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Reliability of net-zero energy systems for South Wales

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Abstract

Wales is committed to meeting the Net-zero emissions target by 2050. To meet this challenge unprecedented changes in the energy system are required in South Wales. There are various pathways to achieve net-zero emissions in South Wales. These pathways are usually compared based on their costs. However, energy supply reliability assessment is required to determine the security of these scenario pathways. A probabilistic dynamic reliability assessment framework is proposed, which combines the Improved Universal Generating Function and the Improved Fisher optimal algorithm. This technique reduces the computational burden of reliability assessment by 95% with a similar accuracy compared with Monte Carlo Simulations. The impacts and sensitivities of energy sources and technologies on supply reliability in High Electrification and High Hydrogen scenarios are measured. As the penetration level of local renewables increases five-fold in 2050 compared with 2020, Loss of Load Expectation increases from 3 to 10~12 hours/year in High Electrification and High Hydrogen scenarios. In summer, the reliability of energy supply is more sensitive to changes in the assumptions on failure probabilities of energy conversion devices, whereas the system's reliability in winter is mainly impacted by the availability of imported energy to South Wales.

Keywords: Reliability assessment, Improved Universal Generating Function, Net-zero, Sensitivity analysis, Wales

Nomenclature			
Abbreviations		UGF	Universal Generating Function.
CCS	Carbon Capture and Sequestration.	Parameters	
DET	Dynamic Event Tree.	C_{ij}	Coupling coefficient between input energy i and output energy j (%).
EH	Energy Hub.	h	Bandwidth parameter in KDE.
KDE	Kernel Density Estimation.	$I^{\text{in}}, I^{\text{out}}$	Input and output carriers in Energy Hub.
HE	High Electrification.	l	Number of segments in Fisher method.
HH	High Hydrogen.	α	Percentage of renewable generation used for electricity supply.
HPG	Hydrogen-fired Power Generation.	$\varepsilon_E, \varepsilon_S, \varepsilon_H$	Efficiency of electrolysis, electrical storage and hydrogen-fired power generation plants (%).
IESs	Integrated Energy Systems.	Variables	
IF	Improved Fisher.	A_t, Psl_t	Amount of energy supply and the probability when the amount of energy supply is A_t at time t (MW).
MCS	Monte Carlo Simulation.	$p_{ij}(t)$	Probability that unit i stays at level j at time t .
MSS	Multi-State Systems.	$SR_t, SI_{E,t}, SH_t, BE_t$	Renewable generation, imported electricity, electricity generated from HPG and available electricity in storage at time t (MW).
NMCS	Non-sequential Monte Carlo Simulation.	SI_t, BG_t	Imported hydrogen and linepack at time t (MW).
PDFs	Probability Density Functions.	$\bar{s}_l$	Mean of l -th segment.
PMFs	Probability Mass Functions.	$x_{ij}(t)$	Performance of unit i at level j at time t .
P2G	Power to Gas.	$\overline{\Phi_E}, \overline{\Phi_G}$	Levels of sufficiency for electricity and hydrogen system (MW).
RGD	Renewable Generation Distribution.		

SMCS	Sequential Monte Carlo Simulation.
SMR	Steam Methane Reforming

1 Introduction

The United Kingdom (UK) government announced a net-zero emissions target to be achieved by 2050. Scotland and Wales have also set net-zero emission targets within their devolved administrations over the same time frame. South Wales region has the ambition to achieve this decarbonised vision through cost-effective and economically productive pathways [1].

To achieve the goal of net-zero greenhouse gas emissions, the deployment of available clean energy technologies, e.g. renewable sources, electrical vehicles, Carbon Capture and Sequestration (CCS) and hydrogen [2] and consumer behaviour change are required. Hydrogen if produced from fossil fuels through Steam Methane Reforming (SMR) with CCS or electrolysis (powered by renewables, nuclear, etc) can be considered as low or carbon free. Given possible divergent development of the energy system, two decarbonisation scenario pathways, High Hydrogen (HH) and High Electrification (HE) are considered for the South Wales region [3]. In the two scenarios, the region may decarbonise heat, either mainly through electrification or with a switch-over to hydrogen.

Several analyses have investigated the possibility of net-zero emissions by 2050 and the steps needed for the transition [4]. Although different decarbonisation pathways have been compared from their technical and economic perspectives, the comparisons among these scenario pathways from the viewpoint of reliability are lacking.

In previous years, various reliability assessment methods have been proposed for individual energy systems, such as natural gas pipeline networks [5] and power systems [6]. However, these reliability assessment technologies are not applicable for Integrated Energy Systems (IESs) because of the nature of the multi-time scale, complex network topology and hydraulic processes [7, 8].

Many reliability assessment methods have been developed. The reliability assessment methods are divided into two categories [9]: model-driven and data-driven methods. Model-driven reliability assessment methods include analytical methods and simulation methods. Classical analytical models based on statistics and probability theory such as the state enumeration method and Bayesian Networks [10] cannot analyse systems' complex dynamic behaviours by using abstract network models. Therefore, the Monte Carlo Simulation (MCS) methodology combined with physical models is widely used [11].

MCS are divided into Sequential MCS (SMCS) and Non-sequential MCS (NMCS) methods. NMCS methods usually adopt the probability distribution functions of uncertain factors and sample random realisations of variables without considering the variables' state transition and time series [6]. For example, Wang et al. [12] used the Markov model combined with the state-space method to analyse the reliability and availability of building cooling, heating and power system. Su et al. developed a systematic method for reliability analysis [13], in which renewable power generation, energy demands and components' states were sampled by MCS according to their probability distribution functions in the supply reliability assessment of IESs.

Static evolution methods have been developed to improve the computational efficiency of MCS such as the Latin hypercube sampling method and importance sampling method. Kou et al. [14] used a reliability evaluation algorithm with fully distributed communication to assess the state of IES based on NMCS. The first-order [15], second-order [16] and central moment [17] methods were used to analyse the reliability of IES based on the deterministic probability distributions of uncertain factors.

However, non-sequential methods have limitations, such as only considering the metrics across the full analysis period and ignoring the sequential details of variables [18]. A units' failure characteristics can be affected by their degree of use and intensity of the load. Also, energy demands, renewables generation levels, redundancy levels

change with respect to time. Therefore, it is difficult to comprehensively describe the volatility and uncertainty of variables without considering state transition and time-varying characteristics through NMCS [19].

SMCS methods are capable of performing simulations considering the system's time sequence and transfer process of component states. Considering physical mechanisms and dynamics in IES, sequential methods have been widely used. Zeng et al. [14] used an SMCS to evaluate the reliability of Integrated Power-Gas Systems. All the components were described by a two-state model, and each state was designed to last for a random period. In the energy supply reliability assessment method, Li et al. [20] used the SMCS method to simulate the system timing state over various time spans. Chaudry et al. [21] used the SMCS model to investigate the reliability of the energy infrastructure across the combined gas and electricity networks. These methods are relatively time-consuming due to thousands of simulations.

In recent years, machine learning and big data methods have been widely used in the energy field, e.g. system modelling [22] and load forecast [23]. The data-driven reliability assessment methods combined with artificial intelligence algorithms and MCS are developed in [24]. Li et al. [25] used an IES reliability assessment method by combining system reconfiguration based on smart agent communication with SMCS. Chi et al. [26] provided a data-driven supply reliability assessment framework for IESs, in which probabilistic Deep Learning and Gaussian Mixture Model-Hidden Markov Model are combined. However, the relations between the reliability parameters of components, environmental parameters, system states and reliability indices are difficult to identify and explain in data-driven reliability methods.

The Universal Generating Function (UGF), is a model-driven reliability analysis technique for Multi-State Systems (MSS), and is improved and developed in [19, 27]. As different performance and failure states of units and systems can be presented by UGF, this method is widely applied for steady-state MSS reliability assessment. Some

analyses have focused on this method for analysing the reliability of IES [28, 29]. For example, in order to assess the reliability of integrated natural gas and power systems, Bao et al. [30] used UGFs to model the stochastic characteristics of units and a system UGF is developed to describe the performance of the overall system. In the assessment of the reliability of IESs, Ma et al. [31] built UGFs to describe the performance substitution and sharing mechanisms of IESs.

However, the traditional UGF method for reliability assessment have disregarded the sequential details of systems and timing information. Therefore, the improved universal generating function method has been developed to describe the dynamic characteristics of systems in the assessment of reliability [18, 32].

Most of the papers reviewed, focused on the reliability assessment methodology and therefore utilised simplified and self-designed scenario test cases. For example, Chi et al. used an IEEE-11 test system with a 7-node natural gas network to validate the efficiency of the proposed reliability assessment framework. Cao et al. [33] analysed the impacts of dynamic characteristics of gas and heat systems on energy losses and reliability during contingencies by using an integrated gas, power and heat testing system. Lei et al. [34] developed an impact-increment-based state enumeration method to analyse the reliability of IESs.

Although some used real IES data, their analysis mainly discussed the usefulness and accuracy of their proposed methods. Fu et al. [33] used a real micro-IES in northern China to validate the efficiency of the central moment method in the estimation of failure probability. Chen et al. [35] used a practical IES based on the Belgian 20-bus gas network and distribution system in a city of Guangdong China, as a case to verify the effectiveness and practicability of the method.

Only a limited number of studies performed comprehensive analysis of system reliability for real regions. For example, in Ref. [21], the GB gas and electricity network

scenario that depicts a hypothesized generation capacity mix and network in the year 2020 is used in the investigation of impact of given uncertainties on the system supply reliability. Qadrdan et al. [36] analysed the impacts of various low carbon strategies on regional expansion of the GB combined gas and electricity network gas network in the 2050s.

Many studies have contributed to the improvement of reliability assessment frameworks but the goal of providing deep system reliability insights to specific regions across different scenarios is lacking. The supply reliability assessment of specific regions demonstrates whether the system can respond effectively to unexpected changes in supply and demand, and are essential for governments, regulators and system operators to examine the security of systems from an operational and planning perspective.

Most studies have used the MCS-based reliability assessment method to analyse the reliability of IESs. Although some high sampling efficiency methods are used to reduce the computational burden, it's difficult for these methods to realise real-time reliability assessment. Data-driven reliability assessment methods are limited as the relationship between system state parameters and reliability indices are difficult to explain. Therefore, it is vital to provide an efficient reliability assessment framework.

Given the concerns around the efficiency and usefulness of proposed reliability assessment methods, insights into the system reliability for specific regions are necessary to identify the system's reliability across different sourcing and operation strategies.

A comprehensive and novel reliability assessment framework is developed to assess the reliability of two configurations of the South Wales energy system in 2050. The contributions of the work are summarised as follows:

1). In traditional UGFs, Probability Mass Functions (PMFs) of uncertain factors are based on assumptions as the distributions of variables are difficult to represent comprehensively. In this paper, PMFs of variables are calculated from probability density functions obtained from historical data through the improved fisher method. Also, an optimisation model is developed to optimise the allocation of energy which has critical effect on the system supply reliability.

2). A systematic dynamic reliability assessment framework that combines the Improved UGF, Kernel Density Estimation method, improved Fisher methods and optimisation model is developed. The method can evaluate systems' dynamic supply reliability with high accuracy and efficiency.

3). This study investigates energy supply reliability in 2050 across distinct net-zero energy futures in South Wales, which provides deep system reliability insights to South Wales across different scenarios.

2 Methodology

A systematic framework, which allows the assessment of supply reliability is shown in Fig. 1 and described as follows:

1). Firstly, future energy data is produced. Based on the projected data from the Dataset companion report [3] and historical hourly data [37], the hourly profiles of energy demand and renewable generation were obtained based on the energy technologies assumed in 2050.

2). Secondly, the Probability Density Functions (PDFs) of variables in each hour, e.g. hydrogen demand, electricity demand and renewable generation, are produced by Kernel Density Estimation (KDE) based on the projected data.

3). Then, an Improved Fisher (IF) method is proposed to convert PDFs into PMFs. UGFs of the system's components are developed based on the given performance distributions (PMFs).

4). Finally, according to the system structure and optimisation operator which describes the operating principles, the system's UGF can be constructed to analyse the supply reliability of the net-zero energy system for South Wales in 2050.

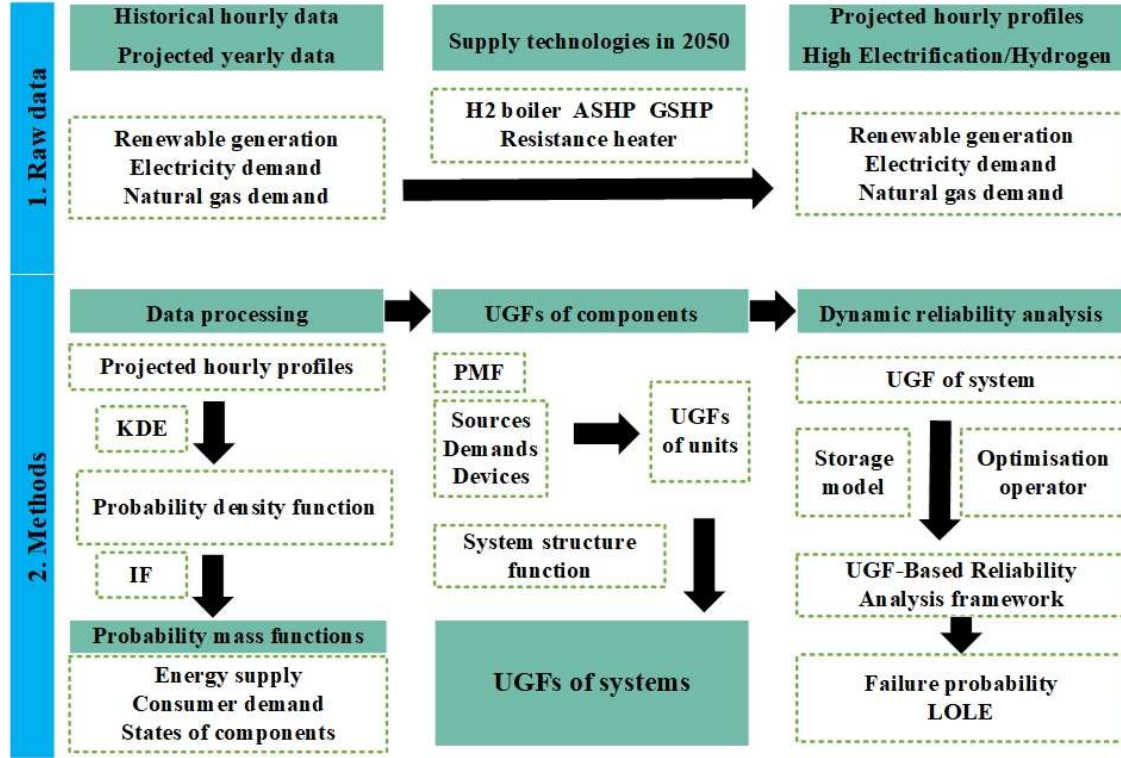


Fig. 1. Structure of the proposed framework.

2.1 Data Processing

The energy data in 2050 is projected. First, the projections of total energy consumption and renewable generation in South Wales across the HH and HE scenarios in 2050 are obtained from [3]. We assumed that the energy demand for heating will change with heating technologies in different scenarios. The underlying demand, transport and industrial demand will increase or fall by a certain percentage as shown in Appendix A Table A.1. Based on the types and capacities of energy technologies in 2050 in different scenarios (in Appendix A Table A.2), hourly demand for hydrogen and electricity were calculated with references to hourly historical data. As there is not much historical data for hydrogen demand, natural gas demand profiles were used as proxies.

To build the uncertainty models, KDE and IF are proposed to produce the PMFs of variables as shown in Fig. 2. For continuous variables the KDE method is used, but the uncertainty model can be built directly by the IF method for discrete variables.

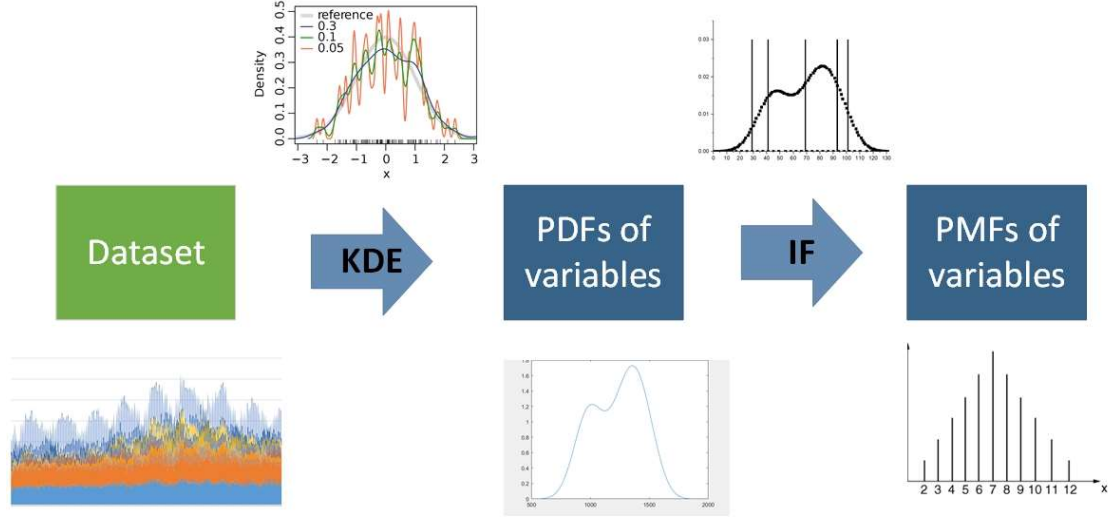


Fig. 2. Data processing.

1) KDE models: The PDFs of variables are produced by the KDE model. KDE is a non-parametric estimation method which can provide comprehensive information by converting the conditional quantiles obtained above into continuous probability density functions [38, 39]. KDE is widely used in power load probability density forecasting [40] and renewables outputs forecasting [41], thus, KDE is used in this work. The definition of KDE is as follows:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x-x_i}{h}\right) \quad (1)$$

where K is the kernel function, which includes the uniform kernel, triangle kernel, etc.; h is the bandwidth parameter; n is the sample size; x_i is the sample. The bandwidth parameter significantly impacts the estimation results. Normal scale, plug in, biased cross-validation, and least-square cross validation are usually used for data with specific distribution characteristics. As KDE models with normal scale performed the best in fitting the probability distribution of time series [38], we used this bandwidth parameter in the model. The Gaussian kernel function is used in this work:

$$K(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \quad (2)$$

2) Improved Fisher Method: Based on PDFs produced by KDE, the IF method is used to generate PMFs. The Fisher algorithm is an optimal classification method for ordered samples, which allows minimisation of the deviations within each class and

maximisation of the difference among classes [42, 43]. The IF method can be used to segment a probability density function by clustering and analysing the data on that function by considering the attributes of the probability information [44]. The IF method has been used in many fields for optimal partitions and has shown good performance [45-48].

It was assumed that a sequence of discrete data $s_1, s_2, \dots, s_n$, is divided into L segments. The set $\{s_i, s_{i+1}, \dots, s_j\}$ is defined as the objects in a group. In the traditional Fisher method, the diameter $D(i, j)$ for the segment $L_k = \{s_i, s_{i+1}, \dots, s_j\}$ is calculated first as follows:

$$D(i, j) = \sum_{r=i}^j (s_r - \bar{s}_l), \quad 1 \leq i < j \leq n \quad (3)$$

where $\bar{s}_l$ is the mean of l -th segment. The continuous variables are PDFs and are converted to PMFs. This equation is adapted as follows:

$$\overline{D(i, j)} = \int_i^j (x_{a=i} p_{a=i} - \frac{\int x p}{j-i})^2 \quad (4)$$

where x is the performance of variable a ; p is the probability that unit a remains at this level.

Let $P(n, l)$ denote a partition of objects $\{s_1, s_2, \dots, s_n\}$ into l groups. The objective function of the errors across optimal partitions can be presented as:

$$E[P(n, l)] = \min \sum_{j=1}^l \bar{D}(i_j, i_{j+1} - 1) \quad (5)$$

Therefore, when n and l are defined, the optimal partition P^* is obtained. The solving process of the objective function is based on the recurrence formula [49]:

$$\begin{cases} E[P(n, 2)] = \min_{2 \leq j \leq n} \{\bar{D}(1, j-1) + \bar{D}(j, n)\} \\ E[P(n, l)] = \min_{l \leq j \leq n} \{E[P(j-1, l-1)] + \bar{D}(j, n)\} \end{cases} \quad (6)$$

Finally, the minimum number of segments is predefined as follows:

$$\omega(l) = \left| \frac{E[P(n, l-1)] - E[P(n, l)]}{l - (l-1)} \right| - \left| \frac{E[P(n, l)] - E[P(n, l+1)]}{l+1 - l} \right| \quad (7)$$

As l increases, the maximum value of $\omega(l)$ is reached and then, the corresponding l is the minimum number of segments.

2.2 Energy Hub Model

The Energy Hub (EH) is defined as an interface between energy sources, loads, energy infrastructures directly or via conversion equipment [50]. Different energy suppliers at the input ports and various energy consumers at the output ports are coupled and connected through a matrix model of the EH as shown in (8):

$$\begin{pmatrix} I_1^{in} \\ I_2^{in} \\ \vdots \\ I_n^{in} \end{pmatrix} \begin{pmatrix} C_{11} & C_{12} & \cdots & C_{1n} \\ C_{21} & C_{22} & \cdots & C_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ C_{m1} & C_{m2} & \cdots & C_{mn} \end{pmatrix} = \begin{pmatrix} I_1^{out} \\ I_2^{out} \\ \vdots \\ I_m^{out} \end{pmatrix} \quad (8)$$

where I^{in} and I^{out} are the input and output carriers, respectively; C_{ij} is the coupling coefficient between input energy i and output energy j .

Two energy hub models for South Wales for the year 2050 are proposed. Due to the diverging impacts on the energy system, two scenarios are defined: HE and HH, as shown in Fig. 3. ε_E is the efficiency of electrolysis; C represents the baseline values of capacities of different technologies; $(1-\alpha)$ of local renewable electricity is converted to hydrogen while α of renewable generation is used for electricity supply. The outputs of electrolysis plants ($C_{E,t}$) and hydrogen-fired power generation plants ($C_{H,t}$) and charge states of electrical storage devices are limited by the constraints:

$$0 \leq C_{E,t} \leq C_{E,\max}, 0 \leq C_{s,t} \leq C_{s,\max}, 0 \leq C_{H,t} \leq C_{s,\max} \quad (9)$$

where $C_{E,\max}$, $C_{s,\max}$ and $C_{H,\max}$ are the maximum capacity of the electrolysis plant, electrical storage device and hydrogen-fired power generation plant, respectively.

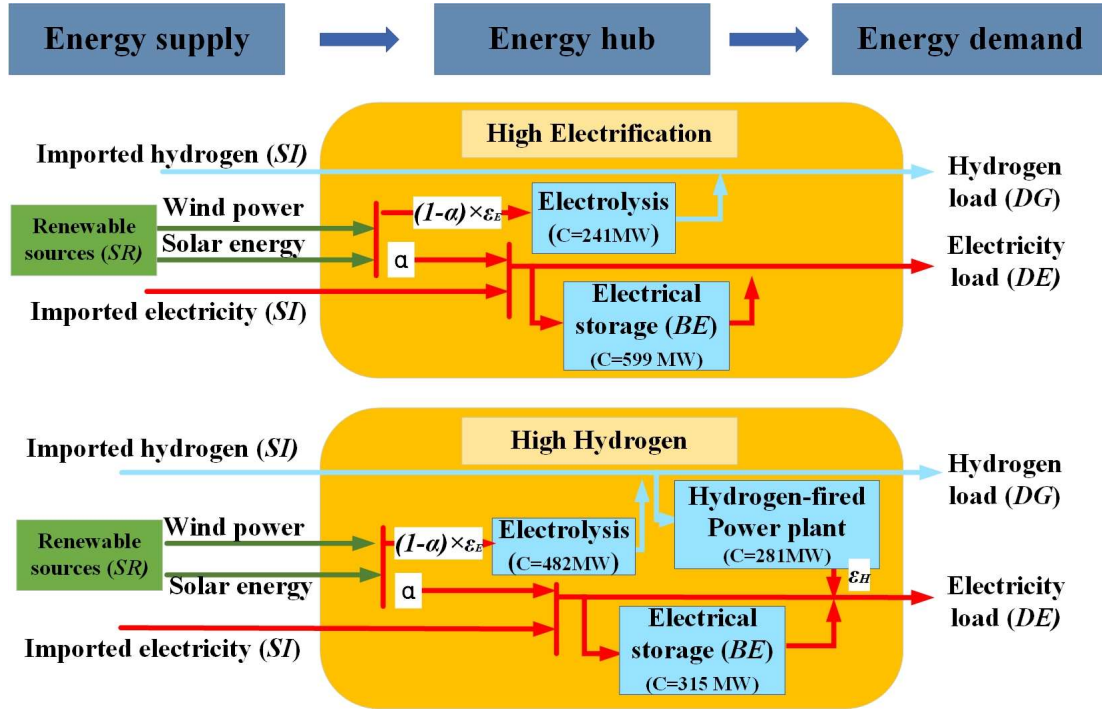


Fig. 3. Energy hub models for the two scenarios.

In the HE scenario, electrification is prioritised as the solution for heat, industry and transport. The main technologies are electrolysis and electrical storage. In the HH scenario, the majority of heat requirements for domestic and industrial clusters are fuelled by hydrogen. Electrical storage devices, electrolysis plants, hydrogen-fired power plants and linepack are considered.

2.3 Definition of Components and Systems

The energy system consists of the electricity system and hydrogen networks, as shown in Fig. 3. Each subsystem consists of s_i supply units, d_i demand units and b_i storage units. The available capacities of electrolysis plants, electrical devices and HPGs are subjected to random variables C_E , C_S and C_H with given PMFs, respectively. The maximum capacities are shown in Fig. 3. The efficiencies of electrolysis plants, electrical devices and HPGs are $\epsilon_E=0.9$, $\epsilon_S=0.9$ and $\epsilon_H=0.9$, respectively.

As shown in Fig. 3, the energy supply consisting of electricity and hydrogen mainly comes from imports and local renewables. $(1-\alpha)$ of local renewable electricity is converted to hydrogen while α is used for electricity supply. Therefore, the supply of

electricity from networks can be denoted as:

$$SE_t = SI_{E,t} + \alpha \times SR_t + SH_t + BE_t \quad (10)$$

where SR_t , $SI_{E,t}$, SH_t and BE_t represent renewable generations, imported electricity, electricity generated from HPG and available electricity in storage at time t , respectively.

The supply of hydrogen is denoted as:

$$SG_t = \varepsilon_e \times ((1 - \alpha) \times SR_t + SP_t) + SI_t + BG_t \quad (11)$$

where SI_t and BG_t denote imported hydrogen and linepack at time t , respectively.

$\varepsilon_e \times ((1 - \alpha) \times SR_t + SP_t)$ is the hydrogen generated from electrolysis devices, where SP_t represents electricity supply from electrical storage.

2.4 UGF-Based Reliability Analysis

The improved UGF is used as a technique to allow dynamic analysis. The multi-state unit is presented by a discrete random variable $X_i(t)$, with a probability mass function:

$$\{(x_{i1}(t), p_{i1}(t)), (x_{i2}(t), p_{i2}(t)), \dots, (x_{in_i}(t), p_{in_i}(t))\} \quad (12)$$

where $x_{ij}(t)$ represents the performance level of component i at level j at time t ; $p_{ij}(t)$ is the probability that component i remains at level j at time t , $j = 1, \dots, n_i$. The system structure function f is denoted as $Y(t) = f(X_1(t), X_2(t), \dots, X_m(t))$, which represents the performance level of the system. Based on the improved UGF method, variable X_i at time t is represented as:

$$u_{X_i}(z, t) = \sum_{j=1}^{n_i} p_{ij}(t) z^{x_{ij}(t)} \quad (13)$$

where $u_{(X_i)}$ is the UGF model of X_i ; z itself has no obvious meaning and value; the coefficient of $z^{x(t)}$ equals the probability that random variable X equals $x(t)$. As $X_1, X_2, \dots, X_n$ are independent random variables and their corresponding probability function P_i , their functional operation result can be obtained through the operation of UGF. We assume that $Y = X_1 + X_2 + \dots + X_n$, therefore Y is expressed in UGF model as:

$$\begin{aligned}
U_Y(z, t) &= \varphi_f \{u_{X_1}(z, t), u_{X_2}(z, t), \dots, u_{X_m}(z, t)\} \\
&= \otimes_{\varphi_f} \left(\sum_{j=1}^{n_1} p_{1j}(t) z^{x_{1j}(t)}, \sum_{j=1}^{n_2} p_{2j}(t) z^{x_{2j}(t)}, \dots, \sum_{j=1}^{n_m} p_{mj}(t) z^{x_{mj}(t)} \right) \\
&= \sum_{j=1}^{n_1} \dots \sum_{j=1}^{n_m} \left(\prod_{i=1}^m p_{ij}(t) z^{\varphi_f \{x_{1j}(t), \dots, x_{mj}(t)\}} \right)
\end{aligned} \tag{14}$$

where $\otimes$ is a summation operator with respect to all variables. In other cases, we can define the definition of operator $\otimes$ based on the specific cases.

Based on the UGF method and EH models, the framework of reliability analysis is shown in Fig. 4.

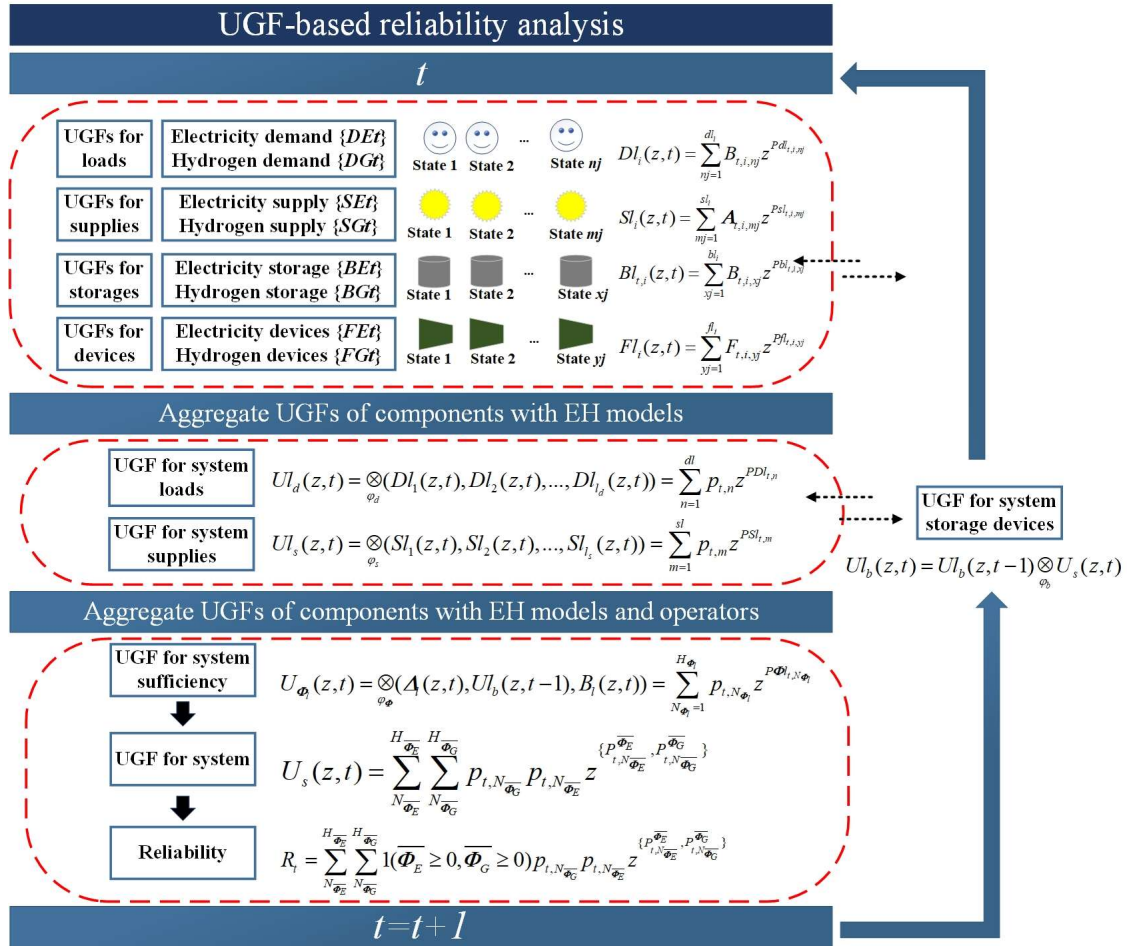


Fig. 4. Reliability assessment framework.

Firstly, in this system, UGFs of components, e.g. demands, sources, storage devices, and other devices (P2G (Power to Gas) and HPG (Hydrogen-fired Power Generation)),

are developed to represent their performances.

Then, we defined three operators $\otimes_{\varphi_d}$, $\otimes_{\varphi_s}$ and $\otimes_{\varphi_b}$, representing the relationships among users, the relationships among each energy source and the Energy Hub configuration, respectively, to construct the system UGF. Based on the operators, UGFs of components and EH models, the UGF for the whole system is obtained.

Finally, we used an optimisation model to optimise the distribution of renewable generation electricity as they can be used directly or converted to hydrogen, which impacts the system supply reliability. The system UGF model is used as an objective function in the optimisation model. The supply reliability can be assessed by this framework. This process is described mathematically as follows:

1) UGFs of Components: The amount of renewable generation and imported energy, customer's demand and the state of devices are impacted by various factors. Hence, multi-state models for energy sources are used to characterise their stochastic behaviour as follows:

$$\begin{aligned}
 Sl_i(z, t) &= \sum_{mj=1}^{sl_i} A_{t,i,mj} z^{Psl_{t,i,mj}}, \quad Dl_i(z, t) = \sum_{nj=1}^{dl_i} D_{t,i,nj} z^{Pdl_{t,i,nj}} \\
 Bl_{t,i}(z, t) &= \sum_{xj=1}^{bl_i} B_{t,i,xj} z^{Pbl_{t,i,xj}}, \quad Fl_i(z, t) = \sum_{yj=1}^{fl_i} F_{t,i,yj} z^{Pfl_{t,i,yj}} \\
 l &\in \{E(\text{electricity}), G(\text{hydrogen})\}
 \end{aligned} \tag{15}$$

where Sl , Dl , Bl and Fl represent UGFs of supply, demand, storage and devices, respectively. For example, when $l=E$, SE_t is electricity supply, which takes on the values from the set $se_{t,j1} = \{se_{t,j1,1}, se_{t,j1,2}, \dots, se_{t,j1,se_{j1}}\}$ with probability $Pr(SE_{t,j1} = se_{t,j1,se_{j1}})$. Psl_t and A_t are energy supply and the related probability at time t .

2) UGF of The System: Considering EH models, the multi-state models of the energy source and demand for the whole system are represented by the aggregation of sources

and demands, respectively. The UGF of the supply and demand for electricity and hydrogen are expressed as

$$\begin{aligned} UL_s(z, t) &= \bigotimes_{\varphi_s} (Sl_1(z, t), \dots, Sl_{l_s}(z, t)) = \sum_{m=1}^{sl} p_{t,m} z^{PSL_{t,m}} \\ UL_d(z, t) &= \bigotimes_{\varphi_d} (Dl_1(z, t), \dots, Dl_{l_d}(z, t)) = \sum_{n=1}^{dl} p_{t,n} z^{PDL_{t,n}} \end{aligned} \quad (16)$$

where $PSL_{t,m}$ and $P_{t,m}$ are the amount of energy supply from the system and the related probability at time t ; $PDL_{t,n}$ and $P_{t,n}$ are the amount of energy demand from the system and the related probability at time t .

Sufficiency and deficiency (SD) are defined as the difference between the demand and supply whilst considering transmission losses. The UGFs of SD are constructed as:

$$\begin{aligned} U_{\Phi_l}(z, t) &= \bigotimes_{\varphi_{\Phi}} (UL_s(z, t), UL_d(z, t), UL_b(z, t-1), B_l(z, t)) \\ &= \sum_{N_{\Phi_l}=1}^{H_{\Phi_l}} p_{t, N_{\Phi_l}} z^{P\Phi_{l, N_{\Phi_l}}} \end{aligned} \quad (17)$$

where UL_b is the UGFs of the available energy from storage devices; B_l is the UGF of the maximum storage capacity of the energy from storage devices; $p_{t, N_{\Phi_l}}$ and $P\Phi_{l, N_{\Phi_l}}$ are the probability and the amount of SD of the system at time t , respectively.

The available energy from storage devices varies with time. Therefore, UL_b is calculated as

$$UL_b(z, t) = UL_b(z, t-1) \bigotimes_{\varphi_b} U_s(z, t) \quad (18)$$

Based on UGFs of components, the UGF of the system is constructed as

$$\begin{aligned}
U_s(z, t) &= \otimes_{\phi} (U_{\phi_E}(z, t), U_{\phi_G}(z, t), BE(z, t), BG(z, t), \dots, \\
&UE_b(z, t-1), UG_b(z, t-1)) \\
&= \sum_{N_{\phi_E}=1}^{H_{\phi_E}} \dots \sum_{N_{U_E}=1}^{H_{U_E}} p_{t, N_{U_E}} \dots p_{t, N_{\phi_G}} z^{\{P_{\phi_E, N_{\phi_E}}, P_{\phi_G, N_{\phi_G}}, \dots, \{PU_{E, N_{U_E}}\}\}} \\
&= \sum_{N_{\phi_E}=1}^{H_{\phi_E}} \sum_{N_{\phi_G}=1}^{H_{\phi_G}} p_{t, N_{\phi_G}} p_{t, N_{\phi_E}} z^{\{P_{t, N_{\phi_E}}^{\phi_E}, P_{t, N_{\phi_G}}^{\phi_G}\}}
\end{aligned} \tag{19}$$

where $P_{t, N_{\phi_E}}^{\phi_E}$ and $P_{t, N_{\phi_G}}^{\phi_G}$ are the failure probability of the electricity and hydrogen systems at time t , respectively; $p_{t, N_{\phi_G}}$ and $p_{t, N_{\phi_E}}$ are the probability when the failure probabilities are $P_{t, N_{\phi_G}}^{\phi_G}$ and $P_{t, N_{\phi_E}}^{\phi_E}$, respectively. The supply reliability of the system can be calculated by updating the UGF with time, as follows:

$$R_t = \sum_{N_{\phi_E}=1}^{H_{\phi_E}} \sum_{N_{\phi_G}=1}^{H_{\phi_G}} 1(\overline{\phi_E} \geq 0, \overline{\phi_G} \geq 0) p_{t, N_{\phi_G}} p_{t, N_{\phi_E}} z^{\{P_{t, N_{\phi_E}}^{\phi_E}, P_{t, N_{\phi_G}}^{\phi_G}\}} \tag{20}$$

where $\overline{\phi_E}$ and $\overline{\phi_G}$ are the levels of sufficiency for the electricity and hydrogen systems, respectively.

3) The system UGF model (Eq. 20) is used as the objective function in this optimisation model as shown in Eq. 21. The optimisation model is used to determine the amount of local renewable electricity used to produce hydrogen as it has an impact on the system's reliability, and it is trying to reduce the failure probability of the system.

Genetic Algorithm [13, 51] is used as the optimisation technique. α is set as the decision variable to determine the renewables distribution mode with the lowest system failure probability as the objective (fitness value function) is to maximise the supply reliability for the whole system, which is derived from Eq. (20). The optimisation algorithm flow diagram is shown in Fig. 5.

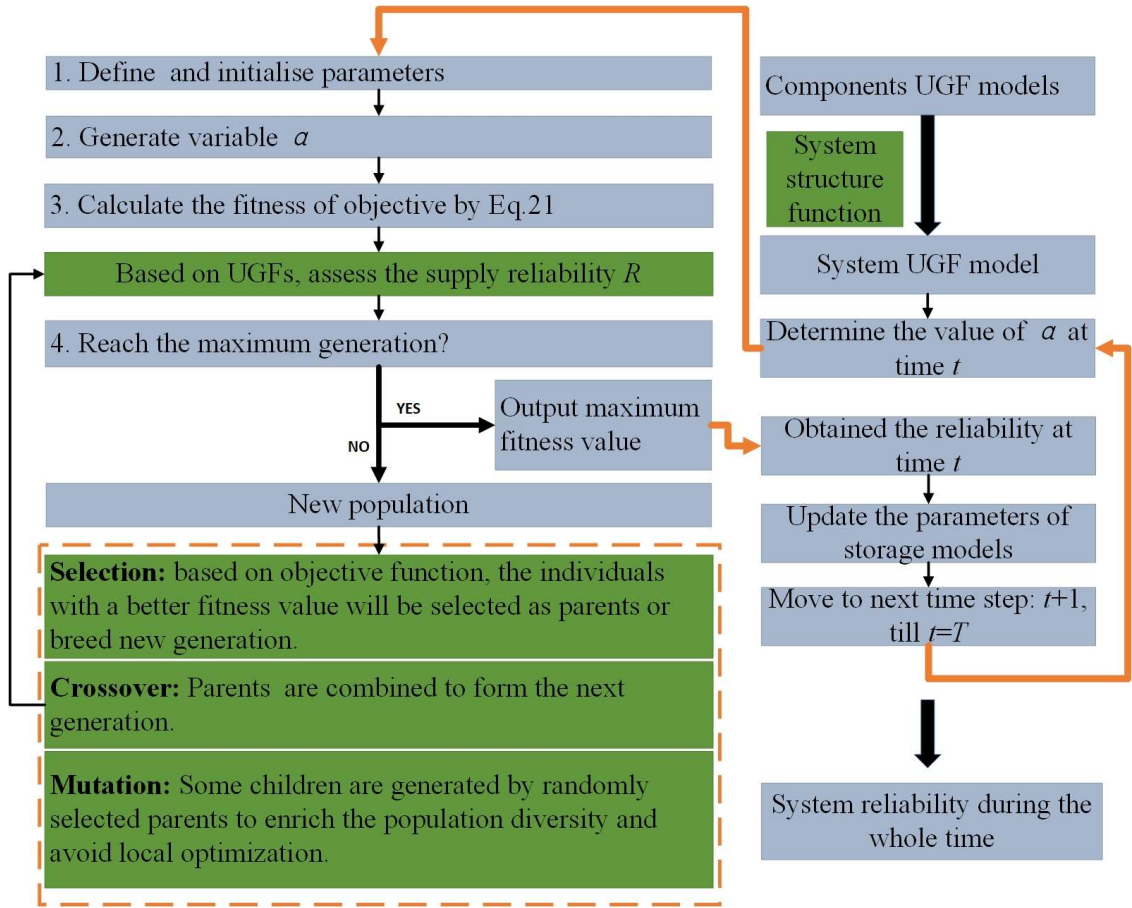


Fig. 5. The structure of the optimisation model.

$$\max f = R_t = \sum_{N_{\Phi_E}}^H \sum_{N_{\Phi_G}}^H 1(\overline{\Phi_E} \geq 0, \overline{\Phi_G} \geq 0) p_{t, N_{\Phi_G}} p_{t, N_{\Phi_E}} z^{\{P_{t, N_{\Phi_E}}^{\overline{\Phi_E}}, P_{t, N_{\Phi_G}}^{\overline{\Phi_G}}\}} \quad (21)$$

The solution space of this optimization problem can be written as $\{\alpha\}$. The constraints for α are:

$$0 \leq \alpha \leq 1 \quad (22)$$

When $\alpha=0$, all available renewable electricity is used to generate hydrogen; when $\alpha=1$, no renewable electricity is used to generate hydrogen.

$$0 \leq C_{E,t} \leq C_{E,\max}, 0 \leq C_{s,t} \leq C_{s,\max}, 0 \leq C_{H,t} \leq C_{s,\max} \quad (23)$$

where $C_{E,\max}$, $C_{S,\max}$ and $C_{H,\max}$ are the maximum capacity of the electrolysis plant, electrical storage device and hydrogen-fired power generation plant, respectively.

The parameters settings for the GA are shown in Appendix A Table A.3.

3 Case study

Three case studies are defined. In Case 1, the efficiency and mathematical accuracy of the proposed framework is validated by comparing it to other methods. In Case 2, the differences in supply reliability of energy systems in 2020 and 2050 in South Wales for both scenarios are analysed. Case 3 is designed to examine the impacts of energy sources, P2G, HPG, and the capacity of electrical storage on the system's supply reliability. All the simulations are undertaken in MATLAB by a computer with Intel(R) Xeon (R) E5-2687W v4 CPU at 3.0 GHz with 64 GB of RAM.

3.1 The efficiency of the proposed framework

To validate the mathematical correctness and computational efficiency of the proposed framework, the supply reliability of the energy system was assessed and compared with MCS technique based on the data (in 2020) used in the proposed method.

The reliability assessment errors of the proposed method and MCS across different scenarios are shown in Fig. 6, where 'Seg' is the number of state space in PDF. The PDF integrates the variable for the given random number (state space) which is equal to the probability for the random variable.

The convergence error is set to 5% in the MCS [30]. This implies that if the error of the proposed method is less than 5%, the proposed method can be regarded as good as MCS. With increased number of Segs, errors fluctuate until the number of Segs reaches a critical value and the error converges. The maximum number for the critical value is ~85 in these cases. However, once the number of Segs goes beyond 30 the results closely match MCS outputs. This indicates that the proposed method can obtain accurate results when Seg is set higher than 30 as shown in Fig. 6 (the maximum error is 5.1%).

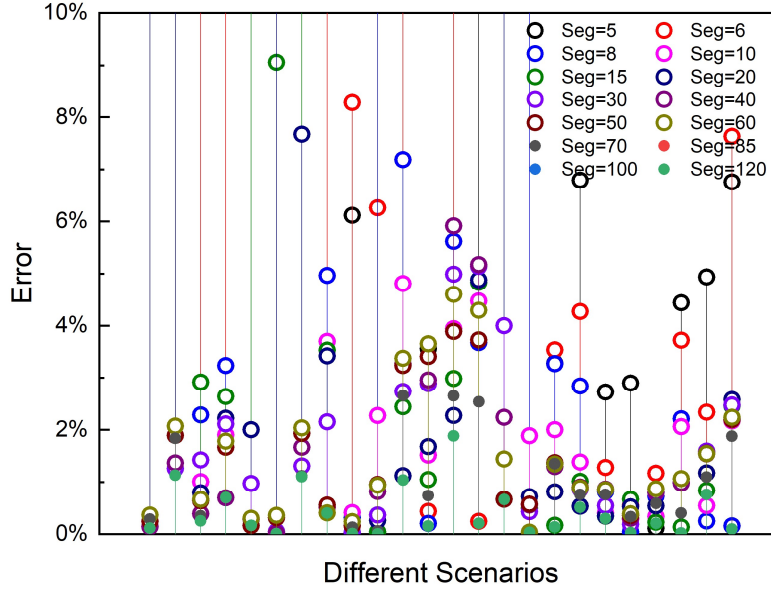


Fig. 6. The errors between the proposed method and MCS across different scenarios.

The average computation times of the proposed method, MCS, Latin Hypercube Sampling (LHS) method [52, 53], and Hamiltonian Monte Carlo (HMC) [54] across different scenarios are compared in Table 1. The average computation times of the proposed method are far lower than MCS. The average computation time is 10.32s when the number of Seg is 60 whereas it is 730.9s in the MCS method due to nearly 100000 simulations. Although the LHS method and HMC can reduce the number of simulations necessary to achieve a reasonably accurate result, the computation times are still relatively high. The results indicate that the proposed method is far more efficient than other methods.

Table 1. Average Computation Times of the Proposed Method and Other Methods

Seg	30	40	50	60	100	MCS	LHS	HMC
Time (s)	1.72	3.86	8.20	10.32	31.21	730.90	194.26	122.30

3.2 System supply reliability in South Wales in 2020 and 2050

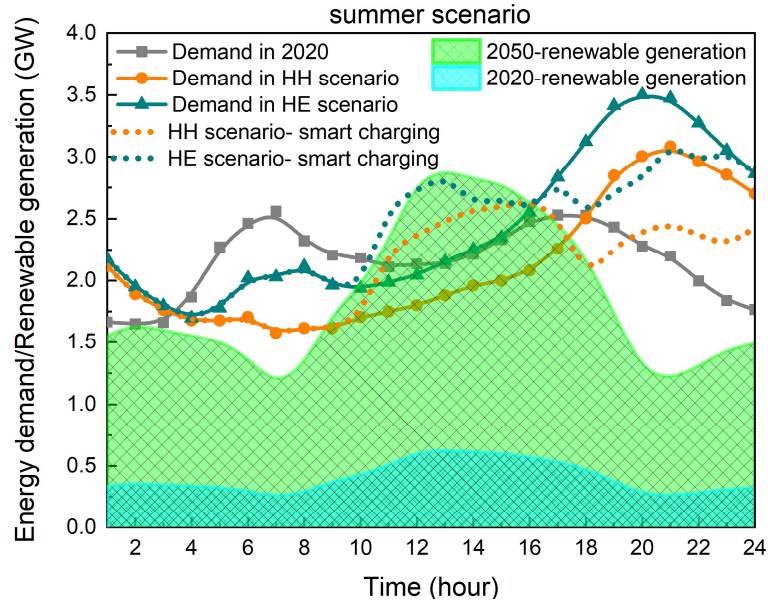
The share of renewable sources in 2020 and the projected share in 2050 in South Wales for the HE and HH scenarios are shown in Table 2. In 2020, energy demand includes natural gas demand and electricity demand and only 6% of energy is generated from local renewable generation. 70% of electricity is imported to South Wales and the

remaining electricity is generated from gas-fired generation plants. In 2050, energy demand consists of electricity and hydrogen demand as shown in Table 2. Electricity demand includes domestic heat and non-heat (lighting, air conditioning, etc.), non-domestic heat (commercial heat, etc), industrial and transport demand. Hydrogen demand includes industrial, heat and transport demand.

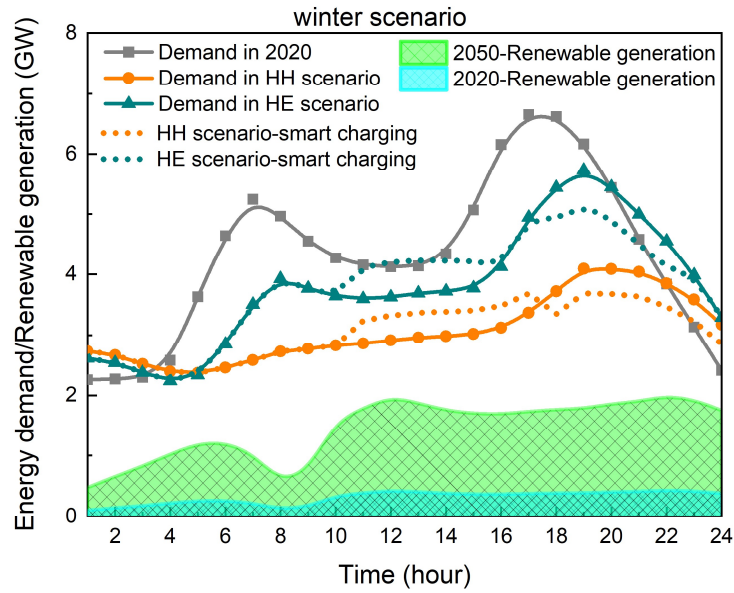
Table 2. The Share of Local Renewable Sources, Energy demands in Different Scenarios [3]

Scenario	Local supply	Imports		Electricity demand (TWh)	Gas demand (TWh)
	Renewables (%)	Electricity (%)	Hydrogen (%)		
Baseline (2020)	6	70%	100	22.1	10.7 (Natural Gas)
HE (2050)	40	47	64	18.9	4.4 (Hydrogen)
HH (2050)	30	39	81	16	15 (Hydrogen)

Fig. 7 shows typical summer and winter day electricity demand profiles (not including P2G) across different scenarios. Electricity demand increases at hours 0-6 and hours 18-22 due to EV charging. Therefore, the supply failure probabilities during hours 20-24 increase in 2050 across both scenarios compared with 2020 due to the changes in consumption behaviours of consumers as shown in Fig. 8.



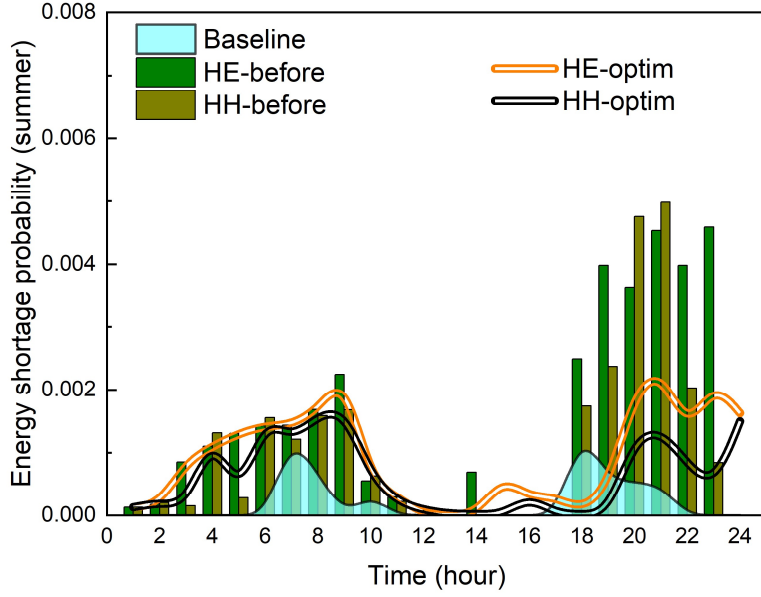
(a) Summer scenarios



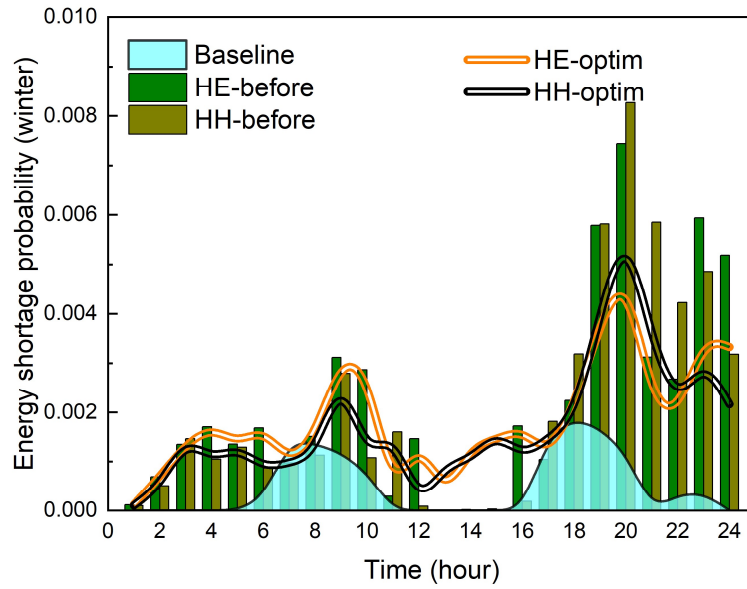
(b) Winter scenarios

Fig. 7. Example electricity demand profiles for different scenarios.

The supply reliability across different scenarios with and without smart charging of EVs (electrical vehicles) are shown in Fig. 8. In this work, the failure probability refers to the probability of supply not meeting demand.



(a) Summer scenarios.



(b) Winter scenarios.

Fig. 8. The supply failure probability of the system ('-before' refers to the scenarios without smart charging and '-optim' refers to the scenarios with smart charging.)

The supply reliability of the system degrades in 2050 in all scenarios. This is due to increased penetration levels of local renewable sources from 6% (in 2020) to 30% (HH scenario) and 40% (HE scenario). Variability in generation for renewables leads to frequent fluctuations in the supply of energy.

Smart charging of EVs which shifts some EV demand to periods where renewable generation utilisation is maximised is capable of improving system supply reliability. As shown in Table 3, LOLEs are reduced by 37% and 43% in HE and HH summer scenarios due to smart charging. LOLEs are reduced by 18% and 16% in HE and HH winter scenarios. This is because energy demand including electricity and hydrogen demand is always higher than renewable generation during the day in winter. Thus, smart charging exhibits lower impacts during winter.

Table 3. LOLEs of Different Scenarios

Scenario (hours/year)	Baseline	HE- before	HE- optim	HH- before	HH- optim
Winter	4.34	19.54	16.04	18.32	15.29
Summer	1.91	12.80	8.13	9.41	5.40
Sum	6.25	32.34	24.17	27.73	20.69

3.3 The impact of components on system reliability

The impacts of component failure probabilities on supply reliability for the HE and HH scenarios in South Wales is analysed. For Fig. 9-12, the reliability of the base case (in 2050) is assessed without considering component failure probabilities. The case ‘All’ (in 2050) considers the failure probabilities of all components. The cases ‘HPG’ only considers the failure probability of HPG plants, etc.

1) HH summer scenario. As shown in Fig. 9, at hours 3-6, 20 and 22 on an average day (the contributions varied from 20% to 83%), the outputs from wind farms contribute considerably to system supply reliability as the majority of electricity and hydrogen are generated from wind farms. PV systems impact supply reliability at hours 11-17 (the average contribution is more than 40%) when the solar radiation is relatively strong. This indicates that system supply reliability is dependent on renewable generation when they are the main source of energy. HPG has much more influence on system supply reliability at hours 0-8 and 17-24 on an average day as the contribution

is nearly 100% during some hours. During periods when renewable generation is low, HPG is required to respond quickly to electricity demand as the capacity of electricity storage is limited.

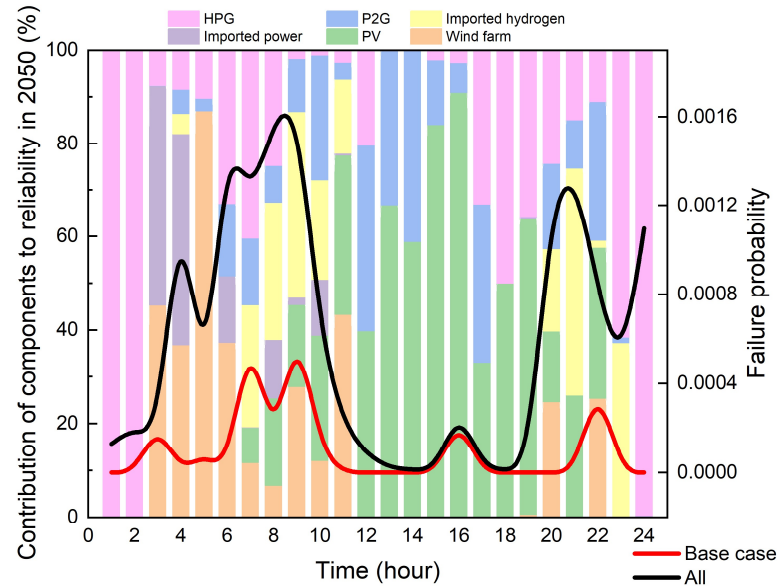


Fig. 9. Contribution of components to system reliability in HH-summer scenario. (The length of the column in different colours refers to the contribution of components to system reliability at each hour. The “base case” and “all” lines refer to the failure probability in the two scenarios.)

2) HH winter scenario. Solar irradiation is very low during the day in winter, therefore the influence of PV systems can be neglected as shown in Fig. 10 the LOLE of the PV case is 2.3 hours/year. With greater energy demand, imported energy increases to more than 70% of the total energy supply. Therefore, the importance of imported energy on the supply reliability of energy systems increases in winter. As shown in Fig. 10, LOLEs of IP (Imported electricity), IH (Imported hydrogen) and wind farm cases are 7.8 hours/year and 8.4 hours/year which are higher than LOLEs of PV, P2G (2.5 hours/year) and HPG (4.9 hours/year) cases.

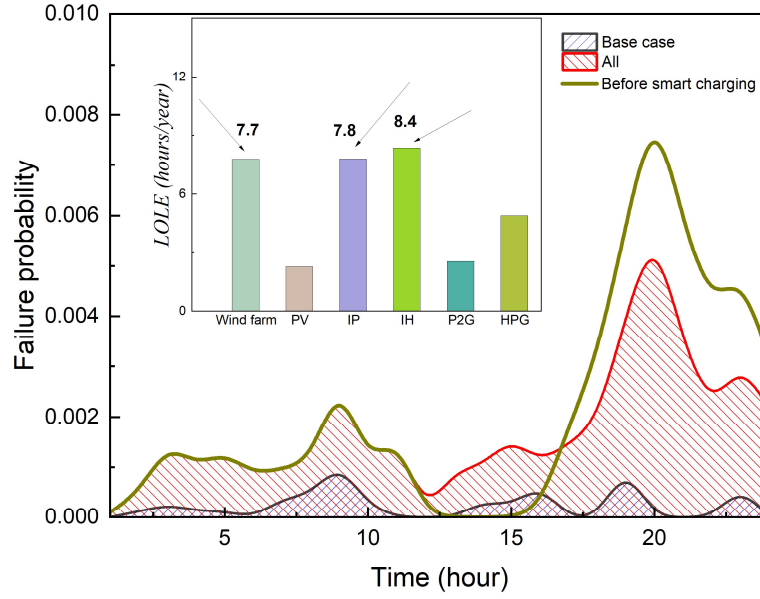


Fig. 10. Influence of various components on system supply reliability in HH-winter scenario. (The bar chart in the figure shows the results of LOLE when specific factors, such as the failure of wind farms, PV systems, etc, are considered in the reliability assesement)

3) HE summer scenario. Fig. 11 shows the main contributing factors impacting supply reliability across an average summer day. During hours 0-7 on an average day, HPG performs a significant role in maintaining supply reliability in the HE summer scenario, for example, the supply failure probability is over 0.14% at hour 7. This is because electricity generated through HPG is the main source for electricity supply while electricity reserve is limited especially during the evening. Although the electricity reserve in HE summer is bigger than that in HH summer, the capacity of electricity storage is still lower than demand. At hours 11-15, renewable generation is high, and PV contributes greatly to system supply reliability. The failure probability is only 0.005% when the failure of PV is considered.

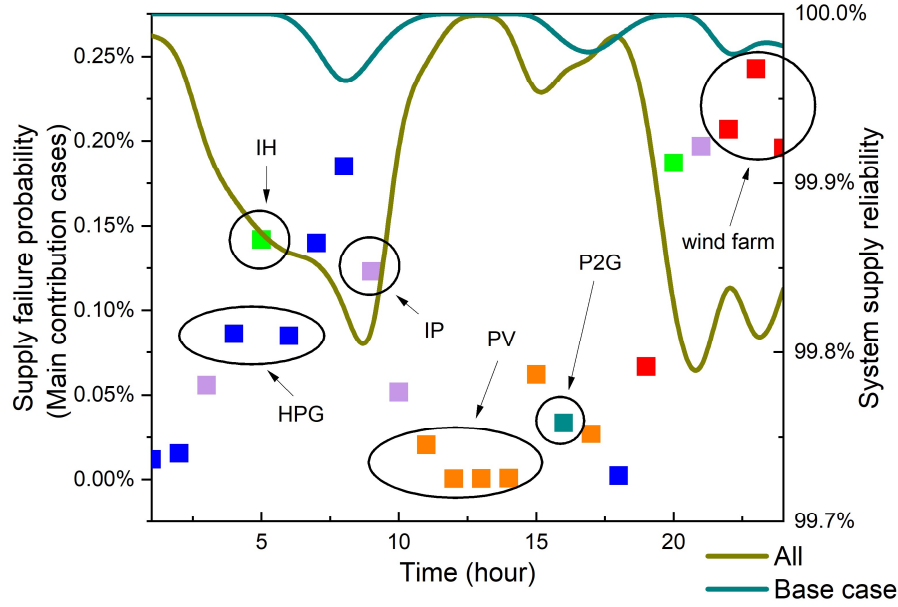


Fig. 11. The main contributors to system supply failure in HE summer scenario. (The “all” and “base case” lines show the supply reliability on the right Y-axis. The colour of the small squares shows the main contribution impacting supply reliability and the coordinates shows the supply failure probability for the case. The main contribution refers to the highest failure probability when a particular factor is considered in the reliability assessment.)

4) HE winter scenario. The impact of imported energy supply failure on the reliability in this scenario is emphasised as more than 60% of energy is imported to South Wales. As shown in Fig. 12, the contributions of P2G and HPG on system supply reliability increased from 10.3% and 14.1% to 13% and 18.8% compared with the HH-winter scenario. There is increased importance on energy conversion technologies because the energy system relies on their flexibility for energy storage and supply as the percentage of local renewable electricity in total energy supply is higher in the HE winter scenario as shown in Table 2.

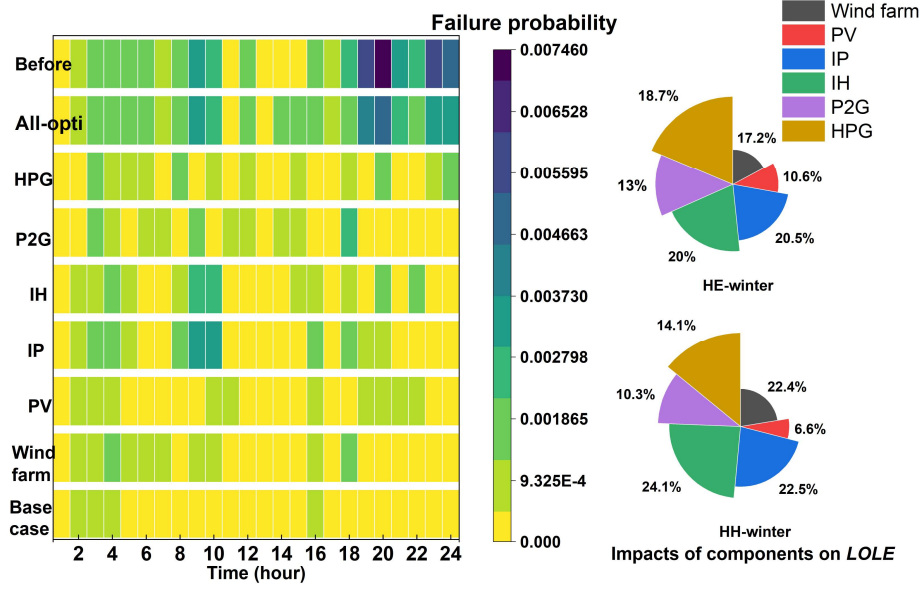


Fig. 12. Comparison between HE-winter and HH-winter scenarios. (The supply failure probability of each case is shown on the left. For example, the “HPG” refers to the case in which the failure of HPG is considered.)

5) Comparison between HE and HH scenarios. As shown in Table 4, system reliability is higher in HH scenarios in summer as LOLE is approximately 5.4 hours/year compared with HE scenarios in summer with ~8.1 hours/year. However, the supply reliabilities are similar in winter. This is mainly due to energy storage capacity limitations which impact the flexibility and resilience of the system in HE summer scenarios. In winter, energy is mainly supplied through imports, therefore the system reduces its dependence on energy technologies such as HPG and P2G.

Table 4. Results of *LOLE* Across Different Scenarios (hours/year)

Scenario	WF	PV	IE	IH	P2G	HPG	All
HH-summer	3.12	2.09	1.33	2.68	2.68	3.15	5.401
HH-winter	7.76	2.28	7.78	8.35	3.55	4.89	15.30
HE-summer	4.42	3.00	4.55	4.50	2.97	2.42	8.07
HE-winter	5.17	3.20	6.17	6.02	3.90	5.63	16.04

The reliability of P2G and HPG devices is essential in summer scenarios whereas

energy imports are more important in winter in HH scenario. The highest LOLE is 3.15 hours/year for the HPG case in summer whilst the LOLE for the IH case (8.35 hours/year) is the highest in winter. The system operates without any issues with renewable generation and energy conversion technologies performing a key role in summer. When the energy demand increases in winter, the dependence on imported energy significantly reduces the reliability of the system in both scenarios.

3.4 Sensitivity analysis of components

Sensitivity analysis is performed to investigate the impact of the variations of components' states on system supply reliability. As the conditions of components such as wind farm, PV farm and imported energy were similar in HE and HH scenarios but the capacity and importance of P2G, HPG are different. The degree of sensitivity of P2G, HPG, and the maximum capacity of electrical storage on system supply reliability are simulated to analyse how the changes of the failure rate of these components impact the system supply reliability in the two scenarios. Each parameter is varied over a range of values around the baseline value.

1) Sensitivity analysis of P2G. LOLE increases as the failure probability of P2G varied from 1% to 9% as shown in Fig. 13. The impacts of variation in P2G failure probabilities are more significant in summer as LOLEs increase from 30% to 100%, respectively whereas, during winter, LOLEs increase slightly. The results shows that LOLE increase from 15.3 hours/year to 16.4 hours/year. P2G devices are more significant to system reliability in the HE-summer scenario as the majority of hydrogen is supplied through electrolysis. However, in HH-summer, hydrogen is partially supplied through imports due to the limited capacity of P2G plants.

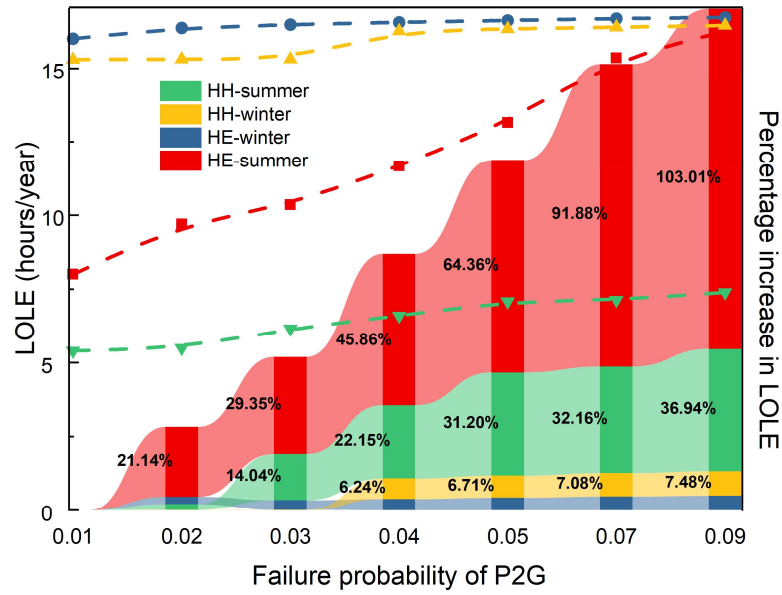


Fig. 13. Impact of P2G failure probability variation on system reliability. (The dot lines refer to the LOLE as the failure probability of P2G varies from 1% to 9% on the left Y-axis. The area charts refer to the percentage increase in LOLE on the right Y-axis.)

2) Sensitivity analysis of HPG. In summer, as the failure probability of HPG plants is varied, it has a significant impact on the system supply failure probability, which increases between 80% to 120% as shown in Fig. 14. In winter, system supply reliability is less sensitive to changes in the failure probability of HPG as it increases from 5% to 53%. In summer, most of the surplus renewable electricity is converted into hydrogen and the majority of electricity is generated through HPG when the available renewable electricity is low. Therefore, with imports increasing in winter, the importance of HPG decreases.

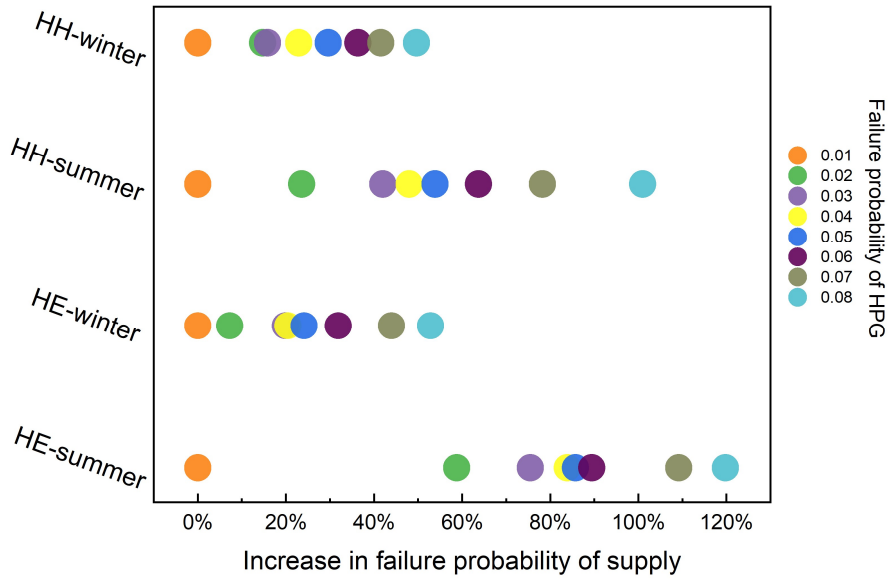


Fig. 14. Impact of HPG failure probability variation on system reliability. (The colour of small circles refer to the failure probability of HPG that varies from 0.01 to 0.08. The coordinate of the circle gives the failure probability in each scenario.)

3) Sensitivity analysis of the maximum capacity of electrical storage. The study reveals an inverse relationship between the system supply failure probability and the maximum capacity of electrical storage. In HH scenarios, system supply reliability is more sensitive to the maximum capacity of electrical storage than in HE scenarios. As shown in Fig. 15, the average increase in failure probability changes from -16% to -75% in HH scenarios whereas the average increase changes from -4% to -44% in HE scenarios. This is because electricity demand is low in the HH scenarios. Therefore, the increased electrical storage capacity can greatly improve the balance between electricity demand and supply. In HE scenarios, electricity demand is much higher than the electrical storage capacity. Thus, the increase in electrical storage capacity only marginally improves the system's supply reliability.

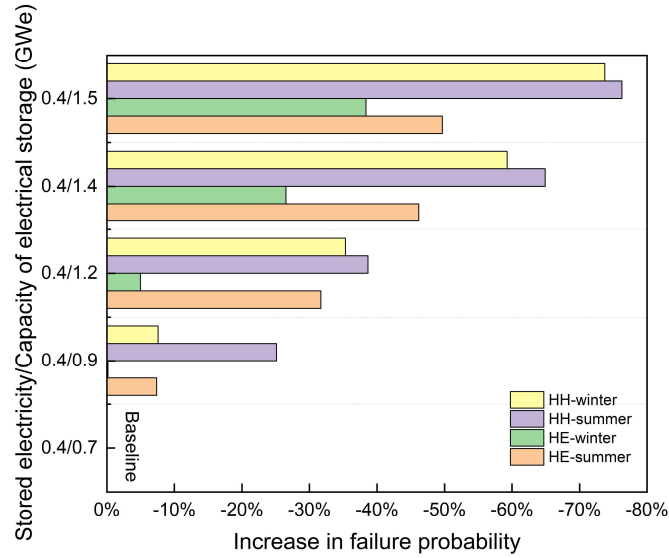


Fig. 15. Impact of variations in maximum capacity of electrical storage on system supply reliability. (Five cases are shown on the left Y-axis and the length of the column refers to the increase in supply failure probability across each scenario.)

4) Summary. System supply reliability is more sensitive to changes in failure probabilities of P2G, HPG and the maximum capacity of electrical storage in summer as shown in Fig. 16. This is because P2G and HPG generate the majority of hydrogen and electricity when renewables are the main energy sources and imports are lower. When demand increases in winter, they have less impact on system supply reliability because most of the energy is from imports. The impacts of the changes in maximum electrical storage capacity on system supply reliability in HE scenarios are lower because the capacity of storage is limited.

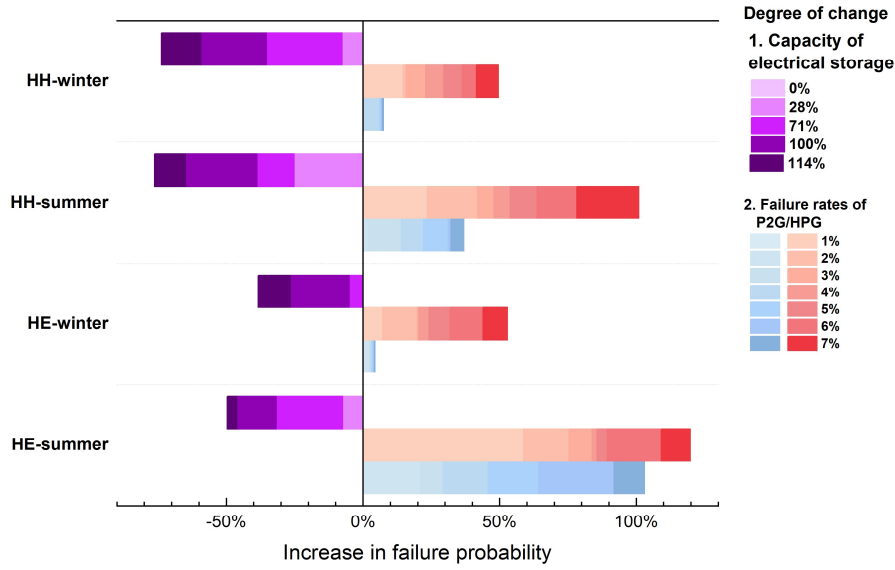


Fig. 16. Impact of each variable on system reliability. (The gradually darker color indicates a deepening of the degree of change across the cases. The pink one refers to the capacity of electricity storage. Blue one refers to the failure rate of P2G and Red one refers to the failure rate of HPG. The increase in failure probability is shown on the X-axis for each scenario.)

4 Conclusion

The supply reliability of the net-zero energy system for South Wales in 2050 is investigated through the implementation of a novel systematic reliability assessment framework. The dynamic reliability assessment framework, which combines the improved UGF and Fisher methods, matches the accuracy of MCS and reduces the computational time to solution. Using this framework, the changes in reliability from 2020 to 2050 for the energy system in South Wales are analysed. The impacts of components on system supply reliability across different scenarios in South Wales are also investigated.

1) Compared with the year 2020, the system supply reliability reduces in 2050. Loss of Load Expectation increases from 3.12 hours/year in 2020 to 12.09 and 10.35 hours/year in High Electrification and High Hydrogen scenarios as the penetration levels of local renewables increase by more than five-fold in 2050 from 6% in 2020.

2) HH scenarios offer more supply reliability than HE scenarios in summer (LOLE of 5.4 hours/year and 8.1 hours/year) whereas the supply reliability is similar in winter (LOLE of 15 hours/year and 16 hours/year). This is mainly because electricity storage capacity limitations impact the resilience of the system in HE summer scenarios and P2G and HPG are required to provide flexibility. Besides, the percentage of energy supplied locally is higher in HE scenarios. In winter, the main energy sources are supplied from imports therefore the system reduces its dependence on energy storage and energy conversion technologies.

3) The impact of components on system supply reliability varies across scenarios. PV contributes little to system supply reliability due to weak solar irradiation in winter scenarios, the LOLE of the PV case is the lowest at 2.3 hours/year. P2G and HPG contribute more to system supply reliability in summer scenarios whereas imported energy is more important in winter scenarios. The highest LOLE is 3.15 hours/year for the HPG case in summer whilst the LOLE for the IH case at 8.35 hours/year is the highest in winter.

4) System supply reliability is more sensitive to changes in the failure probabilities of P2G, HPG and the maximum capacity of electrical storage in summer than in winter. The LOLEs of the P2G case and HPG case increase from 30% to 100% and 80% to 120% in summer, whereas, LOLEs increase from 3% to 8% and from 5 to 53 during winter as the failure rate of P2G and HPG plants are varied. This is because P2G and HPG account for most of the energy conversion and supply when renewables are the main primary source of energy. When demand increases in winter, most of the energy is from imports.

The accuracy of future energy data is important for practical scenario analysis. The base data used in this work is produced by Regen on behalf of Western Power Distribution and Wales and West Utilities, which like all data has potential inaccuracies and limitations and further future work could be done to improve the accuracy of the data sources. In this work, the energy hub is used to describe the structure of the energy system and the Probability Mass Functions (PMFs) of uncertain factors that are used to

represent the performance of variables. The mathematical correctness and computational efficiency of PMFs of uncertain factors were validated. However, the physical and hydraulic characteristics of the energy system influences the transportation capacity of electricity grids and hydrogen systems, which may affect the accuracy of the reliability assessment. Therefore, a possible future enhancement that includes modelling hydrogen networks and electrical system constraints and their integration into the overall reliability assessment framework.

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Appendix A

Table A.1. Changes in energy demand

	PV capacity	Wind capacity	Sector	Transport	Heat	Industry	Other
High Electrification (TWh)	2.7	6.4	Hydrogen	0.8	0.1	3.6	
			Electricity	3	4.9	1.6	8.6
High Hydrogen (TWh)			Hydrogen	1	7.8	5.8	
			Electricity	2.7	2.5	0.5	10.3

Table A.2. The types and capacities of technologies for heating in different scenarios

Scenarios		Technology	Installed number (k)	Total demand MWh/year
Domestic	Baseline (2019)	gas boilers	820	9674
		oil boilers	100	
		electric heating	70	
		biomass boilers	10	
	High Electrification (2050)	ASHP	620	8736
		Electric heating	90	
		Gas HHP	30	
		H2 HHP	35	
		GSHP	200	
		Heat network -GSHP	180	
	High Hydrogen (2050)	Hydrogen ready boiler	700	9032
		H2 HHP	30	
		ASHP	180	

		GSHP	40	
		Electric heating	70	
Non-domestic	Baseline (2019)	Gas boiler	42	
		Air conditioning	6	3403
		Electric heating	27	
		ASHP	35	
	High Electrification (2050)	GSHP	10	
		Heat network -GSHP	9	3376
		Air conditioning	6	
		Electric heating	35	
		Hydrogen ready boiler	35	
		H2 HHP	4	3403
		ASHP	14	
	High Hydrogen (2050)	Air conditioning	6	
		Electric heating	27	

Table A.3. Parameters setting of GA

Parameter	Value
Population size	80
Crossover fraction	0.8
Function tolerance	1e-3
Generation number	200

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