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Impact of dynamic aspects on economics of fuel cell based micro co-generation in low carbon futures

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ABSTRACT

This article evaluates the impact of a range of dynamic performance parameters on the techno-economics of fuel cell based micro co-generation. The main novelties in methodology are: (1) Analysis in the context of future power system decarbonisation, (2) Use of the Long Run Marginal Cost of electricity, (3) Combination of the above with dynamic aspects such as start-up cost, ramping limit, turn down ratio, minimum up time and minimum down time and (4) Identification of sensitive parameters for future research. To this end it combines a national level energy systems model with an individual heating system model. A case study of the United Kingdom is considered for the year 2035. Economic viability of fuel cell based micro co-generation hinges upon the use of an optimized control strategy. With such a control strategy, a hot start-up approach offers much greater economic potential than a cold start-up approach. The best case ratio of maximum allowable hot standby power to the nominal value is 4.2 while the ratio for cold start is only 1.1. Combinations involving low ramping limits less than 70 W/min and limited turn down ratios above 35% need to be avoided as they seriously hinder economic performance.

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1. Introduction

Energy systems across the world are faced with significant challenges as they are faced with the prospect of potentially severe consequences due climate change [1]. The energy sector has to contend with ensuring affordability, reliability and sustainability in a continuously evolving landscape [2]. This means the system now has to incorporate increasing contributions from new sources, namely low carbon and distributed energy resources, that complement or eventually replace conventional centralised energy provision [3].

Against this backdrop, fuel cell based micro co-generation is a promising technology that has several advantages. Their high overall efficiencies allow them to considerably reduce primary energy consumption, and transmission losses are enabled via co-locating the system with the demand [4]. They can run on natural gas and thereby capitalise on existing supply network infrastructure. By providing both electricity and heat they help offset the import of electricity and hence reduce associated energy cost. Their high electrical efficiencies and low heat to power ratios also make them well suited for the demand profiles encountered in the domestic sector [5]. As large scale uptake of fuel cell based micro co-generation can also help avoid reinforcement of generation capacity, this technology could potentially play a significant role in energy systems of the future [6]. Hence there is a pressing need for tools that can assess the viability of this technology in energy systems of the future.

The rest of this article is structured as follows: The next section presents the background context to this problem, reviewing the current status and studies to date. This is followed by the methodology applied herein to characterise fuel cell based micro co-generation and the possible energy systems it could operate within. The results are then presented and discussed, leading to conclusions.

1.1. Previous literature

Previous literature is assessed by analysing whether the modelling approach suits the objective of the study. This article incorporates dynamic aspects of fuel cells into the operation of the micro cogeneration system in a low carbon future. It aims to evaluate two factors: firstly whether such dynamic aspects have an

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impact on the economics of such systems and secondly to identify which aspects of design impact the economics the most. Hence the modelling approach selected should be able to provide recommendations regarding aspects of fuel cell based micro cogeneration that should be prioritized in the future.

1.1.1. Simulation based models

In simulation based approaches emphasis is laid on modelling responses to parameters that undergo change, for example, power or heat demand, temperature variations within a building, rate of heat exchange etc. The model steps through time and simulates how the components react to the changes in circumstances. The operating strategies are predefined and only serve as inputs to the model.

One type of simulation model makes use of subroutines that can characterise operation by using simple arithmetic operations. This can be done since the model assumes a constant output either at maximum capacity [7] or with the addition of ON/OFF logic [8]. In other cases the output follows either thermal or electric demand [9,10]. The techno-economic results obtained are similar to first order calculations usually done in spreadsheets for off-design evaluation of fuel cell based micro cogeneration.

Another group of models calculate demand profiles from external parameters such as climatic conditions, building materials, building designs and occupancy patterns. In case the fuel cell micro cogeneration unit is operated in load following mode, equipment specifications are necessary for part load efficiencies. These models can represent thermal interactions by using either lumped thermal capacitances [11], or commercial building simulations packages such as eQUEST [12], DesignBuilder [13] or TRNSYS [14]. Sophisticated models describing the physics, chemistry and electrochemistry also exist [15].

The main drawback of this approach is inefficiency. This is so because it does not involve strategic planning. Merely following the load can lead to problems while incorporating dynamic characteristics. The unit could be sensitive to load fluctuations and switch on the fuel cell for a brief blip in demand but be forced to remain active in the following periods which have no demand due to minimum up time specifications. In a similar fashion, the model could shut the unit down because the current period has no demand but be forced to remain inactive due to minimum down time specifications and thus miss out on energy savings when demand increases. Since they do not consider operation beyond just the current period, they cannot describe the operation of thermal energy storage units either.

It can be argued that the constant output capacity can be designed such that it serves the base load or minimum load that the system serves at all points of time. While this may be true for large heat networks and community based cogeneration units, residential household demand can dip to zero and remain there for sustained periods of time. During this time the micro cogeneration unit is dumping heat, wasting fuel. It is also losing a significant amount of money if the electricity export tariff is not large enough to improve economics.

Another limitation is that they are better suited for well-developed and mature technologies whose characteristics are already well known. As fuel cells are still considered to be an emerging technology, we need tools that can assess the best way to design and operate a future system rather than a more detailed analysis of existing configurations.

1.1.2. Design optimization

Optimization with respect to fuel cell based micro cogeneration very often refers to the selection of a static design operating point. These operating conditions either minimise energy consumption or maximize efficiency. Naturally it follows that all the components of the fuel cell micro cogeneration unit need to be described in such models. This means that detailed models of the balance of plant are also necessary. Components described can include the fuel processor, shift reactor, reformer, blower, pre-heater, heat exchangers and burner.

Gandiglio et al. [16] make use of a method known as pinch analysis for design optimization. Pinch analysis is commonly used to optimize heat exchanger networks for a plant or process. This involves accounting for hot/cold streams and heat sources. The pinch point method specifies parameters such as the ideal temperature settings and network configurations for the micro cogeneration unit. Xie et al. [17] make use of energy-exergy balances to support their analysis. Analysis separates useful streams such electricity and hot water from streams that are not useful such as flue gases and condensate from the water separator. A process flow simulator is used to support the analysis. The effect of system parameters such as steam to carbon ratio, air to carbon ratio, hydrogen utilization efficiency on system performance are also evaluated. Barelli et al. [18] analyse a similar concept based on energy-exergy analysis and process flow simulators. It involves the soft linking of electrochemical phenomena represented in FORTRAN with the process flow phenomena in AspenPlus [19]. This is done since AspenPlus does not support electrochemical reactions. Modelling the polarization curve which is a result of the electrochemical portion of the model is of utmost importance while calculating the output power from the micro cogeneration unit. Design analysis can also differ in the type of models involved. The simplest methods use zero-dimensional models [18] with black box representations where the focus is on mapping input and output quantities. When geometry is to be taken into account, one-dimensional [20] and two-dimensional [21] models are used.

Fuel cell models can also be combined with evolutionary programming to determine optimal operating points [22]. Here empirical relations from experimental data are used to represent the equipment for faster simulation. This allows for a large number of model runs which are necessary to prevent the algorithm from settling for a local maxima instead of the global maxima.

Design optimization focuses on the variation of operating parameters to select a static set-point. Such set points are meant to be conducive for efficient long term operation without interruption. As mentioned earlier, the demand profiles encountered in a residential household do not have a minimum base load value. Hence, the static operation is likely to lead to inefficient operation.

Another limitation is that they provide very little information on the gaps in existing technology. This article deals with the change in performance in scenarios where the design parameters themselves are subject to change. Design optimization is rooted in technology rich descriptions of current units and does not provide room for changes that could be encountered in the future.

1.1.3. Optimal operation models

This approach involves the calculation of the best possible operating strategies through the use of optimization solvers. This is different from the previous approach which does not allow the set point to deviate from an optimal design point. In general, such models consist of an objective which minimises cost, energy or emissions and constraints on capacity and feasible operating envelope of the equipment.

The work of Wakui et al. [23] focuses on the situation in Japan and hence has been influenced by the prevailing policy conditions. The export of electricity back to the grid is not allowed in this country. Hence, micro cogeneration systems had to find alternative solutions to handle surplus electricity. One approach is to use the battery storage in plug-in hybrid electric vehicles [23]. This

reference also evaluates the possibility of switching the cogeneration unit ON/OFF once a day. Such start-stop operation is enabled since the local demand is very low during the night. It is worth noting that it incorporates both electrical and thermal storage. This allows the system to decouple supply from demand in both electrical and thermal domains. This configuration along with an optimal operating strategy is seen to provide significant energy savings.

A subsequent reference by the same authors, Aki et al. [24], deals with a modification of the problem described above. The authors tackle the no-electricity-export rule by grouping together households. This model allows the exchange of electricity and hot water between dwellings. By doing this the model can capitalise on complementary demand profiles. The energy management system consists of three layers: prediction, optimization and real time operation. Prediction of supply and demand values happens a day in advance, optimization happens every hour based on these predictions and real time operation tracks system variables continuously. A receding horizon control approach is employed. Here, the planning horizon is always extended for a specific number of time steps ahead of the current time period. Hence, by continuously revising the operating strategy, the model is able to mitigate risks associated with uncertainties in the prediction layer.

Environmental factors take centre stage in the work by Adam et al. [25]. The optimization problem aims to minimise the emissions in contrast to costs. A Mixed Integer Linear Program has been formulated to represent the fuel cell micro cogeneration unit, boiler and thermal storage tank. This model also calculates the optimal size of these components as well. The results indicate that the fuel cell micro cogeneration unit is better suited for houses whose electrical demand was comparable to thermal demand. This is a consequence of the heat to power ratio of the fuel cell which is close to unity.

The origins of the model described in this article can be traced back to the work of Hawkes et al. [26–28]. This article adapts many features from these references: the comparison with a baseline involving boiler and grid electricity, the minimisation of energy cost and the use of Equivalent Annual Cost as a measure of economics. These references have made use of non-linear programming mathematics for fuel cell based micro co-generation units. Since such nonlinear problems were not suited to capturing parameters such as start-up, minimum up time and minimum down time, an improved Mixed Integer Linear Program (MILP) formulation was used in Ref. [29]. The model described in this article adapts a similar formulation with an important improvement. This article is based on a low carbon future scenario with high penetration of solar, wind and nuclear sources while [29] was based on conditions that prevail in the present day energy system.

The optimal operation model is capable of quantifying the change in key techno-economic criteria with respect to parameters which represent the dynamic characteristics of fuel cells. A sensitivity analysis of such models has the potential to identify design parameters that are likely to have a large impact on the energy and emission savings. It offers sufficient detail and computational tractability to generate practical insights into the parameters that need to be prioritized during product design. Hence, this approach has been used in this article.

1.2. Novelty and contributions

1.2.1. Broader landscape

The first two contributions of this paper have also been discussed in our previous work [30]. Hence, these are the main contributions with respect to the broader set of literature on this topic.

1.2.1.1. Novelty I - power system decarbonisation. This article adds to existing literature by analysing of the economics of fuel cell based micro co-generation in the context of overall power system decarbonisation, and specifically focusing on technical performance aspects of the micro co-generation. Examples of studies analysing the intersection between broader energy systems and the supply of heat can be found in Refs. [31–34]. Such tools view energy systems from a macro level perspective and hence necessarily involve aggregated representations of regional, national or global participants [35]. Information on the economics and operation of individual consumers is lost in such studies which use coarse grained representations. Hence more detailed representations of the end user are required to assess the solutions provided by emerging technologies. Even when individual representations are used as seen in Refs. [5,36], the discussion of future scenarios is limited to the change in carbon intensity of electricity generation. Our work adds to these by using a detailed power dispatch model to simulate generator operation and market prices in the future scenario.

1.2.1.2. Novelty II – long run marginal cost of electricity. Fuel cell based micro co-generation systems of the future will have to operate in a significantly different energy system compared to what is seen today. Decarbonisation of the electricity grid is expected to underpin any carbon mitigation strategy that is designed to check the rise in global temperature [37]. We have shown in our earlier work [38] that decarbonisation through an increase in renewable and nuclear capacity will result in significantly lower wholesale electricity prices in the future. Such weak revenue streams are bound to make it difficult for power plants to break even. The long run electricity price regime incorporates capital cost and utilization into a fixed power purchase agreement. This solution that mitigates this risk through the use of an electricity price regime that makes use of the long run marginal cost of generation instead of the short run marginal cost regime which is common in today's systems.

1.2.2. Specific to this article

This article contains modifications that improve upon the work presented by the authors in Ref. [30].

1.2.2.1. Novelty III – combination of the above with fuel cell dynamics. This article expands upon the work in Ref. [30] through explicit characterisation of dynamic aspects of fuel cell based micro co-generation systems, namely; start-up cost, ramping limit, minimum up time, minimum down time and turn down ratio. These parameters are important since fuel cell micro co-generation systems require a multitude of sub systems to function in tandem: the fuel processor, the fuel reformer, the stack, power electronics, actuators, control loops etc. [4]. The operation of each sub systems has implications in terms of performance of the overall unit. For example, since the fuel cell is likely to have more thermal mass than conventional heating systems it is likely to incur a greater energy cost while warming up or starting [29]. The dynamics of the fuel processor, reformer and balance of plant determine how quickly the micro co-generation unit can modulate output and hence influence the ramping limit [39]. Thermal characteristics such as minimum stack temperature and thermal cycling affect parameters such as turn down ratio, minimum up time and minimum down time [40]. Therefore, the model described in this article can help identify which aspects will improve the economic performance of fuel cell based micro co-generation.

1.2.2.2. Novelty IV – identification of sensitive design specifications for future research. By making use of a sensitivity analysis that varies design parameters, this article is able to provide guidelines

regarding which specifications affect performance the most. This type of optimization is different from what is seen in existing literature as discussed in Section 1.1. While a lot of effort has been put into the analysis of existing technologies, the literature does not discuss the concept of making use of existing tools to feed information back to the design process to establish future priorities.

2. Methodology

2.1. Model overview

This work combines a macro national level electricity system model with the operation of a micro level individual consumer model to simulate operation fuel cell based micro co-generation in the year 2035. The macro level model simulates power dispatch of all generators in a power grid and the micro level model simulates the heating system in an individual household as shown in Fig. 1. The main link between these two models is the electricity price profile. This is a time varying parameter that is dependent upon the energy mix and the electricity price regime adopted by the electricity grid. In this article we make use an energy mix that is characterized by high penetration of low carbon sources coupled with an electricity price regime that makes use of the Long Run Marginal Cost of electricity. Detailed descriptions of the power dispatch model and electricity price regimes have been covered in our previous works [38] and [30]. It is worth noting that this article intentionally makes use of a generic fuel cell description. Particular focus is on characterising the impact of inter-temporal specifications which can be the focus of future research on fuel cell technologies. The data ranges used in the sensitivity studies have purposefully been kept large enough to encompass both high temperature and low temperature fuel cells. The following sections will focus on the consumer side model which highlights the contributions of this article.

2.2. Individual heating system description

This model represents the operation of a fuel cell based micro co-generation within an individual household. The house is also equipped with a natural gas boiler, a thermal energy storage tank and a connection to the central grid. The interactions between each of these components are shown in Fig. 2. The system is exposed to time varying electricity prices, import is charged at retail price and export attracts revenue at wholesale price. The inputs from the power dispatch model provide the wholesale price. Wholesale prices are uplifted by taxes, fuel duties and policy cost recovery based on data from the UK government [41] to calculate retail prices.

2.3. Mathematical model

The model makes use of two control strategies: heat led and optimization based. Heat led control does not require an iterative solver. It simply follows the heat load by dispatching the micro cogeneration unit first and then using the auxiliary boiler to supply

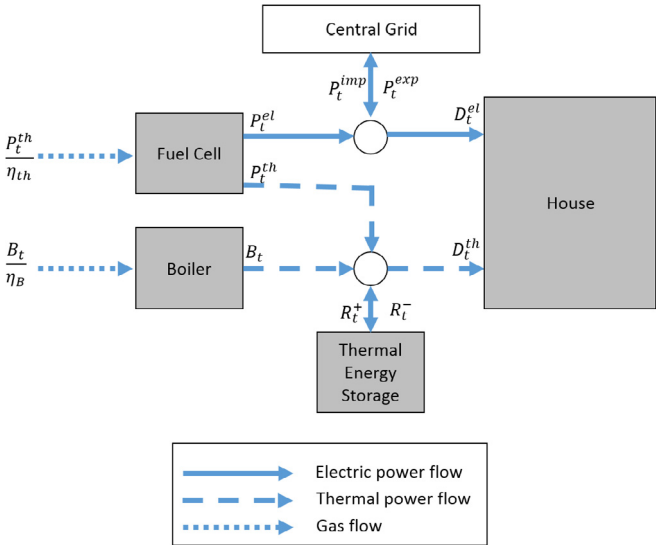


Fig. 2. Heating system schematic.

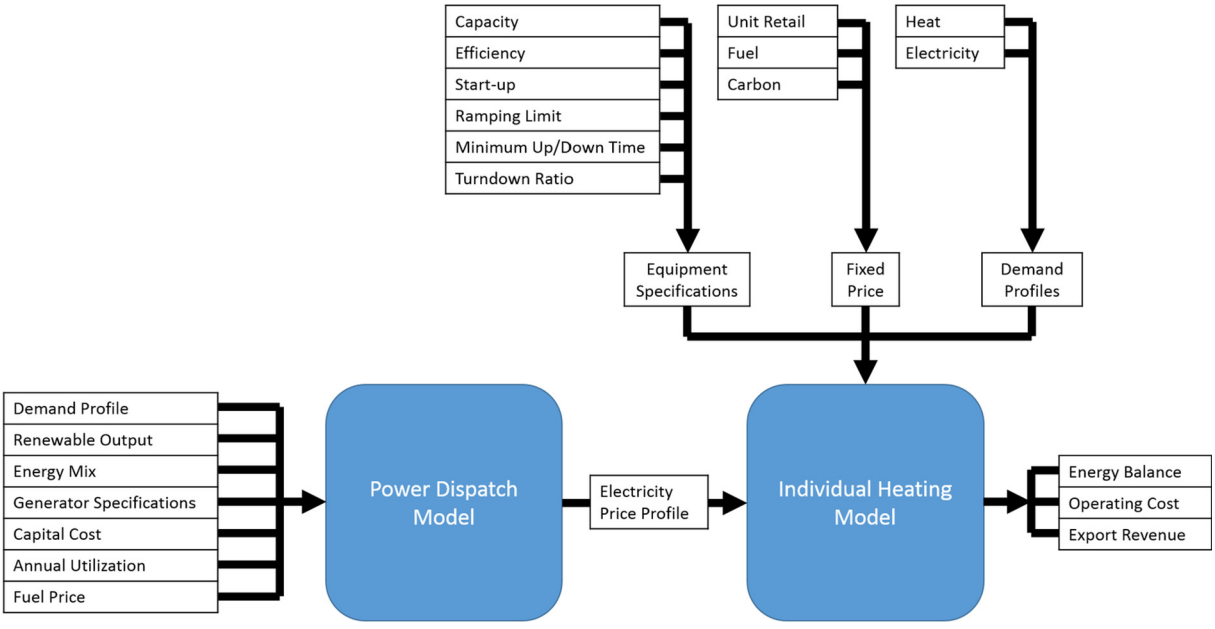


Fig. 1. Model description.

the rest. Any excess electricity generated is exported back to the grid. The optimization based model is a mixed integer linear program. The structure of the optimization problem can be summarised as:

- Objective
  - Minimise (operating cost − export revenue)
- Subject to
  - Electrical and thermal load balance
  - Feasible operating envelope
  - Thermal energy storage operation

This model is applied to a set of representative days in a year. The representative day selection algorithm is presented in Appendix A. Each day is divided into five minute intervals. The results from each day are weighted approximately equally to calculate the annual performance indices used for comparison.

It is worth noting that this approach intentionally adopts a generic and technology agnostic approach to describing the fuel cell based cogeneration unit. Although the component-wise operation may vary, their dynamics can be captured by using mathematical abstractions. Dynamic characteristics are chosen such they are capable of representing the operation and interactions without going into individual component level detail. This applies to different fuel cell technologies, using different electrolytes, catalysts, reformers, fuel processors etc. The same applies to different balance of plant equipment such as power electronics, actuators, control loops etc.

This model is meant to represent future technologies. They describe characteristic of fuel cell based micro cogeneration units that have not been developed yet. For this reason, we do not compare the chosen parameters with existing technologies. Validation is outside the scope of the current set of objectives. But this does not discount the ability of optimization problems to represent fuel cell based micro cogeneration units. Several references have used mixed integer linear programs for existing systems as discussed in Section 1.1.3.

As explained earlier, this article improves upon our previous work [30] by accounting for dynamic characteristics of fuel cells that could potentially affect their economic case in low carbon futures. All of these parameters fall under the feasible operating envelope category. They have been summarised in Table 1.

Details regarding mathematical modelling of these constraints are presented below. Descriptions of the symbols used are present in Appendix B.

2.3.1. Objective

As explained earlier the objective is to minimise the difference between operating cost and export revenue. This is shown in Equation (1).

$$\mathrm{Q} = \sum_{t \in T} (O_t - E_t) \tag{1}$$

2.3.2. Operating cost

Natural gas is consumed by both the boiler and the micro co-generation unit. This incurs a fuel and carbon cost. Electricity from the central grid is charged at the time varying import price. Start-up cost depends on whether the system is using the cold or hot start-up method. When using the cold start-up method a fixed cost is incurred each time the micro co-generation unit is started up as shown in Equation (2).

$$O_t = \left(\frac{P_t^{th}}{\eta_{th}} + \frac{B_t}{\eta_B}\right)(\alpha_{gas} + \alpha_{CO2} e_{gas}) + P_t^{imp} \alpha_t^{imp} + \alpha_{SUC} \varphi_t^{SU} \tag{2}$$

When using hot start-up a fixed cost is incurred whenever the micro co-generation unit is not active as shown in Equation (3).

$$O_t = \left(\frac{P_t^{th}}{\eta_{th}} + \frac{B_t}{\eta_B}\right)(\alpha_{gas} + \alpha_{CO2} e_{gas}) + P_t^{imp} \alpha_t^{imp} + \alpha_{SUH}\left(1 - \varphi_t^{A}\right) \tag{3}$$

2.3.3. Export revenue

Export revenue is the product of electricity exported and the export price of electricity summed over all periods as shown in Equation (4).

$$E_t = P_t^{exp} \alpha_t^{wholesale} \tag{4}$$

2.3.4. Electrical load balance

Generation and import are on the left side of Equation (5). Demand and export are on the right side of Equation (5).

$$P_t^{imp} + P_t^{el} = P_t^{exp} + D_t^{el} \tag{5}$$

2.3.5. Thermal load balance

Generation and heat supplied by installed technology are on the left side of Equation (6). Demand and storage are on the right side of Equation (6).

$$B_t + P_t^{th} = D_t^{th} + R_t^{+} - R_t^{-} \tag{6}$$

2.3.6. Start-up and shut down logic

Start-up and shut down indicators are a function of whether the state of the micro co-generation unit has changed in consecutive time periods as shown in Equation (7).

$$\varphi_t^{SU} - \varphi_t^{SD} = \varphi_t^{A} - \varphi_{t-1}^{A} \tag{7}$$

2.3.7. Heat to power ratio

This parameter governs the relation between thermal and electrical power supplied by a micro co-generation unit as shown in Equation (8).

$$P_t^{el} = \eta_{el}\left(\frac{P_t^{th}}{\eta_{th}}\right) \tag{8}$$

2.3.8. Ramping limits

This is the limit on the difference between the outputs in consecutive time periods. It applied to both upward and downward directions as shown in Equation (8) and Equation (10).

$$P_t^{el} - P_{t-1}^{el} \le \beta_{rmp} \tag{9}$$

$$P_{t-1}^{el} - P_t^{el} \le \beta_{rmp} \tag{10}$$

2.3.9. Component operation limits

Both the boiler and micro co-generation units have associated

capacity limits. These are modelled by Equation (11) and Equation (12).

$$0 \leq B_t \leq \overline{B} \tag{11}$$

$$\beta_{tdr}\overline{P^{el}} \leq P_t^{el} \leq \overline{P^{el}}\varphi_t^A \tag{12}$$

2.3.10. Minimum down time

Equation (13) enforces the minimum down time constraint for all consecutive sets of periods of lengthβ_{mdt}. Equation (14) makes sure that if the unit is shut down in the last $\beta_{mdt} - 1$ periods it will remain offline until the end of the planning horizon.

$$\sum_{k=t}^{t+\beta_{mdt}-1}\left(1-\varphi_k^A\right) \geq \beta_{mdt}\varphi_t^{SD} \quad \forall t = 1\cdots T_{end} - \beta_{mdt} + 1 \tag{13}$$

$$\sum_{k=t}^{T_{end}}\left(1-\varphi_k^A-\varphi_t^{SD}\right) \geq 0 \quad \forall t = T_{end} - \beta_{mdt} + 2\cdots T_{end} \tag{14}$$

2.3.11. Minimum up time

Equation (15) enforces the minimum up time constraint for all consecutive sets of periods of lengthβ_{mut}. Equation (16) makes sure that if the unit is started up in the last $\beta_{mut} - 1$ periods it will remain online until the end of the planning horizon.

$$\sum_{k=t}^{t+\beta_{mut}-1}\left(\varphi_k^A\right) \geq \beta_{mut}\varphi_t^{SU} \quad \forall t = 1\cdots T_{end} - \beta_{mut} + 1 \tag{15}$$

$$\sum_{k=t}^{T_{end}}\left(\varphi_k^A-\varphi_t^{SU}\right) \geq 0 \quad \forall t = T_{end} - \beta_{mut} + 2\cdots T_{end} \tag{16}$$

2.3.12. Thermal energy storage

These equations govern thermal storage operation. Current state of charge is a function of previous state of charge and the charging/discharging level in the current period as shown in Equation (17). The storage unit is not allowed to charge and discharge simultaneously according to Equation (18). Charging and discharging limits are governed by Equation (19) and Equation (20). The state of charge at the beginning of the planning horizon is the same as that seen at the end according to Equation (21). Storage capacity is defined by Equation (22).

$$S_t = S_{t-1} + \eta_{ch}R_t^+ - \frac{R_t^-}{\eta_{disch}} \tag{17}$$

$$\varphi_t^+ + \varphi_t^- \leq 1 \tag{18}$$

$$0 \leq R_t^+ \leq \overline{S}\varphi_t^+ \tag{19}$$

$$0 \leq R_t^- \leq \overline{S}\varphi_t^- \tag{20}$$

$$S_1 = S_{T_{end}} \tag{21}$$

$$0 \leq S_t \leq \overline{S} \tag{22}$$

2.3.13. Equivalent annual cost

Equivalent Annual Cost (EAC) which is defined as the export revenue subtracted from the sum of annualized capital and operational costs. Revenue and operational costs are weighted according to sample weights of representative days as shown in Equation (23).

$$C = \Psi\frac{r}{1-\frac{1}{(1+r)^L}} + \sum_{k\in K} w_k\left(\sum_{t\in T}(O_t - E_t)\right) \tag{23}$$

2.4. Data used in the simulations

Natural gas prices are from the UK government's projections for the year 2035 [41]. Carbon prices are based on the non-traded price of carbon data in the UK government's valuation of energy use and greenhouse gas emissions [42]. The uplift of wholesale price to give retail price is based on projections generated by the UK government [41]. Capital costs in the year 2035 are within the ranges specified in Ref. [43] and cross-referenced with the UK TIMES model [44]. The electricity and heat demand profiles for the individual house are sourced from Ref. [45]. Further details are presented in Table 2 and Table 3.

3. Results and discussion

3.1. Power dispatch model

3.1.1. Analysis of wholesale electricity prices in the long run electricity price regime

This section deals with the factors that drive wholesale prices in the long run electricity price regime. It should be noted that the overall price is the marginal cost of the most expensive generator online at any point of time. The dispatch of generators is based on long run costs that account for amortised upfront costs, annual utilization and maintenance in addition to fuel, carbon and start-up costs. Thus renewable sources also have an associated cost.

Operation of the long run regime on a spring day is shown in Fig. 3(a) and (c). There is plenty of sunlight and wind as seen in Fig. 3(a). Fossil fuel generators are not necessary except after 6 p.m. since sunlight dies down in the evening. The operation of nuclear and wind till 7 a.m. results in relatively low values of electricity price as seen in Fig. 3(c). Injection of solar power increases price towards mid-day. The marginal cost of solar power is larger than wind due to a lower value of capacity factor. A further increase in electricity price is seen beyond 6 p.m. due to the dispatch of Coal units fitted with Carbon Capture and Storage (CCS). As utilization of conventional generators decreases significantly in a low carbon future, their marginal cost is larger.

Operation of the long run regime on a winter day is shown in Fig. 3(b) and (d). There is lesser sunlight but plenty of wind as seen in Fig. 3(b). The electricity price increases at 7:30 a.m. due to the dispatch of two Coal units fitted with Carbon Capture and Storage (CCS) that responded to an increase in demand. They were dispatched since these units have the lowest long run marginal costs after nuclear units. These units remain online and serve demand at various points when renewable output and pumped storage falls short of overall consumption. This results in a higher electricity price between 7:30 a.m. and 8 p.m. as seen in Fig. 3(d). The relatively higher values of electricity price after these units go offline at 8 p.m. is due to the associated cost of pumped storage discharge.

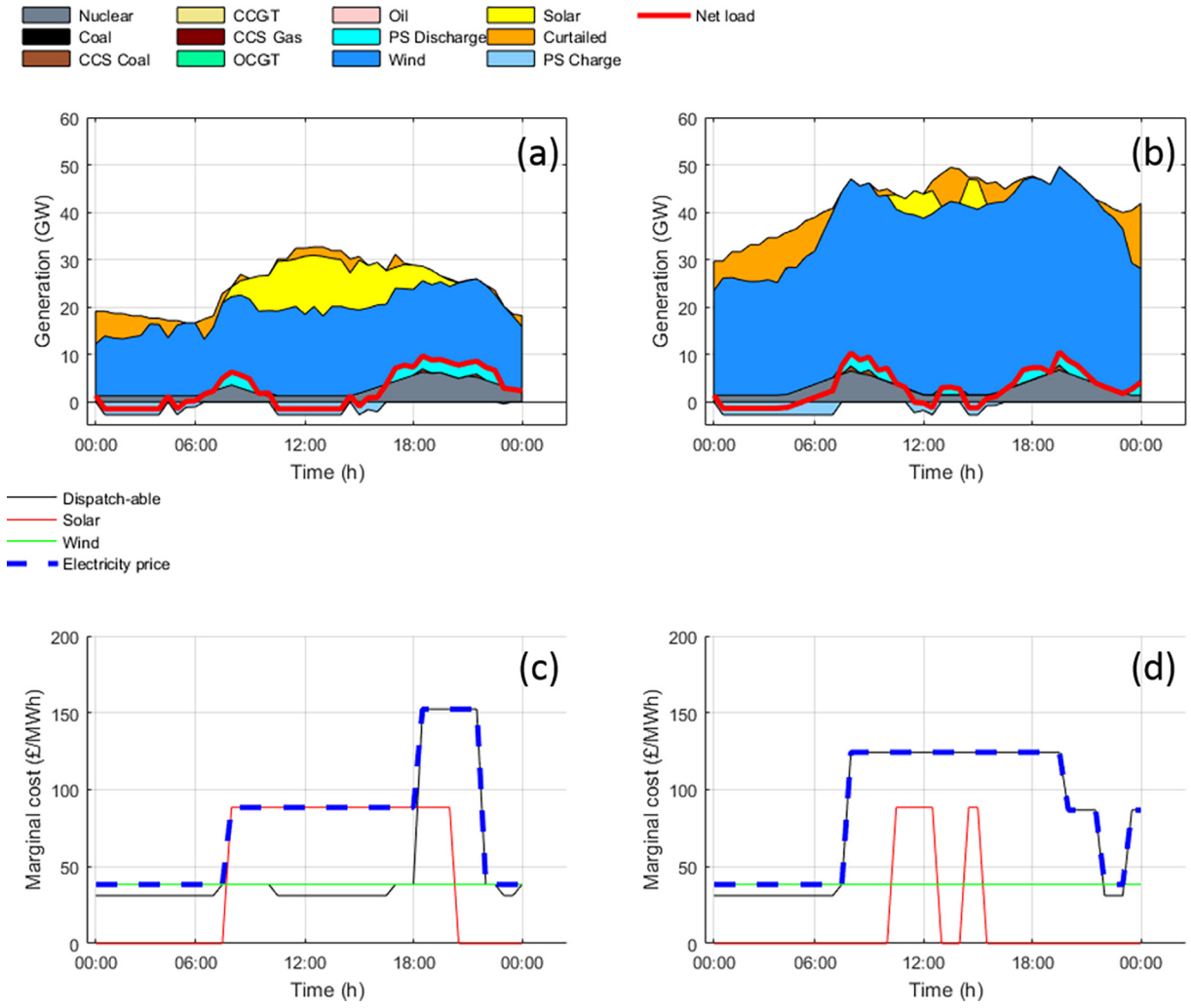


Fig. 3. Analysis of wholesale electricity prices in the long run electricity price regime (a) Dispatch on a spring day (b) Dispatch on a winter day (c) Marginal costs on a spring day (d) Marginal costs on a winter day.

3.2. Fuel cell micro cogeneration

This article has prioritized the analysis of some parameters over others. Start-up is seen to be critical for consumers and designers alike. Hence, analysis of sensitivity to cold and hot start-ups are performed for all cases considered. In order to limit the number of parameters analysed to a manageable value, we include certain modifications. Firstly, minimum up time is equal to minimum down time. And second, we do not vary the values of parameters which have zero impact on economics when incorporated separately into a particular control strategy.

3.2.1. Identification of significant parameters

We incorporate each of the following dynamic parameters into the simulation separately: turn down ratio, minimum up/down time and ramping limit. These parameters are varied between their respective maximum and minimum values which are summarised in Table 4. These ranges are based on nominal values from Ref. [4].

The range of the Equivalent Annual Cost values obtained for each parameter is shown in Fig. 4. The aim is to identify the most important parameters for analysis of the heat led and optimization based control strategies. The range of values associated with various values of turn down ratio and minimum up/down times is zero for heat led and optimization based control strategies respectively. This implies that these parameters do not affect operation. Hence turn down ratio and minimum up/down times are left out of the analysis of heat led and optimization based control strategies respectively.

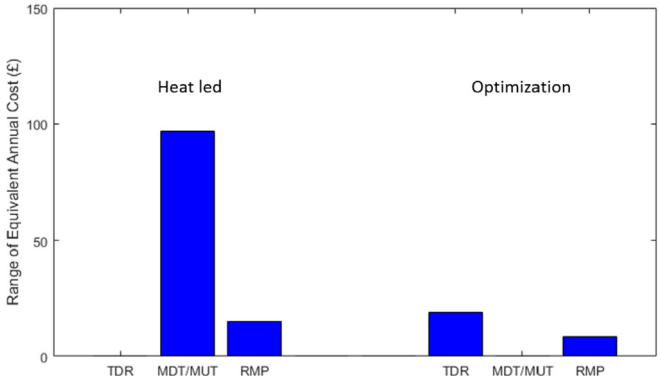


Fig. 4. Range of Equivalent Annual Costs for each dynamic parameter in the initial simulation (TDR – Turn down ratio, MDT – Minimum down time, MUT – Minimum up time and RMP – Ramping limit).

Table 1
Dynamic parameters.

Parameter	Description	Physical Relevance
Turn down ratio	The ratio between the minimum and maximum output of the fuel cell micro co-generation unit.	Minimum stack temperature
Minimum up time	The minimum amount of time for which the micro co-generation unit need to remain online once it has been activated.	Prevention of rapid cycling;
Minimum down time	The minimum amount of time for which the micro co-generation unit has to remain offline once it has been shut down.	Prevention of rapid cycling; Cool down period
Ramping limit	The limit on the rate at which the output of the micro co-generation unit can be modulated.	Interactions between equipment; Functioning within safe operating envelope
Cold start-up	The energy cost of starting up the micro co-generation unit when it has been allowed to cool down when offline.	Pre-heating of stack, fuel and air; operation of blowers
Hot start-up	The energy cost of keeping the micro co-generation unit on standby mode when offline.	Maintenance of stack, fuel and air temperature

Table 2
Details related to the building.

Parameter	Value
Region	Northern Ireland
Building Type	Mid Terrace
Building Age	1969
Total Floor Area	77 m^2
Internal Volume	193 m^3
Fuel	Natural gas
Annual Electrical Demand	5938 kWh
Annual Heat Demand	16670 kWh

3.2.2. Analysis of heat led control

Let us first analyse the physical phenomena that drive performance. Since it is not feasible to present all of the sensitivity data points, we focus on the extremes. The best case scenario involves the lowest minimum up/down time and the highest ramping limit. This is because a high ramping limit allows the system to react to changes in demand most effectively. And a small minimum up/down time means that the system can shut down and start-up without any constraints that force it to do otherwise. Hence, it follows that the worst case scenario involves the highest minimum up/down time and the lowest ramping limit.

Electrical and thermal power balances are presented in Fig. 5. This figure shows how each of the subsystems are operated to satisfy local demand. The operating principle is simple: follow heat demand by using cogeneration first and the auxiliary boiler next. Export excess and import any deficit in electricity. The effect of dynamic parameters can be seen by comparing the figures on the left to the ones on the right. In Fig. 5 (c) the system is more reactive and has the flexibility to follow demand. The cogeneration system is able to immediately operate at rated capacity around 4 a.m. when heat demand increases. This is not the case in Fig. 5(d) where the system has to wait until 5 a.m. to reach rated capacity. The minimum up/down time also affects operation. When the minimum down time value is only half an hour in the best case scenario, the system is able to shut down around 10 a.m. and start up at noon when demand reappears as seen in Fig. 5(c). But in the worst case the system is not able to start generation until 2 p.m. as seen in Fig. 5 (d). Minimum up time comes into play around 4:30 p.m. in Fig. 5(d) When the system is not able to shut down even through there is no local heat demand. It is worth noting that it is able to reach a low value of output only around 4:30 p.m. due a low ramping limit that restrains the cogeneration unit.

The heat led operating strategy does not depend on the start-up method. Hence, the EAC without start-up cost values are identical for the hot and cold start-up methods. The variation of EAC without start up is shown in Fig. 6. Minimum up/down time has a stronger effect on performance than the ramping limit. This can be seen by the change in colour of the contour plot from half an hour to four hours. The EAC increases by eighty pounds within the sensitivity range investigated for minimum up/down time. The most important implication of these results is that with a heat led strategy the unit is never economically viable in the sensitivity range considered. This can be seen from the fact that in even without start-up costs, the EAC value is always above the boiler baseline which is £ 2630. As discussed in Section 1.1.1, the main drawback of this

Table 3
Heating system parameters.[a]

Parameter	Description	Units	Range	Chosen Value	Ref.
α_{CO2}	Non-traded price of carbon	£/kg	0.113	0.113	[42]
α_{gas}	Natural gas price	£/kWh	0.045	0.045	[41]
η_B	Efficiency of natural gas boiler	–	0.8–0.9	0.86	[46–50]
η_{ch}, η_{disch}	Charging/discharging efficiency of TES	–	0.4–0.97	0.9	[51–53]
η_{el}	Electrical efficiency	–	0.3–0.45	0.45	[54–56]
η_{th}	Thermal efficiency	–	0.39–0.48	0.45	[54–56]
Ψ (Boiler)	Upfront cost	£	2200–2500	2328.1	[44,45,57]
Ψ (Fuel cell)	Upfront cost	£	1775–15152	5037	[43,44,55,58,59]
Ψ (Fuel cell reformer)	Upfront cost	£	240–3800	717.4	[44,60,61]
Ψ (TES)	Upfront cost	£	50–1300	415.4	[44,62,63]
$\overline{B}$	Capacity of natural gas boiler	kW	–	30	–
L	Lifespan	years	10–15	15	[54,55,64]
$\overline{P^{el}}$	Electrical capacity of cogeneration unit	kW	–	1	–
r	Discount rate	%	–	3	–
$\overline{S}$	Capacity of thermal energy storage	kWh	–	5	–
w	Sample weights of representative days	Days	–	[91;91;91;92]	–

[a] Note that a complete fuel cell micro co-generation system requires a fuel cell, fuel cell reformer, TES and boiler. The cost of the fuel cell is assumed to include all balance of plant except the reformer. Reliability is beyond the scope of this article and maintenance costs are assumed to be negligible.

Table 4
Ranges of sensitivity values for each of the dynamic parameters. Note: Nominal values were taken from Ref. [4].

Parameter	Units	Nominal	Minimum	Maximum
Turn down ratio	–	0.2	0.2	0.5
Minimum up/down time	h	1	0.5	4
Ramping limit	W/5min	250–1000	100	1000

approach is inefficiency. Hence if the system is operated in heat led mode, it does not justify the investment made in this technology.

3.2.3. Analysis of optimization based control

Let us start by considering the EAC without start-up. Hot and cold values were identical for the heat led control strategy because the operating strategy is independent of start-up cost. We perform the same exercise for the optimization based control strategies as any differences will quickly rule out identical strategies. Table 5 shows the absolute values of EAC without start-up and Table 6 shows the difference between the hot and cold start-up. It can be seen from Table 6 that the difference is less than one-thousandth of the absolute value. This means that the economics are similar but it remains to be seen if the operating strategies are close to each other as well. To evaluate this, we compared the difference between dispatch strategies of the micro co-generation unit.

To ascertain whether they are identical we need to compare the hot and cold strategies first and then compare the difference in operating strategies for various start-up sensitivity values for both hot and cold start-up approaches. The results summarised in Table 7. Individual dispatch values for the micro co-generation unit are deemed to be identical if the difference between them is less than10^{-6} W. Nominal values of 0.2 kW for hot standby power and 1 kWh for cold start-up energy cost are from Refs. [65] and [66] respectively.

An overwhelming fraction of non-zero dispatch values are identical. This implies that the dispatch optimization based control strategy is also independent of the type of start-up method used and the magnitude of the start-up cost specified. Hence we proceed to analyse the difference in operating strategies when there is a difference in turn down ratio and ramping limit. This analysis also presents the difference in physical phenomena.

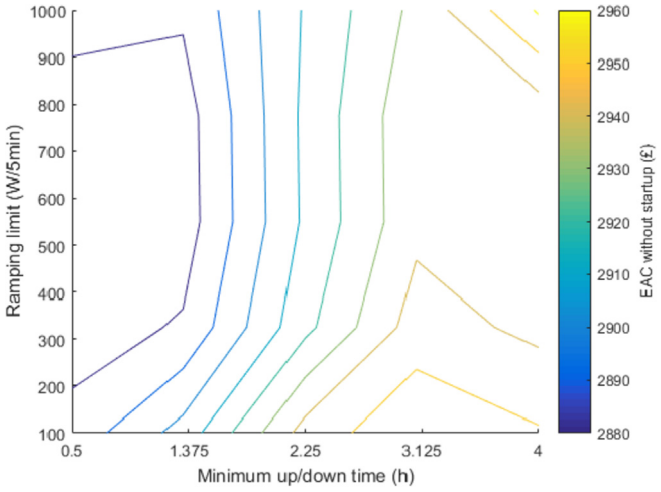


Fig. 6. Variation of EAC without start-up cost.

Table 5
EAC without start-up (£).

	Value	Turn Down Ratio				
		0.2	0.275	035	0.425	0.5
Ramping Limit (W/5min)	100	3147.2	3147.2	3147.2	3147.2	3147.2
	325	2612.7	2612.9	3147.2	3147.2	3147.2
	550	2611.9	2612.2	2614.6	2622.4	2633.1
	775	2611.9	2612.1	2614.5	2622.4	2633.1
	1000	2611.9	2612.1	2614.5	2622.4	2633.1

Optimization cannot make use of the extremes in sensitivity data as seen in the previous section. This can be explained by analysing the cycling patterns in Table 8 and Table 9. They present the number of starts and the percentage of time spent in hot standby mode. It can be seen that the cogeneration unit is not

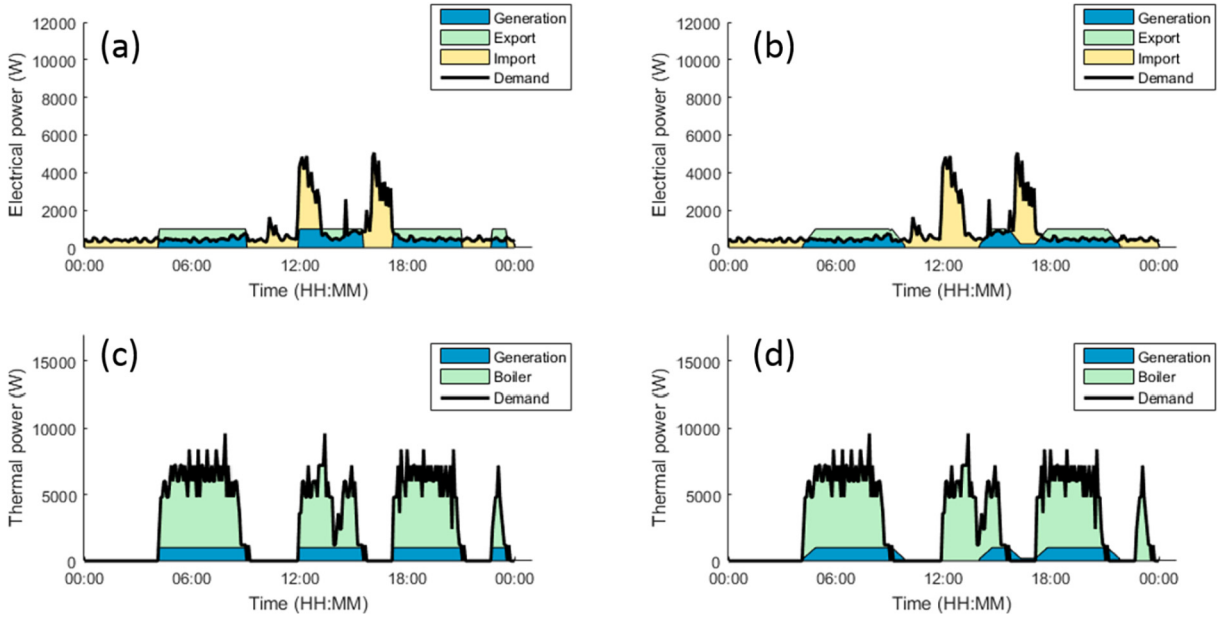


Fig. 5. Physical phenomena that drive performance. Best case: (a) and (c). Worst case: (b) and (d).

Table 6
Difference between hot and cold start - EAC without start-up (£).

	Value	Turn Down Ratio				
		0.2	0.275	035	0.425	0.5
Ramping Limit (W/5min)	100	0.0	0.0	0.0	0.0	0.0
	325	0.0	0.0	0.0	0.0	0.0
	550	0.0	0.0	0.0	−0.3	−1.6
	775	0.0	0.0	0.0	−0.2	−1.6
	1000	0.0	0.0	0.0	−0.2	−1.6

Table 7
Comparison of optimization based operating strategies.

Comparison	Percentage of identical elements
Hot standby power (0.2 kW) Vs Cold start-up cost (1 kWh)	98.5
Hot standby power (0.2 kW) Vs Hot standby power (0.3 kW)	99.6
Hot standby power (0.2 kW) Vs Hot standby power (0.4 kW)	99.5
Hot standby power (0.2 kW) Vs Hot standby power (0.5 kW)	99.4
Hot standby power (0.2 kW) Vs Hot standby power (0.6 kW)	99.4
Cold start-up cost (1 kWh) Vs Cold start-up cost (1.5 kWh)	99.8
Cold start-up cost (1 kWh) Vs Cold start-up cost (2 kWh)	99.7
Cold start-up cost (1 kWh) Vs Cold start-up cost (2.5 kWh)	99.7
Cold start-up cost (1 kWh) Vs Cold start-up cost (3 kWh)	99.7

switched on when subjected to certain combinations. This is evident from the number of starts falling to zero and the portion of time spent in hot standby mode goes up to one hundred percent. One of these combinations is the worst case scenario with the lowest ramping limit and the highest turn down ratio. In these cases the optimization problem chooses to stick to the boiler and grid electricity since switching on the cogeneration unit is more expensive. Hence the best and worst combinations in which the cogeneration unit is operational are (0.2 turn down ratio, 1000 W/5min ramping limit) and (0.5 turn down ratio, 550 W/5min ramping limit) respectively.

Physical phenomena in the two cases considered are shown in Fig. 7. Inspection of Fig. 7(b) and (f) shows that the output of the cogeneration system able to track load changes better between midnight and 8 a.m., but the worst case chooses a constant output level due to the low ramping limit and high turn down ratio. The output is increased to maximum capacity between 8 a.m. and 9 p.m. in both cases due to high electricity prices. When the difference between rated capacity and on-site load is positive, electricity is exported to the grid. Thermal phenomena for the best case are shown in Fig. 7(c) and (d). The respective counterparts for the worst case are shown in Fig. 7 (g) and Fig. 7(h). Strategic planning allows the system to store up energy when there is no heat demand and discharge when heat demand increases. Hence the presence of thermal storage decouples the heat supply from demand to a certain extent. As the thermal output is directly linked to electrical output, the shapes seen Fig. 7(c) are a consequence of those seen in Fig. 7(b). The variation in output is not as clear in Fig. 7(c) as the scale of heat demand is larger in comparison to the output of the cogeneration unit. Similarly in the worst case, thermal output is dependent on electrical output as seen in Fig. 7(f)–7(h). Thermal storage is charged three times in both cases, between 7 a.m. and 10:30 a.m., between 11:30 a.m. and 2 p.m. and between 7:30 p.m. and 9 p.m. as seen in Fig. 7(d) and (h).

Table 8
Cold start cycling pattern - Number of starts.

	Value	Turn Down Ratio				
		0.2	0.275	035	0.425	0.5
Ramping Limit	100	0	0	0	0	0
	325	365	365	0	0	0
	550	365	365	365	365	365
	775	365	365	365	365	365
	1000	365	365	365	365	365

Table 9
Hot start cycling pattern - Percentage of time spent in hot standby mode.

	Value	Turn Down Ratio				
		0.2	0.275	035	0.425	0.5
Ramping Limit	100	100.00	100.00	100.00	100.00	100.00
	325	5.54	5.54	100.00	100.00	100.00
	550	5.54	5.54	5.54	7.02	8.75
	775	5.54	5.54	5.54	7.10	8.75
	1000	5.54	5.54	5.54	7.10	8.75

Even though the operating patterns look similar to the naked eye, the numbers in Table 5 show that there are subtle differences. It can be seen from Table 5 that some of the values of EAC are above the boiler baseline of £ 2630. The inclusion of start-up cost impairs performance even further in these cases. Hence there is room for accommodating start-up cost only when the EAC values are below the boiler baseline. The following section quantifies the maximum start-up cost that can be incurred before the system is no longer economically viable.

With this information, the maximum start-up cost can be calculated. This is shown in Table 10 and Table 11. These tables contain omit entries where the EAC without start-up was greater than the boiler baseline. As expected, cases involving low turn down ratios and high ramping limits fare better than others. They produce the highest maximum allowable start-up costs. In Table 10, values below 1 kWh, which is the nominal value, are not economically viable. Hence the turn down ratio has to be lower than 0.35 if the system is to be economically viable with cold start-up. In contrast, a higher fraction of values in the hot start-up approach are above the nominal value of 0.2 kW in Table 11 and are hence economically viable. The system does particularly well when subject to low turn down ratios.

4. Conclusion

In this paper, a novel approach to modelling fuel cell based micro co-generation in low carbon futures has been presented. It evaluates the impact of dynamic constraints on the economics of the fuel cell micro co-generation. Particular emphasis is laid on the difference between two control strategies: heat led and optimization based and two start-up methods: allowing the unit to cool down (cold start-up) when inactive and keeping it on hot standby mode (hot start-up).

The results indicate that fuel cell based micro co-generation continues to be a promising technology even when potentially limiting dynamic constraints are taken into account. Economic viability is bent upon the use of an optimization based control strategy. Heat led strategies are seen to push the equivalent annual cost above the boiler baseline even without accounting for start-up cost.

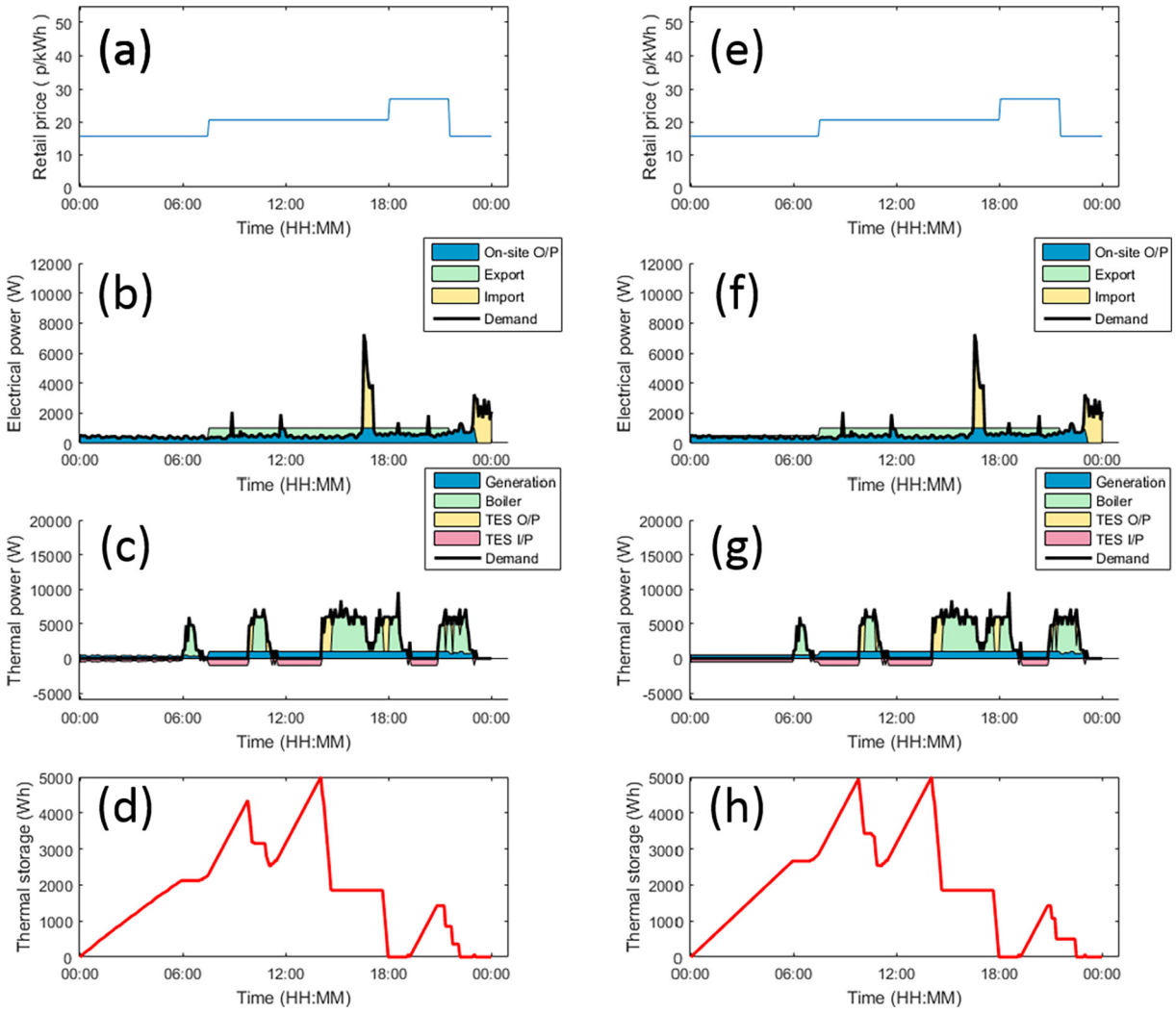


Fig. 7. Physical phenomena that drive performance. Best case: (a) to (d). Worst case: (e) to (h).

Table 10
Maximum cold start-up cost (kWh).

	Value	Turn Down Ratio				
		0.2	0.275	035	0.425	0.5
Ramping Limit	100	–	–	–	–	–
	325	1.08	1.06	–	–	–
	550	1.13	1.11	0.97	0.49	–
	775	1.13	1.12	0.97	0.49	–
	1000	1.13	1.12	0.97	0.49	–

Table 11
Maximum hot stand by power (kW).

	Value	Turn Down Ratio				
		0.2	0.275	035	0.425	0.5
Ramping Limit	100	–	–	–	–	–
	325	0.81	0.80	–	–	–
	550	0.85	0.84	0.73	0.31	–
	775	0.85	0.84	0.73	0.32	–
	1000	0.85	0.84	0.73	0.32	–

Even with an optimized operating strategy in place, the micro co-generation unit is rendered useless when subjected to a combination of low ramping limits less than 70 W/min and high turn down ratios above 35%. The optimization problem chooses to not use the fuel cell at all since the costs outweigh the benefits of onsite generation. Such combinations need to be avoided.

Given that the micro co-generation unit is operational, the start-up cost influences the economics more than the turn down ratio and ramping limits. Results indicate that the hot start-up approach offers much greater leeway to designers. The maximum allowable hot standby power is above the nominal value for turn down ratios less than or equal to 0.425. The ratio between the maximum allowable and nominal hot standby power ranges from 1.5 to 4.2. The same cannot be said about cold start up. This approach requires turn down ratios less than or equal to 0.275 to be viable. Here the ratio between maximum and nominal start-up cost ranges from 0.5 to 1.1. This is because the fraction of time spent in hot standby mode is less than ten percent. Thus the unit is economically viable even if the hot standby power is considerably higher than the nominal value found in literature.

Future research can relay the control instructions from the

optimization problem to a transient model that incorporates component level detail. This analysis can reveal if the interactions between sub-systems and control loops cause the plant to be inefficient or stray outside the safe operating envelope. Improvements involving other objectives such as environmental performance and multi-criteria analysis are also potential future directions.

Acknowledgements

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Appendix A. Sample Day Selection Algorithm

This section describes how the typical days were selected. Three parameters drive the selection process: coincidence, thermal demand and electrical demand. Instantaneous coincidence for the current time period is defined as the lower value when comparing electrical and thermal demand. The algorithm makes use of the sum of all instantaneous coincidence values in a day. While thermal and electrical demand values are expected indices for sample day selection, coincidence is not. This is done because coincidence of electrical and thermal demand is a deciding factor for micro cogeneration performance. This parameter determines the savings that can be gained via the combined production of heat and power. The following steps are repeated for every season.

Sequence	Description
Step 1	Calculate sum of all instantaneous values for each day for the three parameters mentioned: coincidence, thermal demand and electrical demand. This provides us with a total value for each parameter in each day of sample data.
Step 2	Calculate the mean of the total values for all days. This overall mean is calculated for all three parameters.
Step 3	Calculate relative deviation of total values for each day from the overall mean. Relative deviation for each day = (Day total − Overall mean)/(Overall mean) Again this is done for all three parameters.
Step 4	An error value is assigned to each day. This error is the sum of relative deviations for the three parameters.
Step 5	Pick the day with the least error value.

Appendix B. List of Symbols

Sets	
T	Set of all time periods $t \in T$
K	Set of all sample days $k \in K$
Parameters	
α_{gas}	Natural gas price (p/kWh)
α_{CO2}	Non-traded price of carbon (£/kg)
α_t^{imp}	Retail price of electricity (£/kWh)
α_{SUC}	Cold start-up cost of micro co-generation unit (£)
α_{SUH}	Hot standby cost of micro co-generation (kWh)
$\alpha_t^{wholesale}$	Wholesale price of electricity (p/kWh)
β_{mdt}	Minimum down time (five minute periods)
β_{mut}	Minimum up time (five minute periods)
β_{rmp}	Ramping limit (kW)
β_{tdr}	Turn down ratio
η_B	Efficiency of natural gas boiler
η_{ch}	Charging efficiency of thermal energy storage
η_{disch}	Discharging efficiency of thermal energy storage
η_{el}	Electrical efficiency of CHP unit
η_{th}	Thermal efficiency of CHP unit
Ψ	Upfront cost of heating technology (£)
$\overline{B}$	Capacity of natural gas boiler (kW)
D_t^{el}	Electricity demand in the heating system model (kW)
D_t^{th}	Thermal demand in the heating system model (kW)
L	Lifetime of heating technology (years)
$\overline{P^{el}}$	Electrical capacity of CHP unit (kW)
r	Discount rate (%)
$\overline{S}$	Capacity of thermal energy storage (kWh)
T_{end}	End of the planning horizon for the heating system model
w_k	Weight of sample day k
Binary variables	
φ_t^+	Charging mode indicator for thermal energy storage
φ_t^-	Discharging mode indicator for thermal energy storage
φ_t^A	Active indicator for micro co-generation unit
φ_t^{SD}	Shut down indicator for micro co-generation unit
φ_t^{SU}	Start-up indicator for micro co-generation unit
Continuous variables	
B_t	Thermal output of the boiler in period t (kWh)
C	Equivalent Annual Cost of heating technology (£)
E_t	Export revenue generated by the heating system (£)
O_t	Operating cost of the heating system (£)
P_t^{exp}	Electricity exported by CHP unit in period t (kW)
P_t^{el}	Electricity generated by the CHP unit (kW)
P_t^{imp}	Electricity imported in period t (kW)
P_t^{th}	Thermal output of CHP unit in period t (kW)
Q	Objective function in the heating system (£)
R_t^+	Charging of thermal energy storage (kW)
R_t^-	Discharge from thermal energy storage (kW)
S_t	Storage level in the thermal energy storage (kWh)

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