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TECHNO-ECONOMIC STUDY OF OUTPUT-FLEXIBLE LIGHT WATER NUCLEAR REACTOR SYSTEMS WITH CRYOGENIC ENERGY STORAGE

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Keywords   uncertainty analysis, power grid economics, energy storage, nuclear power

JEL Classification   C15 - Statistical Simulation Methods: General

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I. INTRODUCTION

CHARLES Forsberg of the Massachusetts Institute of Technology has opined that the challenge for the future of nuclear power is not simply to reduce costs – it is to increase revenues [1]. The authors have been inspired by that challenge and have sought to address, and assess it with respect to currently available technologies.

In recent decades the costs of nuclear power plant construction have risen, but price premiums for baseload electricity have largely been elusive. This study explores the viability of a new economic proposition involving the coupling of a nuclear power plant with a cryogenic energy storage system with the intention of supplying variable electrical power to the grid to capitalise on peak spot market pricing. The focus on market-led design is a novel study of this system.

As renewables become more integrated into power grids, there will come a greater need for the provision of either grid-scale electricity storage or load-following (dispatchable) power supply. The former is currently either expensive (batteries), only useful for specific purposes (flywheels) or requires specific terrain for siting (pumped hydroelectric storage) [2]. The latter typically requires either the costly curtailment of intermittent renewable sources (costly because the operator and by extension the consumer pay for power that is not used) or the use of carbon-releasing fuels, most commonly natural gas.

Nuclear power plants have some potential to fulfil a load-following role, as they do in France [3, 4]. They cannot, however, generally be ramped as fast as natural gas plants [5]. There are also significant financial implications in running a high capital cost, low fuel cost plant at anything other than maximum capacity.

There is a plethora of energy storage options available [2]. One of the most developed of these is CES (cryogenic energy storage) which has an operating pilot plant in the UK. CES involves using excess electricity to run air liquefaction equipment, liquefying ambient air and storing it in an insulated tank. When energy is in demand, this air is released, evaporated, expanded and run through turbomachinery to generate electricity. Alone, this has a potential round-trip efficiency of around 50% [6]. This fact highlights one of the key issues common in novel energy storage systems; roundtrip efficiencies are usually too low for these systems to be financially viable by buying power when it is cheap (in excess) and selling it when it is expensive (in demand). The low temperature of the power discharge side of this system presents extra opportunity for thermal power plants; CES is able to extract low-grade heat from these plants that would otherwise be considered waste, boosting the effective round-trip efficiency.

UK baseload plants receive revenue based on their volume sales and the price for that electricity. The actual price paid per MWh is often agreed a years or months in advance by way of contracts between the generators and suppliers but in principle can also be determined by the day-ahead bidding market. The next generation of NPPs (Nuclear Power Plants) in the UK is expected sell energy on a CFD (Contract for Difference) basis for a part of their operational lifetime. Under this agreement, a generator is guaranteed a fixed sale price for each MWh of electricity they produce. Where the market price is lower than this 'strike price', the shortfall is made up by the utilities and

paid to the generator. When the market price exceeds the strike price, the excess is paid back to the utility from the generator. Strike prices are indexed to the Consumer Prices Index. This work proposes an alternative system whereby part of the NPP's revenue is determined by bidding into the spot market, as is done by highly dispatchable gas power plants [7], in an attempt to minimise the required CFD price and its ratepayer subsidisation. The plant's power output over one day is shown in figure 1.

The CFD system guarantees revenue for large low-carbon power generation projects with high capital investment in order to reduce the financial risk of these projects [8]. The strike price for the Hinkley Point C NPP is £92.50/MWh, reducing to £89.50/MWh if a second plant is built at the Sizewell C site. These rates are guaranteed for 35 years. Current spot market prices are almost always lower than the strike price, with the peak price exceeding £89.50 on only 400 days during 2008 to 2015 [9], implying that selling all of a plant's power on a CFD basis is far less risky than trying to sell part of its power into the spot market. These prices are expressed in 2012 equivalents, as are all prices described in this paper, for the sake of simplicity.

This raises the question of why any nuclear power plant operator would forego a guaranteed return for the sake of bidding into the spot market. An important consideration is more recent developments in CFD prices, particularly the agreed strike prices of £57.50/MWh for two new windfarms. Whether such a price is sustainable in the offshore wind sector is a subject of debate [10-12], however energy generation is a highly competitive market and since strike prices are ultimately paid for by the consumer, it is entirely reasonable to expect that nuclear power will have to be more competitive in the future to remain relevant and provide value for money. Indeed, such competition drives consumer electricity prices down.

Furthermore, the aforementioned nuclear strike prices were agreed for a period of 35 years – significantly less than the expected lifetimes of the plants [13]. This means that the plants will ultimately require further contract negotiation or be at the mercy of day-ahead baseload prices following the expiration of the strike price agreement. Prices in this market have historically been, on average, lower than spot market prices [9], and certainly lower than the strike price. Only CFD agreements where strike prices are agreed for the period of the model (30 years) are considered in this study.

This study will consider an NPP that runs as a baseload heat generator in all cases. Plant configurations will be considered that include CES systems that allow the plant to vary its output, allowing it to provide peaking power to the grid during periods of high demand (and consequentially high electricity price). The output profile for such a plant is shown in Fig. 1. The plant design and capacity will be optimised from a financial standpoint to maximise the profitability of the plant.

This paper will study both the technical and financial viability of a nuclear power plant coupled to a CES system using computer modelling. Previous groups [14-17] have optimised a CES system from an engineering standpoint with or without a coupled NPP and others [18, 19] have considered the scheduling of similar plants in energy markets. This paper's novel approach of market-led design, and the use of the financial model to inform the engineering design, addresses this knowledge gap in a spirit similar to other techno-economic analyses [20, 21] and to load-following NPP studies [22].

The remainder of the paper is split into five sections. The first will discuss the overall approach to modelling. The second and third will go into more detail on the engineering and financial models respectively. The fourth will discuss the results of the models and the final section will discuss the overarching conclusions of this study.

II. MODELLING APPROACH

The aim of this study is to assess the performance of different system designs in the UK electricity market. In order to achieve this, the plant was first studied using an engineering model to optimise the process and size the plant components. The resulting bill of materials was then used to estimate the plant costs. Finally, the performance of the resultant plant designs was assessed using a Monte Carlo financial simulation. Assessments were made using a range of user-defined strike price values to determine the minimum strike price required for NPP profitability. The combined NPP and CES system was then modelled to determine how volatile the SPOT market would need to become in order for the inclusion of CES to become a profitable scenario. The parameters used for the market-led optimisation study are shown in Tables I, II and III.

The engineering model was developed using the Modelica modelling language and the Dymola simulation environment. Dymola allows construction of the overall process model built up in a modular fashion using individual component models. This allows multiple system configurations to be designed and optimised for round-trip efficiency relatively quickly, whilst still allowing the flexibility to study the most important components in the required level of detail to allow their sizing.

This engineering model was used to study component sizing for a CES system linked to a light water SMR (Small Modular Reactor). SMRs are the most interesting for this study because their modular nature allows the system to adopt a variety of sizes, thus filling a variety of niches within the electricity market. The SMR chosen is the PWR (Pressurised Water Reactor) developed by NuScale, simply because it is by far the
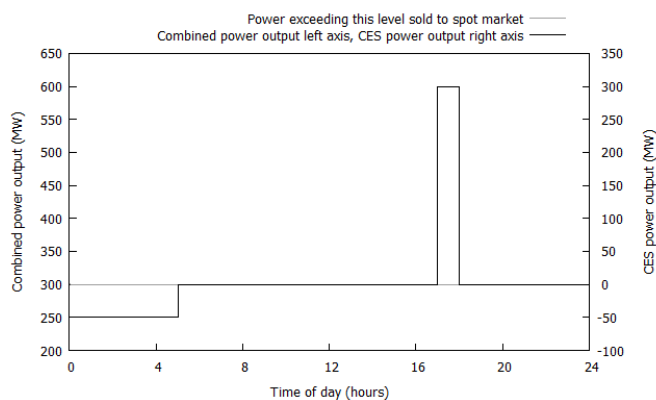

Fig. 1: Output profile of combined NPP and CES plant (configuration 3 in table IV)
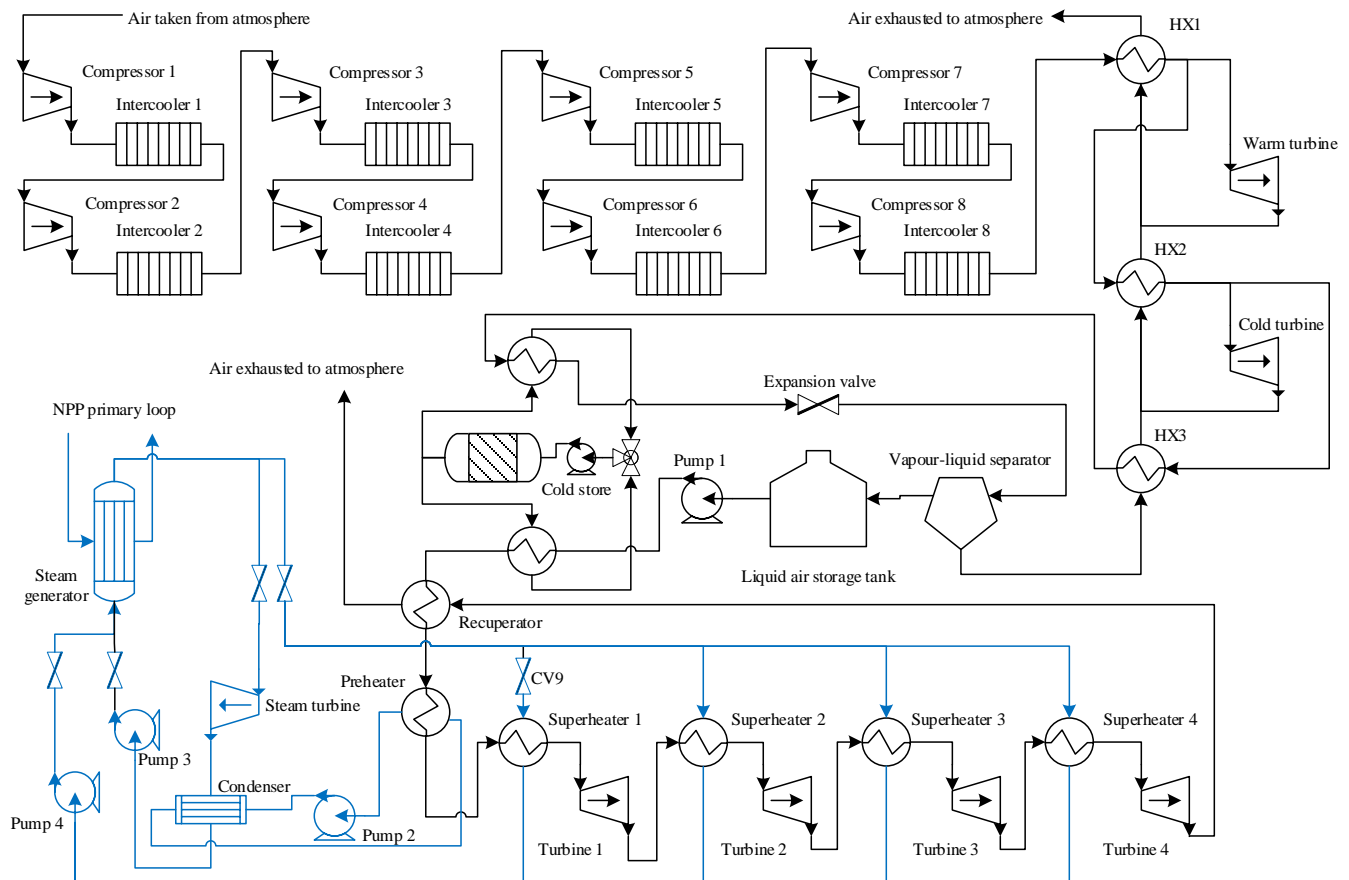
Fig. 2: Plant layout. CES plant shown in black, NPP secondary loop shown in blue.

closest to market of the current SMR designs of unit size less than 300 MWe.

The CES plant configuration is highly flexible. The size of the plant itself is limited only by the available electrical power of the coupled nuclear reactor. In addition, the power ratings of the charge and discharge sides of the plant are entirely independent. Whilst the charge capacity is determined by the size of the air storage tank and the cold store, the rate at which it is charged or discharged is determined only by the compression train and powertrain component sizes.

A financial model was developed in Microsoft Excel using the Palisade @RISK plugin. @RISK adds Monte Carlo modelling functionality to Excel, which, rather than producing a single value for the NPV (Net Present Value) of a project, produces an NPV probability distribution. This is a graphic that indicates the relative likelihood of potential NPVs for the project. This provides insight into the relative economic risk of investing in different designs, exactly the intent of this study.

Monte Carlo modelling is ideal for projects in which there are several uncertain cost parameters. Rather than providing the model with a set value for such a parameter, the user will provide a probability distribution (ideally fitted to historical data) for the range of possible values that parameter might take. The financial model is then run over thousands of iterations, each of which determines its input parameters using the provided probability distributions. Each of these iterations will produce a different NPV value, which are collated and summarised in the NPV distribution curve mentioned above.

The novel feature of this study is the integration of financial modelling into decision-making for the engineering design. The engineering model is used first to determine power ratings for potential power plant configurations and to size the required components. These initial results are then fed into the financial model to assess the relative financial viability of the different designs, indicating which might be more economically viable. Second runs of both models are then run to determine how the charge and discharge systems would be best sized for the UK electricity market. The engineering model is run in greater detail and components sized. These detailed designs are then used to determine plant capital costs for a more in-depth run of the financial model providing final NPV distributions and payback periods for the chosen designs.

III. DETAILS OF THE ENGINEERING MODEL

The plant layout is largely based on the Highview Power Storage design [14, 16] and the associated studies performed at Birmingham University [15]. The chosen layout is shown in Fig. 2. This model expands on the modelling work done previously by treating heat exchanger components as finite volume models allowing them to be sized and their cost estimated accurately.

This layout shares several key features with the previous studies. The liquefaction process is based on the Claude design where air is sequentially compressed and cooled. The

compressed air is the split, with a portion being expanded isentropically in a turbine and the remainder being expanded adiabatically in a Joule-Thomson valve where it is partially condensed. It is then separated with the liquid fraction being sent to a tank and the vapour fraction being returned to cool the incoming air stream.

This layout also features a system most commonly referred to as cold recycle, which cools some medium, typically a gravel bed, using the air being vaporised during the discharge phase then uses that medium to cool the incoming air during the storage of energy. In an actual system, several cold stores can be set up in parallel and flow diverted as one heats up during storage or one reaches its minimum temperature during discharge [15].

Dymola models are built up from individual component models coded in Modelica, a language made up of several user-maintained libraries. The Modelica Standard Library and the ThermoPower library [24, 25] form a key part of this model. The former consists of the standard set of commands and connectors and forms the basis of the Modelica language. The latter is geared towards the analysis of thermodynamic systems and contains a number of components tailored to this task. Each component performs a specific function and different components interact via nodes. Fluid flow nodes transit fluid properties including enthalpy, pressure and mass flow rate while heat transfer nodes allow transfer of heat between components.

Thermodynamic property data for air and water is also important in this model. The software CoolProp has been used for thermodynamic properties of air [26] and water [27] and is referenced using the ExternalMedia library [28].

The most important components used in this model will now be detailed in turn. The most relevant equations are detailed; conservation of mass and energy equations and isentropic efficiency equations are omitted for brevity but are included within the models themselves. In the following equations, subscript v is used to indicate convective heat transfers and subscript d is used to indicate conductive heat transfers.

A. Heat exchangers

Heat exchanger models consist of two finite volume fluid flow models connected via heat transfer nodes through a finite volume model of a metal tube. The flow models are based on the ThermoPower one-dimensional flow regimes but include simplified pressure drop models where pressure out of the flow is a fraction of the pressure in:

$$p_{\text{out}} = \xi p_{\text{in}} \tag{1}$$

where p_{in} and p_{out} are the pressures at the component inlet and outlet respectively and ξ is a nominal pressure drop factor.

Convective heat transfer rates, $\dot{Q}_{\text{v}}$, between a fluid and its adjacent surfaces occurs through heat transfer nodes and is calculated for a finite volume, i:

$$\dot{Q}_{\text{v}} = \alpha A_{\text{surf}.i}\left(T_{f,i} - T_{s,i}\right) \tag{2}$$

where A_{surf} is the heat transfer surface area, α is the convective heat transfer coefficient and T_f and T_s are the temperatures of the fluid and the surface respectively. Thus, a positive heat transfer rate represents heat flow from the fluid into the surface.

In the metal tube, the rate of change of temperature of a volume i is calculated by:

$$M_i c \frac{dT_i}{dt} = \dot{Q}_{\text{v, inside}} + \dot{Q}_{\text{v, outside}} + \dot{Q}_{\text{d}, i} - \dot{Q}_{\text{d}, i-1} \tag{3}$$

where M_i is the mass of the volume, c is the specific heat capacity of the metal, $\dot{Q}_{\text{v, inside}}$ and $\dot{Q}_{\text{v, outside}}$ are the convective heat transfers between the inside and outside surfaces and their adjacent fluid flows and T_i is the temperature of the volume. $\dot{Q}_{\text{d}, i}$ is the axial conductive heat flow rate into volume i from the adjacent volume $i + 1$, calculated by:

$$\dot{Q}_{d,i} = \frac{k A_{sect}(T_{i+1} - T_i)}{d} \tag{4}$$

where k is the thermal conductivity of the metal, A_{sect} is the cross-sectional area of the tube and d is the distance between the centres of adjacent volumes.

A counter-current regime is used which equates the highest temperature volume of one flow with the lowest temperature volume of the other.

B. Turbines

Turbine power, $\dot{W}$, is given by:

$$\dot{W}_{\text{turbine}} = \dot{m}(h_{\text{out}} - h_{\text{in}})\eta_{\text{turbine}} \tag{5}$$

where $\dot{m}$ is the mass flow rate through the turbine, h_{in} and h_{out} are the respective specific enthalpies of the air flowing into and out of the turbine based on the pressure ratio and η_{turbine} is the mechanical efficiency of the turbine, defined as the ratio of actual work output to the total energy available from the expanded fluid. Isentropic efficiency for the model is shown in table I.

C. Compressors

Compressor power, $\dot{W}$, is given by:

$$\dot{W}_{\text{compressor}} = \frac{\dot{m}(h_{\text{out}} - h_{\text{in}})}{\eta_{\text{compressor}}} \tag{6}$$

where $\dot{m}$ is the mass flow rate through the compressor, h_{in} and h_{out} are the respective specific enthalpies of the air flowing into and out of the compressor and $\eta_{\text{compressor}}$ is the mechanical efficiency of the compressor, defined as the ratio of useful work done to the actual work required. Isentropic efficiency used for the model is shown in table I.

D. Pumps

The power, $\dot{W}$, of liquid pumps is calculated using:

$$\dot{W}_{\text{pump}} = \frac{\dot{V}\Delta p}{\eta_{\text{pump}}} \qquad (7)$$

where $\dot{V}$ is the volumetric flow rate through the pump, Δp is the pressure increase and η_{pump} is the mechanical efficiency of the pump.

E. Gravel bed

The gravel bed model consists of a finite volume fluid flow model (the same as those used for heat exchanger models) connected to a finite volume model of the gravel bed itself. Convective and axial conductive heat transfer rates are calculated in the same way as for the metal tube model discussed in section A above. The convective heat transfer coefficient, α, is calculated using an empirical correlation [29, 30]:

$$\alpha = \frac{700}{6(1-\varepsilon)}\left(\frac{\dot{m}}{A_{\text{sect}}}\right)^{0.76} d_p^{0.24} \qquad (8)$$

where $\dot{m}$ is the mass flow rate through the bed, ε is the void fraction and d_p is the diameter of the gravel used in the bed.

F. Separation

Following expansion, the resulting fluid is separated, and the resulting liquid and vapour fractions are determined using:

$$H_{\text{liquid}} = (1 - X_{\text{mix}})\dot{m}_{\text{mix}}h_{\text{bubble}} \qquad (9)$$

$$H_{\text{vapour}} = H_{\text{mix}} - H_{\text{liquid}} \qquad (10)$$

$$\dot{m}_{\text{vapour}} = X_{\text{mix}}\dot{m}_{\text{mix}} \qquad (11)$$

$$\dot{m}_{\text{liquid}} = X_{\text{mix}}\dot{m}_{\text{mix}} \qquad (12)$$

where H_{mix}, H_{vapour} and H_{liquid} are the respective enthalpies of the incoming mixture, the outgoing vapour and the outgoing liquid. $\dot{m}_{\text{mix}}$, $\dot{m}_{\text{vapour}}$ and $\dot{m}_{\text{liquid}}$ are mass flow rates defined using similar subscripts. X_{mix} is the vapour quality of the incoming mixture.

The approach to modelling was to first validate the heat exchanger and turbomachinery models against real-world systems [6, 31] to set the parameters for heat transfer coefficients and efficiencies. The CES system was then optimised for the chosen reactor size to determine power ratings and component sizes over a range of charge and discharge rates. This information is then considered within the financial model.

IV. DETAILS OF THE FINANCIAL MODEL

The financial model was built in Excel using the @RISK plugin to allow Monte Carlo financial modelling of the plant. The user defines a number of certain and uncertain parameters relating to the cost of the plant, as shown in Table I, and these are used to define the upfront capital expenditure and build cost.

Broadly, the model is a discounted cash flow analysis with uncertain input and time series parameters. It assesses the market conditions required for plant profitability at two discount rates; a 3% and a 7% discount rate. The former is considered to be representative of a public asset model of the

TABLE I
FIXED MODEL PARAMETERS

Parameter	Value
Compressor isentropic efficiency	85%
Turbine isentropic efficiency	85%
Strike-price (£/MWh) *	55-75
NPP baseload capacity (MWe)	300
CES charge rate (MWe)	50
CES discharge rate (MWe) *	30-300
CES storage capacity (tonnes) *	120.6-1206
Discount rate (%) *	3-7
NPP asset cost (£/kW)	3,500
NPP initial annual operation and maintenance cost (£m)	30
CES initial annual operation and maintenance cost (£m)	5
Reactor refuel costs (£m)	10
Reactor fuel time (days)	500
Reactor refuel downtime (days)	10

* denotes parameters that are user-defined (example ranges shown)

plant in question whilst the latter is intended to represent a semi-commercial context where at least part of the risk of the project is borne by the state.

Equipment capital cost is estimated from the plant designs generated by the engineering model using the method described in [32]. The total capital investment for equipment is first estimated from the known prices using the scaling equation:

$$C(A) = C(B)\left(\frac{S(A)}{S(B)}\right)^X \qquad (13)$$

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 of equipment A and B respectively and X is a cost exponent for the type of equipment. Known equipment costs were scaled using the Chemical Engineering plant cost index [33-35].

With knowledge of the capital cost of the main pieces of equipment, total CES plant cost was estimated by the process described in [32], which estimates ancillary costs from the equipment capital cost using a set of factors. Due to the uncertainty inherent in this process, the CES plant cost was itself determined in a Monte Carlo model, with PERT (Program Evaluation and Review Technique) distributions used for each factor. A scaled Beta distribution was then fit to the results output and used in the main financial model, producing the distributions shown in Table II. The required changes to the NPP secondary loop (see section V) were factored into this cost.

The main financial model is split into two phases; construction and operation. During the construction phase, costs are assessed on an annual basis using the user-defined construction cost. NPP cost is defined as £3,500/kW [36] and scaled using a factor defined by probability distribution. The duration of construction is strongly linked to total cost and is defined by a binomial probability distribution correlated to plant NPP cost factor using a copula. Construction itself is split into two phases; a mobilisation phase where costs are split

across years and a critical path following where the remaining costs are spent upfront. Two scenarios were considered; a first of a kind (FOAK) scenario where the NPP cost is likely to be significantly higher than the designer-estimated cost and an nth of a kind (NOAK) scenario where the cost is thought to be more certain.

The parameters for all probability distributions in the final model are shown in Table II. Three types of distributions were used. PERT is a simplified beta distribution defined using the minimum, maximum and most likely parameters. Binomial distributions are similarly shaped but take discrete whole number values based on a shift value, describing the first possible value, n, the number of values after the initial and p, defining the weighting of probabilities towards the maximum value as a real number between 0 and 1. BetaGeneral distributions are another variant of beta distributions and are scaled to maximum and minimum values and defined by shape parameters α_1 and α_2.

Following the construction phase, the model uses a more detailed approach to simulate the plant operation on a half-hourly basis. This plant would sell its variable power into the spot market and sell its fixed power on a CFD basis. The assumption is made that the plant can sell its energy at the per MWh strike price during charge and baseload phases, i.e. at any point at or below the horizontal line in Fig. 1, and that only the peak power (the difference between the discharge and baseload power ratings) is sold on the spot market.

The most important part of this simulation is the forecasting of electricity prices. This is done using a combination of statistical time series models which are fitted to past data. Many time series models for electricity price forecasting have been developed and implemented over the years [37]. Fitting was attempted with a range of time series models including MA (Moving Average), AR (AutoRegressive) and BM (Brownian Motion) models, with fits ranked according to AIC (Akaike information criterion), which estimates the quality of the statistical model fit to the available data.

Series fitting are complicated by patterns in electricity price variation, preventing the sole use of statistical time series models. In the UK, prices show daily, weekly and annual seasonality, but remain highly variable and difficult to predict accurately. Spot market prices were provided by the UK Energy Data Centre and used to develop the electricity price forecasting model. The dataset [9] covers the years from 2008 to 2015, which provides insight into the characteristics of daily and seasonal variation and volatility during time of both high and low volatility. The data was analysed in detail and used to develop a model for electricity price forecasting.

The variation of the UK electricity price from the daily mean shows a demonstrable pattern with daily, weekly and seasonal variation. Characteristics such as the peaks and troughs in the price are thought to be driven by demand resulting from public behaviour. For example, during the winter, the electricity price peaks between 17:00 and 18:00, when the majority of the population arrives home from work, but at a time when offices are still consuming power. As days get longer into the summer, this peak occurs later in the day and is less pronounced. Peaks that occur in the middle of the day are much more prominent in

TABLE II
MONTE CARLO PROBABILITY DISTRIBUTION PARAMETERS

PERT distribution parameters	FOAK			NOAK		
	Minimum	Most likely	Maximum	Minimum	Most likely	Maximum
NPP spending factor	1	1.7	2	1	1.1	1.3
Binomial distribution parameters	n	p	shift	n	p	shift
NPP construction time - mobilisation	1	0.6	2	0	0.4	2
NPP construction time – critical path	2	0.6	3	1	0.4	3
CES construction time – mobilisation	1	0.6	1	1	0.2	1
CES construction time – critical path	1	0.6	1	1	0.4	1
BetaGeneral distribution parameters			α_1	α_2	Minimum /£m	Maximum /£m
CES configuration 1 (slow discharge)			9.8763	16.457	20.9	23.3
CES configuration 2 (moderate discharge)			7.7810	13.202	44.5	51.9
CES configuration 3 (rapid discharge)			10.949	21.242	66.3	80.0

TABLE III
MONTE CARLO TIME SERIES PARAMETERS

ARMA time series parameters	Mean	Volatility	Auto-regressive coefficient	Moving average coefficient
Daily average electricity price (A_D)	User-defined	User-defined	0.8	-0.2
First order MA parameters	Mean	Volatility	Moving average coefficient	Initial error term
Half-hourly error value (ε_t)	0	User-defined	0.6	0
Consumer Price Index (CPI)	0.225	0.002	0.823	0

Configuration	0	1	2	3
Charge power (MW)	0	50	50	50
Charge flow rate (tonnes/h)	0	222	222	222
Discharge power (MW)	0	30	150	300
Discharge flow rate (tonnes/hr)	0	241.2	1,206	2,412
Storage capacity (tonnes)	0	120.6	603	1,206

the middle of summer, presumably at the height of commercial air conditioning use. At night time, the price falls and these troughs are much deeper during the summer when less power is being used. At weekends, the summer midday peaks are far less pronounced, and the night time troughs occur later and become deeper.

Because the daily price profiles are considered to be behaviourally driven, the forecasting model uses historical data to shape the profiles. The amplitude of the price profiles is user-defined to allow different hypothetical scenarios to be explored. Data analysis demonstrates that the actual half-hourly prices can still vary significantly, and a time series model is thus introduced to include a deviation from the price profile, hereafter termed an error. Thus, each half-hourly price (P) calculation is formed of three components:

$$P = (\varepsilon_t + V_t) \times A_D \qquad (14)$$

where A_D is the average price for that day, V_t is the variance from that average for the given period and ε_t is the error in the given price period. The variance is based on the historically shaped daily profiles with combined with user-defined multipliers. The daily averages and period errors are a part of the Monte Carlo model and are given by time series models.

The model uses a first-order ARMA model (combination of AR and MA models) to predict daily price averages and first order first order MA models to predict the error value and the CPI by year. The parameters for these series were fit to historical data, as shown in table III, except where parameter variation was necessary to test different scenarios. Both the time series model parameters and the daily price profile amplitudes are user-defined to explore both high and low volatility scenarios. Individual time series are used for each year of the financial model and parameters are user-defined every five years to allow the exploration of scenarios where volatility changes over time. Where this occurs, parameters are interpolated for the intervening years. Daily price curves are shaped based on the average of the available data as a multiple of the daily mean. These can be amplified by a user-defined factor to increase or decrease the amplitude of the daily curve.

Because of the high level of variation in electricity prices, there are times when the price will be lower and hence less favourable for system discharge. Hence, the model contains an algorithm to decide how the plant will operate over each half hour period. The plant can either operate in charge mode, where

some power is diverted to the CES plant and air is liquefied, in discharge mode, where air is released from the CES plant and additional power is generated or in baseload, where the nuclear power plant operates at its nameplate capacity. To facilitate this, there must be a threshold price such that the system is discharged only when a profit can be made.

This decision-making regime sets the threshold price as a multiple of the current strike price, depending on the efficiency of the system. Furthermore, discharge only occurs following 17:00. This ensures that air is only released when the energy it would generate can be sold for more than the air cost to liquefy in the first place.

This decision-making regime is intended to emulate the way an operator would rationally choose to run the plant. Without foreknowledge of electricity prices, they would have to bid into the day-ahead spot market; their minimum bid being an appropriate multiple of the strike price based on round-trip efficiency. Similar modelling approaches could be used to forecast electricity prices and make decisions on the time periods that would be bid for and the prices that would be bid.

V. RESULTS

The initial run of engineering modelling was performed using idealised heat exchange parameters, with large values of surface area and heat transfer coefficients to ensure optimal heat transfer between fluids. The number of volumes for finite volume models was limited to 100 to limit computation load. Models were tested assuming a 300 MW NuScale PWR plant providing 402 kg/s of steam at a pressure of 3.5 MPa and a temperature of 573.15 K. The authors note the recent improvements in NuScale plant design, however this study is based on the secondary loop design in the most recent regulatory application.

Multiple power cycle configurations for the nuclear plant's secondary loop, the air discharge cycle and the interaction between the two were considered. A configuration where a portion of the secondary loop steam was bled off and sent to heat the air prior to expansion in the turbines, as shown in Fig. 2, gave the highest gross power output and round-trip efficiency for the plant. The trade-off between reduction of secondary loop power output and the improvement of air power output was considered in detail and the system optimised to maximise the combined power output.

The approach to CFD pricing means that only peaking power is sold to the spot market as per Fig. 2. As a result, the charge power rating has no effect on the project revenue. Varying the storage size of the plant consistently gave higher annual revenues for plants that discharge fully in a single half hour period than for any other size of storage. Since larger sized tanks would increase plant capital investment CES plants that stored only enough liquefied air for a single half-hour period quickly became the focus for further study. Plants that were faster to discharge came with the expected revenue increases, but would cost significantly more capital, so it was decided to study a range of plants in the final round of modelling, as shown in table III. Here, configuration 0 is an NPP only design. These plant designs were studied in much greater detail in the
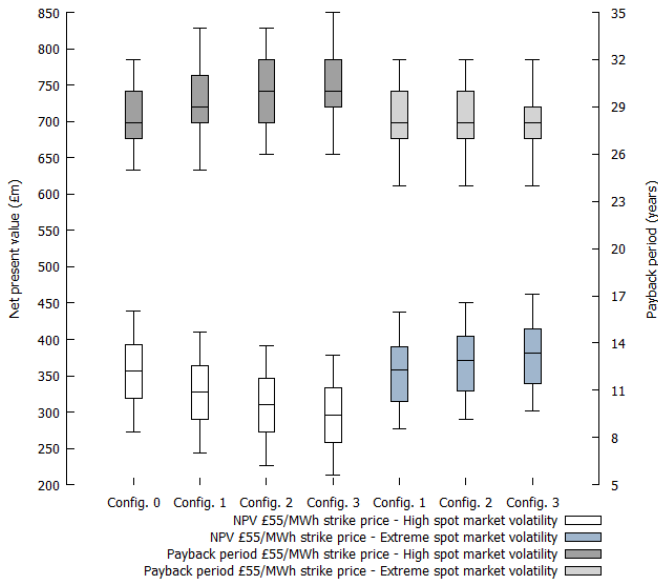
Fig. 4: Notable financial model results as boxplots at 7% discount rate for NOAK scenario; boxes show upper and lower quartiles; whiskers show 90th percentiles.
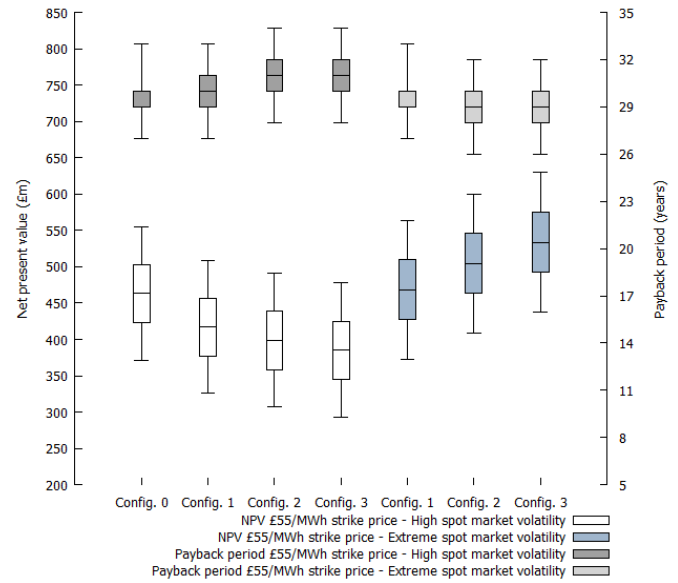
Fig. 3: Notable financial model results as boxplots at 3% discount rate for NOAK scenario; boxes show upper and lower quartiles; whiskers show 90th percentiles.

engineering model and heat exchanger components sized to allow plant cost estimation as described in section IV.

Different spot market conditions were explored in scenarios and driven by two parameters; firstly, the average daily price used in the ARMA model and secondly an amplification factor used to modify the amplitude of the daily price curve and describe price volatility over a day. Low volatility scenarios use a multiplier of 0.8, giving a similar shape to prices from 2013. High volatility scenarios use a multiplier of 2, reminiscent of 2008 price curves. These are the lowest and highest years of record in terms of daily price variance.

The performance of combined NPP and CES plants compares unfavourably to an NPP only design, even in the most favourable of realistic scenarios, as shown in Fig. 4. There is simply not enough of an increase in revenue to cover the additional cost of the CES plant. Indeed, even with the cost benefits implied by economies of scale with larger plants as seen in table II, the NPV distribution unequivocally improves as CES plant size tends to zero, shown by the dark grey boxplots in Fig. 4 and Fig. 3, where smaller CES plant exhibit a more favourable NPV and the NPP-only configuration is the most profitable.

NPP only results are favourable in FOAK scenarios at an initial strike price of £75/MWh or higher, and if the estimated costs for the SMR offered by NuScale can be realised, as in the NOAK scenario, strike prices of £55/MWh are sufficient to ensure an acceptable return on project investment. The latter of these results is summarised in Fig. 4 under high volatility, along with the corresponding plants incorporating CES.

Analysis was performed to determine how high spot market prices would have to be for coupling CES to become attractive; when the daily peak spot market price approaches £350/MWh in winter and £200/MWh in summer, either through an increase in daily curve amplitude or an increase in overall spot market prices. This is marked as 'extreme spot pricing' in Fig. 4 and Fig. 3. In cases of such high volatility, the more rapid discharge plants perform better than the slower discharge plants in all cases, where the larger CES plant with higher configuration numbers outperform the smaller plants.

Analysis was also performed to determine whether the plant being funded and run as a public asset could improve economic performance. This was performed at a discount rate of 3%. Whilst a lower discount rate enhances long-term future revenues within the NPV, relatively extreme spot market prices are still required, with peak prices approaching £210/MWh in winter and £150/MWh in summer. As before, the comparison is expressed in Fig. 3.

VI. DISCUSSION

The engineering results clearly demonstrate that the charge and discharge rates for the air storage system are, for the most part, entirely independent. Since compressors can be sized appropriate to the charge rate, specific energy input for liquefying air is the same for all charge rates. Since optimising power output for the air power system demands that steam be diverted from the nuclear power plant's secondary loop, ratio of steam diverted away can be tailored for output power, and the specific energy output is the same across the full range of discharge rates. However, the NPP capacity is a limiting factor on the discharge rate, as increasing mass flow rate in the discharge cycle will eventually diminish specific output per unit mass of air due to the reduction in peak outlet temperature.

An important caveat on the independency of the charge and discharge cycles is that the input and output rates are required to be proportional, given the shared components shown in Fig. 1, namely the liquid air storage tank and the cold store. The system studied herein is thus envisaged to be a scheduled plant via the day-ahead spot market and the design is not suitable as

an emergency balancing plant, due to the fact that the system must be fully discharged before the subsequent charge cycle.

Whilst a plant with integrated CES invariably performs poorly compared to one without, the financial model results highlight that a system that discharges all liquefied air over a single half hour period is best for the UK electricity market. Indeed, such a system performs far better than one that discharges over a full hour. Because only the peak power is sold to the spot market, there is no discernible benefit of a given storage rate.

Another important output of this paper is the demonstration that, provided the spot market is sufficiently volatile to incentivise the addition of the CES plant, larger discharge rates provider larger and faster returns on investment.

Two discount rates have been studied. As would be expected, the lower discount rate permits profitability at a lower strike price. Ultimately however, this study has shown that the case for CES remains weak in both cases, unless extremely high spot market price volatility occurs in the future. Despite the difficulty in justifying the inclusion of a CES system in a nuclear plant, this study should be useful to plant designers as a novel examination of the economic performance of such a plant and might prove useful as the effects of a changing generator portfolio on the spot market are better understood.

Ultimately, this paper contributes to the point of view that market volatility alone is unlikely to be a sufficiently large driver to make propositions such as the proposed plant financially viable. Operators of such a plant are likely to be reliant on ancillary payments for additional revenue and further work in this area should consider possible approaches to incentivising construction of energy storage systems.

VII. ACKNOWLEDGEMENT

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