed plant to be reliant on revenue streams from provision of grid ancillary services, such a constraint would be detrimental to plant economics.

The insights as regards NPP secondary loop pressures speak to compatibility of different NPP designs with the LAES system. These insights of the engineering model are of value to designers of prospective systems. In particular, the peak operating pressure of the NPP secondary loop will affect the saturation temperature of the steam supplied to the discharge cycle of the LAES plant, in turn affecting the peak discharge temperature and the discharge power. The results in section V imply that higher secondary loop pressures and hence higher saturation temperatures yield favourable LAES plant performance, implying that alternative NPP designs, such as boiling water SMRs might offer a better coupling option. Examination of such systems could be worthy of further study.

On the whole, the economic study presented in section V paints a bleak picture for the proposed plant design. For a hybrid plant to be of value to designers of prospective systems. In particular, the peak operating pressure of the NPP secondary loop will affect the saturation temperature of the steam supplied to the discharge cycle of the LAES plant, in turn affecting the peak discharge temperature and the discharge power. The results in section V imply that higher secondary loop pressures and hence higher saturation temperatures yield favourable LAES plant performance, implying that alternative NPP designs, such as boiling water SMRs might offer a better coupling option. Examination of such systems could be worthy of further study.

On the other hand, a benefit of the hybrid plant might be that the access to the guaranteed electricity prices of the NPP provides a price ceiling for charging the LAES plant that would otherwise be at the mercy of the spot market. This could present de-risking opportunities for investors in ESSs.

The methodology itself presents a more robust approach to economic analyses of ESSs than existing literature in the field. The coupling of engineering and financial modelling captures the real costs of increasing system efficiency. The methodology is by far the most detailed treatment of market-led engineering design in contemporary literature that the authors are aware of.

7. Discussion and wider applicability

The most meritorious part of this study lies in the methodology developed and in the financial model, rather than in the specific case study in which it has been used. The nature of the financial model, particularly the way in which spot market prices are modelled, storage capacity utilisation is tracked and operating decisions are made, could be tailored to alternative asymmetric ESSs without major changes.

A recently emerged approach to economically evaluating ESSs is that of LCOS (levelized cost of storage), which has been applied to LAES plants in several studies (Tafone et al., 2020; Tafone et al., 2019). It could be reasonably argued that this work is complementary to such approaches and provides insights that LCOS does not.

LCOS uses expected load factors and plant capital cost to define the cost per MWh that stored energy must be sold at for the plant to be profitable. This is most valuable when one attempts to set a subsidy which will sufficiently incentivise investment in a certain energy storage proposal. It cannot, however, provide insights as to how much such a subsidy is likely to cost the ratepayer under real-world market conditions. The model herein would be able to contribute to such insights.

These insights are of considerable value to governments who would seek to incentivise the construction of ESSs through a subsidy approach. It is possible to imagine a subsidy analogous to CfD pricing where ESSs are guaranteed a sale price for their electrical output, such as a cap and floor mechanism. LCOS provides a method by which a floor price sufficient to entice private investment might be calculated. The study presented in this paper provides a means of calculating what such a subsidy would likely cost the ratepayer in different market conditions. It is in this sense that the approach described both contrasts and complements LCOS.

An additional advantage of this modelling approach is that the model can be updated as new information becomes available. As the effect of increased renewables penetrations on the electricity becomes better understood in the coming years, the model could be readily utilised with up-to-date electricity price data, increasing its forecasting accuracy in the near-to-medium-term.

The work presented considers the case study of a hybrid NPP-LAES as a particular example of a hybrid NPP-ESS. The work has been premised on the notion that the proximity of the LAES and the low-grade heat of the NPP will provide beneficial synergies. As it turns out these synergies are small and, as we have seen, the concept of an NPP-LAES hybrid only becomes viable in relatively extreme (e.g. very high price volatility) scenarios. Consequently, the authors are attracted to the notion that an NPP and an LAES should both be part of the same hybrid facility might actually be masking opportunities that might exist if the two functions
were entirely separate within a liberalised electricity market. There may be circumstances where a separate and free-standing merchant LAES facility might be preferable to one tied to a nearby NPP. Such questions would need further research for robust conclusions to be drawn.

Finally, the authors note that an NPP entirely separate from any coupling to a LAES might represent a more attractive commercial proposition if optimised for load following operations without energy storage. In the work reported here an assumption has been made that the market data used has supported - electricity cannot have a negative price. There are scenarios whereby an optimised load-following NPP might be more profitable than a traditional NPP running baseload. The five modes of operation surveyed in this paper do not consider a stand-alone NPP in load following mode. A full techno-economic assessment of a pure load following NPP, without ESS, would benefit from a different model than the one presented here.

In summarisation, whilst the results of this methodology and modelling approach might not be favourable to the system it was developed to study, the approach itself has far broader applicability and might be of use to the wider energy storage community.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Acknowledgements

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### Appendix

#### Table 4

Monte Carlo probability distribution parameters for financial model

<table>
<thead>
<tr>
<th>PERT distribution parameters</th>
<th>Minimum</th>
<th>Most likely</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPP spending factor</td>
<td>1</td>
<td>1.1</td>
<td>1.3</td>
</tr>
<tr>
<td>Binomial distribution parameters</td>
<td>n</td>
<td>p</td>
<td>shift</td>
</tr>
<tr>
<td>NPP construction time - mobilisation</td>
<td>0</td>
<td>0.4</td>
<td>2</td>
</tr>
<tr>
<td>NPP construction time – critical path</td>
<td>1</td>
<td>0.4</td>
<td>3</td>
</tr>
<tr>
<td>LAES construction time – mobilisation</td>
<td>1</td>
<td>0.2</td>
<td>1</td>
</tr>
<tr>
<td>LAES construction time – critical path</td>
<td>1</td>
<td>0.4</td>
<td>1</td>
</tr>
</tbody>
</table>

#### Table 5

Monte Carlo time series parameters for electricity price prediction

<table>
<thead>
<tr>
<th>ARMA time series parameters</th>
<th>Mean</th>
<th>Volatility</th>
<th>Auto-regressive coefficient</th>
<th>Moving average coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily average electricity price ($A_{\text{D}}$)</td>
<td>See table 7</td>
<td>8</td>
<td>0.8</td>
<td>–0.2</td>
</tr>
<tr>
<td>First order MA parameters</td>
<td>Mean</td>
<td>Volatility</td>
<td>Moving average coefficient</td>
<td>Initial error term</td>
</tr>
<tr>
<td>Half-hourly error value ($\epsilon_t$)</td>
<td>0</td>
<td>0.12</td>
<td>0.6</td>
<td>0</td>
</tr>
<tr>
<td>Consumer Price Index (CPI)</td>
<td>0.225</td>
<td>0.002</td>
<td>0.823</td>
<td>0</td>
</tr>
</tbody>
</table>

#### Table 6

Monte Carlo Probability distribution parameters for hybrid plant financial modelling

| Hybrid plant performance parameters | Hybrid plant cost parameters |
|---|---|---|---|
| Sim # | Compression stages | Expansion stages | Charge power (kW) | Discharge power (kW) | Round trip efficiency | $\alpha_1$ | $\alpha_2$ | Minimum (\textbf{m}) | Maximum (\textbf{m}) |
| 1 | 2 | 2 | 145,179 | 405,270 | 27.9% | 10.398 | 19.143 | 101.3 | 124.5 |
| 2 | 2 | 3 | 127,350 | 391,500 | 30.7% | 9.3579 | 16.216 | 103.1 | 125.1 |
| 3 | 2 | 4 | 122,256 | 397,440 | 32.5% | 9.4947 | 17.165 | 107.3 | 130.6 |
| 4 | 4 | 2 | 118,503 | 405,270 | 34.2% | 9.2377 | 16.207 | 105.5 | 127.9 |
| 5 | 4 | 3 | 103,950 | 391,500 | 37.7% | 9.7422 | 17.77 | 106.7 | 130.5 |
| 6 | 4 | 4 | 99,792 | 397,440 | 39.8% | 9.01 | 16.015 | 111.0 | 134.4 |
| 7 | 6 | 2 | 110,808 | 405,270 | 36.6% | 10.507 | 19.31 | 108.6 | 133.8 |
| 8 | 6 | 3 | 97,200 | 391,500 | 40.3% | 9.5496 | 17.249 | 110.1 | 134.2 |
| 9 | 6 | 4 | 93,312 | 397,440 | 42.6% | 10.851 | 21.03 | 113.6 | 141.0 |
| 10 | 8 | 2 | 107,217 | 405,270 | 37.8% | 10.377 | 19.066 | 112.1 | 137.8 |
| 11 | 8 | 3 | 94,050 | 391,500 | 41.6% | 9.9871 | 17.527 | 113.0 | 137.9 |
| 12 | 8 | 4 | 90,288 | 397,440 | 44.0% | 10.566 | 20.266 | 116.8 | 144.5 |
### Table 7

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
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</thead>
<tbody>
<tr>
<td>NPP plant base capital cost (£m)</td>
<td>1050</td>
<td>Compressor isentropic efficiency</td>
<td>85%</td>
</tr>
<tr>
<td>Starting CFD price (£/MWh)</td>
<td>55</td>
<td>Turbine isentropic efficiency</td>
<td>85%</td>
</tr>
<tr>
<td>Plant costs spent during mobilisation</td>
<td>30%</td>
<td>Day average $\mu_{factor}$, all years, A simulations (£/MWh)</td>
<td>100</td>
</tr>
<tr>
<td>Annual fixed NPP O&amp;M costs (£m)</td>
<td>30</td>
<td>Day average $\mu_{factor}$, all years, B simulations (£/MWh)</td>
<td>220</td>
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<tr>
<td>NPP refuel costs (£m)</td>
<td>10</td>
<td>Amplitude factor $\alpha$ simulations C1/4/7/10/13</td>
<td>2</td>
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<tr>
<td>Annual fixed LAS O&amp;M costs as a fraction of plant cost</td>
<td>1.5%</td>
<td>Amplitude factor $\alpha$ simulations C2/5/8/11/14</td>
<td>2.5</td>
</tr>
<tr>
<td>NPP fuel load duration (days)</td>
<td>500</td>
<td>Amplitude factor $\alpha$ simulations C3/6/9/12/15</td>
<td>3</td>
</tr>
<tr>
<td>NPP time to refuel (days)</td>
<td>10</td>
<td>Duration of high market prices simulations D1/5</td>
<td>30</td>
</tr>
<tr>
<td>Charge window start time</td>
<td>00:30:00</td>
<td>Duration of high market prices simulations D2/6</td>
<td>25</td>
</tr>
<tr>
<td>Charge window end time</td>
<td>06:00:00</td>
<td>Duration of high market prices simulations D3/7</td>
<td>20</td>
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<tr>
<td>Discharge window start time</td>
<td>17:30:00</td>
<td>Discount rate</td>
<td>7%</td>
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<tr>
<td>Discharge window end time</td>
<td>23:30:00</td>
<td></td>
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