Carbon-emission Reduction of Hybrid Renewable Energy System Stochastic Day-Ahead Scheduling

Ilaria Sorrenti[1*], Theis Bo Harild Rasmussen[2], Qiuwei Wu[3], Shi You[1]

[1] Department of Wind Power and Energy Systems, Technical University of Denmark, 2800 Kgs. Lyngby, Denmark

[2] Watts, Brogade 19E, 4600 Køge

[3] Environmental Science and Renewable Technology Center, Tsinghua-Berkeley Shenzhen Institute, Shenzhen, 518071, China

* Corresponding author. ilaso@dtu.dk (I.S.)

Manuscript submitted February 16, 2023; revised May 8, 2023; accepted June 10, 2023; published October 9, 2023.
doi: 10.12720/sgce.12.4.91-99

Abstract: In light of new energy policies, energy systems should face the challenge of mitigating CO_2. Although environmental sustainability is a hot topic, Day-ahead (DA) scheduling is approached by prioritising the economic perspective, risking sub-optimal CO_2 emission. To highlight the current model limitation, this paper proposes an approach for minimising CO_2 during operation inspired by the Carbon Emission Flow (CEF) method, not revealed by cost optimisation. Although this approach assumes complete energy system control and is less likely to be used for real-world energy dispatching, such a tool creates awareness among stakeholders about the minimum CO_2 limit and the consequences of using specific components or external sources. For this purpose, CEF cost and emission results are compared with cost minimisation with/without CO_2 taxation, confirming that current optimisations objectives cannot achieve the lowest CO_2 emission level. The performances are compared with indices assessing sustainability with insights on dispatching strategies and system components that affect emissions and costs. Finally, to detect if the taxation strategy is suitable for reaching the lowest CO_2 in DA scheduling, a sensitivity analysis was carried out by increasing taxation prices up to 5-times, concluding it would increase costs without reaching the minimum set by the proposed approach.

Key words: Carbon minimisation, carbon-taxes Day-ahead scheduling, hybrid renewable energy systems, sustainable indices

1. Introduction

The massive use of fossil fuels has created environmental consequences that require mitigation management. Embracing this new need, several energy systems exist intending to address environmental sustainability. Energy systems are moving towards a green transition policy, hybridising energy systems while maintaining high living standards and cost-effective operation [1]. Reducing carbon emissions during the operation of energy systems is key to achieving national targets. Some energy systems arise from the intention to mitigate system emissions, such as Hybrid Renewable Energy Systems (HRES) that integrate Renewable Energy Sources (RES), integrating such as Electricity (EPS), Natural Gas (NGS) and district heating (DHS). Recently, the hydrogen carrier embedded in Power-to-Synthetic Natural Gas (PtSNG) units has been receiving attention from these systems as they can transform renewable electricity into heat and gas [2]. Despite this, the system operation objectives prioritise minimising costs. Liberalised energy markets follow the rules and structures and are typically cost-minimising. Energy markets can be subjected to CO_2 taxes to account for this, which could lead to sub-optimal emission levels, leading to a dual minimisation of costs and emissions if adequately assessed. However, taxation imposes additional costs on other sectors and constraints on ideology and uncertainties about the purpose of the tax, potentially creating unfair conditions in neighbouring countries with different compositions of generation profiles and primary energy source conditions.

An HRES DA scheduling focusing on PtSNG in Espoo was conducted to study the cost-effective design and operation of the future urban energy system for decarbonisation [3]. The results show that Espoo can achieve carbon neutrality by using PtSNG, saving costs, heat storage and transmission capacity. Despite this, the zero-emissions analysis was performed as a post-processing task involving a sensitivity analysis of the PtSNG size. Therefore, carbon fluxes were not optimised but accounted for. A multi-objective optimisation related to pollution costs and carbon emissions is conducted for a microgrid considering electric vehicle penetration [4]. In addition, a method for determining DA schedules, considering CO_2 emissions and costs from the national grid, is examined in [5], where a procedure is developed to obtain the trade-off solution between costs and CO_2 emissions by including significant wind power penetration and developing plug-in electric vehicles. An analysis regarding the Carbon Emission Flow (CEF) accounting during the operation was conceived, modelling the fundamental equations to model and identify the CO_2 of the system at all its points during the operation for a multi-energy system, but only a-posteriori [6,7]. Assessing emissions during DA scheduling may reveal interactions in the system that have not yet been detected, and assessing the environmental sustainability of the HRES requires the introduction of new variables that take into account emissions of CO_2. These approaches lead to optimal operation without any control of carbon emissions, assuming that using RES or adopting hydrogen per se can decarbonise the energy system.

Unlike previous works, where the objective is to minimise the operating cost with/without carbon-tax this paper proposes a model to address carbon minimisation by introducing new variables and carbon constraints inspired by the CEF to address a stochastic DA scheduling.

To this end, a stochastic CO_2 minimisation is modelled as a benchmark to achieve by a responsible market performed by a single operational entity. The proposed objective is compared with cost minimisation with/without carbon-tax in terms of costs and emissions. In addition, two sustainable indices are proposed evaluating carbon performance during operation in terms of the average value of carbon emission sent to loads during operations and CO_2 intensity sent to loads normalised to the worst case. The lack of indices in the literature limits the sustainability evaluation from comparing the system's performance during operation. The indices proposed in this paper facilitate the benefits of the illustrated model and help identify the sustainable impact of the hybrid system components. Finally, a carbon-tax sensitivity analysis is performed, which shows fundamental considerations on carbon emissions during operation and the limitations of the scheduling in the literature so far. The mathematical problem formulation, stochastic procedure and indices are presented in Method. The Result section shows the outcomes of the day-ahead scheduling comparisons, including costs, carbon emissions, indices and carbon-tax sensitivity analysis. Finally, the main insights and considerations are summarised in the Conclusions.

Nomenclature				
$\boldsymbol{b}$	Branch	$\boldsymbol{n}$		Node
$\boldsymbol{DA}$	Day-ahead	$\boldsymbol{\Sigma}$		Set of Scenario
$\boldsymbol{M}$	Methanator	$\boldsymbol{\sigma}$		Scenario
$\boldsymbol{N}$	Set of general variables	$\boldsymbol{c_p}$	[MWh/kg/^{0}C]	Heat capacity of water
$\boldsymbol{RT}$	Real-time	$\boldsymbol{\pi_\sigma}$	[-]	Probability of a scenario
$\boldsymbol{S}$	Storage	$\boldsymbol{BES}$	[MWh]	Battery energy storage
$\boldsymbol{S/R}$	Supply return circuit in DHS	$\boldsymbol{CO_2}$	[kg]	Carbon dioxide
$\boldsymbol{T}$	Set of time	$\boldsymbol{Cost}$	[$]	Operational Cost
$\boldsymbol{UG}$	Utility national grid	$\boldsymbol{P}$	[MW]	Power
$\boldsymbol{g}$	Generator	$\boldsymbol{c}$	[$/MWh]	Cost coefficient
$\boldsymbol{in/out}$	Inlet/outlet of a tube	$\boldsymbol{co_2}$	[kg/MWh]	Carbon dioxide coefficient
$\boldsymbol{l}$	Load	$\boldsymbol{t}$	[h]	Time
$\boldsymbol{loss}$	Loss in a pipe or tube	$\boldsymbol{tax}$	[$/MWh]	Carbon tax coefficient
		$\boldsymbol{T}$	[^{0}C]	Temperature

2. Method

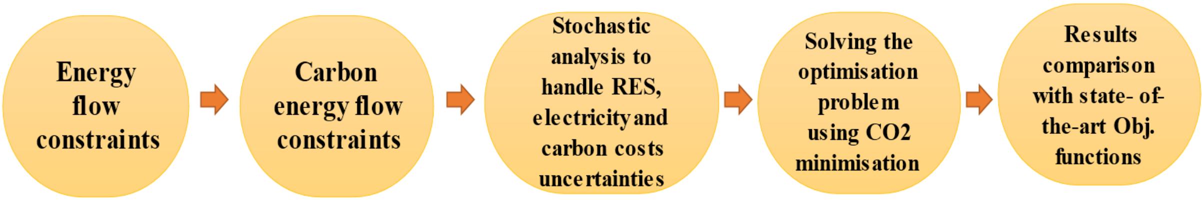

Fig. 1. Procedure to perform day-ahead stochastic carbon minimization.

This section shows the method to model the stochastic DA scheduling for HRES, accounting constraints, and variables. Physical laws describing HRES and components are shown in [8] for the basic theory, while the carbon flow and the stochastic procedure are shown in this section. Finally, the indices and the objective functions compared are presented. Fig. (1) summarises the method.

2.1. Carbon energy flow constraints

As a basic concept, the energy flow transports a certain amount of CO_2 at any time t and part of HRES (nodes, pipes, lines and components). Assuming the CO_2 is uniformly distributed in the energy flow, the relationship between power and CO_2 can be modelled using a coefficient $co_2\ (t)\left[\frac{kg}{MWh}\right]$. In principle, $co_2\ (t)$ is unknown, so the non-linear constraint can be linearised using McCormick's multi-bi-variate relaxation [8]. Not considering the life cycle assessment, the carbon emissions from RES are zero.

2.1.1. CO_2 flow in EPS

The relationships presented in Eq. (1-2) represent the mass balance in nodes n and lines b, following the mass conservation at any hour t. The entering CO_2 at nodes is equal to the exiting carbon amount. Electrical lines do not store power; hence neither does CO_2. The system is linear if the system only consists of loads and generators in which the carbon emission is known. Conversely, if EPS is equipped with BES, the mathematical formulation becomes non-linear.

$$CO_{2_n}\ (t) = 0 \tag{1}$$

$$\sum_{\forall b \in n} CO_{2_{b_{in}}}\ (t) - \sum_{\forall b \in n} CO_{2_{b_{out}}}\ (t) = 0 \tag{2}$$

2.1.2. CO_2 flow in storage component

The battery energy storage system (BES) component introduces non-linearity into the EPS. The model can be applied to any energy storage system in HRES. The amount of CO_2 must comply with Eq. (3), hourly $CO_{2_S}{}^{+}(t)$ be injected into the storage or $CO_{2_S}^{-}(t)$ released from the component according to the dynamics established by the energy flows, as shown in Eq. (4). BES is the storage capacity, and $\eta_{CO2r}, \eta_{CO2c}, \eta_{CO2d}$ are the rest, charge, and discharge CO_2 efficiency, respectively.

$$co_{2_S}(t)\left[\frac{kg}{MWh}\right] = \frac{CO2_S\ (t)}{BES\ (t)} \tag{3}$$

$$CO2_S\ (t) = \frac{CO2_S(t-1)}{\eta_{CO2_r}} + \frac{CO_{2_S}{}^{+}(t)}{\eta_{CO2_c}} - CO_{2_S}^{-}(t) \cdot \eta_{CO2_d} \tag{4}$$

2.1.3. CO_2 flow in NGS

The NGS can be modelled as unique storage as the gas mixing in the pipelines is slow [9], so a single carbon coefficient is considered for all pipes. Eq. (5) shows the carbon balance at any time, accounting for generator

g, demand l, storage S and losses $loss$.

$$CO_{2_{NGS}}(t) = CO_{2_{NGS}}(t-1) + \sum CO_{2_g}(t) - \frac{CO_{2_S}{}^{+}(t)}{\eta_{CO2c}} + CO_{2_S}^{-}(t) \cdot \eta_{CO2d} - CO_{2_l}(t) + CO_{2_{loss}}(t) \tag{5}$$

2.1.4. CO_2 flow in DHS

The heating network consists of heat sources, loads and supply/return heating pipes. Heat is produced by the sources and transported to the load by water circulation in the pipes. The general structure of a heating network is modelled as in [7], showing that different arrows clearly distinguish the supply/return S/R energy flows. At the inlet/ outlet in/out, the carbon emission could be expressed as in Eq. (6). Losses cause the dissipation of carbon emission as in Eq. (7), where $T_{b_{LOSS}}$ is the temperature loss in the supply and return pipes. In each pipe, the resulting CO_2 is mixed with the energy fluxes as in Eq. (8). Finally, the carbon coefficient at the inlet and outlet has the same value [7].

$$CO_{2_{n\,in/out}}^{S/R}(t) = co_{2_n}^{S/R}(t) \cdot c_p \cdot T_{\mathrm{n}_{in/out}}^{S/R}(t) \tag{6}$$

$$CO_{loss}^{S/R}(t) = co_{2_{in_{loss}}}^{S/R}(t) \cdot c_p \cdot T_{b\ loss}^{S/R}(t) \tag{7}$$

$$\sum_{\forall b \in n_{in}} CO_{2_{b_{in}}}^{S/R}(t) - \sum_{\forall b \in n_{out}} CO_{2_{b_{out}}}^{S/R}(t) + \sum_{\forall n} CO_{2_n}^{S/R}(t-1) = \sum_{\forall n} CO_{2_n}^{S/R}(t) \tag{8}$$

2.1.5. CO_2 flow in coupling units

Linking units allow energy and carbon to transfer among energy systems. The linking units receive a carbon amount equal to that in the input stream. However, each linking unit has a specific conversion efficiency that increases the amount of carbon in the outflow, thus increasing the carbon content to produce that flow [3]. The output carbon flux is the sum of the input carbon flux received from EPS and the carbon content in electrical energy to activate the component, as in PtSNG and EB. It is not true for CHP, whose resulting CO_2 is the sum of the carbon from the NGS tubes divided by the efficiency of the component plus the carbon generated to burn the gas.

2.2. Stochastic model

Deviations may occur from what was established the day before about the share of renewables, and consequently, carbon emission in the electricity flow and the demand may deviate from the forecast made in the DA. Therefore, the load deviation must be adjusted in the intraday phase. In this paper, the intraday phase is not considered, and DA decisions are made only with Real-Time (RT) uncertainties. DA and RT scheduling handle future uncertainties with different strategies and time scales. A stochastic approach is adopted to evaluate DA scheduling to consider RES, price and CO_2 emission uncertainties in EPS, as NGS and DHS energy markets are more stable than EPS, so uncertainties are not considered variables in the stochastic process. The method is the classification tree to predict scenarios using the Matlab tool based on [10]. The tool highlights partial dependencies between uncertainties by performing classification, linear regression and next-day prediction. The selected variables and the process is schematised in Fig.2. The tree is constructed based on the number of data; the more the data are, the higher the number of leaves (i.e., scenarios $\sigma \epsilon \Sigma$) in the tree. A tree with many leaves tends to have a lower test accuracy than its training accuracy (substitution), and a shallow tree is easy to interpret. K-fold validation is applied to obtain the optimal number of scenarios [11] and, subsequently, to calculate the probability π_σ that scenario can happen.

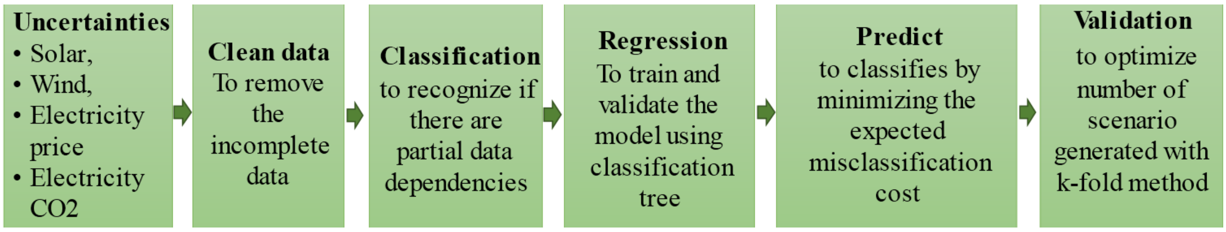

Fig. 2. Procedure of Stochastic DA scheduling for scenario generation using Classification Tree and K-fold validation

2.3. Objective functions

To demonstrate the potential of the proposed approach, an objective function (OF) was defined, accounting for carbon emissions during operation:

- OF1: Carbon flow minimisation within HRES, as in Eq. (9).

${CO_2}_M^{DA}(t)$ is the CO_2 subtracted to the system from the Methanator reaction as in [12]. The operation of OF1 is compared with two state-of-the-art objective functions neglecting carbon flux constraints. By applying the CEF a-posteriori, system performances can be confronted regarding costs and carbon emissions.

- OF2: Cost minimisation accounting for carbon taxes as in Eq. (10). c_{UG} is the cost and $P^{DA}_{UG_{NGS}}$ the power from the national grids.
- OF3: Cost minimisation without accounting for the carbon tax, as in Eq. (11).

OF1
$$\begin{aligned} {CO_2}_{HRES}[kg] = \sum_{t=1}^{T}\Bigg(&\sum_{g\epsilon N_g} {CO_2}_g^{DA}(t) + \sum_{l\epsilon N_{loss}} {CO_2}_{loss}^{DA}(t) + \sum_{b\epsilon N_b} {CO_2}_b^{DA}(t) + \sum_{S\epsilon N_S} {CO_2}_S^{DA}(t) - {CO_2}_M^{DA}(t) \\ &+ \sum_{\sigma=1}^{\Sigma} \pi_\sigma \cdot \Bigg(\sum_{g\epsilon N_g} {CO_2}_g^{RT}(t,\sigma) + \sum_{l\epsilon N_{loss}} {CO_2}_{loss}^{RT}(t,\sigma) + \sum_{b\epsilon N_b} {CO_2}_b^{RT}(t,\sigma) + \sum_{S\epsilon N_S} {CO_2}_S^{RT}(t,\sigma) - {CO_2}_M^{RT}(t,\sigma)\Bigg)\Bigg) \end{aligned} \tag{9}$$

OF2
$$\begin{aligned} Cost_{HRES}[\$] = \sum_{t=1}^{T}\Bigg(&c^{DA}_{UG_{EPS}}(t) \cdot P^{DA}_{UG_{EPS}}(t) + c^{DA}_{UG_{NGS}}(t) \cdot P^{DA}_{UG_{NGS}}(t) + tax_{UG_{EPS}}(t) \cdot P^{DA}_{UG_{EPS}}(t) + tax_{UG_{NGS}}(t) \cdot P^{DA}_{UG_{NGS}}(t) \\ &+ \sum_{\sigma=1}^{\Sigma} \pi_\sigma \\ &\cdot \left(c^{RT}_{UG_{EPS}}(t,\sigma) \cdot P^{RT}_{UG_{EPS}}(t,\sigma) + c^{RT}_{UG_{NGS}}(t,\sigma) \cdot P^{RT}_{UG_{NGS}}(t,\sigma) + tax_{UG_{EPS}}(t,\sigma) \cdot P^{RT}_{UG_{EPS}}(t,\sigma) + tax_{UG_{NGS}}(t) \cdot P^{RT}_{UG_{NGS}}(t,\sigma)\right)\Bigg) \end{aligned} \tag{10}$$

OF3
$$\begin{aligned} Cost_{HRES}[\$] = \sum_{t=1}^{T}\Bigg(&c^{DA}_{UG_{EPS}}(t) \cdot P^{DA}_{UG_{EPS}}(t) + c^{DA}_{UG_{NGS}}(t) \cdot P^{DA}_{UG_{NGS}}(t) \\ &+ \sum_{\sigma=1}^{\Sigma} \pi_\sigma \cdot \left(c^{RT}_{UG_{EPS}}(t,\sigma) \cdot P^{RT}_{UG_{EPS}}(t,\sigma) + c^{RT}_{UG_{NGS}}(t,\sigma) \cdot P^{RT}_{UG_{NGS}}(t,\sigma)\right)\Bigg) \end{aligned} \tag{11}$$

2.4. Indices

Two indices are proposed to evaluate the carbon emission performance, comparing the operation with different OF. Eq. (12) shows the carbon concentration index to the loads by expressing the average daily amount ${CO_2}_l$ per unit of power delivered P_l. Eq.(13) shows the CO_2 intensity index expressing the carbon amount emitted from the load normalised to co_2^{wc}; the highest CO_2 delivered from a generator as in Eq.(14). While ${CO_2}_c$ allows comparing different objective functions of the same system and energy demand, ${co_2}_I$ can compare any operation. Furthermore, the latter provides information on the amount of CO_2 generated during the operation: whether it decreased or increased compared to the system's CO_2 sources.

$${CO_2}_c\left[\frac{kg}{MWh}\right] = \sum_{t=1}^{T} \frac{\sum_{l=1}^{N_l} {CO_2}_l(t)}{\sum_{l=1}^{N_l} P_l(t)} \tag{12}$$

$${co_2}_I[-] = \sum_{t=1}^{T} \frac{\sum_{l=1}^{N_l} {CO_2}_l(t)}{\sum_{l=1}^{N_l} CO^{WC}_{2_g}(t)}\ ;\ \ CO_2^{WC}(t)\ [kg] = \sum_{t=1}^{T} \max_{g\ \in\ N_g}\left({CO_2}_g(t)\right) \tag{13}$$

3. Results

The approach proposed is tested for a solar-wind HRES grid-connected with the danish gas and electric grid in a stochastic DA scheduling inspired by [12,13]. The EPS is an 8 bus-system, and the NGS and DHS are 5 node-systems. The linearised stochastic DA scheduling is solved by testing the three OF presented in Section 2.3 with a MILP optimisation revealing the optimal operation in terms of cost and CO_2. For OF1, a further linearisation was necessary to overcome the non-linearity of CO_2 constraints burdening the computational cost substantially. The OF comparison will be performed to evaluate the carbon analysis's CEF a posteriori. Finally, the CO_2 indices are used to evaluate the optimal operations.

3.1. Input data

The stochastic DA scheduling considers data for the Danish Bornholm Island in January 2021. The input data are solar and wind generation, carbon and cost from the national grids. For the stochastic analysis, scenarios are generated considering the wind and solar hourly data considering 10 years to build scenarios using the approach described in the Method section. Electricity and gas prices and carbon emissions are from [12].

3.2. Optimal costs and CO_2 emissions

The optimal operation of the compared OF is summarised in Fig. 3 (a) in terms of operating costs (x-axes) and carbon emissions (y-axes). The proposed approach that uses OF1 achieves the lowest CO_2 generation in the HRES, saving almost 480 kg of CO_2 during operation compared to OF3. On the other hand, OF1 has the highest operation cost, reaching 8 k$. The difference in the cost of operations relates to the different use of the electricity and gas network supplies. The analysis reveals this is due to different PtSNG and CHP components operations and hydrogen storage exploitation. In OF1, electricity from RES and the national grid is stored during the morning to supply the loads afterwards.

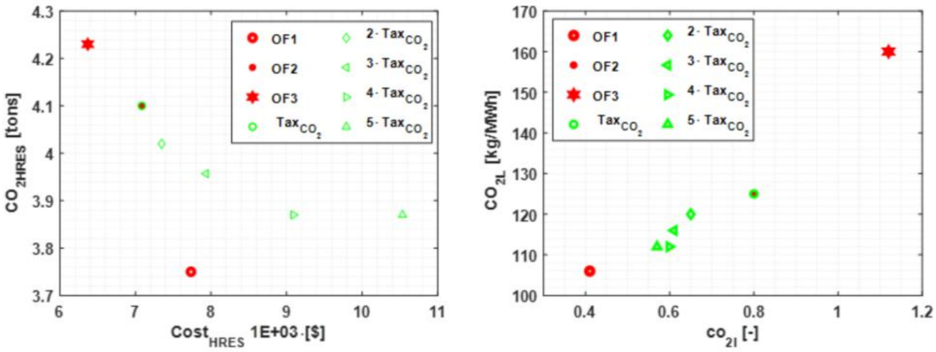

Fig. 3. (a) Indices optimal operation evaluation (b) Carbon emissions and optimal cost confrontation using different OF.

On the other hand, OF3 exploits CHP as it is a flexible component, supplying all loads, and the external gas grid costs are relatively low and sometimes cheaper than electricity. In fact, at some hours of the day, CHP is cheaper than PtSNG as the operating cost of PtSNG is higher than CHP after 6:00 am, as shown in Fig. (4). Although OF3 exploits gas for economic reasons, the gas emissions from the national grid are also lower than those from electricity. OF3 has higher emissions as most of the gas is used to supply the other grids via CHP. CHP burns the gas increasing the CO_2 share of the entire HRES. Furthermore, CHP lacks flexibility; it must immediately and simultaneously supply EPS and DHS, even if inconvenient. Only OF1 considers the CO_2 share, highlighting the model advantage from an environmental perspective. In fact, as OF3 exploits PtSNG only for two hours, no CO_2 subtracted from the methanation to HRES is accounted for. It is impossible to consider the share increased by CHP operation in the flows. With the DA CEF scheduling, the use of the gas system increases the amount of carbon in the gas transport pipes (due to leaks) and in the combustion conversion.

In OF3, 63% of the total emissions are due to carbon losses and gas combustion, whereas in OF1, these losses are 40%. So, OF1 has lower emissions and better use of pipelines, methanation, and the sporadic use of CHP, saving 33% compared to OF3. Finally, OF2 involves a trade-off between costs and emissions. CHP works in the morning, as taxes on the electricity grid are higher than those on the gas grid [14]. Therefore, the use of gas is not as favoured as in OF3, resulting in an average solution between the others.

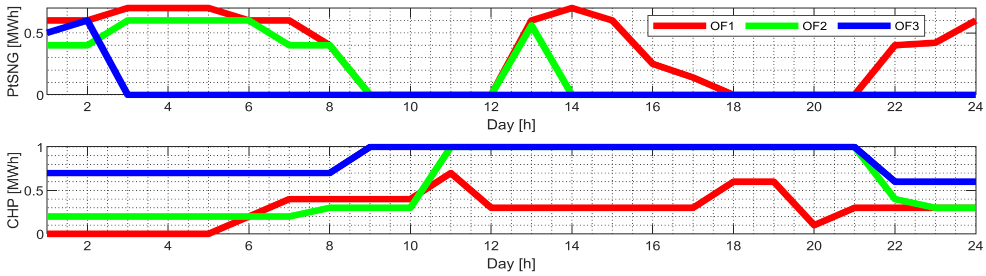

Fig. 4. PtSNG and CHP energy breakdown.

3.3. Carbon emission indices

The HRES performance in the three considered OF are evaluated as shown in Fig. 3 (b), with the load concentration index (y-axes) and CO_2 intensity (x-axes), shown by the red points. Focusing on the load concentration, the values increase progressively in OF1-2-3. Considering the averages gas and electricity CO_2 emissions networks are 92 and 188 [kg/MWh], respectively, OF3 has a higher CO_{2_C} than the external generators, even though OF3 uses the gas network more, which has a lower carbon input. The reason is by using NGS to supply energy to EPS and DHS, CO_2 is significantly increased, leading the loads to have a higher amount of CO_2 than the CO_2 produced by the system and almost doubling the value of the gas grid. Quite a similar behaviour occurs using OF2, whose additional taxes make the utilisation of the grids more efficient. Results are slightly below those obtained by OF1 but still above the average of NGS, concluding that OF3 could lead to fallacious results. The largest CO_2 share comes from CHP, while PtSNG generates a reduced CO_2 concentration due to the Methanator. Finally, OF1 shows that the massive use of renewables and PtSNG, even if it is not economically convenient, is beneficial from a sustainable perspective, which, by economising on the energies in HRES, achieves an emission index of 106, slightly above gas emissions. Regarding co_{2_l}, OF1-2 have an index minor than one, concluding that compared to the worst case, there is still a saved quantity, 60% and 20%, respectively. In OF3, the index is 12% higher than for CO_2^{WC}, concluding that components such as CHP harm the CO_2 input to loads.

3.4. Hydrogen tank in PtSNG unit

This section analyses hydrogen storage's role during energy dispatching; Table 1 shows the results for a 1 MW electrolyser with a 5 MWh storage. OF1 has two morning charging peaks exploiting RES and one in the afternoon; due to line capacity limitation of the grid and because the renewables are still used in the morning, necessitating charging the storage again, increasing the operational cost, not happening in OF2-3 as the gas grid is often cheaper. In OF2, peaks occur during the morning, storing RES power and releasing them in the afternoon, avoiding paying the carbon tax. Finally, only one peak is in OF3 during the morning to store some of the electricity from RES.

Table 1. Hydrogen storage tank during operation.

Objective function	Hour of charge [h]	Maximum capacity [MWh]	Maximum electrolyser power [MW]	Number of peaks [-]
OF1	8	3.6	0.7	3
OF2	5	2.1	0.6	2
OF3	2	1.0	0.6	1

3.5. Carbon tax sensitivity analysis

A sensitivity analysis is performed for OF2, assuming an increase of carbon taxation value up to 5 times. The cost and relative emissions are shown in Fig. 3(a) and Fig. 3(b), evaluating performance with the indices. It is evident that operating cost increases as taxation increases, even growing rapidly, while the decrease in CO_2 in the system reaches a plateau, converging towards OF1 but without reaching the minimum threshold reached by OF1. To minimise CO_2, the proposed approach can reach the benchmark but with a cost increase of 21% (and an emission reduction of 15%). If carbon taxation increases, a level of CO_2 emissions comparable to OF1 can be achieved, but with a higher cost.

4. Conclusions

To create awareness of CO_2 emitted during DA operation, this paper proposed a mathematical model to minimise CO_2 emissions in a multi-energy system while also considering energy flows and market costs. The model performance was compared to the usual cost minimisation with/without CO_2 taxations to highlight the possible misdirection caused by the scheduling of state-of-the-art cost minimisation, leading to increased CO2 emissions. Results show that the proposed approach defines the minimum limit of CO_2 emitted during DA scheduling, while the lowest cost is reached through the usual cost minimisation and the highest carbon emission. A trade-off between them is identified using cost optimisation with carbon taxes. Therefore, a sensitivity analysis detected how the taxation system could affect GHG reduction and arrive at CO_2 minimisation. The results show that raising taxes increases the operational costs well above the CO_2 minimisation (if the current values are tripled) at the cost of not reaching the CO_2 minimisation found with the model in this paper. It also shows that the taxation system is not the best method, as the costs for the grid would become substantial, but we would still have a minimal CO_2 improvement that is not appreciable, as it creates a sort of plateau that 'tends' to the value established by the CO_2 minimisation without reaching it. The comparison with the indices shows that the most significant amount of CO_2 avoided and sent to loads occurs in CO_2 minimisation, while in pure cost minimisation, the CO_2 is even greater than that from external networks due to CHP usage to supply the other networks, not highlighted with previous studies. Although CHP is advantageous from a monetary perspective, CHP generates a CO_2 amount higher than is emitted from the Danish electricity and gas grids, leading to an increased CO_2 released to loads overall, concluding that the use of the gas market is inconvenient from an emissions perspective alone, as this generates more CO_2 during operation. Although national electricity has a higher average CO_2 emission coefficient than the gas grid, the PtSNG component even reduces these emissions through methanation. Finally, this study highlights the strong impact that the penetration of renewables would have on the use of PtSNG. If this were to increase, PtSNG would significantly reduce costs and emissions.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All authors conceptualise the work, Sorrenti I. and Rasmussen T. analysed the data, and Sorrenti I. conducted the research and wrote the paper.

Acknowledgements

This work was financially supported by Sino-Danish Centre for Education and Research (SDC) and the Heat4RES.

References

[1] Nathalie Girouard, Elianna Konialis CTPT. OECD Green Growth Studies. IEA; 2012. https://doi.org/www.oecd.org/greengrowth.

[2] Burre, J., Bongartz, D., Brée, L., Roh, K., Mitsos, A. (2020). Power-to-X: Between electricity storage, e-production, and demand side management. *Chemie-Ingenieur-Technik*, 92, 74–84. https://doi.org/10.1002/cite.201900102.

[3] Ikäheimo, J., Weiss, R., Kiviluoma, J., Pursiheimo, E., Lindroos, T. J. (2022). Impact of power-to-gas on the cost and design of the future low-carbon urban energy system. *Appl Energy*, 305, 117713. https://doi.org/10.1016/j.apenergy.2021.117713.

[4] Habib, H. U. R., Subramaniam, U., Waqar, A., Farhan, B. S., Kotb, K. M., Wang, S. (2020). Energy cost optimisation of hybrid renewables based V2G microgrid considering multi objective function by using artificial bee colony optimisation. *IEEE Access*, 8, 62076–93, https://doi.org/10.1109/ACCESS.2020.2984537.

[5] Yamashita, D., Yokoyama, R., Niimura, T. (2013). Thermal unit scheduling for CO_2 reduction including wind power and electric vehicles. *J Adv Comput Intell Intell Informatics*, 17, 109–15. https://doi.org/10.20965/jaciii.2013.p0109.

[6] Cheng, Y., Liu, M., Chen, H., Yang, Z. (2020). Optimization of multi-carrier energy system based on new operation mechanism modelling of power-to-gas integrated with CO_2-based electrothermal energy storage. Energy 2020, 119269. https://doi.org/10.1016/j.energy.2020.119269.

[7] Cheng, Y., Zhang, N., Wang, Y., Yang, J., Kang, C., Xia, Q. (2019). Modeling carbon emission flow in multiple energy systems. *IEEE Trans Smart Grid*, 10, 3562–74. https://doi.org/10.1109/TSG.2018.2830775.

[8] Castro, P. M. (2015). Tightening piecewise McCormick relaxations for bilinear problems. *Comput Chem Eng,* 72, 300–11. https://doi.org/10.1016/j.compchemeng.2014.03.025.

[9] Yang, J., Zhang, N., Kang, C., Xia, Q. (2018). Effect of natural gas flow dynamics in robust generation scheduling under wind uncertainty. *IEEE Trans Power Syst*, 33, 2087–97. https://doi.org/10.1109/TPWRS.2017.2733222.

[10] Gehrke, J. (2011). Classification and regression trees. *Encycl Data Warehous Min*, 246–80, https://doi.org/10.4018/9781591405573.ch027.

[11] Hastie, T. et al. (2009). Statistics The Elements of Statistical Learning. *Math Intell*, 27, 83–85.

[12] Sorrenti, I., Member, S., Singlitico, A., Rasmussen, T. B. H., You, S. (2022). Sustainability analysis and Power-to-Methane mathematical model comparison of hybrid renewable energy system day-ahead scheduling. In: *IEEE*, editor. IC-REST, Tirana, 1–5. https://doi.org/978-1-6654-0971-1/22.

[13] Turk, A., Zeng, Q., Wu, Q., Nielsen, A. H. (2020). Optimal operation of integrated electrical, district heating and natural gas system in wind dominated power system. *Int J Smart Grid Clean Energy*, 237–46, https://doi.org/10.12720/sgce.9.2.237-246.

[14] Use TE. Taxing Energy Use 2019 : Country Note – Norway. OECD 2019:1–8. https://doi.org/http://oe.cd/TEU2019.