ARTICLE IN PRESS

INTERNATIONAL JOURNAL OF HYDROGEN ENERGY XXX (XXXX) XXX

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/he

Probabilistic modelling of seasonal energy demand patterns in the transition from natural gas to hydrogen for an urban energy district

Massimiliano Manfren, Karla M. Gonzalez-Carreon, AbuBakr S. Bahaj*

Energy & Climate Change Division, Sustainable Energy Research Group, School of Engineering, University of Southampton, Boldrewood Campus, Southampton, SO16 7QF, United Kingdom

HIGHLIGHTS

- Hydrogen role in the transition to low carbon energy systems for urban energy district.
- Data-driven urban energy modelling using regression-based approaches.
- Probabilistic modelling of energy demand in terms of electricity and fuels.
- Climate change impact and energy efficiency measures accounting.
- Seasonal variations of energy demand patterns from short-term to long-term scenarios.

ARTICLE INFO

Article history:
Received 31 March 2023
Received in revised form
25 May 2023
Accepted 30 May 2023
Available online xxx

Keywords:
Energy transition
Hydrogen
Urban energy modelling
Data-driven methods
Regression-based approaches
Probabilistic modelling

ABSTRACT

The transition to a low-carbon energy system can be depicted as a "great reconfiguration" from a socio-technical perspective that carries the risk of impact shifts. Electrification with the objective of achieving rapidly deep decarbonisation must be accompanied by effective efficiency and flexibility measures. Hydrogen can be a preferred option in the decarbonisation process where electrification of end-uses is difficult or impractical as well as for long-term storage in energy infrastructure characterised by a large penetration of renewable energy sources. Notwithstanding the current uncertainties regarding costs, environmental impact and the inherent difficulties of increasing rapidly supply capacity, hydrogen can represent a solution to be used in multi-energy systems with combined heat and power (CHP), in particular in urban energy districts. In fact, while achieving carbon savings with natural gas fuelled CHP is not possible when low grid carbon intensity factors are present, it may still be possible to use it to provide flexibility services and to reduce emissions further with switch from natural gas to hydrogen. In this paper, a commercially established urban district energy scheme located in Southampton (United Kingdom) is analysed with the goal of exploring potential variations in its energy demand. The study proposes the use of scalable data-driven methods and probabilistic simulation to generate seasonal energy demand patterns representing the potential short-term and long-term evolution of the energy district.

* *Corresponding author.*
E-mail address: M.Manfren@soton.ac.uk (M. Manfren).

https://doi.org/10.1016/j.ijhydene.2023.05.337

Please cite this article as: Manfren M et al., Probabilistic modelling of seasonal energy demand patterns in the transition from natural gas to hydrogen for an urban energy district, International Journal of Hydrogen Energy, https://doi.org/10.1016/j.ijhydene.2023.05.337

Introduction

The acceleration of change and innovation in socio-technical systems [1] towards low carbon emission can be described as a great reconfiguration [2] that carries with it the risk of shifts of impacts, when multiple systems are interacting. An example in this sense is electrification of multiple sectors of the economy with the goal of deep decarbonisation, in countries which have low grid carbon intensity factors. In the absence of adequate efficiency [3] and flexibility measures [4], a "naive" electrification process could require enormous investments in renewables and seasonal storage capacity [5] in order to meet the massive demand increase caused by the conversion from fossil fuels to electricity. Further, a rapid and large increase of the cost of electricity at national scale would clearly conflict with the idea of "just" transition [6] and generate social tensions which could exacerbate other conflicts between at the economic level happening in low-carbon reorientation processes [7].

In this framework hydrogen represent an opportunity, in combination with electrification, renewables and energy efficiency and flexibility measures already mentioned, to create effective decarbonisation pathways without exacerbating tensions and conflicts. Depending on the way it is produced [8], hydrogen can provide different environmental benefits [9] or drawbacks; techniques such as knowledge maps can help in the conceptualization [10] of its role also in economic terms [11], with the scope of orienting policies and investments (ideally following a coherent roadmap). Among the different "colors" of hydrogen [9], "blue" and "green" ones seem at present the one that are more likely to have a large scale uptake in the future [12]. However, as discussed before, the acceleration of change poses relevant questions regarding sourcing of hydrogen across different sectors of the economy [13] and the possibility to expand the capacity rapidly enough to cope with the sharply increasing demand [14], acknowledging the necessity of enabling market mechanisms and the dependence on technologies like electrolyzers [15] for green hydrogen.

Going back the problem of the switch from fossil fuels to electricity, hydrogen represents a privileged option where electrification of end-uses is difficult or even impractical, such as in heavy-duty transportation [16] and maritime sector [17], as well as for long-term storage [18], notwithstanding current limitations. With respect to the latter aspect, nowadays, pumped hydro is the most widely employed technology for long-term storage; nevertheless, its use is restricted by country-specific characteristics. In relation to electric grid operation, while there are increasingly competitive choices for short-term storage (to cope with intra-daily to weekly, day-to-day) and flexibility, there is little to no alternative (other than pumped hydro, previously mentioned) to hydrogen for long-term energy storage in particular. Hydrogen might be a scalable option for the evolution of integrated energy systems [19] with significant implications for the achievement of sustainable development goals (SDGs) at global scale [20]. Despite this potential, there are still considerable uncertainties regarding the costs and environmental impact of blue hydrogen [21] produced from fossil fuels using carbon capture and sequestration (CCS), which would require large scale projects [22]. Moreover, the economic competitiveness of green hydrogen depends on the dynamics of electricity costs in scenarios with a significant proportion of renewables [18].

All the uncertainties inherent to technical aspects mentioned above can become barriers to technological change when seen from a "bottom-up" perspective and they could undermine the acceleration of decarbonisation process. In this paper, a commercially established city centre district energy scheme located in Southampton, UK, is analysed with the scope of identifying variations in seasonal energy demand patterns in its potential short-term to long-term evolution, considering the impact of climate-change, efficiency measures and switch from fossil fuels to hydrogen and/or electrification. The goal of the research is investigating whether the seasonal energy demand patterns may become an issues in the transition of the district towards low carbon targets, due to supply constraints, and what is the magnitude of the technological change required. The combination of seasonal, weekly (day-to-day) and intra-day variability has to be carefully considered in the process of electrification for the design of short-term storage and flexibility measures together with long-term storage (in a long-term perspective) and efficiency measures, aimed at reducing the overall energy consumption. This study proposes the use of scalable and interpretable data-driven methods [23] and probabilistic simulation, used here for an exploratory analysis of seasonal profile evolution, which could continue further with the inclusion of dynamic hourly and sub-hourly data. The rationale behind the choice of the methodology is illustrated in Literature review and then synthesized in its fundamental aspects in Methodology.

Literature review

As described in the introduction, in the acceleration of technological changes towards low carbon emission target, there are little to no alternatives to hydrogen for long-term storage of energy [24] and for end-uses where electrification is impractical. Making hydrogen carriers work synergistically with renewable energy sources (RES) is a great challenge and emerging paradigms such as Power to Gas [19], Power to Hydrogen [25] and Power to X [26] are proposing potential solutions in this direction, considering the issue of sourcing for different sector of the economy.

Yet, there are inherent concerns in terms of environmental impact and costs that may create significant barriers to innovation and new investments when seen from a bottom-up perspective, such as in the case of the urban energy district chosen as case study. In the research of solutions for the evolution of the energy district towards low carbon target, a techno-economic modelling approach weighting costs and environmental performance may be. However, the uncertainties related to the cost of blue and green hydrogen in the UK context at this stage make it difficult to provide a definitive response. In addition, at the urban scale, the interaction between efficiency [3] and flexibility measures [4] and the concurrent impact of climate change increase uncertainty (and consequently investment risks) even more. Thus, the fundamental objective of this study is an exploratory

Please cite this article as: Manfren M et al., Probabilistic modelling of seasonal energy demand patterns in the transition from natural gas to hydrogen for an urban energy district, International Journal of Hydrogen Energy, https://doi.org/10.1016/j.ijhydene.2023.05.337

investigation based on the quantification of the probable seasonal demand pattern variations in short and long-term perspectives.

In order to give a framework for the analysis in this study, the Southampton urban energy district is a multi-energy system which could benefit from the use of hydrogen for its combined heat and power (CHP) system as a replacement of natural gas, supporting in the long-term also seasonal energy storage strategies [27]. At present, the research for the application of hydrogen solutions at local scale, in particular in off-grid and island systems [28] characterised by high penetration of RES [29] is evolving quite rapidly, while national scale policies and solutions [30] are in many cases unclear. In the UK context, the interdependency of electricity and gas network operation from an adequacy and security perspective has been investigated by Antenucci and Sansavini [31] indicating contingencies that can jeopardize security, while distributed power-to-gas options have been explored by De Corato et al. [32], showing how they can contribute to aggregated flexibility in a substantial way. At present, the use of hydrogen in gas distribution grids [33], in percentages up to maximum of around 20%, is a largely debated solution in the UK and many other countries.

On the other hand, the large scale deployment of a carbon capture and sequestration (CCS) infrastructure to support blue hydrogen uptake is debated as well, in relation to costs [22], but also in relation to the actual environmental impact, notwistanding the moot question of indirect emissions from natural gas leakage [34], which are seldom considered. Additionally, the rapid evolution of the carbon intensity of the UK electric systems implies a complete reconsideration of the role of hydrogen technologies, even of the higher efficiency ones such as fuel cells [35]; in particular hydrogen for space-heating is deemed not competitive by multiple studies, synthesized by Rosenow [36], even considering multiple criteria in the evaluation. This lack of competitiveness does not undermine its application in situations with specific technological constraints and in niche applications [37,38] but, in general, electrification of heating with heat pumps (HP) seems the most viable option at least for countries where the carbon intensity of the grid is low and decreasing in time due to the installation of RES capacity. Nonetheless, energy districts and multi-energy systems [39], designed to provide energy services in systems characterised by multiple carriers/commodities in an optimised ways [40], are normally characterised by the presence of natural gas fuelled CHP at present. Evidence of the role CHP in the different UK geographic areas and sectors and can be found in recent statistics [41], which indicate also the average capacity factors [42]. Natural gas fuelled CHP operation in conditions with high prices of gas and low carbon emissions for the grid is suboptimal, in the sense that it does not deliver carbon saving and may be not very competitive in economic terms, but it can still be relevant to enhance grid flexibility, as discussed by Ahn et al. [43] and D'Ettorre et al. [4], and is “de facto” a critical assets in cities [44] which can shape the development of low carbon infrastructures at urban scale [45], ideally switch to hydrogen where possible. Hydrogen fuelled CHP can use consolidated technologies such as reciprocating engines (internal combustion engines, ICE) [46] in the short-term, or more sophisticated options such as fuel cells [47], which will assume more and more importance in future decarbonisation pathways [48]. The peculiar aspects of fuel cell technologies are illustrated by Sharaf and Orhan [49], while recent development are reviewed by Fan et al. [50], indicating how ICE can use hydrogen for stationary applications such as CHP and why fuel cells offer better performance. Indeed, the development of fuel cells is crucial to accelerate the decarbonisation process [51] and it is clearly connected to issue of a rapid deployment of hydrogen infrastructures [52] with adequate storage capability to foster the penetration of RES [53].

Going back to the problem of designing and operating CHP systems, indications are given in the best practices for selecting, installing and operating CHP in buildings [54] by CIBSE, as well as in the more recent Code of Practice for the UK heat networks, published by the same institution [55]. In the latter, the importance of energy performance benchmarking is stressed. Indeed, energy benchmarking is relevant from both a bottom-up [56] and top-down [57] perspective. As part of the benchmarking process, normalisation with respect to weather and specific operational conditions is crucial (i.e. providing a normalised metered energy consumption) and a consolidated approach is the one based on variable-base degree-days (VB-DD) regression algorithms (frequently referred to as change-point methods), originally proposed by Kissock et al. in the Inverse Modeling Tool (IMT) [58], which have been included in ASHRAE 14:2014 [59] and has been steadily evolving over time with the introduction of algorithmic techniques for the selection of base temperatures [60], the grid search of optimal models [61] and the use of dummy variables and energy signatures [23]. This regression-based approaches are effective with monthly and daily data, their applicability can be extended to more detailed time series data, on the order of hours and minutes leading to Advanced Measurement and Verification (M&V) or M&V 2.0 [62,63]. M&V techniques can provide solid basis for energy benchmarking, but their application is not limited to this specific field. There is actually evidence that variable-base degree-days regression algorithms methods are versatile enough to be used for a variety of purposes throughout the building life cycle [64]. The analytics generated by models fitted on measured data can be used for multiple applications in the built environment [65], where spatial and temporal scalability (monthly, daily, hourly, sub-hourly interval data) is crucial to overcome practical problems by learning case specific insights. In general, a variable-base heating and cooling degree-days evolution can help us track the effect of climate-change [66], while retaining intrinsic (or ante-hoc) “interpretability” (i.e. the possibility for a data-driven model to be easily understood in human terms and verified) [23], as opposed to post-hoc “interpretability” [67]. Additionally, in terms of large scale applications of regression-based and time series approaches (using VB-DD), Petkov and Gabrielli conducted an analysis focused on low carbon multi-energy systems [27], other studies at utility [68,69] and urban scale [70,71] share similar modelling principles. Moving to small scale problems, it is possible to find applications focused on deep energy retrofit of buildings [72] as well, with applicability that can be extended from buildings to districts [73]. Finally, regression-based approaches can be used also to support the calibration of more detailed building energy simulation models, discussed in a systematic review by Chong et al. [74].

Methodology

Literature review reveals that regression and time series techniques leveraging variable-base degree-days (VB-DD) can be applied to a variety of issues, ranging from large scale to small scale studies. In this study we adopt a "bottom-up" perspective, given the characteristics of the case study, an urban energy district. In the attempt to mitigate the risks inherent to "acceleration challenges" in decarbonisation [1], regarding in particular the switch from natural gas to electricity, part of the research focuses on the definition and use of a scalable modelling approach that could, in principle, enable the identification of solutions that are coherent and consistent across multiple temporal and spatial scales of analysis, for the reasons mentioned in Literature review. The methodology proposed articulates therefore in three fundamental steps.

- Pre-processing of weather data, in particular outdoor air temperatures using measured data (for model parameter identification, under uncertainty) and typical reference year (TRY) climate data files for simulation in present state conditions and in probabilistic climate change scenarios.
- Identification of piece-wise linear model parameters (i.e. slope, intercept and change-point, which represent the balance-point temperature for the calculation of variable-base degree days) and other parameters used in the computation for the baseline configuration (i.e. operation of the district in present state conditions).
- Probabilistic simulation by applying probability distributions to the piece-wise linear model parameters and summarizing the results with descriptive statistics (min, average, median, max).

Throughout the research, the generated statistics are compared to the baseline assumptions in order to detect changes, particularly in regard to seasonal energy demand patterns and overall evolution of energy consumption in the district. In addition to the availability of baseline data for the district, the availability of future meteorological information to model the impact of climate change is a crucial feature of the research process. In the UK, the climate-change impact at present [75] and the risks projected [76] are of interest for multiple institutions and CIBSE created standard weather data files from UKCP18 data, with different scenarios (low, medium, high) and probabilities (10th, 50th and 90th percentile), for 2020, 2050 and 2080. In this study, we use 2020 high and 2050 medium and high scenario to simulate respectively the short-term and long-term evolution of climate-change and quantify its impact in terms of seasonal demand patterns variability.

A series of assumptions were introduced during the creation of the model, including no further capacity increase (the size of the district remains unchanged), light to moderate efficiency measures in end-uses (no radical refurbishment and investment on efficiency), and no additional electric demand resulting from mobility. The choice of constraining the creation of probabilistic scenarios is based on the idea of highlighting the energy demand pattern change that can happen even without disruptive changes for the districts. The characteristics of the probabilistic simulation runs are summarised below in Table 1.

As explained before, the calculation of energy demand patterns relies on piecewise linear energy signature models derived by ASHRAE 14:2014 [59] and reformulated with the use of dummy variables [23,77]. In Table 2 the models are put in relation to the component of the energy balance of the district to which they refer; additional model parameters are then introduced to account for efficiencies and conversion losses within the energy district scheme and to be able to model the presence of multiple energy carriers/commodities [40].

In particular, heating demand model is a 3 parameter one (3-P), characterised by a base-load constant term and a temperature dependent term. The cooling demand model is a 3 parameter (3-P) one as well, where the constant term represents the base cooling load, which is assumed to be supplied by absorption chillers fed by CHP thermal energy (details are reported in Case study description), while the temperature dependent load is served by electric vapour compression chillers (details are reported in Case study description) which are fed by electricity, determining a 2-P cooling model for this component of the electricity demand. Therefore, the total electricity demand is a 5 parameter one (5-P) as it is composed by 2-P and 3-P individual models. The case study data used for the calibration of the baseline energy models are reported in Case study description and the graphical representation of regression models is reported in Results and discussion.

Case study description

The Southampton District Energy Scheme (Southampton Geothermal Heating Company, SGHC) is one of the oldest and largest commercially established city centre district energy schemes in the United Kingdom. In the early 1980s, as part of the urban scale planning to become energy self-sufficient, the council employed a Department of Energy-commissioned geothermal borehole to assess the viability of geothermal heating in the United Kingdom. At that point, the Department of Energy opted not to proceed, due to insufficient resources.

However, Southampton made the decision to proceed with the construction of a district heating system, and in 1986, the scheme began supplying heat from the geothermal borehole to the district heating network. Combined heat and power (CHP) engines and back-up boilers fuelled by natural gas have been added to the primary heat station throughout the years, along with absorption chillers and back-up electric vapour compression machines for cooling (to deal with cooling peaks in particular). Therefore, it provides heating and cooling to a multiplicity of customers, such as residences (apartments and student housing), large office buildings, a large shopping centre with multiple outlets and department stores, a supermarket, hotels, BBC television studios, a swimming and diving complex, and the main police station of the city, among others.

The important phases of the evolution of the district energy plan are documented by Gearty et al. [78] and some additional technical details are provided an IEA report of

Table 1 – Probabilistic energy model assumptions and simulation runs.

Probabilistic simulation run	Description	Climate data	Energy model	Assumptions
1	Baseline – present state	Baseline climate data file.	Energy district technologies	Present state condition of energy district technologies.
			End-use efficiency	No efficiency measure (present state).
2	Short-term evolution	Climate data file UKCP18, high climate change scenario 2020.	Energy district technologies	Present state condition of energy district technologies.
			End-use efficiency	Moderate energy efficiency measures for heating and cooling systems. Moderate efficiency measures for electricity demand not related to cooling.
3	Long-term evolution	Climate data file UKCP18, medium and high climate change scenarios 2050.	Energy district technologies	More efficient CHP option (fuel cell technology), same capacity as in present state condition.
			End-use efficiency	More substantial efficiency measures for heating and cooling systems. Moderate efficiency measures for electricity demand not related to cooling.
4	Long-term evolution	Climate data file UKCP18, medium and high climate change scenario 2050.	Energy district technologies	More efficient CHP option (fuel cell technology), same capacity as in present state condition. Electrification of temperature dependent heating demand with HP (base load covered by CHP) associated with a reduction of supply temperatures for the DH network.
			End-use efficiency	More substantial efficiency measures for heating and cooling systems. Moderate efficiency measures for electricity demand not related to cooling.
5	Long-term evolution	Climate data file UKCP18, medium and high climate change scenario 2050.	Energy district technologies	Complete electrification, electricity from grid for all end-uses, heating demand supplied by HP, cooling by compression chillers.
			End-use efficiency	More substantial efficiency measures for heating and cooling systems. Moderate efficiency measures for electricity demand not related to cooling.

Table 2 – Energy model composition.

Energy	Component	Model type
Thermal	Heating	3-P regression
	Cooling	3-P regression
Electricity	Base load	3-P regression
	Heating	3-P regression
	Cooling	2-P regression
	Total	5-P regression
Fuel	Natural gas/fuel energy	3-P regression

Urban Community Heating and Cooling [79]; a summary of installed capacity by technology is provided in Table 3, while a summary of energy data is reported in Table 4. This information is used, together with other contextual data to develop the regression models introduced in Methodology and reported in Table 2. The models are depicted graphically in Results and discussion.

For the sake of probabilistic modelling, short-term and long-term simulations assume a reduction of the temperature-dependent component of heating energy demand (slope of energy signature model) in the range 5–25% (simulation run 2, Table 1) and 25–40% (simulation runs 3–5, Table 1). Similarly, for probabilistic cooling demand, a decrease of the temperature-dependent portion (slope of energy signature) is considered to be in the range 5–20% for short-term scenarios and 25–30% for long-term scenarios. Finally, a short-term 5–10% reduction and a long-term 10–20% reduction in non-cooling-related electricity demand have been considered. As stated in Table 1, the efficiency measures considered in each case are moderate and quite reasonable, even when contemplating non-radical building interventions and relatively limited investments. Higher percentages of reduction of energy demand due to more radical energy efficiency measures are possible, but not considered at this stage. In addition, the efficiency of combined heat and power (CHP) technologies is based on data from literature and technical datasheets and compared to statistical data for CHP plants operating in the United Kingdom with similar characteristics [42]. Finally, the performance of heat pumps (HP) in the district heating system is computed using a simplified method assuming a COP in the range of 2.6–2.9. For all these model parameters, triangular probability distributions have been considered, defined by the minimum, most likely and maximum value respectively which are in most of the cases symmetric.

Results and discussion

In this section, the findings of probabilistic energy modelling for the Southampton district scheme are presented, starting from the probabilistic calculation of energy demand (Probabilistic energy simulation model assembly), with the intent of highlighting potential seasonal pattern changes (Seasonal energy demand patterns evolution) and the variability in terms of absolute quantities of electricity and fuel energy consumption (Overall energy demand evolution). The latter is especially important because it is currently dominated by natural gas, which may be replaced in the short-term by a mixture of natural gas and hydrogen (or other low carbon fuels), and in the long-term by pure hydrogen (or other low carbon fuels) if the CHP system remains economically viable. In Limitations and further research, limitations and future work are described in relation to the results, which provide an exploratory investigation of the possible evolution paths of the district towards low carbon targets and may be considered as a starting point for further investigation.

Probabilistic energy simulation model assembly

The primary objective of this research is to simulate the evolution, from short-term to long-term scenarios outlined in Table 1, of seasonal energy demand patterns for the energy district. Following the methodology described in Methodology, probabilistic energy signatures were utilised as a starting point to compute the seasonality of energy demand patterns, which are reported in Seasonal energy demand patterns evolution and subsequently aggregated in Overall energy demand evolution. Energy signature is used because it represents the average power over the number of operating hours in the interval under consideration. This allows for the approximate verification of the peak loads for heating and cooling, represented by the value that is found at extremely low (winter) or high (summer) temperatures and should normally be less than the installed capacity, unless the system is undersized or has capacity constraints. Therefore, baseline energy signature models, whose formulation is briefly described in Table 2 and discussed in greater detail in Literature review, are calibrated based on the energy supply data for the district summarised in Table 4, taking into account the physical constraints imposed by the installed capacity as well, as reported in Table 3.

Table 3 – Summary data of the Southampton District Energy Scheme – Installed capacity of energy conversion technologies.

Technology	Energy input (fuel/source)	Energy output	Description	Capacity [MW]
CHP	Natural gas	Electricity Heating	Electric peak power output	6.7
Back-up boilers	Natural gas	Heating	Thermal peak power output	8
Geothermal well	Geothermal energy	Heating	Thermal peak power output	2
Biomass boilers	Biomass	Heating	Thermal peak power output	1
Absorption chiller	Heat (CHP)	Cooling	Cooling peak power output	2
Electric chiller	Electricity	Cooling	Cooling peak power output	13.1

Please cite this article as: Manfren M et al., Probabilistic modelling of seasonal energy demand patterns in the transition from natural gas to hydrogen for an urban energy district, International Journal of Hydrogen Energy, https://doi.org/10.1016/j.ijhydene.2023.05.337

Table 4 – Summary of energy supply data of the Southampton District Energy Scheme.

Energy distribution in the district	Energy supplied to the district	Quantity [GWh]
Electric grid	Electricity	26
District Heating	Heating energy	40
District Cooling	Cooling energy	8

Variations in the data can occur depending on the actual climate and operational conditions in each year, but they are assumed to be representative of an average performance in order to derive slope, intercept, and base load ranges for energy signature models, as shown at the top of Fig. 1.

Owing to the probabilistic characteristics of the calculated models, minimum, mean, and maximum values are presented (i.e. descriptive statistics of modelling results). The baseline model parameters (i.e., intercept, slope, and base load) are then adjusted to account for the (moderate) short-term and (more substantial) long-term impact of energy efficiency measures in the end-uses served by the energy district, as summarised in Table 1. This strategy has been practically evaluated in recent research projects focusing on deep building energy retrofits [72,80] and also in studies at urban scale [70,71].

As anticipated, no capacity expansion has been considered for the CHP unit, which maintains the same size across the

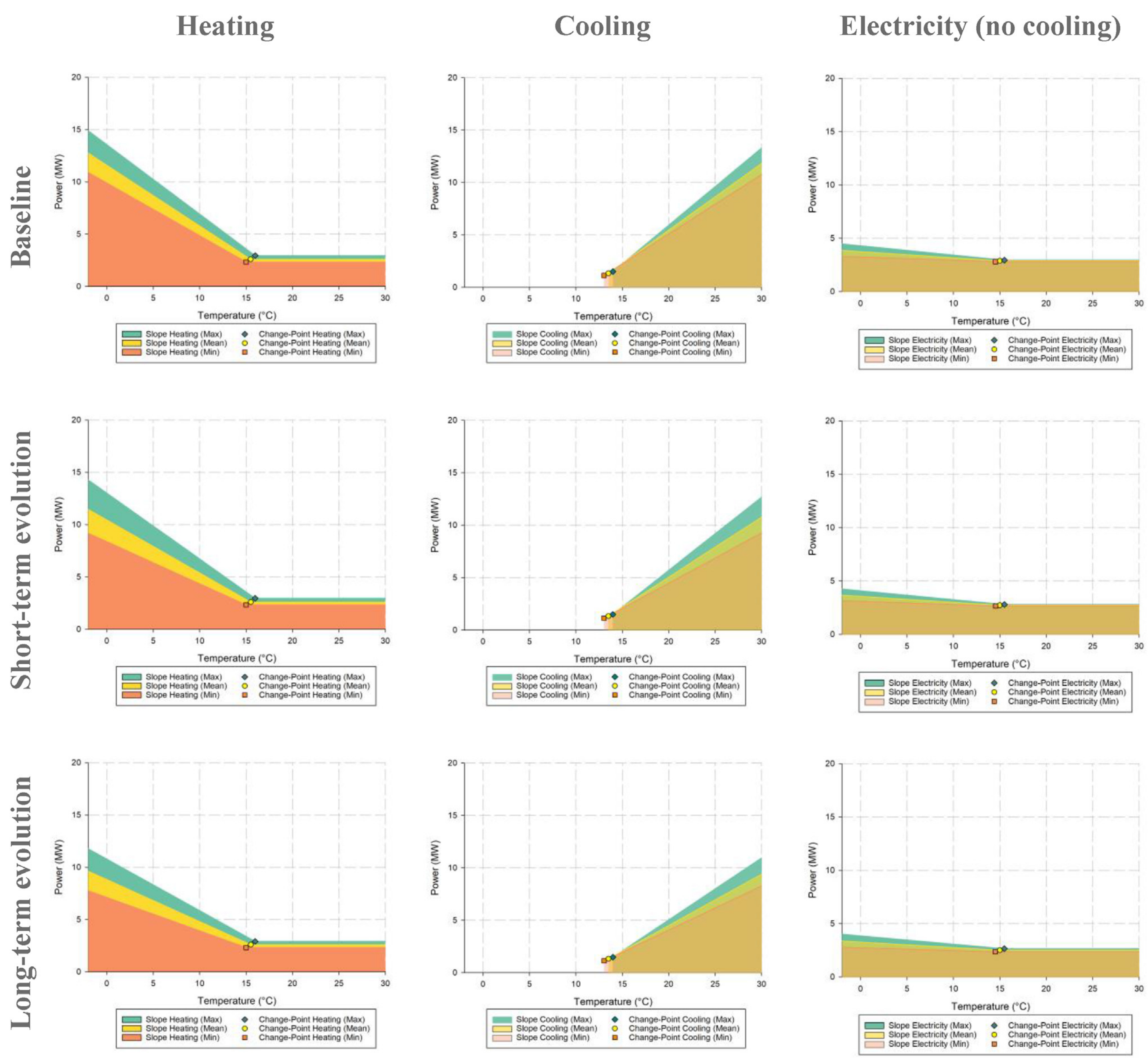

Fig. 1 – Energy signatures used for the probabilistic simulation of the energy demand patterns in the district.

Please cite this article as: Manfren M et al., Probabilistic modelling of seasonal energy demand patterns in the transition from natural gas to hydrogen for an urban energy district, International Journal of Hydrogen Energy, https://doi.org/10.1016/j.ijhydene.2023.05.337

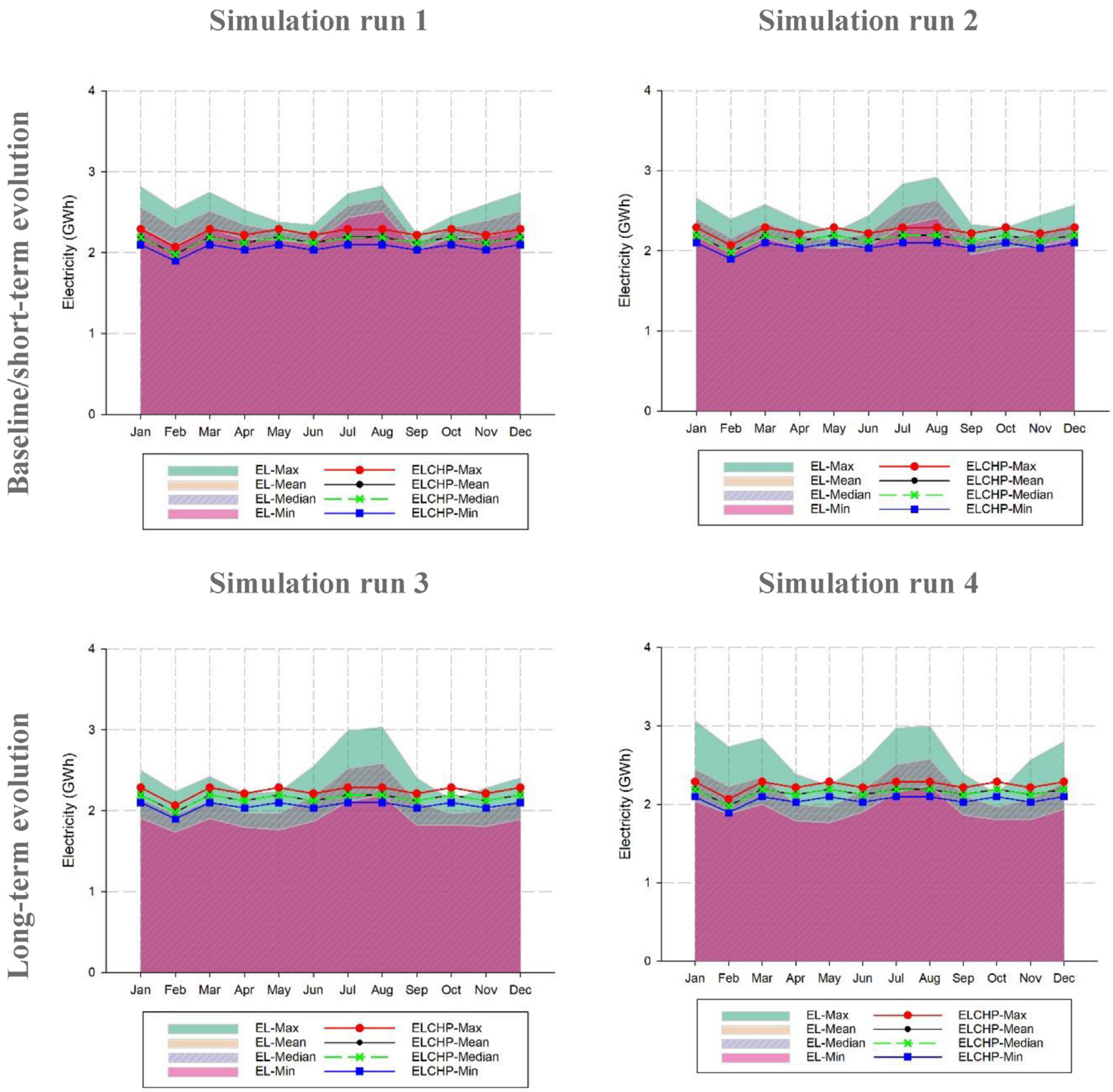

Fig. 2 – Electricity energy monthly demand patterns of the energy district, probabilistic simulation runs 1-4.

different evolution scenarios. However, the substantial reduction of slopes in the energy signature models for the long-term scenario can help reduce the installed peak heating and cooling capacity, which is insignificant for the short-term scenario. This issue may be particularly crucial in regard to the electrification problem, where the coincidence of loads may be detrimental to the grid during periods of peak electric demand. The electricity not related to cooling demand is modelled in a manner similar to thermal energy for heating and cooling in order to account, approximatively, for the modest rise in demand during the winter months, which corresponds to a decrease in daylight hours which, in turn, determines an increase of electricity for lighting uses. The quantities computed with the models displayed in Fig. 1 are then used to calculate the total electricity demand in the district, which is currently mostly met by the CHP, and the total fuel consumption, which is currently dominated by natural gas. The computation takes into account the conversion efficiencies and performance coefficients of the various

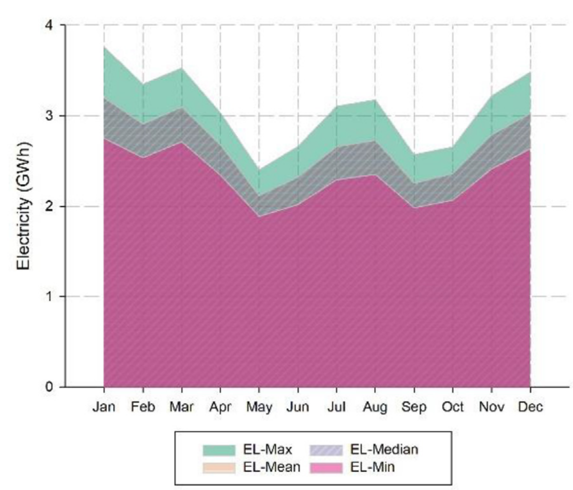

Fig. 3 – Electricity energy monthly demand patterns of the energy district, probabilistic simulation run 5 (complete electrification).

energy district technologies. The seasonality of the energy consumption trends of the district will be explored in Seasonal energy demand patterns evolution.

Seasonal energy demand patterns evolution

Electricity and fuel energy demand projections are the result of applying the probabilistic energy signature models depicted in Fig. 1 in conjunction with probabilistic climate data (outdoor air temperatures) and energy conversion efficiencies of district technologies, as indicated in Methodology. The results are reported hereafter, starting from electricity monthly demand patterns, in Fig. 2. In this figure, the total probabilistic quantity of electricity demand (EL-Max, EL-Mean, EL-Median, EL-Min) is reported together with the portion supplied by CHP (ELCHP-Max, ELCHP-Mean, ELCHP-Median, ELCHP-Min). In this manner, it is possible to identify graphically the electricity quantity supplied by the grid each month as the difference between the total quantity and the portion supplied by the CHP.

Notably, the probabilistic simulation outcomes are significantly symmetric with mean and median values that are almost identical. This is due the choice of triangular symmetric probability distributions for the input parameters in most of the cases, as described in Case study description. Simulation run 1 reveals moderate seasonal variations in electric energy demand throughout the year, slightly higher in winter and summer. In simulation run 2, the impact of climate change results in an increase in summer electricity demand (Fig. 2, top right), which is only partially reduced by energy efficiency measures. The seasonal changes highlighted by simulation run 2 are then amplified in simulation run 3 with increased summer electricity demand (Fig. 2, bottom left). In simulation run 4, back-up boilers are replaced with heat pumps and this increases the electrical demand during the winter season (Fig. 2, bottom right).

Finally, in simulation run 5, reported in Fig. 3, all the demands in the district (heating, cooling, electricity) are supplied by electricity using heat pumps and the geothermal well, with

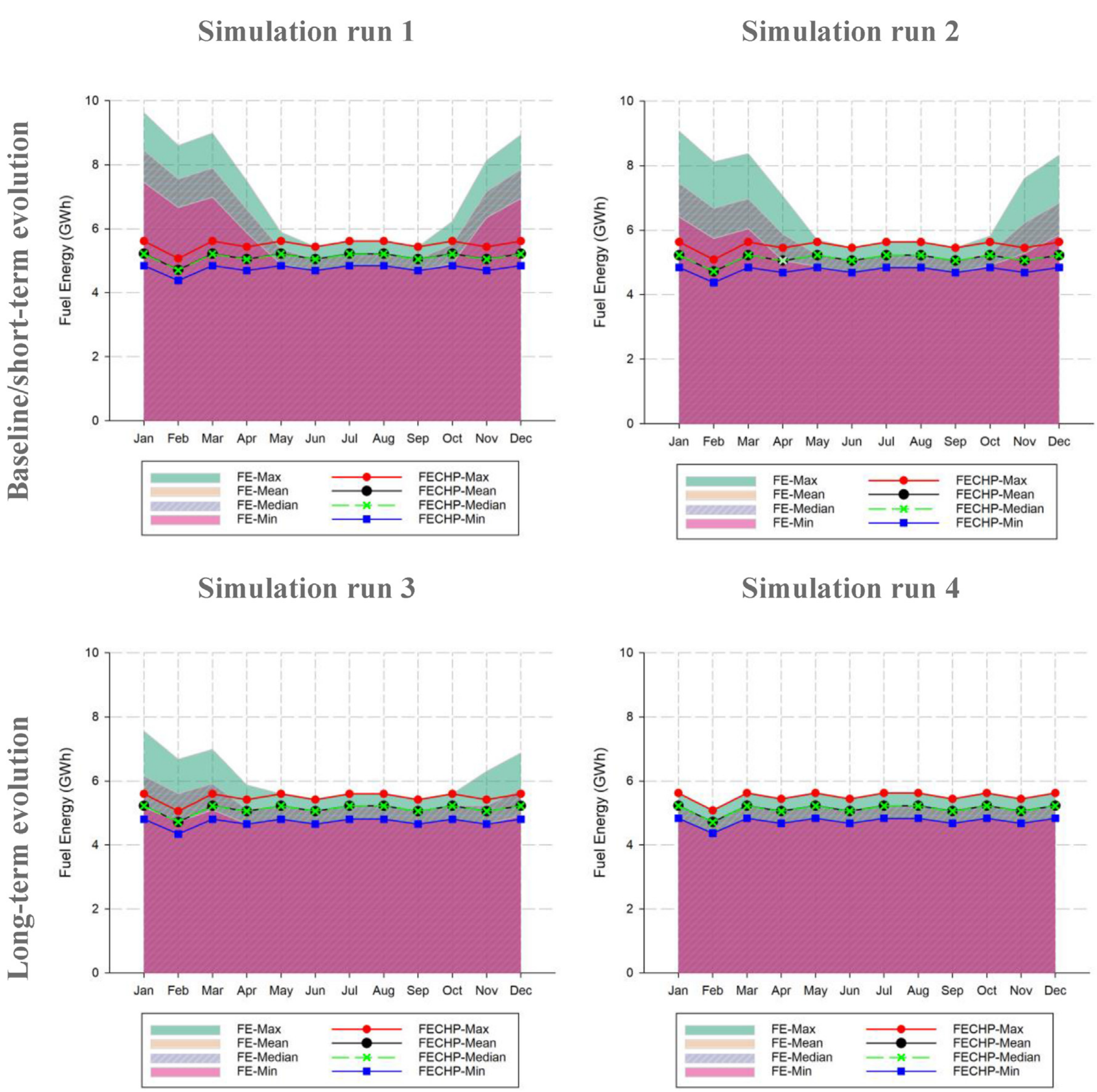

Fig. 4 – Fuel energy monthly demand patterns of the energy district, probabilistic simulation runs 1-4.

Please cite this article as: Manfren M et al., Probabilistic modelling of seasonal energy demand patterns in the transition from natural gas to hydrogen for an urban energy district, International Journal of Hydrogen Energy, https://doi.org/10.1016/j.ijhydene.2023.05.337

Table 5 – Summary statistics of parametric simulation results for electricity.

Probabilistic simulation run	Energy quantity	Minimum GWh	Mean GWh	Median GWh	Maximum GWh
1	EL	27.1	28.8	28.8	30.4
	EL-CHP	24.7	25.8	25.8	26.9
2	EL	25.5	27.5	27.5	29.2
	EL-CHP	24.7	25.8	25.8	27.0
3	EL	23.2	25.6	25.6	27.8
	EL-CHP	24.7	25.8	25.8	27.0
4	EL	24.4	26.7	26.7	29.3
	EL-CHP	24.7	25.8	25.8	27.0
5	EL	29.4	32.2	32.2	35.3

Table 6 – Summary statistics of parametric simulation results for fuel energy.

Probabilistic simulation run	Energy quantity	Minimum GWh	Mean GWh	Median GWh	Maximum GWh
1	FE	68.9	77.2	77.2	85.8
	FE-CHP	57.2	61.6	61.6	67.0
2	FE	63.0	71.2	71.0	78.7
	FE-CHP	56.4	61.4	61.4	66.1
3	FE	57.5	64.9	64.9	71.8
	FE-CHP	56.6	61.6	61.6	66.5
4	FE	56.4	61.5	61.4	65.9
	FE-CHP	56.4	61.5	61.4	65.9

electricity imported from the grid and abandoning the use of CHP (this implies no fuel demand). The effect of efficiency measures and climate change is sensible, with similar considerations to simulation runs 3 and 4, but the absence of the CHP (supplying both electricity and heat to the district in the other configurations) determines a profile with much higher demand values compared to runs 3 and 4 and a larger variability across the different periods of the year. The data plotted refer to monthly values but the presence of a strong dependence of load on outdoor air temperatures could create peak conditions in the grid that are much more pronounced than today, due to coincidence of electric loads in the intra-daily and weekly demand patterns.

Moving to the monthly fuel demand patterns, reported in Fig. 4, it is possible to see how for simulation run 1, on the upper left corner, heating demand results in a substantial rise in fuel demand during winter compared to summer months. In this instance, it is also possible to see that, nonetheless, the CHP fuel demand is the largest part. Then, in simulation run 2 (Fig. 4, top right), a slight decrease in winter fuel demand is shown, due to higher temperatures and moderate energy efficiency measures. After that, in simulation run 3 (Fig. 4, bottom left) the reduction of average temperatures in winter becomes even more evident than in simulation run 2, showing a further decrease of fuel demand in winter. Finally, in simulation run 4 (Fig. 4, bottom right) the remaining fuel demand is almost constant during the year and corresponds to the CHP fuel demand, to the use of heat pumps as a replacement for back-up natural gas boiler and biomass boilers. The aggregation of the results in terms of overall energy demand on yearly basis is discussed in Overall energy demand evolution.

Overall energy demand evolution

The aggregated data for the energy district are provided in Tables 5 and 6 for electricity and fuel use, respectively. Under the assumptions of simulation run 1 (probabilistic baseline configuration), the electricity demand of the district is nearly equal to the electricity supplied by the CHP, as can be seen in Fig. 2 on the upper left corner. Demand in winter and summer is slightly higher than during the intermediate seasons. Demand for fuel energy, reported in Fig. 4, is dominated by the natural gas combined heat and power plant, while the remainder is utilised to fuel back-up natural gas boilers and, to a lesser extent, biomass (Fig. 4, upper left). In this baseline configuration and all subsequent simulation runs, the geothermal well operates continuously as a base-load heat source.

In the short-term evolution scenario, which corresponds to simulation run 2, the overall quantity of electricity demand decreases slightly, but there is an increase in summer demand owing to climate change (Fig. 2, top right), which can be partially mitigated by cooling system efficiency enhancements. As a result of moderate efficiency improvements and climate change, there is a minor decrease in fuel energy (Fig. 4, top right). In this short-term scenario emission can be reduced for example by using a mixture of natural gas and hydrogen, but this intrinsically dependent upon the evolution of the gas infrastructure in that direction, as discussed in Literature review.

In simulation run 3, which aims to simulate a long-term evolution for the energy district while retaining its key energy conversion technologies (CHP, back-up boilers, etc.), efficiency improvements reduce the electricity consumption further compared to the baseline configuration (Fig. 2, bottom left). Climate change (with a substantial increase of average temperatures) and more considerable energy efficiency measures (even if not radical, as indicated in Case study description) diminish the need for fuel energy (Fig. 4, bottom left). In this instance, the heat supplied by back-up boilers is significantly less than in past scenarios, and CHP heat and geothermal wells can meet the majority of demand (the role of boilers becomes less relevant). Depending on future developments in this direction, CHP and back-up boilers can be fuelled by hydrogen or other low-carbon fuel choices to achieve a substantial reduction in carbon emissions compared to today. For example, biomass boilers can provide a low-carbon option to replace back-up boilers, given that the long-term projected demand is far less than it is currently, so the quantity of biomass needed may become relatively small. With fuel-cell technology, CHP would ideally have a greater electric conversion efficiency as well in the long-term.

Afterwards, simulation run 4 considers the use of heat pumps (with a decrease of supply temperature in the district heating network, which necessitates a future adaptation of the building systems as well in the direction of lower supply temperatures) to meet the remaining heat demand not met by CHP heat and geothermal well. Owing to the previously mentioned effects of efficiency measures and climate change, the additional electricity demand is very small in absolute terms, but exhibits a distinct seasonal variation, as depicted in Fig. 2 on the bottom right. Clearly, these seasonal variations would have a significant effect on the operation of the electric grid. Even under this configuration, the decrease in carbon emissions is substantial, given that the long-term emission factors for the electric grid will be lower than they are now due to the increased penetration of RES.

In simulation run 5, we evaluate the usage of the geothermal well in conjunction with the electrification of all heating and cooling technologies in the energy district without the use of CHP technology. Due to the effect of efficiency measures and climate change (already highlighted for simulation runs 3 and 4), the variation in absolute terms of electricity demand is relatively small compared to the baseline configuration in simulation run 1 (from a range estimated between 27.1 and 30.4 GWh in simulation run 1 to a range estimated between 29.4 and 35.4 GWh, in percentage 7–16%). In this instance, the absence of CHP electricity will clearly result in a significantly bigger import from the grid, as depicted in Fig. 3, referring to simulation run 5. Naturally, intra-daily and weekly changes in energy consumption patterns could result in load profiles with much more pronounced peak conditions than at present, which may be constrained by local grid capacity.

In conclusion, despite the fact that the aggregated quantities do not change significantly based on the underlying assumptions of probabilistic simulations, seasonal demand patterns vary significantly, as highlighted in Seasonal energy demand patterns evolution. If the use of hydrogen (or other low carbon fuels) in the CHP will not be economically viable in the near future, the shift of demand to the electric grid may be extremely relevant and clearly subject to restrictions imposed by the local grid capacity.

Limitations and further research

Using an approach that combines data-driven and physics-driven modelling, as explained in Methodology, the research in this paper consisted of an exploratory analysis intended to determine the possible paths of evolution of the energy district demand patterns in light of the low carbon target. Current limitations involve, in particular, the calibration of energy models on more detailed statistical data spanning multiple years and the inclusion of a much larger set of possible conditions for the probabilistic simulation of energy models, encompassing a more in-depth analysis of the potential for end-use efficiency (i.e. more radical efficiency measures). Due to the difficulty of providing reliable estimates at this stage, radical energy efficiency improvements in the built environment were excluded from this work.

In terms of future research, the simulation of seasonal energy demand patterns may be supplemented by an analysis of dynamic load profile data examining intra-daily and weekly variations and, in particular, the peak-to-average ratio, which could aid in the comprehension of the impact of winter and summer peak loads (i.e. critical conditions) on the electric grid at local scale. Furthermore, the future viability and economic competitiveness of hydrogen in the United Kingdom is intrinsically dependent on multiple factors, including the policies that will be adopted and the potential synergies and conflicts in the evolution of national energy infrastructures and global energy markets.

On the one hand, the lack of economic competitiveness of hydrogen and/or its non-effectiveness as a measures for carbon reduction (in the case of blue hydrogen with CCS) would necessitate the development of alternative solutions for the urban energy district considered in this research; on the other hand, the electrification of end-uses without adequate efficiency and flexibility measures could imply peak power demand curtailment. Future study on energy modelling for the city of Southampton will include these factors, to highlight bottlenecks and identify possible compromise solutions.

Conclusions

The need to accelerate the process of transition to low carbon target necessitates a substantial switch in consumption from fossil fuels to electricity, in energy systems where an increasing quota of it is generated from renewables sources, and to low carbon energy carriers such as green and blue hydrogen, which represent an emerging opportunity. The underlying technological change required, combined with the effect of climate change poses the problem of rethinking energy efficiency while addressing the inherent flexibility concerns, determined by the increased electrification of end-uses. In turn, this requires a better understanding of the potential future evolution of energy demand patterns in time, regarding in particular their seasonal variations and the intra-day and weekly variability, as they will be crucial to define solutions for long-term storage (where necessary) and measures for short-term storage and flexibility.

Please cite this article as: Manfren M et al., Probabilistic modelling of seasonal energy demand patterns in the transition from natural gas to hydrogen for an urban energy district, International Journal of Hydrogen Energy, https://doi.org/10.1016/j.ijhydene.2023.05.337

This study proposes the use of scalable data-driven methods and probabilistic simulation to generate seasonal energy demand patterns representing the potential short-term and long-term evolution for the Southampton District Energy Scheme, a commercially established city centre district energy scheme in the United Kingdom. The probabilistic scenarios presented were based on a series of assumptions, namely no further capacity expansion (the dimension of the district remains the same), light to moderate efficiency measures in end-uses (no radical transformation) and no additional electric load determined by mobility. Even under this relatively restrictive assumptions (clearly not exhaustive of the potential future developments of the district), which do not change largely the underlying energy quanties estimated on a yearly basis, the change of seasonal patterns appears to be significant in particular in a long-term perspective; this aspect will have to be considered in the design of future interventions for the district.

Current limitations of this study include the calibration of energy models on more extensive statistical data spanning multiple years and the inclusion of a considerably larger range of possible conditions for probabilistic simulation of energy models, including a deeper analysis of end-use efficiency, which was omitted at this stage due to the lack of detailed information. In future research, seasonal variations may be combined with dynamic (hourly, sub-hourly) load profiles data to analyse intra-daily and day-to-day variations and the peak-to-average ratio, in order to better understand the coincidence of loads in critical winter and summer conditions for the grid. The future viability, economic competitiveness and sustainability of hydrogen, given the uncertainties regarding costs (for both green and blue hydrogen) and actual carbon emission (for blue hydrogen specifically), represent at present important barriers to the bottom-up implementation of hydrogen based solutions at urban scale, even though alternative solutions such as the electrification of end-uses, without proper efficiency and flexibility measures, determines an sharp increase of the risk of power curtailment in critical conditions.

Fundings

This work is part of the activity of the Energy & Climate Change Division, Sustainable Energy Research Group (https://energy.soton.ac.uk/) at University of Southampton. The research was partially funded by the Southampton Marine and Maritime Institute (SMMI) HEIF research collaboration stimulus fund 2022-23 and is also part of the Sustainability Strategy 2020-2025 of University of Southampton (https://www.southampton.ac.uk/susdev/our-approach/sustainability-strategy.page).

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.

REFERENCES

[1] Markard J, Geels FW, Raven R. Challenges in the acceleration of sustainability transitions. Environ Res Lett 2020;15:81001. https://doi.org/10.1088/1748-9326/ab9468.

[2] Geels FW, Turnheim B. The great reconfiguration - a socio-technical analysis of low-carbon transitions in UK electricity, heat, and mobility systems. Cambridge University Press; 2022.

[3] Rosenow J, Eyre N. Reinventing energy efficiency for net zero. Energy Res Social Sci 2022;90:102602. https://doi.org/10.1016/j.erss.2022.102602.

[4] D'Ettorre F, Banaei M, Ebrahimy R, Pourmousavi SA, Blomgren EMV, Kowalski J, et al. Exploiting demand-side flexibility: state-of-the-art, open issues and social perspective. Renew Sustain Energy Rev 2022;165:112605. https://doi.org/10.1016/j.rser.2022.112605.

[5] Buonocore JJ, Salimifard P, Magavi Z, Allen JG. Inefficient building electrification will require massive buildout of renewable energy and seasonal energy storage. Sci Rep 2022;12:11931. https://doi.org/10.1038/s41598-022-15628-2.

[6] Newell PJ, Geels FW, Sovacool BK. Navigating tensions between rapid and just low-carbon transitions. Environ Res Lett 2022;17:41006. https://doi.org/10.1088/1748-9326/ac622a.

[7] Geels FW. Conflicts between economic and low-carbon reorientation processes: insights from a contextual analysis of evolving company strategies in the United Kingdom petrochemical industry (1970–2021). Energy Res Social Sci 2022;91:102729. https://doi.org/10.1016/j.erss.2022.102729.

[8] Ishaq H, Dincer I, Crawford C. A review on hydrogen production and utilization: challenges and opportunities. Int J Hydrogen Energy 2022;47:26238–64. https://doi.org/10.1016/j.ijhydene.2021.11.149.

[9] Ajanovic A, Sayer M, Haas R. The economics and the environmental benignity of different colors of hydrogen. Int J Hydrogen Energy 2022;47:24136–54. https://doi.org/10.1016/j.ijhydene.2022.02.094.

[10] Guevara-Ramírez W, Martínez-de-Alegría I, Río-Belver RM. Evolution of the conceptualization of hydrogen through knowledge maps, energy return on investment (EROI) and national policy strategies. Clean Technol Environ Policy 2023;25:69–91. https://doi.org/10.1007/s10098-022-02388-w.

[11] Kar SK, Harichandan S, Roy B. Bibliometric analysis of the research on hydrogen economy: an analysis of current findings and roadmap ahead. Int J Hydrogen Energy 2022;47:10803–24. https://doi.org/10.1016/j.ijhydene.2022.01.137.

[12] Lagioia G, Spinelli MP, Amicarelli V. Blue and green hydrogen energy to meet European Union decarbonisation objectives. An overview of perspectives and the current state of affairs. Int J Hydrogen Energy 2023;48:1304–22. https://doi.org/10.1016/j.ijhydene.2022.10.044.

[13] Frischmuth F, Härtel P. Hydrogen sourcing strategies and cross-sectoral flexibility trade-offs in net-neutral energy scenarios for Europe. Energy 2022;238:121598. https://doi.org/10.1016/j.energy.2021.121598.

[14] Odenweller A, Ueckerdt F, Nemet GF, Jensterle M, Luderer G. Probabilistic feasibility space of scaling up green hydrogen supply. Nat Energy 2022;7:854–65. https://doi.org/10.1038/s41560-022-01097-4.

[15] Wappler M, Unguder D, Lu X, Ohlmeyer H, Teschke H, Lueke W. Building the green hydrogen market – current state and outlook on green hydrogen demand and electrolyzer manufacturing. Int J Hydrogen Energy 2022;47:33551–70. https://doi.org/10.1016/j.ijhydene.2022.07.253.

[16] Camacho M de las N, Jurburg D, Tanco M. Hydrogen fuel cell heavy-duty trucks: review of main research topics. Int J Hydrogen Energy 2022;47:29505–25. https://doi.org/10.1016/j.ijhydene.2022.06.271.

[17] Di Micco S, Mastropasqua L, Cigolotti V, Minutillo M, Brouwer J. A framework for the replacement analysis of a hydrogen-based polymer electrolyte membrane fuel cell technology on board ships: a step towards decarbonization in the maritime sector. Energy Convers Manag 2022;267:115893. https://doi.org/10.1016/j.enconman.2022.115893.

[18] CEER. Long-term storage CEER "European green deal" white paper series (paper I) relevant to the European commission's hydrogen and energy system integration strategies. 2021.

[19] Nastasi B. Power to Gas and Hydrogen applications to energy systems at different scales – building, District and National level. Int J Hydrogen Energy 2019;44:9485. https://doi.org/10.1016/j.ijhydene.2019.02.197.

[20] Nastasi B, Markovska N, Puksec T, Duić N, Foley A. Techniques and technologies to board on the feasible renewable and sustainable energy systems. Renew Sustain Energy Rev 2023;182:113428. https://doi.org/10.1016/j.rser.2023.113428.

[21] Noussan M, Raimondi PP, Scita R, Hafner M. The role of green and blue hydrogen in the energy transition—a technological and geopolitical perspective. Sustainability 2021;13. https://doi.org/10.3390/su13010298.

[22] Antenucci A, Sansavini G. Extensive CO2 recycling in power systems via Power-to-Gas and network storage. Renew Sustain Energy Rev 2019;100:33–43.

[23] Manfren M, James PAB, Tronchin L. Data-driven building energy modelling – an analysis of the potential for generalisation through interpretable machine learning. Renew Sustain Energy Rev 2022;167:112686. https://doi.org/10.1016/j.rser.2022.112686.

[24] Blanco H, Faaij A. A review at the role of storage in energy systems with a focus on Power to Gas and long-term storage. Renew Sustain Energy Rev 2018;81:1049–86. https://doi.org/10.1016/j.rser.2017.07.062.

[25] Genovese M, Schlüter A, Scionti E, Piraino F, Corigliano O, Fragiacomo P. Power-to-hydrogen and hydrogen-to-X energy systems for the industry of the future in Europe. Int J Hydrogen Energy 2023. https://doi.org/10.1016/j.ijhydene.2023.01.194.

[26] Sorrenti I, Harild Rasmussen TB, You S, Wu Q. The role of power-to-X in hybrid renewable energy systems: a comprehensive review. Renew Sustain Energy Rev 2022;165:112380. https://doi.org/10.1016/j.rser.2022.112380.

[27] Petkov I, Gabrielli P. Power-to-hydrogen as seasonal energy storage: an uncertainty analysis for optimal design of low-carbon multi-energy systems. Appl Energy 2020;274:115197. https://doi.org/10.1016/j.apenergy.2020.115197.

[28] Nastasi B, Mazzoni S. Renewable Hydrogen Energy Communities layouts towards off-grid operation. Energy Convers Manag 2023;291:117293. https://doi.org/10.1016/j.enconman.2023.117293.

[29] Nastasi B, Mazzoni S, Groppi D, Romagnoli A, Astiaso Garcia D. Solar power-to-gas application to an island energy system. Renew Energy 2021;164:1005–16. https://doi.org/10.1016/j.renene.2020.10.055.

[30] Bellocchi S, Colbertaldo P, Manno M, Nastasi B. Assessing the effectiveness of hydrogen pathways: a techno-economic optimisation within an integrated energy system. Energy 2023;263:126017. https://doi.org/10.1016/j.energy.2022.126017.

[31] Antenucci A, Sansavini G. Adequacy and security analysis of interdependent electric and gas networks. Proc Inst Mech Eng O J Risk Reliab 2017;232:121–39. https://doi.org/10.1177/1748006X17715953.

[32] De Corato A, Saedi I, Riaz S, Mancarella P. Aggregated flexibility from multiple power-to-gas units in integrated electricity-gas-hydrogen distribution systems. Elec Power Syst Res 2022;212:108409. https://doi.org/10.1016/j.epsr.2022.108409.

[33] Giehl J, Hollnagel J, Müller-Kirchenbauer J. Assessment of using hydrogen in gas distribution grids. Int J Hydrogen Energy 2023. https://doi.org/10.1016/j.ijhydene.2023.01.060.

[34] Howarth RW, Jacobson MZ. How green is blue hydrogen? Energy Sci Eng 2021;9:1676–87. https://doi.org/10.1002/ese3.956.

[35] Staffell I. Zero carbon infinite COP heat from fuel cell CHP. Appl Energy 2015;147:373–85. https://doi.org/10.1016/j.apenergy.2015.02.089.

[36] Rosenow J. Is heating homes with hydrogen all but a pipe dream? An evidence review. Joule 2022;6:2225–8. https://doi.org/10.1016/j.joule.2022.08.015.

[37] Nastasi B. Renewable hydrogen potential for low-carbon retrofit of the building stocks. Energy Proc 2015;82:944–9. https://doi.org/10.1016/j.egypro.2015.11.847.

[38] Nastasi B, Di Matteo U. Innovative use of hydrogen in energy retrofitting of listed buildings. Energy Proc 2017;111:435–41. https://doi.org/10.1016/j.egypro.2017.03.205.

[39] Alabi TM, Agbajor FD, Yang Z, Lu L, Ogungbile AJ. Strategic potential of multi-energy system towards carbon neutrality: a forward-looking overview. Energy and Built Environment; 2022. https://doi.org/10.1016/j.enbenv.2022.06.007.

[40] Adhikari RS, Aste N, Manfren M. Multi-commodity network flow models for dynamic energy management – smart Grid applications. Energy Proc 2012;14:1374–9. https://doi.org/10.1016/j.egypro.2011.12.1104.

[41] Uk Beis, Energy Trends: September. Combined heat and power in the regions. 2022. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1107350/CHP_in_the_regions_2021.pdf. accessed 21/03/2023 n.d.

[42] Uk BEIS. Digest of UK energy statistics (DUKES). In: Chapter 7: statistics on the contribution made by Combined Heat and Power (CHP) to the UK's energy requirement; 2022. https://www.gov.uk/government/statistics/combined-heat-and-power-chapter-7-digest-of-united-kingdom.

[43] Ahn H, Miller W, Sheaffer P, Tutterow V, Rapp V. Opportunities for installed combined heat and power (CHP) to increase grid flexibility in the U.S. Energy Pol 2021;157:112485. https://doi.org/10.1016/j.enpol.2021.112485.

[44] Roberts S. Infrastructure challenges for the built environment. Energy Pol 2008;36:4563–7. https://doi.org/10.1016/j.enpol.2008.09.010.

[45] Bolton R, Foxon TJ. Urban infrastructure dynamics: market regulation and the shaping of district energy in UK cities. Environ Plann 2013;45:2194–211.

[46] Felseghi R-A, Carcadea E, Raboaca MS, Trufin CN, Filote C. Hydrogen fuel cell technology for the sustainable future of stationary applications. Energies 2019;12. https://doi.org/10.3390/en12234593.

[47] Cigolotti V, Genovese M, Fragiacomo P. Comprehensive review on fuel cell technology for stationary applications as sustainable and efficient poly-generation energy systems. Energies 2021;14. https://doi.org/10.3390/en14164963.

[48] Volkart K, Densing M, De Miglio R, Priem T, Pye S, Cox B. In: Welsch M, Pye S, Keles D, Faure-Schuyer A, Dobbins A, Shivakumar A, et al., editors. Chapter 23 - the role of fuel cells and hydrogen in stationary applications. Academic Press; 2017. p. 189–205. https://doi.org/10.1016/B978-0-12-809806-6.00023-7.

Please cite this article as: Manfren M et al., Probabilistic modelling of seasonal energy demand patterns in the transition from natural gas to hydrogen for an urban energy district, International Journal of Hydrogen Energy, https://doi.org/10.1016/j.ijhydene.2023.05.337

[49] Sharaf OZ, Orhan MF. An overview of fuel cell technology: fundamentals and applications. Renew Sustain Energy Rev 2014;32:810–53. https://doi.org/10.1016/j.rser.2014.01.012.
[50] Fan L, Tu Z, Chan SH. Recent development of hydrogen and fuel cell technologies: a review. Energy Rep 2021;7:8421–46. https://doi.org/10.1016/j.egyr.2021.08.003.
[51] Thomas JM, Edwards PP, Dobson PJ, Owen GP. Decarbonising energy: the developing international activity in hydrogen technologies and fuel cells. J Energy Chem 2020;51:405–15. https://doi.org/10.1016/j.jechem.2020.03.087.
[52] Wang Y, Pang Y, Xu H, Martinez A, Chen KS. PEM Fuel cell and electrolysis cell technologies and hydrogen infrastructure development – a review. Energy Environ Sci 2022;15:2288–328. https://doi.org/10.1039/D2EE00790H.
[53] Widera B. Renewable hydrogen implementations for combined energy storage, transportation and stationary applications. Therm Sci Eng Prog 2020;16:100460. https://doi.org/10.1016/j.tsep.2019.100460.
[54] CIBSE. GPG388 Good Practice Guide Combined heat and power for buildings - selecting, installing and operating CHP in buildings - a guide for building services engineers. 2004.
[55] CIBSE. Heat networks: Code of practice for the UK - CP1. 2020.
[56] Burman E, Hong S-M, Paterson G, Kimpian J, Mumovic D. A comparative study of benchmarking approaches for non-domestic buildings: Part 2 – bottom-up approach. International Journal of Sustainable Built Environment 2014;3:247–61. https://doi.org/10.1016/j.ijsbe.2014.12.001.
[57] Hong S-M, Paterson G, Burman E, Steadman P, Mumovic D. A comparative study of benchmarking approaches for non-domestic buildings: Part 1 – top-down approach. International Journal of Sustainable Built Environment 2013;2:119–30. https://doi.org/10.1016/j.ijsbe.2014.04.001.
[58] Kissock JK, Haberl JS, Claridge DE. Inverse modeling toolkit: numerical algorithms. Build Eng 2003;109:425.
[59] ASHRAE. ASHRAE guideline 14-2014: measurement of energy, demand, and water savings. Atlanta, GA, USA: American Society of Heating, Refrigerating and Air-Conditioning Engineers; 2014. 2014.
[60] Paulus MT, Claridge DE, Culp C. Algorithm for automating the selection of a temperature dependent change point model. Energy Build 2015;87:95–104. https://doi.org/10.1016/j.enbuild.2014.11.033.
[61] Song S, Park CG. Alternative algorithm for automatically driving best-fit building energy baseline models using a data—driven grid search. Sustainability 2019;11. https://doi.org/10.3390/su11246976.
[62] Franconi E, Gee M, Goldberg M, Granderson J, Guiterman T, Li M, et al. The status and promise of advanced M&V: an overview of “M&V 2.0” methods, tools, and applications. 2017.
[63] Gallagher CV, Leahy K, O'Donovan P, Bruton K, O'Sullivan DTJ. Development and application of a machine learning supported methodology for measurement and verification (M&V) 2.0. Energy Build 2018;167:8–22. https://doi.org/10.1016/j.enbuild.2018.02.023.
[64] Manfren M, Nastasi B, Tronchin L. Linking design and operation phase energy performance analysis through regression-based approaches. Front Energy Res 2020;8:288. https://doi.org/10.3389/fenrg.2020.557649.
[65] Manfren M, Sibilla M, Tronchin L. Energy modelling and analytics in the built environment—a review of their role for energy transitions in the construction sector. Energies 2021;14. https://doi.org/10.3390/en14030679.
[66] Spinoni J, Vogt JV, Barbosa P, Dosio A, McCormick N, Bigano A, et al. Changes of heating and cooling degree-days in Europe from 1981 to 2100. Int J Climatol 2018;38:e191–208. https://doi.org/10.1002/joc.5362.
[67] Chen Z, Xiao F, Guo F, Yan J. Interpretable machine learning for building energy management: a state-of-the-art review. Advances in Applied Energy 2023;9:100123. https://doi.org/10.1016/j.adapen.2023.100123.
[68] Acquaviva A, Apiletti D, Attanasio A, Baralis E, Bottaccioli L, Castagnetti FB, et al. Energy signature analysis: knowledge at your fingertips. In: Big data (BigData congress), 2015 IEEE international congress on. IEEE; 2015. p. 543–50.
[69] Oh S, Gardner JF. Large scale energy signature analysis: tools for utility managers and planners. Sustainability 2022;14. https://doi.org/10.3390/su14148649.
[70] Abdolhosseini Qomi MJ, Noshadravan A, Sobstyl JM, Toole J, Ferreira J, Pellenq RJ-MJ-MJ-MJ-MJ-M, et al. Data analytics for simplifying thermal efficiency planning in cities. J R Soc Interface 2016;13:20150971. https://doi.org/10.1098/rsif.2015.0971.
[71] Pasichnyi O, Wallin J, Kordas O. Data-driven building archetypes for urban building energy modelling. Energy 2019;181:360–77. https://doi.org/10.1016/j.energy.2019.04.197.
[72] Grillone B, Mor G, Danov S, Cipriano J, Sumper A. A data-driven methodology for enhanced measurement and verification of energy efficiency savings in commercial buildings. Appl Energy 2021;301:117502. https://doi.org/10.1016/j.apenergy.2021.117502.
[73] Adhikari RS, Aste N, Manfren M. Optimization concepts in district energy design and management – a case study. Energy Proc 2012;14:1386–91. https://doi.org/10.1016/j.egypro.2011.12.1106.
[74] Chong A, Gu Y, Jia H. Calibrating building energy simulation models: a review of the basics to guide future work. Energy Build 2021;253:111533. https://doi.org/10.1016/j.enbuild.2021.111533.
[75] Kendon M, McCarthy M, Jevrejeva S, Matthews A, Sparks T, Garforth J. State of the UK climate 2020. Int J Climatol 2021;41:1–76. https://doi.org/10.1002/joc.7285.
[76] Climate change committee independent assessment of UK climate risk. June 2021. https://www.theccc.org.uk/publication/independent-assessment-of-uk-climate-risk/.
[77] Hyndman RJ, Athanasopoulos G. Forecasting: principles and practice. OTexts; 2018.
[78] Gearty M, Clark B, Smith M. Southampton district energy scheme. VHS Workshop; 2008. p. 25.
[79] IEA-DHP. Urban community heating and cooling: the Southampton district energy scheme, International Energy Agency District Heating and Cooling Programme.
[80] Grillone B, Danov S, Sumper A, Cipriano J, Mor G. A review of deterministic and data-driven methods to quantify energy efficiency savings and to predict retrofitting scenarios in buildings. Renew Sustain Energy Rev 2020;131:110027. https://doi.org/10.1016/j.rser.2020.110027.