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Full Length Article

Modelling of hydrogen blending into the UK natural gas network driven by a solid oxide fuel cell for electricity and district heating system

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ABSTRACT

A thorough investigation of the thermodynamics and economic performance of a cogeneration system based on solid oxide fuel cells that provides heat and power to homes has been carried out in this study. Additionally, different percentages of green hydrogen have been blended with natural gas to examine the techno-economic performance of the suggested cogeneration system. The energy and exergy efficiency of the system rises steadily as the hydrogen blending percentage rises from 0% to 20%, then slightly drops at 50% H_2 blending, and then rises steadily again until 100% H_2 supply. The system's minimal levelised cost of energy was calculated to be 4.64 £/kWh for 100% H_2. Artificial Neural Network (ANN) model was also used to further train a sizable quantity of data that was received from the simulation model. Heat, power, and levelised cost of energy estimates using the ANN model were found to be extremely accurate, with coefficients of determination of 0.99918, 0.99999, and 0.99888, respectively.

1. Introduction

Climate change, which was brought on by millennia of unchecked greenhouse gas (GHG) emissions, is one of today's most pressing issues. The immediate result is an increase in air temperature, which has a number of permanent repercussions on the environment. According to the Paris Agreement, which aims to limit the rise in the average world temperature to a maximum of 2°C over pre-industrial levels, numerous decarbonisation strategies have been devised to minimise these consequences [1]. A move toward a hydrogen economy is one of the various strategies to reduce CO_2 emissions. The expense of building a distribution system for hydrogen is one of the biggest barriers to its use as an energy carrier. Several research suggested utilising the already widespread natural gas (NG) system to get around this problem. In the current pipelines, hydrogen and clean natural gas can be combined.

The integration of H_2 into the natural gas network is being researched in a number of initiatives and has been described in literature as a means of accelerating the transition to a hydrogen economy [2]. This can be used as a way to decarbonise the UK's electricity and district heating systems. One of the main benefits of hydrogen blending is that it allows for the gradual transition to a hydrogen-based energy system, without the need for major infrastructure changes. By blending hydrogen with natural gas, the existing gas grid can continue to be used, while reducing the carbon emissions associated with the use of natural gas. Blending hydrogen with natural gas in the existing gas grid can also be used as a way to store excess renewable energy. When excess renewable energy is generated, it can be used to produce hydrogen through electrolysis [3]. This hydrogen can then be blended with natural gas and injected into the gas grid for later use. Hydrogen blending can also be used in combination with fuel cells to provide low-carbon heat and power. Fuel cells can convert hydrogen and oxygen into electricity, with water as the only by-product. When blended with natural gas, the fuel cells can provide a reliable and low-carbon source of heat and power.

Guandalini et al. [4] concentrated on the effects on high-pressure transport pipes by injecting uneven hydrogen-containing gas mixtures, Abeysekera et al. [5] studied the gas networks. De Vries et al. [6] looked into how natural gas/hydrogen mixes affected the functioning of outdated machinery and home appliances.. Hydrogen blended natural gas can be used in all natural-gas based residential applications (heating, cooking), stationary power generation applications (cogeneration and power production), and transportation applications with significant emission reduction benefits [7]. The infrastructure connecting production, transmission, distribution, storage, and end users relies heavily on

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the natural gas network [8]. It could also be used to store hydrogen [9], albeit the amount of hydrogen that can be stored depends on the cost of the hydrogen [10]. Variations in the final mixture's energy content per unit volume present a significant challenge for applications using mixes of hydrogen and natural gas. Despite having a higher gravimetric energy density than NG (38.8 MJ/Nm^3), hydrogen has a lower heating value (LHV) of just 11.89 MJ/Nm^3. This is due to hydrogen's extremely low density. In order to provide the same quantity of energy to the end user, the blended gas supplier should therefore deliver a larger volume that is based on the proportion of hydrogen in the mixture [11]. Additionally, because to the phenomena of hydrogen embrittlement, which is affected by hydrogen concentration and operating pressure, [12], an increase in hydrogen content could have an impact on the mechanical structure of the steel materials used in pipelines. Several pilot projects were investigated to evaluate the compatibility of gas mixes comprising 15–20% percentages of H_2 without significantly altering the current gas network, with significant cost benefits in terms of deferred expenditure. At the same time there are numerous worries regarding potential pipe sealing leaks, which jeopardise public safety in cities [13]. The performance of integrated system, such as internal combustion engines or gas turbines, that are directly linked to the gas network has been the subject of numerous studies in the studies [14], and [6]. The majority of research show that using a methane/hydrogen combination in ICs can increase efficiency and decrease pollutant emissions [15–17]. To maintain high efficiency levels in turbines, this method entails significant and expensive adjustments to the burners and to the operation parameters [18–20].

In this context fuel cell especially solid oxide fuel cell (SOFC) are coming out to be a very promising and emerging technology that can utilise the both the hydrogen and natural gas or mixture of the two as fuel without any much complexity or substantial modification on the power generation unit. SOFC is now emerging as a very energy efficient technique for power generation resulting from direct chemical conversion of fuel to electricity [21]. When compared to other types of fuel cells and other conventional energy conversion tools, the key advantages of employing SOFC include fuel flexibility, operation without noise pollution, minimal environmental pollutants, and fewer corrosion issues. Nevertheless, high-grade waste heat also comes out of SOFC as a by-product, which may be used in bottoming cycles [22]. A wide range of research has already been conducted on the investigation and evaluation of various SOFC based energy systems for efficient clean power generation. Wang et al. [23] have performed a techno-economic multi-objective optimisation of a tri-generation system combining SOFC, a transcritical CO_2 cycle, a transcritical organic Rankine cycle, and a liquid natural gas (LNG) cold energy recovery system. The optimum exergy efficiency and cost of 56.1%, 16.82 $/h and 66.83%, 12.02 $/h have been reported for atmospheric SOFC system and pressurised SOFC system, respectively. Souza et al. [24] have carried out an economic assessment of a combined heat and power plant producing hydrogen and electricity via steam reforming SOFC system. In the study hydrogen cost of 2.42–5.26 USD/kg and cost of energy above 0.269 USD/kWh have been reported. Zhu et al. [25] have performed a multi-objective optimisation of a SOFC based combined cooling, heating and power (CCHP) system. It has been reported that the system at the optimum condition poses 75% CCHP efficiency, 52% electrical efficiency with a total annual cost of 410 k$. Majority of the studies related to the different integrated systems using SOFC are primarily based on single fuel fed system either by natural gas, or by methane, or by hydrogen or by biogas or syngas. Mejiaet al. [26] analysed the performance and emission characteristics of a SOFC with micro-combined heat and power (SOFC-mCHP) system using various proportions of the fuel mixture of hydrogen (H2) and natural gas (NG). Cinti et al. [7] have performed the detailed thermodynamic analysis of SOFC-mCHP systems while running on fuel that ranges from pure hydrogen to pure methane via fuel mixes known as hythane. Veluswamy et al. [27] have carried out thermodynamic analysis followed by detailed parametric investigation of a SOFC stack using a mixture of bio-methane (biogas) and hydrogen, called biohythane, as an energy feedstock. Basso et al. [28] have carried out an experimental investigation of an internal combustion engine based m-CHP system for residential application using hydrogen-natural gas mixtures (H_2NG) to show the energy and emission performance of the system. Bicer and Khalid [29] have carried out lifecycle analysis of a SOFC integrated combined heat and power generation system using natural gas, hydrogen, ammonia, and methanol as fuel input. Mehr et al. [30] have carried out thermodynamic and economic analysis on four diverse arrangements of natural gas and biogas fuelled SOFC, concentrating on the impact of anode and/or cathode gas recycling. They observed that the thermal efficiency was 6.81% greater for the SOFC with cathode and anode recycling as compared to other arrangements running on natural gas. Overall, hydrogen blending is seen as a promising approach for decarbonising the UK's electricity and district heating systems, as it allows for a gradual transition to a hydrogen-based energy system, while utilising the existing infrastructure, and also it can be used as a way to store excess renewable energy and provide low-carbon heat and power.

It is apparent from the literature that SOFC-powered CHP systems with H_2 blending in natural gas can be a complex process due to the differences in properties between the fuels, such as lower energy content and a higher compressibility of hydrogen. Modelling the process would require knowledge of the properties of the gas mixture, and the specific conditions under which the operation is taking place [31]. This will undoubtedly necessitate a significant development in the levels of dependency on the simultaneous control of several factors. Conventional modelling techniques are unable to identify the ideal range of design values with high conformance due to the increased number of input parameters, the absence of a linear relationship between input and output parameters, and the high computing cost [32]. Modelling paradigms based on artificial intelligence (AI), such as Artificial Neural Network (ANN) [33,34] have a proven track record of success as trustworthy system identification tools with the innate capacity to precisely forecast the complicated non-linear interactions between the input and output parameters [35]. It creates a wide range of possibilities for building complicated SOFC-based CHP systems and other complex systems with improved flexibility for including noisy and nonlinear input [36,37]. The ANN can be trained using historical data from the SOFC to predict the optimal operating conditions for a given set of inputs and can then be used in real-time to control the SOFC and maximise its efficiency and performance.

It can be seen from the above discussion that the detailed thermodynamic and economic performance analysis of SOFC systems for large scale household power supply and district heat supply using natural gas blended with pure hydrogen as fuel has not been studied extensively. Furthermore, the overall techno-economic performance of a SOFC based system using full range variation of hydrogen blending, varying from 0% − 100%, with the natural gas is very rare in the literature. In addition to this, artificial neural network (ANN) based studies of a SOFC based power and district heating system using hydrogen blended natural gas for efficient decarbonisation of the power and heating demand of the UK energy sector have not been investigated in depth earlier, along with the consequences of variation with different design and operating parameters of the SOFC unit and percentage (%) of fuel blending. This is also a first-of-its-kind study in the UK context. The current work aims to develop and successfully implement a reliable system by designing a comprehensive ANN model that will be used to assess the performance characteristics of a SOFC-CHP system. The novelty and major contributions of the present work are as follows:

- SOFC based cogeneration system for district heat network and power generation in UK context.
- Preliminary feasibility study for blending of hydrogen with natural gas applied for fuel cell based system.
- Techno-economic performance optimisation of a SOFC based district heat network system.

- Feasibility study of fuel cell-based pathway for decarbonisation of district heat network in the UK.

2. System description

SOFC based cogeneration system generating power and district heating was modelled, as depicted in Fig. 1. A SOFC stack, an after burner (AB), air preheater (AHE), air compressor (AC), fuel compressor (FC), fuel preheater (FHE), fuel and steam mixer (MIXER), heat recovery steam generator (HRSG) and freshwater pump (PUMP) are all included into the system. Here a typical design for a SOFC system operating at 750°C has been considered. The anode off-gas is completely oxidised in the after burner (AB), where the fuel gas flow and cathode outflow are united. Gases from the afterburner (AB) pass via the air and fuel preheaters (AHE and FHE), which warm the incoming air and fuel before they enter the fuel cell stack and the mixer, respectively. The residual heat of the afterburner gases is recovered at the heat recover steam generator (HRSG) though production of superheated steam. The amount of steam is estimated by the steam to carbon ratio required for the reforming process. After producing the required amount of steam, the residual heat of the afterburner gas is utilised for the hot water generation at 75°C to be supplied for the district heating as shown in the figure. The required amount of steam flow rate is forwarded through the evaporator and superheater section of the HRSG, and rest of the hot water is bypassed from the economiser section of the HRSG to be utilised for the district heating. The fresh water to the HRSG is supplied through a water pump as shown in the figure. The fresh air is compressed by the air compressor slightly above the atmospheric pressure (AC) before sending to the SOFC stack. On the other hand, hydrogen is mixed with the natural gas at different volume percentages and sent to the SOFC stack by the fuel compressor (FC). The amount of mixing of hydrogen fuel (volume percentage) has been varied from 0% (pure natural gas) to 100% (pure hydrogen). For 100% hydrogen fuel input the proposed system does not require the steam for the reforming process in the SOFC stack. So, for this case no HRSG is required for steam generation. All the residual heat of the afterburner gases is recovered through a simple heat exchanger (water heater) for generating only hot water at 75°C to be supplied for the district heating purpose. The system configuration remains the same except the omission of the HRSG which is shown in the Fig. 2.

3. System modeling

3.1. Solid oxide fuel cell for power generation

The solid oxide fuel cell (SOFC) is a high temperature fuel cell which generally operates at 650–1000°C[21]. In this study the SOFC unit is considered to operate at 850°C. SOFCs are highly efficient electrochemical devices which consume hydrogen or methane of natural gas as fuel and converts into electricity without direct combustion of fuel. Among different types of SOFC, an internally reformed type SOFC is considered here for this study. For the present analysis a lumped volume zero-dimensional approach has been followed to do the mass and energy balances at the SOFC unit. Thermo-physical properties and chemical composition of the fuel and air at the fuel cell inlet, fuel utilisation factor, oxidant utilisation factor, cell area, cell temperature, cell voltage are assigned as inputs to the model. After that the model estimates the temperature and pressure at the fuel cell outlet, electrical output, and the composition of the outgoing anode and cathode exhausts through overall energy balance at the fuel cell.

The following relationship may be used to calculate current flow via SOFC [23].

$$I_{FC} = \frac{\dot{m}_{anode,in} \times \left(y_{H_2} + y_{CO} + y_{CH_4}\right) \times 2 \times F}{M_{mol,anode}} \quad (1)$$

where, $y_{H_2}, y_{CO}, y_{CH_4}$ are representing the respective molar fraction of H_2, CO and CH_4 in the incoming gas at anode; F is the Faraday constant. The molar mass and the total mass flow rate of the incoming gas at the

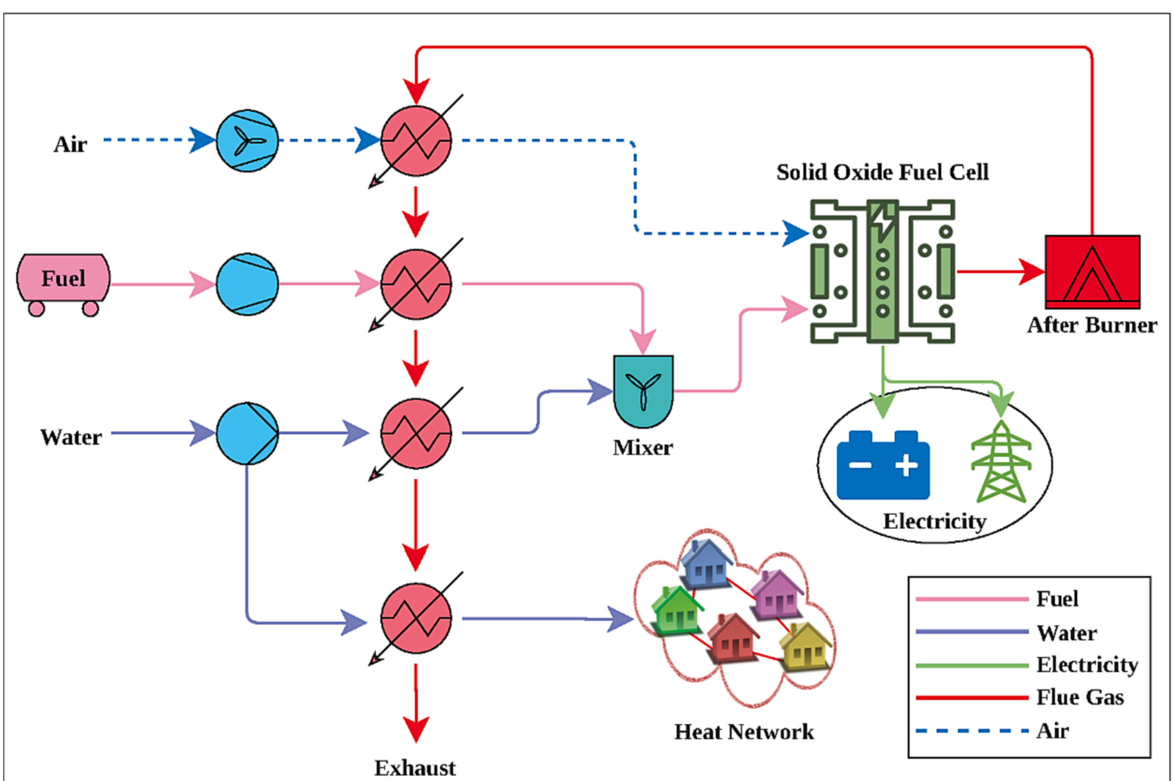

Fig. 1. Arrangement of the proposed system using pure natural gas or combining hydrogen.

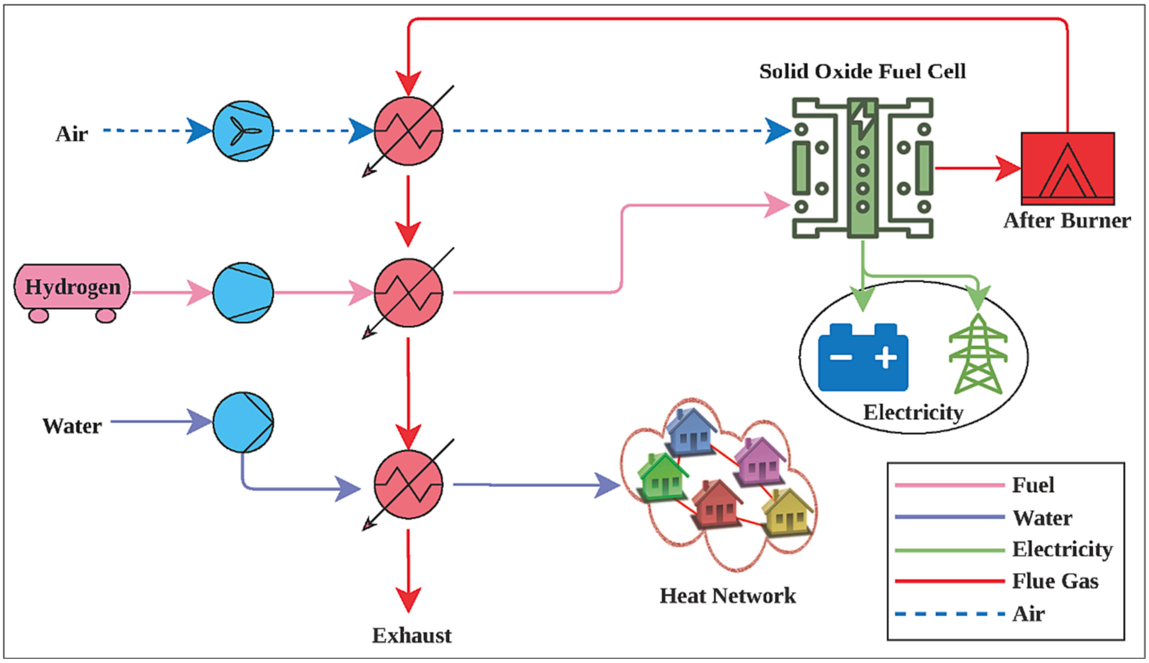

Fig. 2. Layout of the proposed system running on only hydrogen.

anode channel is represented by $M_{mol,anode}$ and $\dot{m}_{anode,in}$, respectively.

The fuel utilisation factor (UF), which measures the actual fuel conversion to the greatest amount possible, is written as the following relation.

$$UF = \frac{I}{I_{FC}} \tag{2}$$

where, I denote actual current flow.

The following equation may be used to calculate the SOFC voltage [38].

$$V_{SOFC} = \frac{\Delta G}{2F} + \frac{RT_{SOFC}}{2F} ln\left(\frac{y_{O_2}^{0.5} \times y_{H_2}}{y_{H_2O}} \times P_{SOFC}^{0.5}\right) - I \times R_{SOFC} \tag{3}$$

where, R_{SOFC} represents the overall resistance per unit area of SOFC; ΔG denotes Gibbs free energy; T_{SOFC} is denoting the temperature at which the SOFC is working; similarly P_{SOFC} denotes the pressure at which the SOFC is running; y_{H_2O} denotes mole fraction of H_2O; y_{O_2} is the mole fraction of O_2, and R is the universal gas constant.

The following estimations can be made for the power produced by SOFC modules [23].

$$W_{SOFC} = N_{SOFC} \times j \times A_{SOFC} \times V_{SOFC} \times \eta_{inv} \tag{4}$$

where, N_{SOFC} is the cell numbers; j denotes the current density; A_{SOFC} represents the cell area; η_{inv} is the inverter efficiency.

3.2. Afterburner (AB)

The fuel that is released from the anode of the solid oxide fuel cell provides a significant degree of heating value because not all of the fuel is consumed at the SOFC unit. Methane, hydrogen, and carbon monoxide are the fuel species that can be burned inside the afterburner. Utilising the oxygen present at the cathode outlet stream, the fuels exiting the anode channel are totally burnt. The afterburner unit considers the following combustion reactions.

$$CH_4 + 2O_2 \leftrightarrow CO_2 + 2H_2O \tag{5}$$

$$CO + \frac{1}{2}O_2 \leftrightarrow CO_2 \tag{6}$$

$$H_2 + \frac{1}{2}O_2 \leftrightarrow H_2O \tag{7}$$

A straightforward energy balance equation has been used to determine the afterburner's exit temperature.

3.3. Air compressor (AC)

The power consumed (W_{AC}) by the air compressor is governed by.

$$W_{AC} = m_{air} \times (h_{out} - h_{in}) \tag{8}$$

where "m" stands for air mass flow rate and "h" stands for air's specific enthalpy at the compressor's input and exit, respectively.

3.4. Air preheater (AHE)

The air preheater's energy balance equation is provided below.

$$m_{afterbuner\ gas} \times (h_{in} - h_{out}) = m_{air} \times (h_{out} - h_{in}) \times \eta_{AHE} \tag{9}$$

where 'η_{AHE}' denotes the effectiveness of the air preheater.

3.5. Fuel compressor (FC)

The power consumed (W_{FC}) by the fuel compressor is governed by.

$$W_{FC} = m_{fuel} \times (h_{out} - h_{in}) \tag{10}$$

3.6. Fuel preheater (FHE)

The fuel preheater's energy balance equation is provided below.

$$m_{afterbuner\ gas} \times (h_{in} - h_{out}) = m_{fuel} \times (h_{out} - h_{in}) \times \eta_{FHE} \tag{11}$$

where 'η_{FHE}' denotes the effectiveness of the fuel preheater.

3.7. Mixer

The mass conservation at the mixer component is given by the following equation.

$$m_{fuel} + m_{steam} = m_{mixture} \tag{12}$$

Assuming no heat loss, the energy balance at the mixer component is estimated as the follows.

$$(m_{fuel} \times h_{fuel}) + (m_{steam} \times h_{steam}) = (m_{mixture} \times h_{mixture}) \quad (13)$$

3.8. Heat recovery steam generator / water heater

The heat recovery steam generators and water heater's energy balance equation are provided below.

$$m_{afterbuner\ gas} \times (h_{in} - h_{out}) = m_{water} \times (h_{out,\ steam} - h_{in,\ water}) \times \eta_{HRSG} \quad (14)$$

$$m_{afterbuner\ gas} \times (h_{in} - h_{out}) = m_{water} \times (h_{out,\ \mathrm{hot\ water}} - h_{in,\ \mathrm{cold}\ water}) \times \eta_{water\ heater} \quad (15)$$

where 'η_{HRSG}' denotes the effectiveness of the HRSG, '$\eta_{water\ heater}$' denotes the effectiveness of the water heater.

3.9. Energy performance modelling

For the thermodynamic performance estimation of the investigated multigeneration energy hub the first law and second law efficiency have been estimated.

The net total power output (W_{net}) is estimated by the following equation.

$$W_{net} = W_{SOFC} - W_{AC} - W_{FC} - W_{water\ pump} \quad (16)$$

The amount of heat supplied to the district heat network ($Q_{District\ \mathrm{heat}}$) from the integrated system is estimated as follows.

$$Q_{District\ \mathrm{heat}} = m_{water} \times (h_{out,\ \mathrm{hot\ water}} - h_{in,\ \mathrm{cold}\ water}) \quad (17)$$

The total energy input (Q_{total}) into the proposed cogeneration system has been estimated by the following equation.

$$Q_{total} = m_{Natural\ gas} \times LHV_{Natural\ gas} + m_{hydrogen} \times LHV_{hydrogen} \quad (18)$$

The energy efficiency of the proposed cogeneration system is estimated as follows.

$$\eta_{energy} = \frac{W_{net} + Q_{District\ \mathrm{heat}}}{Q_{total}} \quad (19)$$

3.10. Exergy performance analysis

Any working fluid stream's exergy (EXG) is the sum of its physical and chemical exergy. Below is stated the mathematical formula for exergy.

$$EXG_{stream} = EXG_{physical} + EXG_{chemical} \quad (20)$$

The physical exergy ($EXG_{physical}$) of the stream is estimated as given below.

$$EXG_{physical} = \sum_{y} (mf)_y \times ((h_y - h_0) - T_0(s_y - s_0)) \quad (21)$$

where, '*mf*' denotes the mole flow rate, 'h' denotes the specific enthalpy, 's' denotes the specific entropy, 'y' denotes the y^{th} species of the flow stream, 'h_0' denotes the specific enthalpy at the reference condition, 's_0' denotes the specific entropy at the reference condition, 'T_0' denotes the reference atmospheric temperature in Kelvin scale.

The chemical exergy ($EXG_{chemical}$) of the stream is estimated as given below.

$$EXG_{chemical} = \sum_{y} (mf)_y \times \left(\sum y_i{*}ce^0 + RT_0 \sum y_i{*}\ln(y_i) \right) \quad (22)$$

where, 'ce^{0}' denotes the specific chemical exergy of the y^{th} species, 'R' denotes the universal gas constant.

The proposed cogeneration system's input exergy (EXG_{input})rate is established by the following equation.

$$EXG_{input} = EXG_{natural\ gas} + EXG_{hydrogen} = (EXG_{physical} + EXG_{chemical})_{natural\ gas} + (EXG_{physical} + EXG_{chemical})_{hydrogen} \quad (23)$$

The proposed cogeneration system's exergetic efficiency (η_{exergy}) has been estimated to be.

$$\eta_{exergy} = \frac{W_{net} + EXG_{District\ \mathrm{heat}}}{EXG_{input}} \quad (24)$$

where, the $EXG_{District\ \mathrm{heat}}$ denotes the exergy value of the district heat supplied from the proposed cogeneration system and is estimated as follows.

$$EXG_{District\ \mathrm{heat}} = Q_{District\ \mathrm{heat}} \times \left(1 - \frac{T_0}{T_{hot\ water}}\right) \quad (25)$$

where, '$T_{hot\ water}$' denotes the hot water temperature in Kelvin scale.

3.11. Economic analysis

The total capital cost (CAPEX) is the sum of all system components and is estimated as follows:

$$CAPEX = \sum_{j} CAP_j \quad (26)$$

where, CAP_i represents capital cost of j^{th} component.

The discount rate is set at 3% [39,40], and the lifetime is set at 30 years. The annual cost of operation and maintenance is projected to be 2.5% of CAPEX [41]. SOFC must be replaced on a regular basis in the system. Annual replacement expenses are expected to be 5% of CAPEX [41]. Table 1 includes the capital costs of several pieces of equipment as well as other important data for economic analysis.

The total yearly cost of the system is the sum of the annual capital cost, annual operating and maintenance cost, annual replacement cost, and annual fuel cost, as stated in the following equation.

$$COST_{Annual} = CAPEX_{Annual} + OPEX_{Annual} + REP_{Annual} + FUEL_{Annual} \quad (27)$$

The following equation may be used to calculate the system's levelised cost of energy (LCOE).

$$LCOE = \frac{COST_{Annual}}{Total\ Energy\ Production} \quad (28)$$

4. Artificial Neural Network (ANN) Modelling

Artificial neural network tool learns from large data using biologically based computational model which includes linear or nonlinear computational elements termed as neurons [50]. In the current study, an ANN model was created to map the relationship between the inputs, such as the percentage of methane and hydrogen in the fuel, the percentage of hydrogen in the fuel, the current density, the percentage of fuel used, and the operating temperature of SOFC, and the outputs, energy efficiency, exergy efficiency, and LCOE. In this work, the

Table 1
Input parameters for economic analysis.

Description	Value	Unit	Ref.
Solid oxide fuel cell for year 2020 and 2022	4500	€/kW	[42]
SOFC cost in year 2050	841	$/kW	[43]
Pump + Compressor + Heat Exchanger + Pipe works	202.5	$/kW	[39]
Hot water storage tanks	20	$/kW	[44]
Natural gas cost for year 2022	7.21	p/kWh	[45]
Natural gas cost for year 2020	2.46	p/kWh	[45]
Natural gas cost for year 2050	5.2	p/kWh	[46]
Green hydrogen cost in year 2020	2.5	$/kg	[47]
Green hydrogen cost in year 2022	2.3	$/kg	[48]
Green hydrogen cost in year 2050	1.15	$/kg	[49]

objective functions were predicted using a multilayer feed-forward neural network model. For output neurons and hidden neurons in the chosen multilayer feed-forward network, a continuous, differentiable log-sigmoid activation function was adopted. 625 data sets were taken into account for the ANN model's various input parameters and design goals. Out of these big data sets, 70% are chosen for the neural network's training, 15% are chosen for cross-validation, and the remaining 15% are chosen for the trained network's testing. The coefficient of determination (R^2) has been taken into consideration in order to assess the effectiveness of the ANN model, and it is defined by the following relation [51].

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(t_i - o_i)}{\sum_{i=1}^{n}(o_i)^2}\right) \tag{29}$$

where "t" stands for the actual output, "o" stands for the predicted output value, and "n" stands for the number of patterns in the data set.

The values of R^2 above 95% and higher are considered that the model is significant.

Since Mean Square Error (MSE) has the incredibly desirable characteristics of differentiability, convexity, and symmetry, it is also selected as the loss function to be minimised because it is an effective statistical indicator for model accuracy verification. Back-propagation neural networks with the Levenberg-Marquardt learning algorithm are taken into account in this model because it is highly recognised for making accurate predictions [51].

Other important statistical error measurement parameters, such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), have also been estimated. The RMSE and MAPE can be defined by the following relations [32,52].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - o_i)^2} \tag{30}$$

$$MAPE = \frac{1}{2}\sum_{i=1}^{n}\left(\left|\frac{t_i - o_i}{o_i}\right|\right) \times 100 \tag{31}$$

In the present ANN model, up to two hidden layers with '2 to 25′ hidden nodes were used in an optimal network topology search, in each of the best iterations. To avoid overlearning the network, network training was stopped as the validation error began to rise. The most effective architecture was determined to have three neurons in the output layer, a hidden layer with nineteen neurons, and five neurons in the input layer (5-19-3).

5. Results and discussions

5.1. Technical performance evaluation

The total power output and the amount of district heat supply from the proposed cogeneration system has been represented in the Fig. 3 at different composition of the fuel blending at the base case operating condition. Keeping the operating parameters fixed for all the fuel blending cases, it can be observed that the net power output increases with the increasing blending percentage of hydrogen from 0% to 20% then decreases marginally at the 50% H_2 blending and again continuously increases both at 80% H_2 blending and 100% H_2 supply. On the other hand, at the same operating condition, the net supply of district heat increases with the increasing blending percentage of hydrogen from 0% to 20% then decreases marginally at the 50% H_2 blending and again increases at the 80% H_2 blending and then decreases at the 100% H_2 supply and eventually become the lowest among all.

The energy and exergy efficiencies of the cogeneration system has been represented in the Fig. 4 at different composition of the fuel blending at the base case operating condition. Keeping the operating parameters fixed for all the fuel blending cases, it can be observed that the energy efficiency gradually increases with the increasing blending percentage of hydrogen from 0% to 20% then decreases marginally at the 50% H_2 blending and again continuously increases till 100% H_2 supply. At the same time, the exergy efficiency of the proposed system at the different blending scenario follows the same trend of the energy efficiency at stated earlier.

5.2. Economic performance evaluation

The LCOE of the proposed cogeneration system has been represented in Fig. 5 at different compositions of fuel blending for the years 2020, 2022, and 2050. The year 2050 is chosen as the UK is committed to be a net zero country by 2050. It is observed that the highest LCOE is

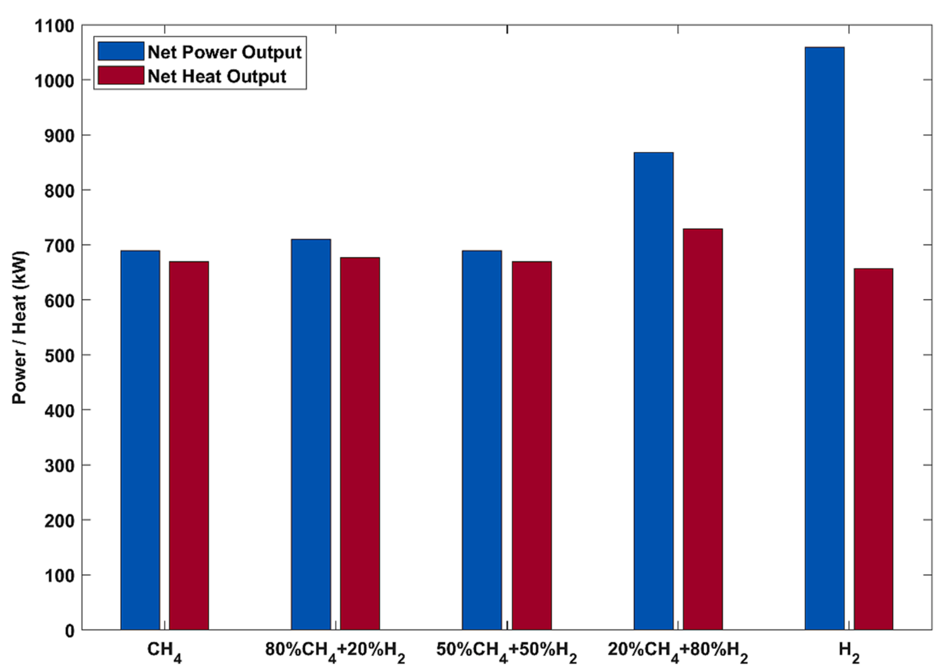

Fig. 3. Power output and district heat supply at different hydrogen blending.

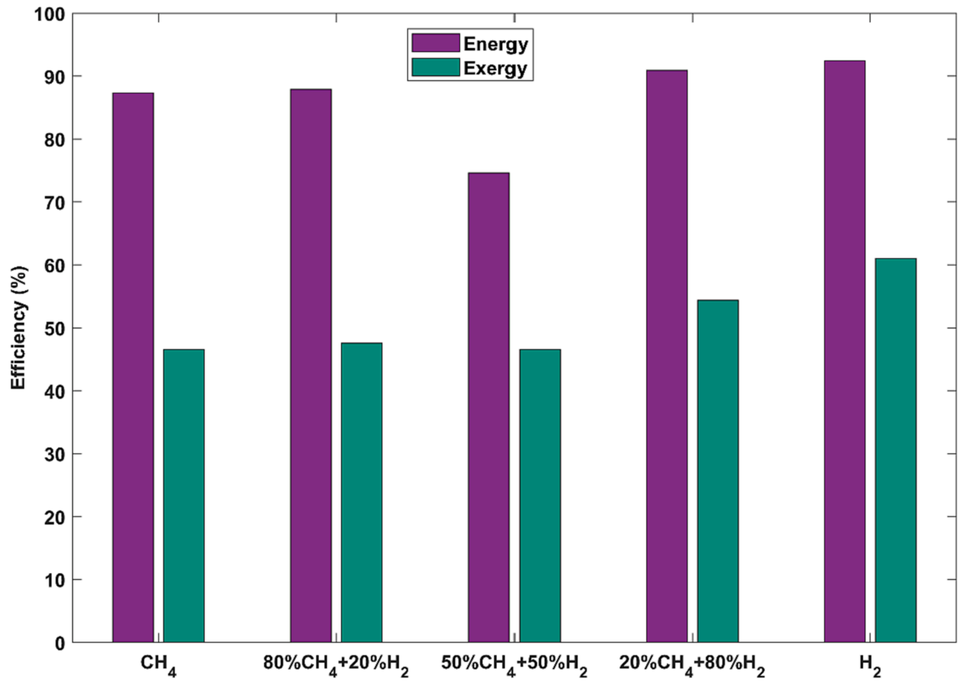

Fig. 4. Energy and exergy efficiency of the proposed system at different hydrogen blending.

obtained for a 100% CH_4 scenario, followed by 80%CH_4 + 20%H_2, 50% CH_4 + 50%H_2, 20%CH_4 + 80%H_2 and 100% LCOE, respectively. It is important to note that the present high cost of SOFC stacks is the major reason for higher LCOE. It is assumed that with progress in research and development and a higher volume of production, the cost of SOFC stack will be reduced. The projected SOFC stack cost in 2050 is considered to be 841 \$/kW. The LCOE of the H_2 based configuration will be minimum in the year 2050.

5.3. ANN modelling results

Based on the energy and exergy modelling study, an Artificial Neural Network (ANN) model was developed to forecast the amount of heat and power produced as well as the levelised cost of energy. Methane share in fuel, hydrogen share in fuel, current density, fuel utilisation and operating temperature of the SOFC were the input parameters. The SOFC output parameter prediction using ANN produced outstanding correlation data, demonstrating the constructed network's commendable predictive capacity for heat, power and LCOE. Fig. 6 depicts the overall network architecture of the selected network.

The projected values and actual observations of the artificial neural network match excellently and consistently across the whole range of operation, as can be shown by looking at Figs. 7, 8, and 9. This highlights the ANN's inherent robustness and sensitivity in its capacity to simultaneously map performance and cost data with accuracy. Fig. 7 shows the heat value as calculated by energy modelling and projected by the

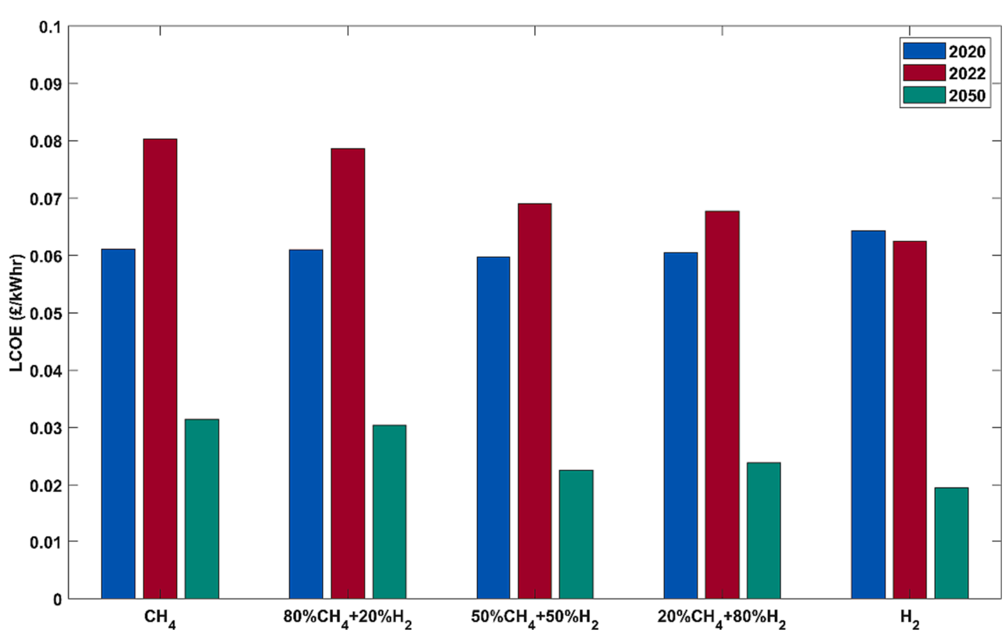

Fig. 5. Levelised cost energy of the proposed system at different hydrogen blending.

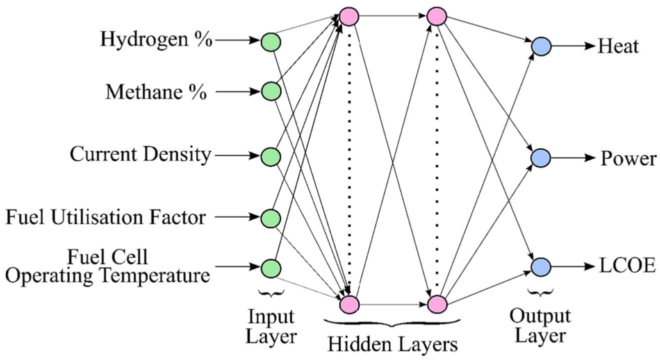

Fig. 6. The proposed ANN models network architecture.

ANN model. From this it is determined that the coefficient of determination (R^2) value was 0.99918, the root mean square error (RMSE) value was 0.5233, and the mean absolute percentage error (MAPE) value was 0.0784%.Analysing Fig. 7, which contrasts the energy model's simulated value with the projected value of power from the ANN model, reveals that the MAPE value was 0.0993%, the RMSE value was 0.5226, and R^2 value was 0.99999. Fig. 8 shows the comparison of levelised cost of energy (LCOE) predictions from an ANN model with simulated data. The RMSE, MAPE, and R^2 for the ANN model prediction of LCOE with energy modelling data were 0.1550, 1.2608% and 0.99888 respectively.

6. Comparison and limitations of the work

In this specific section, we have performed a comprehensive comparison of our SOFC integrated systems with other similar setups. The summarised results presented in Table 2 undeniably indicate the tremendous promise and potential efficiency of our proposed systems from both technical and economic standpoints. It is important to note that the previous studies we referred to in the literature used various investigation methods, such as multi-objective optimisation, exergy analysis, and environmental analysis. However, we believe that our present system can benefit from further analysis with a more rigorous approach, specifically using multi-objective optimisation. This will allow us to delve deeper into the system's performance and explore various trade-offs among different objectives. Additionally, while our current analysis was conducted under steady-state conditions, incorporating dynamic analysis could significantly enhance our understanding of the system dynamics. By simulating the system's behaviour under varying conditions and transient states, we can better predict its response to changes and fluctuations. Therefore, we propose conducting a more in-depth analysis by implementing multi-objective optimisation techniques and incorporating dynamic simulations. This will not only strengthen the validity of our results but also provide valuable insights into the system's behaviour over time. Ultimately, this approach will allow us to optimise the system's performance and ensure its robustness under different operating conditions, making it a more reliable and efficient solution for SOFC integrated systems.

7. Conclusions

In this study, a detailed thermodynamic and economic performance analysis of SOFC based cogeneration system has been performed to supply electricity and heat to households. Additionally, green hydrogen has been blended with natural gas at varying percentage to study the techno-economical performances of the proposed cogeneration system. Furthermore, a large set of data obtained from simulation model were further trained using ANN tools. The major findings of the study are summarised below:

- The net power output increases with the increasing blending percentage of hydrogen from 0% to 20% then decreases marginally at the 50% H_2 blending and again continuously increases both at 80% H_2 blending and 100% H_2 supply.
- The net supply of district heat increases with the increasing blending percentage of hydrogen from 0% to 20% then decreases marginally at the 50% H_2 blending and again increases at the 80% H_2 blending

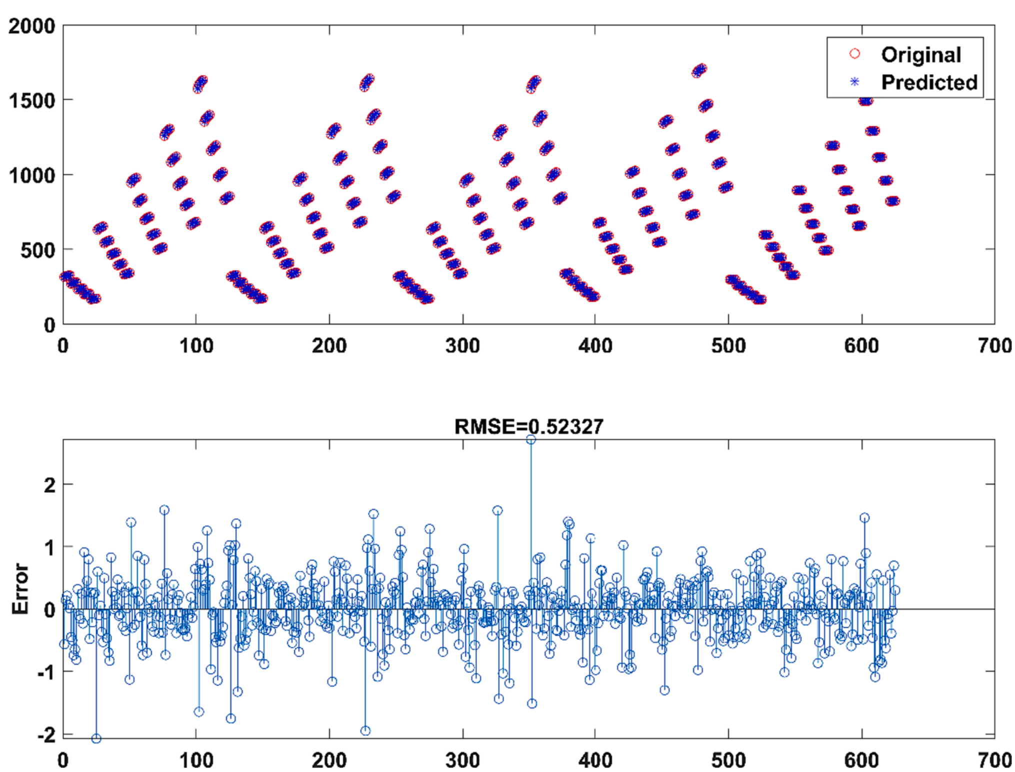

Fig. 7. Comparison of heat output with the ANN predicted data.

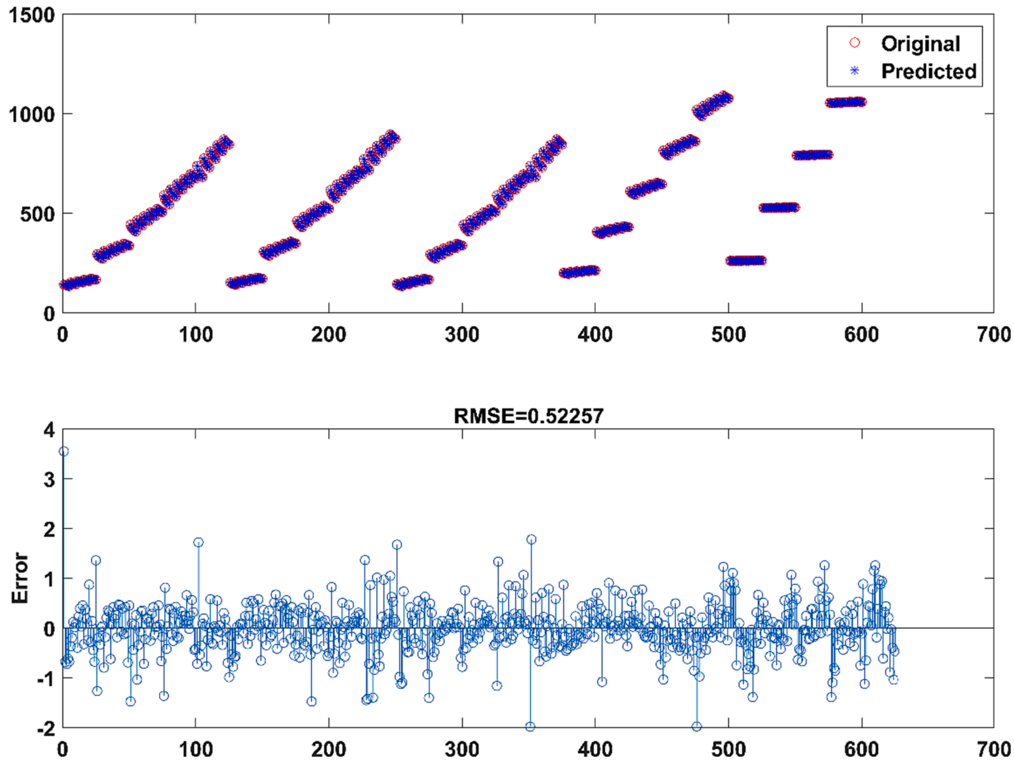

Fig. 8. Comparison of power output with the ANN predicted data.

and then decreases at the 100% H_2 supply and eventually become the lowest among all.

- The energy efficiency and exergy efficiency of the system gradually increase with the increasing blending percentage of hydrogen from 0% to 20% then decrease marginally at the 50% H_2 blending and again continuously increase till 100% H_2 supply.
- It is observed that the highest LCOE is obtained for a 100% CH_4 scenario, followed by 80%CH_4 + 20%H_2, 50%CH_4 + 50%H_2, 20% CH_4 + 80%H_2 and 100% LCOE, respectively.

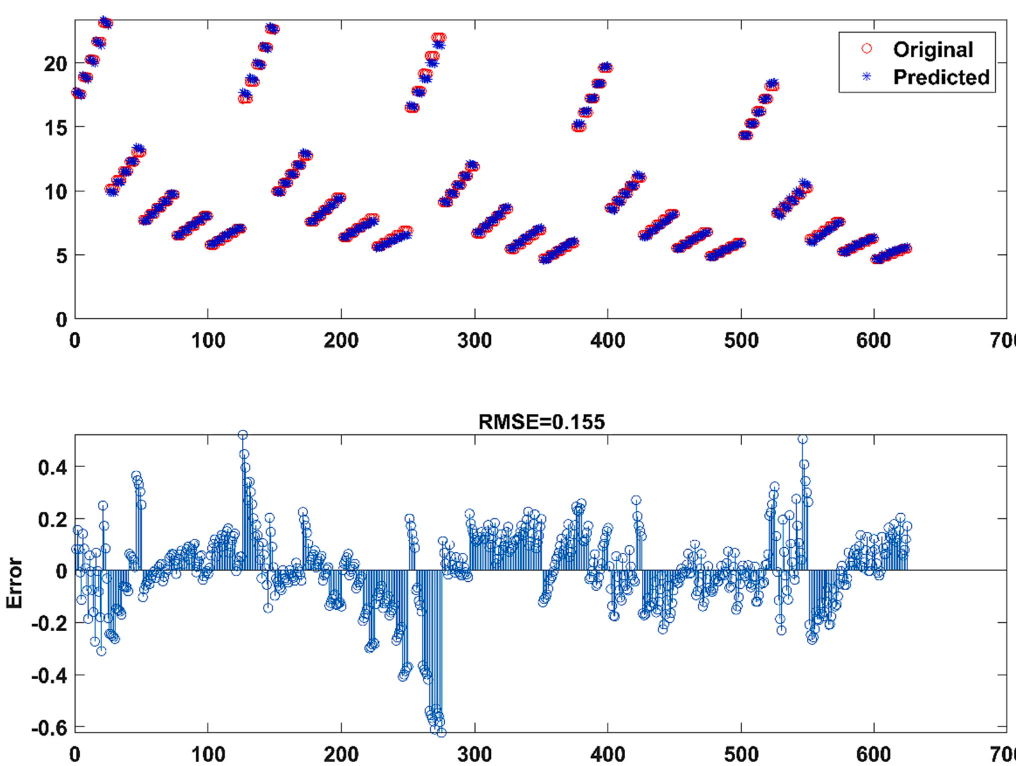

Fig. 9. Comparison of LCOE with the ANN predicted data.

Table 2
Comparison with other SOFC based systems.

System description	Analysis	Results	Reference
SOFC based system fuelled with Ammonia	Thermodynamic analysis, Mult-objective optimisation using ANN-GA	The exergy efficiencies of the conventional and the anode off-gas circulation configurations reported to be 55.91% and 67.30%, respectively.	[53]
SOFC- ORC and transcritical CO_2 cycle based multigeneration system	Energy and exergy analyses	Maximum thermal efficiency, electrical efficiency, and exergy efficiency of the integrated system are reported to be 90.99%, 55.01%, and 53.07%, respectively	[22]
SOFC-ORC- supercritical CO_2 cycle integrated system fuelled by bio-syngas	Thermodynamic, Economic and environmental analyses; Multiobjective optimisation	Highest efficiency is reported to be 48.8%	[54]
SOFC based CHP system fuelled by NG and hydrogen	Energy, exergy and economic analyses; ANN based prediction	Minimum LCOE of the system was estimated to be 4.64£/kWh	This system

- The minimum LCOE of the system was estimated to be 4.64£/kWh.
- Accuracy of ANN model was found to be excellent for heat, power and levelised cost of energy predictions, with the coefficient of determination of 0.99918, 0.99999 and 0.99888, respectively.

This study has been conducted based on the UK scenario. However, the techno economic results and data might be different in other parts of the EU and other parts of the world which might be an interesting comparative study in future. Furthermore, this techno-economic study has been conducted without considering any government schemes or subsidies or any other government economic supports for making the efforts towards decarbonisation of energy systems.

CRediT authorship contribution statement

Samiran Samanta: Conceptualization, Investigation, Methodology, Software, Writing – original draft. **Dibyendu Roy:** Conceptualization, Investigation, Methodology, Software, Writing – original draft. **Sumit Roy:** Conceptualization, Methodology, Software, Supervision, Writing – original draft. **Andrew Smallbone:** Project administration, Resources, Supervision, Writing – review & editing. **Anthony Paul Roskilly:** Supervision, Project administration, Writing – review & editing, Funding acquisition.

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.

Data availability

Data will be made available on request.

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