Co-optimization of Resilient Gas and Electricity Networks; A Novel Possibilistic Chance-Constrained Programming Approach

Vahid Shabazbegian[1], Hossein Ameli[2,*], Mohammad Taghi Ameli[1], Goran Strbac[2], Meysam Qadrdan[3]

1: Department of Electrical Engineering, Shahid Beheshti University, 19839 69411, Tehran, Iran
2: Control and Power group, Imperial College London, SW7 2AZ, UK
3: Institute of Energy, Cardiff University, CF24 3AA, UK

Abstract

Gas-fired power plants are commonly employed to deal with the intermittency of renewable energy resources due to their flexible characteristics. Therefore, the intermittency in the power system transmits to the gas system through the gas-fired power plants, which makes the operation of these systems even more interdependent. This study proposes a novel possibilistic model for the integrated operation of gas and power systems in the presence of electric vehicles and demand response. The model takes into account uncertainty in demand prediction and output power of wind farms, which is based on possibility and necessity theories in fuzzy logic through modeling uncertain parameters by Gaussian membership function. Moreover, a contingency analysis algorithm based on maximin optimization is developed to enhance the resiliency in the integrated operation of these systems by finding the worst-case scenario for the outage of components. The proposed model is implemented on a Belgium gas network and IEEE 24-bus electricity network. It is demonstrated that the possibilistic model allows the gas network to respond to the demand variations by providing a sufficient level of linepack within the pipelines. As a result, gas-fired power plants are supposed to commit more efficiently to cope with the intermittency of wind farms, which reduce the wind curtailment by 26%. Furthermore, it is quantified that through applying the contingency analysis algorithm in presence of demand response and electrical vehicles, the costs of operation and load shedding is reduced up to 17% and 83%, respectively.

Keywords: Possibilistic Chance-Constrained Programming; Scheduling; Resiliency Analysis; Electrical Vehicles; Demand Response; Gas and Power Systems.

* Corresponding author
Email addresses: v.shahbazbagian@mail.sbu.ac.ir (Vahid Shahbazbegian), h.ameli14@imperial.ac.uk (Hossein Ameli), m_ameli@sbu.ac.ir (Mohammad Taghi Ameli), g.strbac@imperial.ac.uk (Goran Strbac), qadrdanm@cardiff.ac.uk (Meysam Qadrdan)

1. Introduction

The changeover to supply energy from renewable resources has started in the electricity sector to deal with the climate change issue [Dagoumas et al., 2019]. A high share of renewable energy sources should be installed to replace the power plants characterized by lower efficiencies and high emissions (e.g., coal power plants) [2019; Peter 2019]. In this regard, due to the flexible characteristics of gas-fired power plants, such as fast ramping rate and short startup time, these plants area potential to deal with the intermittency of renewable energies [Mei et al., 2020]. Accordingly, the intermittency of renewable energies in the power system affects the gas network demand through gas-fired power plants. Moreover, in practice, due to the slow speed of gas within the pipelines, the stored gas in the pipelines (linepack) is used to respond to the rapid variation in the gas demand [Hörnlein, 2019]. The intermittency of renewable energies affects the linepack within the pipelines as well and makes linepack management challenging [He et al., 2018]. Therefore, to cope with the associated challenges to renewables, the integrated operation of gas and Power systems is of great importance.

In He et al. (2018) and Ríos-Mercado and Borraz-Sánchez (2015), the relevant studies on the integrated operation of gas and power systems are reviewed and categorized based on their approaches and analyses. The most relevant stream of literature to this paper is to investigate the role of uncertainty in the integrated operation of gas and power systems. Taking into consideration the uncertainty in this problem makes the problem realistic. For instance, there is uncertainty in the electricity and gas demands prediction due to the randomness inherent and volatility of the high number of consumers [Liang & Liao, 2007]. Furthermore, the integration of renewable energy resources entails uncertainty due to their intermittency that impacts the supply-demand balance. Some previous researchers study the impact of operational uncertainties in the integrated operation of gas and power systems applying stochastic programming to deal with the existing uncertainty in demand prediction [Mirzaei et al., 2019] output power of wind farms [Qadrdan et al., 2014], and gas demand [Shahbazbegian et al., 2020]. A few studies also examine the existing uncertainty in the electricity network applying robust programming and probabilistic programming. The results of these studies indicate that considering uncertainty reduces the cost of operation [Bai et al., 2017], renewable energy curtailment [He et al., 2017], and provides a less challenging operation in case of contingency [Sun et al., 2017]. This is noteworthy to mention that the probabilistic methods, which are used to handle the uncertainty in the reviewed papers, are based on the historical data about uncertain parameters. However, in the case of lack of implementation in the real-world, possibilistic methods are mainly used to solve an optimization problem, which assumes a fuzzy membership function to represent uncertain parameters [Ehsan and Yang, 2019].

Considering the uncertainty and resiliency in the integrated operation of gas and power systems makes the problem even more realistic. As stated in [Jufri et al., 2019], resiliency refers to "the capacity of an energy system to tolerate disturbance and to continue to deliver affordable energy services to consumers. A resilient energy system can speedily recover from shocks and can provide alternative means of satisfying energy service needs in the event of changed external circumstances". Therefore, proposing an approach to examine and increase the resiliency in the integrated operation of gas and power systems reduces the probability of considerable outage and increases the reliability of these systems against potential threats. Despite the importance of resiliency in the operation of energy systems, only a limited number of studies have focused on the resiliency in the integrated operation of energy systems. For instance, Yan et al., 2018, Abdulwahab et al., 2017, and Zhang et al., 2016 determine outage scenarios for different components and solve the stochastic model considering the predetermined scenarios. Hao et al., 2018 determine the worst-case scenario for the outage of components and carried out a robust model that increases the resiliency of the system. The results of these studies show the operation cost and load shedding reduction during the large outages, indicating resiliency enhancement.

On the other hand, in the literature, some studies investigate the role of flexibility options to deal with the existing uncertainty in the integrated networks, such as flexible gas-fired power plants, energy storage systems, and power-to-gas systems. On the other hand, the integration of Electrical Vehicles (EVs) is developing, which can pose some challenges in power systems [Adraktas & Dagoumas, 2019]. EVs can result in extra demand in the electricity network, which needs further investment to increase generation capacity. However, the EV batteries can be considered as distributed storages benefiting from optimal scheduling, while maintaining the mobility and flexibility of EVs is an important aspect to be considered [Haddadian et al., 2015]. Besides, Demand Response (DR) is another flexibility option like the optimal scheduling EVs that facilitates supply-demand balance in the electricity network [Ameli et al., 2020, Ameli et al., 2020a; Zhang et al., 2020]. Among the previous studies, Qadrdan et al. (2015) and Qadrdan et al. (2017) propose a model to investigate the role of flexible gas-fired power plants, electricity storage systems, and power-to-gas systems in the integrated operation of gas and power systems. Ameli et al. (2017) and Ameli et al. (2019), also investigate the role of different flexibility options in this problem, including flexibility in gas infrastructure (i.e., multi-directional compressors). The results of these studies show the benefit of flexibility options in the operation of these systems, including cost reduction and decrease in renewable energies curtailment Another study investigates the role of demand response in the operation of gas and power systems and examines its economic and environmental benefits [Nazari-Heris et al., 2020]. Wang et al. (2020) also proposes a two-stage framework to dispatch power within these energy systems and investigate the carbon intensity control beside the demand response. Some previous studies, on the other hand, examine the role of flexibility options only in the operation of power systems (e.g., UC) under high penetration of renewable energy resources [Yang et al., 2017] or EVs [Wang et al., 2019, Yang et al 2019]. Other studies also take into account uncertainty in renewable resources [Shahbazitabar and Abdi, 2019] and weather conditions [Ahmadi et al., 2019]. The results of these studies show optimal scheduling EVs leads to cost improvement. However, if they are not taken into consideration in the scheduling, the increase in demand imposes challenges into the problem. Moreover, a few studies take into account different types of DR in the operation of the electricity network, such as incentive-based DR [Azizipanah-Abarghooee et al., 2016; Kiran and Kumari, 2016] and virtual-based DR [Roukerd et al., 2019; Reddy et al., 2016]. The obtained results also show the impacts of DR in reducing renewable energy curtailment, which leads to operational cost saving.

By reviewing the previous studies (Table 1), it is revealed that despite the extensive studies of the relevant literature, EVs have not taken into consideration in the integrated operation of gas and power networks. On the other hand, the potential of DR can be used to deal with uncertainty and intermittency of renewable energy resources and facilitates supply-demand balance. Moreover, a few studies have addressed the resiliency in the integrated operation of these systems, although the roles of these measures in preventing wide outages are not deniable. Also, in order to make the decisions more realistic, considering uncertainty in the electricity demand and output power of renewable resources is of great importance since the perfect foresight is not possible.

Motivated by the gap in the literature, at the first step, a model for integrated operation of gas and power systems considering EVs and DR is developed. After that, at the second step, a possibilistic approach is proposed to cope with the inherent uncertainty in renewable power generation and demand, based on the concepts of possibility and necessity theories in the fuzzy logic. This is due to reason that adding EVs causes epistemic uncertainty (i.e., result of lack of implementation in large scale in real world), which decreases the efficiency of probabilistic methods. For this purpose, Gaussian membership function is applied to indicate the uncertain parameters. Moreover, a contingency analysis algorithm is developed in this step to improve the resiliency and prevent huge shortages in supplying demand in case of contingency. This algorithm includes a maximin optimization to detect the worst-case scenario for the outage of components and optimizing the problem based on the worst-case scenario. At the third stage, a real-world case study is employed based on Belgium network to evaluate the practicality as well as the applicability of the proposed model. The main contributions of this study and the overview of this step-by-step process are depicted in Figure 1.

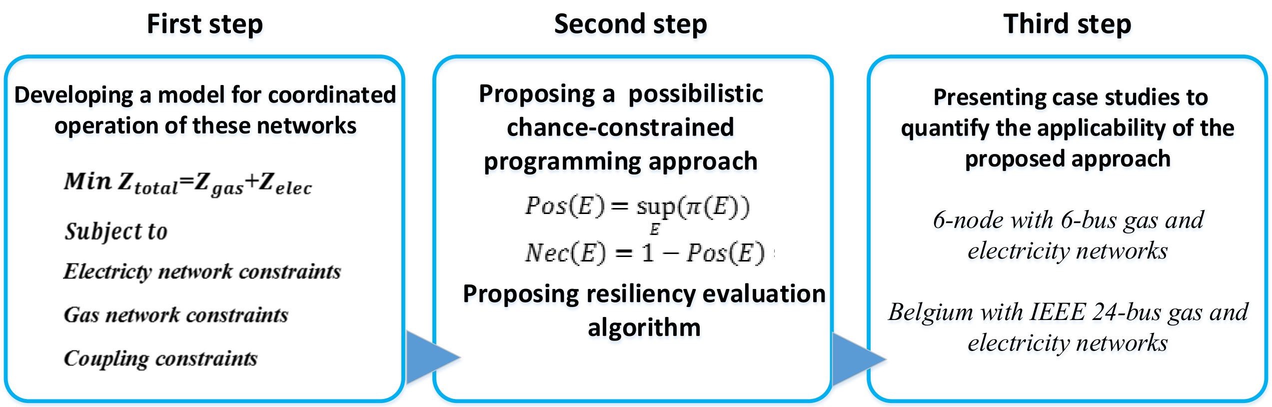

Figure 1. Overview of the proposed co-optimization approach for resilient gas and power operation under uncertainty.

Table 1. Systematic review of the studied papers into integrated operation of gas and power systems.

Number	Authors	Area		Flexibility consideration							Modeling Approach	Solution Method		Resiliency consideration		Uncertainty Approach			Uncertain parameters			
		Power system operation	Integrated operation	DR	EV	Electricity storage	Multi-directional compressor	Gas-storage	Flexible gas-fired plants	Power-to-Gas		Exact	Heuristic	Worst-case scenario	Outage scenario	Stochastic	Possibilistic	Robust	Electricity demand	Gas demand	Output power of renewables	Probable outages
1	Yang et al. (2017)	×			×						MINLP		×									
2	Shahbazitabar et al. (2018)	×			×						MINLP		×			×					×	
3	Ahmadi et al. (2019)	×			×						MILP	×				×			×		×	
4	Wang et al. (2019)	×			×						MINLP		×									
5	Yang et al. (2019)	×			×						MINLP		×									
6	Abarghooee et al. (2016)	×		×							MINLP		×				×		×		×	
7	Durgharikiran et al. (2016)	×		×							MINLP		×				×				×	
8	Poorvaeziroukerd et al. (2019)	×		×							MINLP		×				×				×	
9	Sirkanthreddyk et al. (2016)	×		×							MINLP		×			×					×	
10	Qadrdan et al. (2015)		×						×	×	MINLP	×										
11	Qadrdan et al. (2017)		×			×			×	×	MINLP	×										
12	Ameli et al. (2017)		×				×				MINLP	×										
13	Ameli et al. (2019)		×				×		×		MINLP	×										
14	Abdulwahab et al. (2015)		×								MILP	×				×						×
15	Bai et al. (2016)		×	×			×	×			MINLP	×						×	×		×	
16	He et al. (2017)		×							×	MILP	×						×	×		×	
17	Sun et al. (2017)		×								NLP	×					×		×		×	
18	Mirzaei et al. (2019)		×			×		×		×	MINLP	×				×					×	
19	Shahbazbegian et al. (2020)		×			×		×	×		MINLP	×			×	×			×	×	×	
20	Nazari-Heris et al. (2020)		×	×		×		×		×	MINLP	×				×			×	×	×	
21	Wang et al., 2020		×	×		×				×	MINLP	×										
22	Hao et al. (2018)		×								MINLP	×		×				×				
23	Yan et al. (2018)		×								MINLP	×			×	×						×
*	This study		×	×	×				×		MINLP	×		×			×		×	×	×	

2. Solution methodology

In this section, an enhanced operational model of gas and power systems is presented to develop a possibilistic model. The possibility and necessity theories in fuzzy logic beside Gaussian membership function of uncertain parameters are applied to develop the possibilistic model. This model is proposed to investigate the capability of the gas network in supporting future electricity networks with high penetration of renewable energy sources. Moreover, a contingency analysis is developed to enhance the resiliency of these systems, which consists of two main steps, including employing a maximin approach to find the worst-case scenarios for the outage of components and optimizing the problem based on the scenarios. To deal with the existing uncertainty in the parameters, the role of employing DR and optimal scheduling of EVs are also investigated in the integrated operation of these systems. Indices, parameters, and decision variables which are used in this model are introduced in Appendix A.

2.1. Gas and power systems objective functions and constraints

In this subsection, the objective function for the operation of the gas network is presented (1). The first term of this objective function is the cost of gas injection through the terminals, and the second and the third terms are costs of linepack management and gas load shedding, respectively.

$$OF^{gas} = \sum_{t \epsilon \mathcal{T}} \sum_{y \epsilon \mathcal{Y}} \mathrm{C}^{\mathrm{gas}} \cdot F_{y,t}^{\mathrm{sup}} + \sum_{t \epsilon \mathcal{T}} \sum_{n \epsilon \mathcal{N}} \mathrm{C}^{\mathrm{lp}} \cdot \Delta LP_{n,t} + \sum_{t \epsilon \mathcal{T}} \sum_{n \epsilon \mathcal{N}} \mathrm{C}^{\mathrm{gsh}} \cdot F_{n,t}^{\mathrm{gsh}} \qquad (1)$$

The gas network constraints are presented in (2)-(14). The limitation of gas injection through the terminals is defined in (2). Equation (3) shows the gas flow balance at each node of the gas network and each period. Equation (4) is Panhandle A equation [Osiadacz et al., 1987], which is applied to simulate the compressible gas flow within the pipelines. The pressure limits at each node and gas flow limits within the pipelines are also defined in (5)-(6).

$$F_{y,t}^{\mathrm{sup}} \leq \mathrm{F}_{y}^{\mathrm{sup.max}} \qquad \forall y \epsilon \mathcal{Y}, \forall t \epsilon \mathcal{T} \qquad (2)$$

$$F_{y,t}^{\mathrm{sup}} - F_{p,t}^{\mathrm{pipe}} - F_{c,t}^{\mathrm{comp}} = \mathrm{D}_{n,t}^{\mathrm{gas}} - F_{n,t}^{\mathrm{gsh}} \qquad \forall n \epsilon \mathcal{N}, \forall t \epsilon \mathcal{T} \qquad (3)$$

$$(\pi_{p,t}^{\mathrm{out}})^2 - (\pi_{p,t}^{\mathrm{in}})^2 = \frac{18 \cdot 43\ \mathrm{Le}_{p}}{(\eta_{p})^2 \cdot \mathrm{Di}_{p}^{4 \cdot 854}} \cdot (F_{p,t}^{\mathrm{pipe}})^{1 \cdot 854} \qquad \forall \ell \epsilon \mathcal{L}, \forall t \epsilon \mathcal{T} \qquad (4)$$

$$\pi_{n}^{\mathrm{min}} \leq \pi_{n,t} \leq \pi_{n}^{\mathrm{max}} \qquad \forall n \epsilon \mathcal{N}, \forall t \epsilon \mathcal{T} \qquad (5)$$

$$\mathrm{F}_{p}^{\mathrm{pipe.min}} \leq F_{p,t}^{\mathrm{pipe}} \leq \mathrm{F}_{p}^{\mathrm{pipe.max}} \qquad \forall p \epsilon \mathcal{P}, \forall t \epsilon \mathcal{T} \qquad (6)$$

Compressors are used to boost the pressure between two nodes in the gas system. Equation (7) shows the power consumption of the compressors prime-movers, which is added to the gas flow balance equation.

The operation limits of the compressors are defined in (8)-(10), including pressure ratio limit (8), flow limit (9), and maximum power consumption limit (10).

$$P_{c,t}^{\text{comp}} = \frac{\phi^{\text{comp}} \cdot F_{c,t}^{\text{comp}}}{\eta^{\text{comp}}} \left[\left(\frac{\pi_{c,t}^{out}}{\pi_{c,t}^{in}} \right)^{\frac{1}{\phi_{\text{comp}}}} - 1 \right] \qquad \forall c \epsilon \mathcal{C}, \forall t \epsilon \mathcal{T} \qquad (7)$$

$$1 \leq \frac{\pi_{c,t}^{\text{out}}}{\pi_{c,t}^{\text{in}}} \leq \text{PR}^{\max} \qquad \forall c \epsilon \mathcal{C}, \forall t \epsilon \mathcal{T} \qquad (8)$$

$$F_{c,t}^{\text{comp}} \leq \text{F}_{c}^{\text{comp.max}} \qquad \forall c \epsilon \mathcal{C}, \forall t \epsilon \mathcal{T} \qquad (9)$$

$$P_{c,t}^{\text{comp}} \leq \text{P}_{c}^{\text{comp.max}} \qquad \forall c \epsilon \mathcal{C}, \forall t \epsilon \mathcal{T} \qquad (10)$$

The gas storage operation limits are also indicated in (11)-(14), including gas level limit (11), amount of gas level in gas storage systems (12), and withdrawal and injection gas limits (13)-(14). It should be noted that the actual formulation of gas storage system operation is more complicated than the proposed equations. For the sake of simplification, an acceptable approximation for the operation of these components [Chaudry et al., 2008] is used in this model.

$$\text{GL}_{q}^{\min} \leq GL_{q,t} \leq \text{GL}_{q}^{\max} \qquad \forall q \epsilon Q, \forall t \epsilon \mathcal{T} \qquad (11)$$

$$GL_{q,t} = GL_{q,t-1} + (F_{q,t}^{\text{wd}} - F_{q,t}^{\text{inj}}) \qquad \forall q \epsilon Q, \forall t \epsilon \mathcal{T} \qquad (12)$$

$$0 \leq F_{q,t}^{\text{wd}} \leq \text{F}_{q}^{\text{wd.max}} \qquad \forall q \epsilon Q, \forall t \epsilon \mathcal{T} \qquad (13)$$

$$0 \leq F_{q,t}^{\text{inj}} \leq \text{F}_{q}^{\text{inj.max}} \qquad \forall q \epsilon Q, \forall t \epsilon \mathcal{T} \qquad (14)$$

Equation (15) shows that the linepack through the pipelines is proportional to the average pressure along the pipes in the steady-state condition. The changes in inlet and outlet gas flows of a pipeline are proportional to the supply and demand variations. Furthermore, the change of gas volume equates to the difference between the inlet and outlet flow of the pipeline (law of conservation of mass [Osiadacz et al., 1987]). Therefore, (15) is substituted with (16), which is an approximation of the dynamic state.

$$LP_{p} = \frac{\pi_{p}^{\text{ave}} \cdot \text{V}_{p}}{\rho^{\text{nor}} \text{ZRT}^{\text{nor}}} \qquad \forall p \epsilon \mathcal{P} \qquad (15)$$

$$LP_{p,t} = \text{LP}_{p,t}^{0} + \int_{0}^{t} (F_{p,t}^{\text{pipe.in}} - F_{p,t}^{\text{pipe.out}}) \qquad \forall p \epsilon \mathcal{P}, \forall t \epsilon \mathcal{T} \qquad (16)$$

Equation (17) shows the objective function of the power system operation consisting of three parts. The first part includes the cost of power generation, startup costs, and shutdown costs, which are related to the thermal generating units. The second part of this objective function is the cost of loss of load. The last part of this objective function presents the operational cost of EV is in correlation with charging and discharging of EV batteries.

$$OF^{elec} = \sum_{t\epsilon\mathcal{T}} \sum_{g\epsilon \mathrm{G}} \mathrm{C}_{g}^{\mathrm{th}} \cdot P_{g,t}^{\mathrm{th}} + SU_{g} + SD_{g} \tag{17}$$
$$+ \sum_{t\epsilon\mathcal{T}} \sum_{b\epsilon\mathcal{B}} \mathrm{C}_{b}^{\mathrm{lsh}} \cdot P_{b,t}^{\mathrm{lsh}}$$
$$+ \sum_{t\epsilon\mathcal{T}} \sum_{v\epsilon\mathcal{V}} \mathrm{C}_{v}^{\mathrm{ev}} \cdot P_{v,t}^{\mathrm{ev}}$$

The power system constraints are presented in (18)-(39). In (18)-(19) startup/shutdown costs are defined. In (20)-(21), the minimum uptime/downtime of thermal generating units is indicated.

$$SU_{g,t} \geq \mathrm{K}_{g}.(y_{g,t} - y_{g,t-1}) \qquad \forall g, \forall t\epsilon\mathcal{T} \tag{18}$$

$$SD_{g,t} \geq \mathrm{J}_{g}.(y_{g,t-1} - y_{g,t}) \qquad \forall g, \forall t\epsilon\mathcal{T} \tag{19}$$

$$\sum_{t'} y_{g,t} \geq \mathrm{T}_{g}^{\mathrm{on}}(y_{g,t} - y_{g,t-1}) \qquad \forall g, t'\epsilon\,[1, \mathcal{T} - \mathcal{T}_{\mathrm{g}}^{\mathrm{on}} + 1] \tag{20}$$

$$\sum_{t'} (1 - y_{g,t}) \geq \mathrm{T}_{g}^{\mathrm{off}}.(y_{g,t-1} - y_{g,t}) \qquad \forall g, t'\epsilon\,[1, \mathcal{T} - \mathcal{T}_{\mathrm{g}}^{\mathrm{off}} + 1] \tag{21}$$

Equation (22) defines the power flow balance at each bus and each period. Equations (23)-(24), shows a simple demand response model. Equations (25)-(26) defines the maximum/minimum stable output power of thermal generation units and wind farms, respectively.

$$P_{g,t}^{\mathrm{th}} + P_{b,t}^{\mathrm{wind}} - \left(P_{v,t}^{\mathrm{ev.dch}} - P_{v,t}^{\mathrm{ev.ch}}\right) - P_{\ell,t}^{\mathrm{line}} - P_{b,t}^{\mathrm{lsh}} = D_{b,t}^{elec} \qquad \forall b\epsilon\mathcal{B}, \forall t\epsilon\mathcal{T} \tag{22}$$

$$(1 - \varsigma).\mathrm{P}_{b,t}^{\mathrm{elec.load}} \leq D_{b,t}^{\mathrm{elec}} \leq (1 + \varsigma).\mathrm{P}_{b,t}^{\mathrm{elec.load}}\ ;\ 0 \leq \varsigma \leq 1 \qquad \forall b\epsilon\mathcal{B}, \forall t\epsilon\mathcal{T} \tag{23}$$

$$\sum_{t\epsilon\mathcal{T}} D_{b,t}^{\mathrm{elec}} = \sum_{t\epsilon\mathcal{T}} \mathrm{P}_{b,t}^{\mathrm{elec.load}} \qquad \forall b\epsilon\mathcal{B} \tag{24}$$

$$y_{g,t}.\mathrm{P}_{g,t}^{\mathrm{th.min}} \leq P_{g,t}^{\mathrm{th}} \leq y_{g,t}.\mathrm{P}_{g,t}^{\mathrm{th.max}} \qquad \forall g\epsilon\mathrm{G}, \forall t\epsilon\mathcal{T} \tag{25}$$

$$0 \leq P_{b,t}^{\mathrm{wind}} \leq \mathrm{P}_{b,t}^{\mathrm{wind.avail}} \qquad \forall b\epsilon\mathcal{B}, \forall t\epsilon\mathcal{T} \tag{26}$$

The ramp-up/down constrains of thermal generating units are indicated in (27)-(28). It refers to the capability of power generation units to change their output power. As mentioned earlier, the fast ramping rate makes gas-fired power plants an appropriate option to deal with the intermittency of renewable energy resources.

$$P_{g,t}^{\mathrm{th}} - P_{g,t-1}^{\mathrm{th}} \leq \mathrm{RU}_{g}.y_{g,t-1} + \mathrm{SUR}_{g}.(y_{g,t} - y_{g,t-1}) \qquad \forall g\epsilon\mathrm{G}, \forall t\epsilon\mathcal{T} \tag{27}$$

$$P_{g,t-1}^{\mathrm{th}} - P_{g,t}^{\mathrm{th}} \leq \mathrm{RD}_{g}.y_{g,t} + \mathrm{SDR}_{g}.(y_{g,t-1} - y_{g,t}) \qquad \forall g\epsilon\mathrm{G}, \forall t\epsilon\mathcal{T} \tag{28}$$

In (29), power flow through transmission lines is expressed, and in (30), the capacity of transmission lines is limited. These constraints are proposed to prevent overheating and loss of power within the transmission lines.

$$P_{\ell,t}^{\text{line}} = (\delta_{\ell,t}^{\text{in}} - \delta_{\ell,t}^{\text{out}})/\mathrm{X}_{\ell} \qquad \forall \ell \epsilon \mathcal{L}, \forall t \epsilon \mathcal{T} \qquad (29)$$

$$-P_{\ell.t}^{\text{line.min}} \leq P_{\ell.t}^{\text{line}} \leq P_{\ell.t}^{\text{line.max}} \qquad \forall \ell \epsilon \mathcal{L}, \forall t \epsilon \mathcal{T} \qquad (30)$$

The reserve requirements are also determined in (31), which is necessary to provide the supply-demand balance [Ahmadi et al., 2019]. As the reserve help to provide the balance of generation and demand in each timescale, it prevents frequency deviations.

$$\sum_{g \epsilon \mathrm{G}} P_{g,t}^{\text{th.max}} \geq \mathrm{SRR}_{t} + \sum_{b \epsilon \mathcal{B}} \mathrm{D}_{b,t}^{\text{elec}} \qquad \forall t \epsilon \mathcal{T} \qquad (31)$$

There are a few constraints that indicate the operational constraints of the EVs. For example, in (32)-(33), the net hourly charged energy and the dispatched power of each EV are introduced. Equation (34) illustrates the status of EVs which are connected to the grid. Charging and discharging power of these EVs are limited in (35)-(36). The amount of stored energy in the EVs is calculated in (37), which is limited in (38) -(39).

$$E_{v,t}^{ev.net} = P_{v,t}^{\text{ev.dc}} - \eta_{v} P_{v,t}^{\text{ev.ch}} \qquad \forall v \epsilon \mathcal{V}, \forall t \epsilon \mathcal{T} \qquad (32)$$

$$P_{v,t}^{\text{ev}} = P_{v,t}^{\text{ev.dch}} - P_{v,t}^{\text{ev.ch}} \qquad \forall v \epsilon \mathcal{V}, \forall t \epsilon \mathcal{T} \qquad (33)$$

$$I_{v,t}^{\text{ev.ch}} + I_{v,t}^{\text{ev.dch}} \leq 1 \qquad \forall v \epsilon \mathcal{V}, \forall t \epsilon \mathcal{T} \qquad (34)$$

$$I_{v,t}^{\text{ev.ch}}.\,\mathrm{P}_{v,t}^{\text{ev.ch.min}} \leq P_{v,t}^{\text{ev.ch}} \leq I_{v,t}^{\text{ev.ch}}.\,\mathrm{P}_{v,t}^{\text{ev.ch.max}} \qquad \forall v \epsilon \mathcal{V}, \forall t \epsilon \mathcal{T} \qquad (35)$$

$$I_{v,t}^{\text{ev.dch}}.\,\mathrm{P}_{v,t}^{\text{ev.dch.min}} \leq P_{v,t}^{\text{ev.dch}} \leq I_{v,t}^{\text{ev.dch}}.\,\mathrm{P}_{v,t}^{\text{ev.dch.max}} \qquad \forall v \epsilon \mathcal{V}, \forall t \epsilon \mathcal{T} \qquad (36)$$

$$E_{v,t}^{\text{ev}} = E_{v,t-1}^{\text{ev}} + E_{v,t}^{\text{ev.net}} \qquad \forall v \epsilon \mathcal{V}, \forall t \epsilon \mathcal{T} \qquad (37)$$

$$\mathrm{E}_{v,t}^{\text{ev.ch.min}} \leq E_{v,t}^{\text{ev.ch}} \leq \mathrm{E}_{v,t}^{\text{ev.ch.max}} \qquad \forall v \epsilon \mathcal{V}, \forall t \epsilon \mathcal{T} \qquad (38)$$

$$\mathrm{E}_{v,0}^{\text{ev}} = E_{v,T}^{\text{ev}} \qquad \forall v \epsilon \mathcal{V}, \forall t \epsilon \mathcal{T} \qquad (39)$$

Gas-fired power plants and electrically-driven compressors are the mainly coupling components of gas and power systems. In order to optimize the integrated operation of these systems, the sum of gas and power systems' objective functions is minimized (40) subject to the constraints of both systems. Furthermore, the gas consumption of gas-fired generators is added to the gas flow balance, which is calculated in (41). The electricity consumption of compressors is also added to the power flow balance equation (42).

$$OF^{\text{total}} = OF^{\text{gas}} + OF^{\text{elec}} \qquad (40)$$

$$F_{g,t}^{\text{gen}} = \upsilon \cdot \text{HV} \cdot P_{g,t}^{\text{th}} \qquad \forall g \epsilon \text{G}, \forall t \epsilon \mathcal{T} \qquad (41)$$

$$P_{g,t}^{\text{th}} + P_{b,t}^{\text{wind}} - \left(P_{v,t}^{\text{ev.dch}} - P_{v,t}^{\text{ev.ch}}\right) - P_{\ell,t}^{\text{line}} - P_{c,t}^{\text{comp}} - P_{b,t}^{\text{lsh}} = \text{D}_{b,t}^{\text{elec}} \qquad \forall b \epsilon \mathcal{B}, \forall t \epsilon \mathcal{T} \qquad (42)$$

2.2. Possibilistic chance-constrained programming

In this section, a Possibilistic Chance-Constrained Programming (PCCP) is introduced, in which Gaussian membership function is utilized to show the uncertainty in the parameters. The PCCP is a fuzzy programming approach, which is applied to cope with uncertainty in the objectives and constraints. This approach can be applied to deal with uncertain data even on both sides of possibilistic constraints. The PCCP provides a minimum level of confidence to meet chance constraints by applying both possibility (Pos) (e.g., the most optimistic level for data occurrence) and necessity (Nec) (e.g., the most pessimistic possible level for data occurrence) [Liu & Guan, 2016]. However, in a real-world situation, decision makers' opinions may change between the most pessimistic and the most optimistic attitudes. Therefore, the amount of compensatory fuzzy measure is determined which is called Me and this concept is used to model the uncertainty in the parameters in this problem (see Appendix B).

The main purpose of developing possibilistic approach is the epistemic uncertainty due to connecting large scale vehicle fleets to the power system. The reason is that no adequate historical data is available to calculate the probability of events [Xu & Zhou, 2013]. Therefore, possibilistic approach are more practical in this case [Hadadian et al., 2015].

As a result, in the integrated operation of gas and power systems, constraints (3), (22), and (26) (gas flow balance, electricity flow balance, and maximum/minimum output power of wind farms, respectively) are substituted with (43)-(45) to take into account uncertainty in gas demand, electricity demand, and output power of wind farms.

$$F_{y,t}^{\text{sup}} - F_{p,t}^{\text{pipe}} - F_{c,t}^{\text{comp}} + F_{n,t}^{\text{gsh}} \geq \sigma^{\text{gas}} \sqrt{\frac{\alpha\sqrt{2.\pi.\sigma^{\text{gas}}} - \gamma}{1-\gamma}} + \text{D}_{n,t}^{\text{gas.mean}} \qquad \forall n \epsilon \mathcal{N}, \forall t \epsilon \mathcal{T} \qquad (43)$$

$$P_{g,t}^{\text{th}} + P_{b,t}^{\text{wind}} - \left(P_{v,t}^{\text{ev.dch}} - P_{v,t}^{\text{ev.ch}}\right) - P_{\ell,t}^{\text{line}} - P_{c,t}^{\text{comp}} - P_{b,t}^{\text{lsh}} \geq \sigma^{\text{elec}} \sqrt{\frac{\alpha\sqrt{2.\pi.\sigma^{\text{elec}}} - \gamma}{1-\gamma}} + \text{D}_{b,t}^{\text{elec.mean}} \qquad \forall b \epsilon \mathcal{B}, \forall t \epsilon \mathcal{T} \qquad (44)$$

$$0 \leq P_{b,t}^{\text{wind}} \leq P_{b,t}^{\text{wind.mean}} - \sigma \sqrt{\frac{\beta\sqrt{2.\pi.\sigma^{\text{wind}}} - \gamma}{1-\gamma}} \qquad \forall b \epsilon \mathcal{B}, \forall t \epsilon \mathcal{T} \qquad (45)$$

2.3. Resiliency evaluation algorithm

During the wide outages, the resiliency of energy systems, such as gas and power systems, cannot be investigated independently due to the coupling components (e.g., gas-fired power plants). Therefore, in this section, a resiliency analysis algorithm is developed to prevent wide outages in the gas and power systems in the case of contingency. This algorithm consists of two main stages, including (1) finding the worst-case scenarios among a set of probable outages of electrical lines or gas pipelines that leads to greatest amount of load shedding and the greatest amount of cost of operation as a consequence) and (2) optimizing the integrated operation of these networks and changing parameter settings of PCCP based on the scenario in the last step to reduce the probable consequences, such as the amount of load shedding. In Figure 2, the proposed algorithm is depicted and each step is explained in the following.

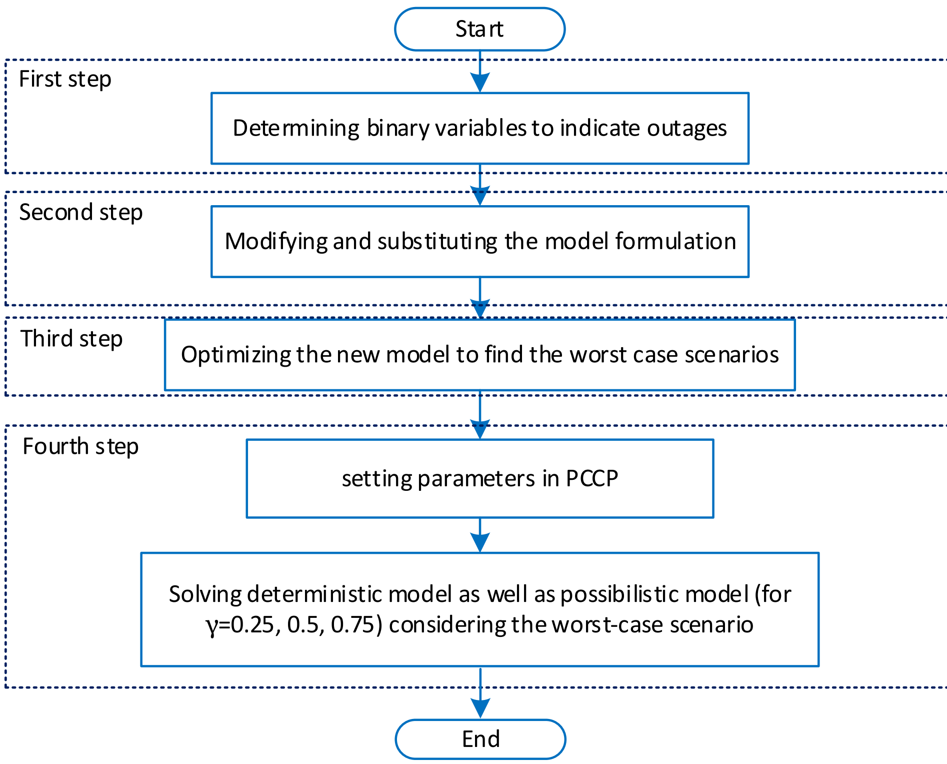

Figure 2. Four steps of resiliency analysis algorithm for the co-optimization of gas and power systems operation.

According to this algorithm, four steps should be implemented. At the first step, binary variables should be determined to simulate the outage of components. In the second step, the constraints related to the maximum/minimum gas flow and electricity flow through gas pipelines and electrical lines are substituted. After that, in the third stage, a maximin approach is employed, and by solving the optimization problem, the worst-case scenario for outage of an electrical line and a gas pipelines, which leads to the largest amount of load shedding and gas shedding, is recognized. This is noteworthy to mention that limiting the sum of the determined binary variables in this, the number of outages can be limited, although the outages of an electrical line and a pipeline are examined as the worst-case scenario in this study (i.e., $\sum_{\ell} \omega'_{\ell} = 1$ and $\sum_{\wp} \omega_{\wp} = 1$). After finding the worst-case scenario, in the fourth step, the integrated operation of gas and power systems is optimized considering the determined outage scenarios in the last step (i.e., the worst-case scenario) with and without considering uncertainty. After implementing this algorithm, decision-maker compares the amount of shedding in both networks considering different parameters setting to reach minimum shedding in the case of outages. It should be mentioned that this approach optimizes the model considering the worst-case outage that means it can provide a lower level of shedding in other cases. Besides, changing parameter setting affects the robustness, and the aim of this analysis is to achieve a more solution robustness. Therefore, achieving a more robust solution, this approach is supposed to increase the resiliency of these systems against the probable incidents, such as outage of components.

Step 1: Binary variables are added to indicate the outage of components in the power system (46)-(47). A component (e.g., electrical line and pipeline) is out of service when the binary variable is equal to one.

$$\omega = \begin{cases} 1 \text{ if gas pipline } \mathscr{p} \text{ is out of service} \\ 0 \text{ O.W.} \end{cases} \tag{46}$$

$$\omega' = \begin{cases} 1 \text{ if electrical line } \ell \text{ is out of service} \\ 0 \text{ O.W.} \end{cases} \tag{47}$$

Step 2: Some constraints of gas and power systems are substituted and modified, including gas flow and electricity flow limit (48)-(49).

$$(1-\omega).\,\mathrm{F}_{\mathscr{p}}^{\mathrm{pipe.min}} \leq F_{\mathscr{p}.t}^{\mathrm{pipe}} \leq (1-\omega).\,\mathrm{F}_{\mathscr{p}}^{\mathrm{pipe.max}} \qquad \forall \mathscr{p}\epsilon\mathcal{P}, \forall t\epsilon\mathcal{T} \tag{48}$$

$$-(1-\omega').\,\mathrm{P}_{\ell.t}^{\mathrm{line.min}} \leq P_{\ell.t}^{\mathrm{line}} \leq (1-\omega').\,\mathrm{P}_{\ell.t}^{\mathrm{line.max}} \qquad \forall \ell\epsilon\mathcal{L}, \forall t\epsilon\mathcal{T} \tag{49}$$

Step 3: To find the worst-case scenarios for the outage of electrical lines and outage of pipelines, the following objective function is optimized subject to (48)-(49) and other gas and power systems' constraints. The proposed model maximizes the sum of load shedding and gas shedding and provides the worst-case scenarios by applying a maximin technique (50).

$$\begin{aligned} \text{Max Min } \Big(\Big(& \sum_{n\epsilon\mathcal{N}} D_{n.t}^{\mathrm{gas}} - \sum_{y\epsilon\mathcal{Y}} F_{y.t}^{\mathrm{sup}} + \sum_{\mathscr{p}\epsilon\mathcal{P}} F_{\mathscr{p}.t}^{\mathrm{pipe}} + \sum_{c\epsilon\mathcal{C}} F_{c.t}^{\mathrm{comp}} \Big) + \upsilon \cdot \mathrm{HV}. \Big(\sum_{b\epsilon\mathcal{B}} D_{b.t}^{\mathrm{elec}} \\ & - \sum_{g\epsilon\mathcal{B}} P_{g.t}^{\mathrm{th}} - \sum_{b\epsilon\mathcal{B}} P_{b.t}^{\mathrm{wind}} + \sum_{v\epsilon\mathcal{V}} \big(P_{v.t}^{\mathrm{ev.dch}} - P_{v.t}^{\mathrm{ev.ch}} \big) \\ & + \sum_{\ell\in(\mathcal{B}.\mathcal{B}')} P_{\ell.t}^{\mathrm{line}} + \sum_{c\epsilon\mathcal{C}} P_{c.t}^{\mathrm{comp}} \Big) \Big) \end{aligned} \tag{50}$$

Step 4: The original problem (i.e., the PCCP for the integrated operation of gas and power systems) is solved considering the worst-case scenarios.

It should be mentioned that changing the parameter in the PCCP can change the attitude to the uncertainty in this problem from optimistic to pessimistic. Although being pessimistic can provide more robust solutions when the uncertain parameters change considerably like other approaches which have been introduced to deal with uncertainty [Soyster, 1973 and Bertsimas and Sim, 2004], it should be considered in the last step that it gives up a large amount of cost. Therefore, this analysis is conducted to achieve a preferable tradeoff by decision makers.

3. Case study

Two test systems are introduced, including a 6-node gas network with a 6-bus electricity network and the Belgium gas network with the IEEE 24-bus electricity network. It should be noted that the first case study is introduced to analyze the results and investigate the applicability of the proposed approach more clearly, and the second case is to validate the practicality of this method in larger-scale problems. Each test system is introduced in detail as follows:

3.1. 6-node gas network with 6-bus electricity network

The topology of 6-node with 6-bus gas and electricity networks is demonstrated in Figure 3. The electricity system consists of six buses, six transmission lines, three thermal power plants, and a wind farm. More specific data about this case study are introduced in Appendix C. It should be mentioned that the link between gas network and the gas-fired power plant is demonstrated by a blue dashed line.

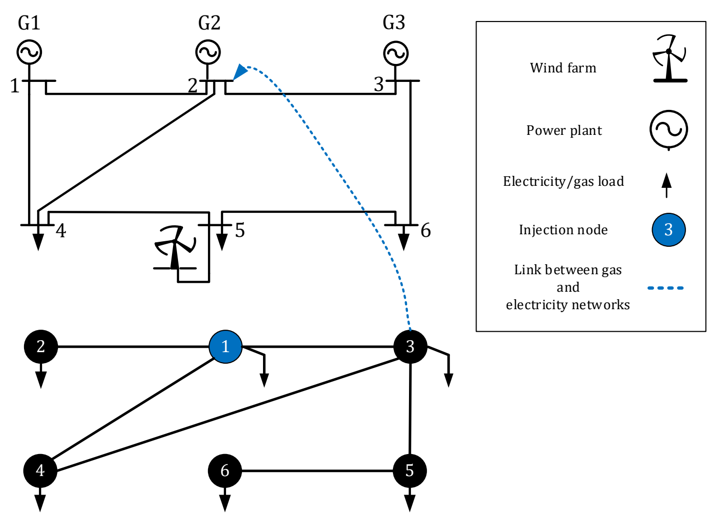

Figure 3. Six-bus and six-node gas and electricity networks test system (the first case study).

3.2. Belgium gas network with IEEE 24-bus electricity network

Belgium is going to make progress in the electricity sector and decrease its dependency on fossil fuel consumption by increasing the share of renewable energy resources [IEA, 2020]. For this aim, the most challenging issue is to meet demand and ensure the security of the energy system under the high penetration of renewable energies. On the other hand, Belgium's gas network is well-developed, which is appropriately integrated with the gas networks of its neighbors [Munoz et al. 2011]. As a result, in this country, the integrated operation of gas and power systems can be an appropriate option to deal with the intermittency of renewable energy resources by using gas-fired power plants more efficiently. Therefore, a case study is introduced, consisting of a high-pressure gas system in Belgium (Figure 4) [Sun et al., 2017; De Wolf & Smeers, 2000] and the IEEE 24-bus reliability test system (Figure 5) [Ordoudis, et al., 2016]. More specific data about the gas and power systems are introduced in Appendix D. According to the legend, the links between gas nodes and gas-fired power plants are recognizable.

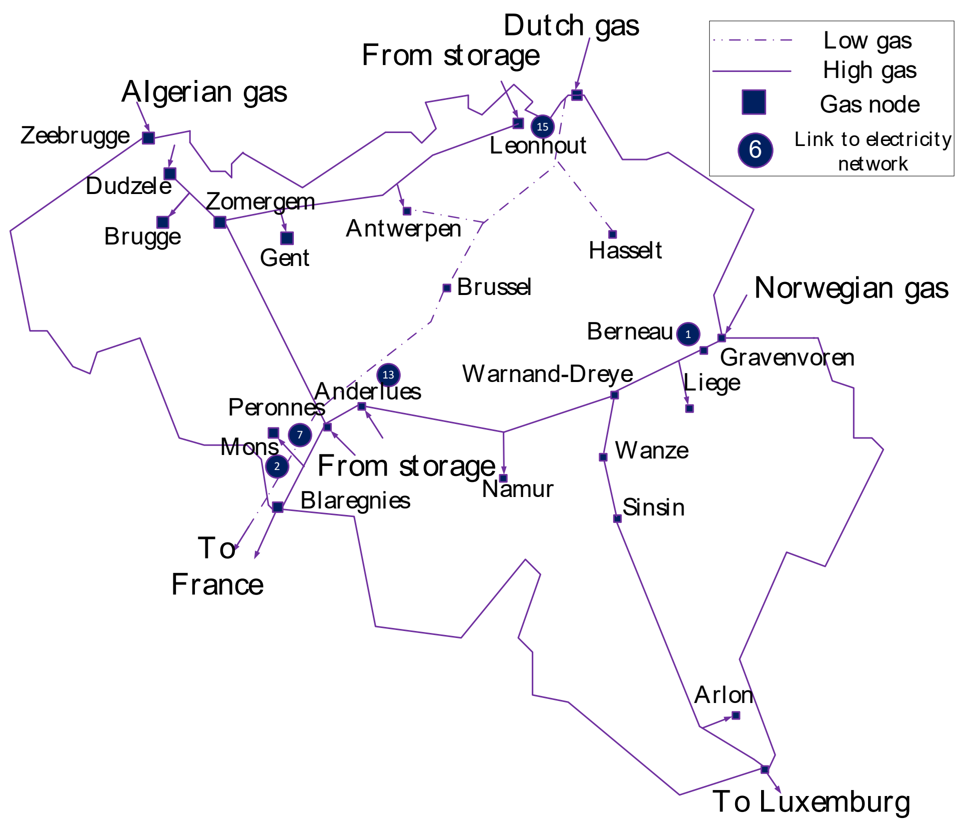

Figure 4. Belgium gas network (the second case study).

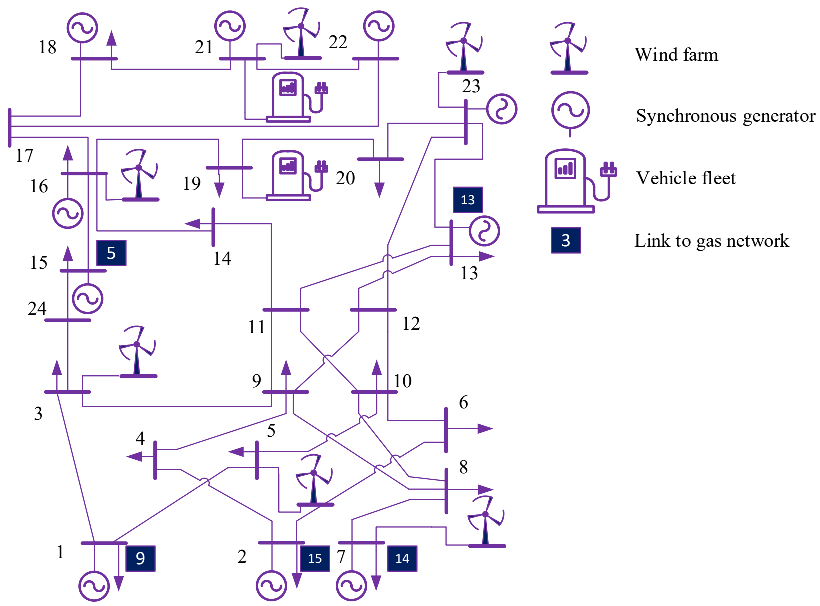

Figure 5. IEEE 24-bus electricity network (the second case study).

To evaluate the performance of the proposed PCCP, the modeling is implemented on the introduced test systems under normal operation. Afterwards, the resiliency algorithm is employed to analyze the operation of gas and power systems under contingencies. Furthermore, the impact of EVs and DR on the operation of these systems under normal and contingency conditions is quantified.

4. Results and discussions

In this section, the value of uncertainty, as well as resiliency consideration in the integrated operation of gas and power systems are quantified. Furthermore, the role of EVs and DR in this problem is taken into consideration. As mentioned earlier, two case studies are used to investigate the applicability of the proposed approach, including 6-bus electricity network with 6-node gas network and 24-bus electricity network with Belgium gas network. It should be noted that the proposed Mixed-Integer Nonlinear Program (MINLP) problem is solved in the Generalized and Algebraic Modeling System optimization package (GAMS) via Discrete and Continuous Optimizer solver (DICOPT) using a Core i7 computer with 2.40 GHz CPU and 16 GB of RAM. The algorithm in DICOPT is based on a decomposition method provided in [Soroudi, 2017]. The decomposition method that is applied to this solver reduces the complexity of the model (due to splitting the problem to the Mixed-Integer Linear Program (MILP) and Nonlinear Program (NLP) instead of the original MINLP problem), and therefore obtaining the global optimum is more likely.

4.1. Test system 1: 6-bus electricity network with 6-node gas network

Implementing the proposed approach in 6-bus with 6-node gas and electricity networks, the model consists of 6448 equations, 6341 continuous variables, and 1425 binary variables, which takes less than 30 seconds to solve the proposed model.

4.1.1. Gas network analysis under normal operation condition

Figure 6 shows the amount of injected natural gas through the terminal. As depicted, applying the PCCP approach to deal with the uncertainty in the model reduces the oscillations of gas injection through the terminal (e.g. from 06:00 to 11:00 and from 15:00 to 19:00). The decrease in the gas injection oscillations reduces the changes in linepack within the pipelines. Therefore, it prevents a low level of natural gas within the pipelines that enhances the capability of the gas network to deal with the changes in the demand. This is due to the slow speed of gas transport from supply nodes to the demand nodes, and hence linepack is usually consumed to deal with rapid changes in the network. On the other hand, through increasing γ (i.e., being more pessimistic) the oscillations are reduced more efficiently. However, when γ is equal to 0.25 (i.e., being more optimistic), the oscillations are evident due to the decrease in the gas injection during off-peak hours and increase in the gas injection during peak hours to avoid the extra amount of gas injection.

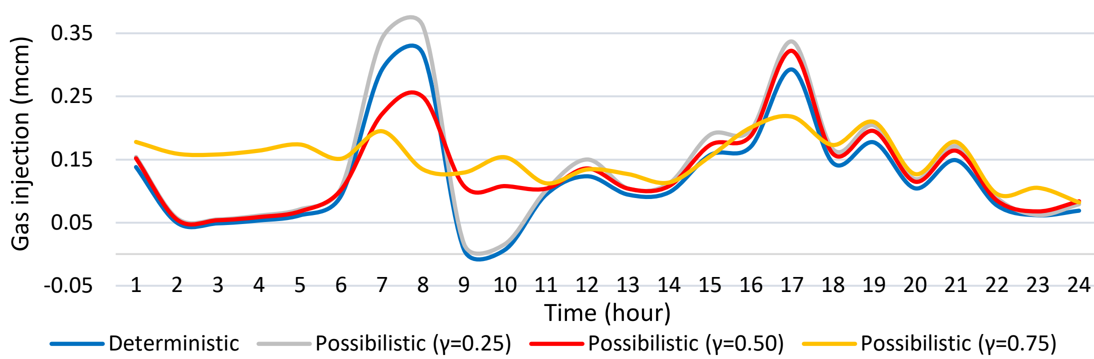

Figure 6. Gas injection through supply node with and without uncertainty consideration in the first case study.

Figure 7 shows the sum of the linepack through the pipelines during the operation period. As expected, reducing the changes in gas injection leads to the reduction in the linepack (e.g. from 06:00 to 11:00 and from 15:00 to 19:00). An increase in γ from 0.25 to 0.75 reduces the changes in the sum of the linepack through the pipelines due to moderating the gas injection through the terminal. A more balanced amount of natural gas within the pipelines provides more flexibility to support the electricity network. This is due to the fact that, a high level of linepack within the pipelines can deal with rapid changes in the gas network and supply the required amount of natural gas for gas-fired power plants.

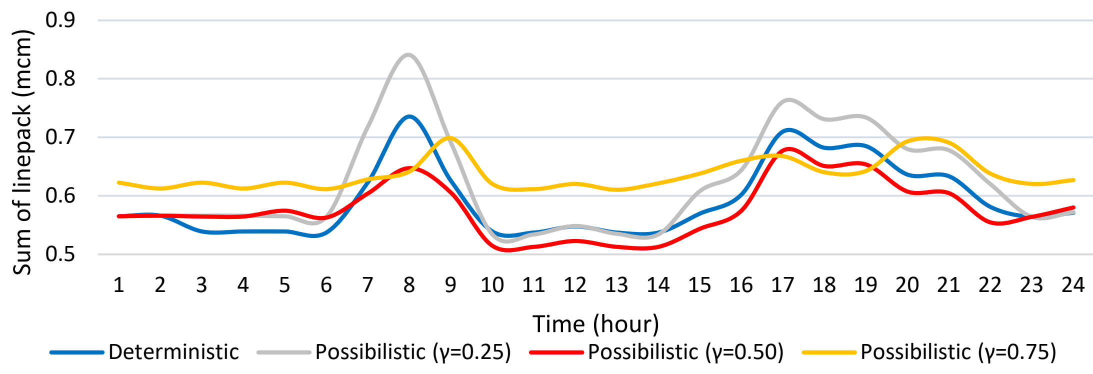

Figure 7. Sum of linepack within the pipelines with and without uncertainty consideration in the first case study.

4.1.2. Electricity network analysis under normal operation condition

In Figure 8, the output power of three generating units beside the wind farm is presented using PCCP when γ is equal to 0.75. As depicted, the flexible gas-fired power plant (i.e., generation unit 2) is mostly used to deal with the fluctuation in the electricity demand and intermittency of wind farm output power (e.g., from 11:00 to 21:00). This is due to the characteristics of gas-fired power plants, including short startup/shutdown time, fast ramping rate, and low cost of startup/shutdown. Moreover, in Figure 9, the cumulative output power of each generating unit is demonstrated. As depicted, when γ is equal to 0.75, the gas-fired power plant takes part more efficiently in providing the supply-demand balance. This is due to the adequate level of linepack within the pipelines that increases the flexibility of the gas network to provide the demand to the gas plant. Therefore, the capability of the gas-fired generating unit acting as a backup to wind generation increases wind accommodation in the electricity network (provide 65 MW more from lowest to most), which leads to emission reduction.

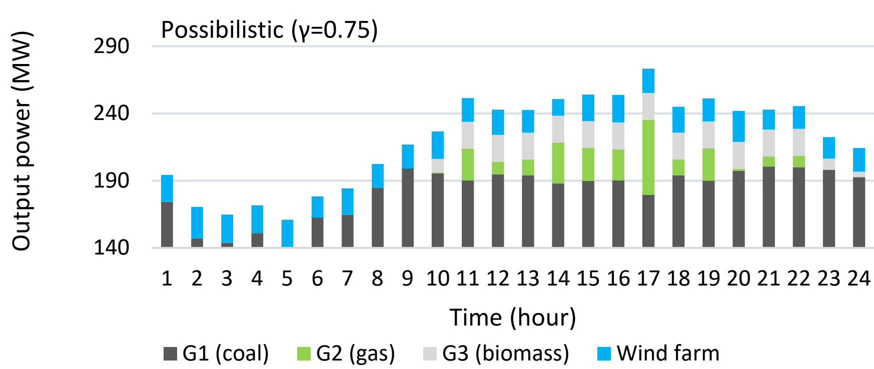

Figure 8. Output power of the power generation units in the first case study.

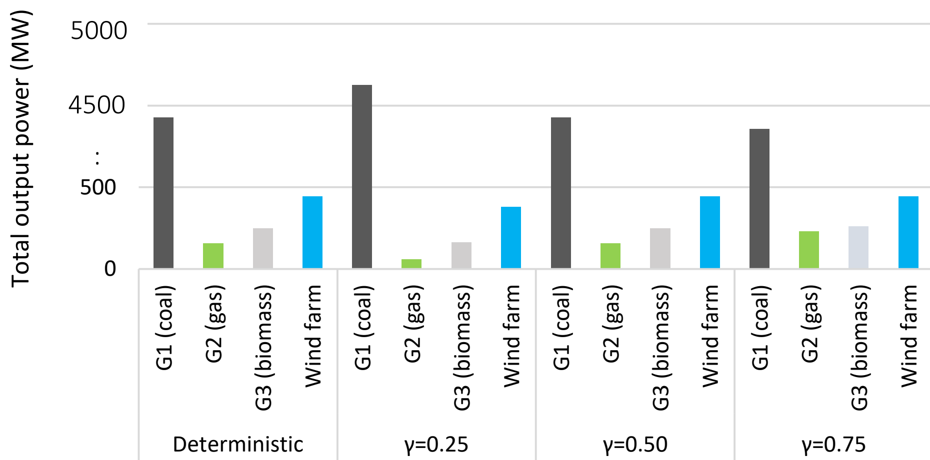

Figure 9. Total output power of the power generation units in the first case study.

4.1.3. Cost and resiliency analysis

In Table 2, the total cost of operation and energy not supplied level are indicated with and without implementing the resiliency analysis algorithm. The results show implementing the resiliency analysis algorithm leads to reducing the operation cost as well as energy not supplied level in the case of outage occurrence. For example, in the normal operation, since there is no outage, the operation cost of gas and power systems is lower compared to when the resiliency algorithm is implemented. However, when the transmission line 1-2 and pipeline 1-3 are out of service (i.e., the worst-case scenarios based on maximin approach), the resiliency analysis algorithm provides the solution with lower cost and energy not supplied level. This is due to the fact that in this algorithm, the possibilistic model of the gas and power systems are optimized considering a pessimistic viewpoint. Furthermore, in this algorithm, applying a more pessimistic approach to deal with uncertainty improves the operation of these networks in the case of contingency (i.e., due to a high level of linepack that increases the flexibility of the gas-fired generating units). As a result, wind farms are operating more efficiently and hence less wind curtailment happens.

Table 2. Costs of operation and energy not supplied level enhancement through the resiliency analysis in the first case study**.**

	Deterministic		**PCCP (γ=0.25)**		**PCCP (γ=0.50)**		**PCCP (γ=0.75)**	
Resiliency consideration	No	Yes	No	Yes	No	Yes	No	Yes
Energy not supplied (MWh)	-	221.11	-	54.22	-	49.72	-	41.86
Cost of electricity network (m$)	0.0682	1.145	0.0609	0.634	0.0682	0.568	0.0689	0.472
Cost of gas network (m$)	1.0727	1.263	0.9593	1.672	1.0727	1.637	1.1176	1.612
Total cost (m$)	1.1409	2.408	1.0203	2.306	1.1409	2.205	1.1865	2.084

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4.2. Test system 2: Belgium gas network with IEEE 24-bus electricity network

Implementing the proposed approach in Belgium gas network with IEEE 24-bus electricity networks, the model consists of 13566 equations, 12830 continuous variables, and 2175 binary variables. Besides, it takes less than 240 seconds to solve the proposed model. The obtained results are presented in the following, such as natural gas injection through the terminal, linepack within the pipelines, output power of the generating units, and costs of the optimal operation. Furthermore, the role of EVs and DR in the integrated operation of gas and power systems is investigated.

4.2.1. Gas network analysis under normal operation condition

The gas network analysis shows that employing PCCP approach moderates the gas injection through the terminals, e.g. from 02:00 to 06:00 and from 14:00 to 24:00 (Figure 10). Moreover, it can be stated that increasing γ reduces the oscillations, due to the fact that through a more pessimistic approach, a higher level of linepack within the pipelines is required to support the supply-demand balance. Therefore, this prevents a low level of natural gas through the pipelines, which increases the capability of the gas network to deal with the changes.

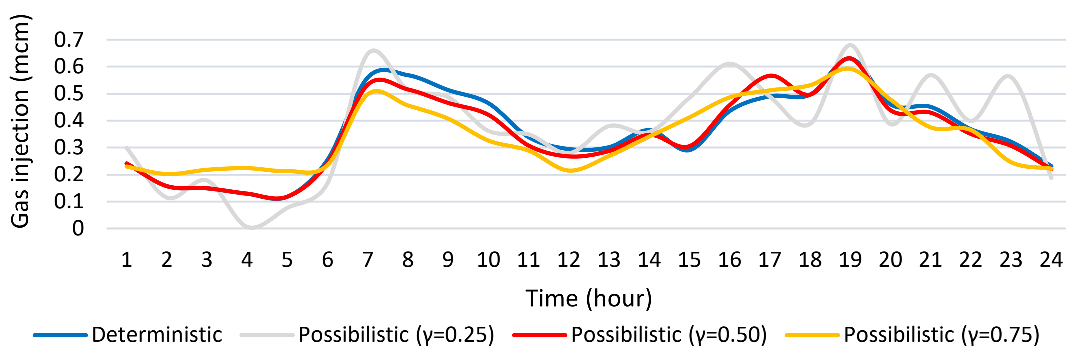

Figure 10. Gas injection through supply node with and without uncertainty consideration in the second case study.

Through carrying out the PCCP to cope with the existing uncertainty in the model, increase in γ reduces the oscillations in linepack within the pipelines, e.g. from 02:00 to 08:00 and from 11:00 to 14:00 (Figure 11). The moderate level of linepack increases the capability of the gas network to deal with the rapid changes in demand-side. On the other hand, in Figure 12, the electrical power consumption of compressor is depicted. A moderate level of gas within the pipelines leads to less operation of compressors that reduces the cost of electricity network operation.

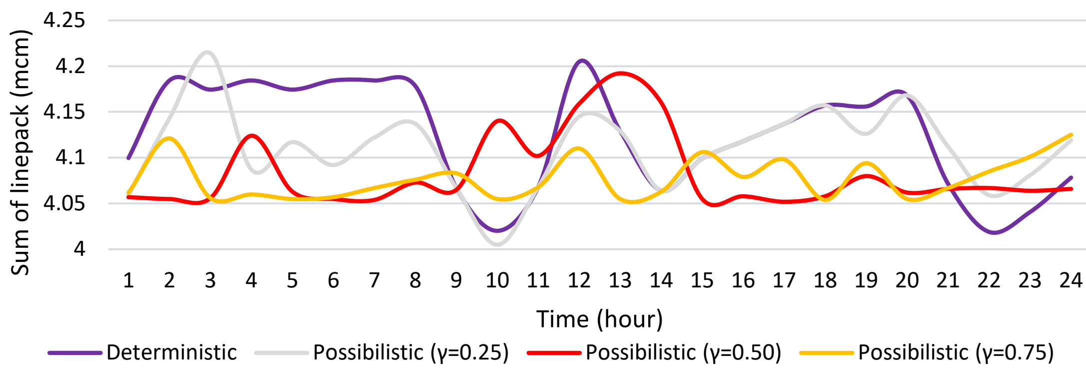

Figure 11. Sum of linepack within the pipelines with and without uncertainty in the second case study.

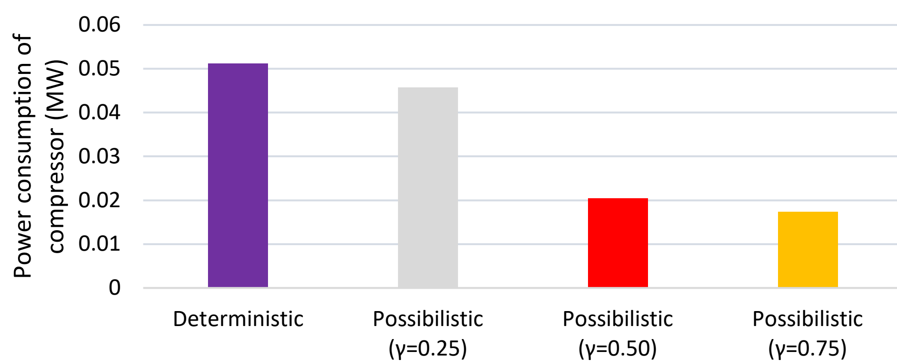

Figure 12. Power consumption of compressor with and without uncertainty consideration in the second case study.

4.2.2. Output power of generating units' analysis under normal operation condition

The total output power of main generation technologies is demonstrated in Figure 13. As mentioned previously, flexible gas-fired power plants operate to deal with the intermittency of wind farm output power in the peak hours of electricity demand. This is due to the characteristics of these generating units, such as high ramping rate and short startup time. Moreover, when γ is equal to 0.75, the gas-fired power plant generate about 800 MW more in providing the supply-demand balance and leads to less wind curtailment. (e.g. ۸۵۰ MW less compared to deterministic model).

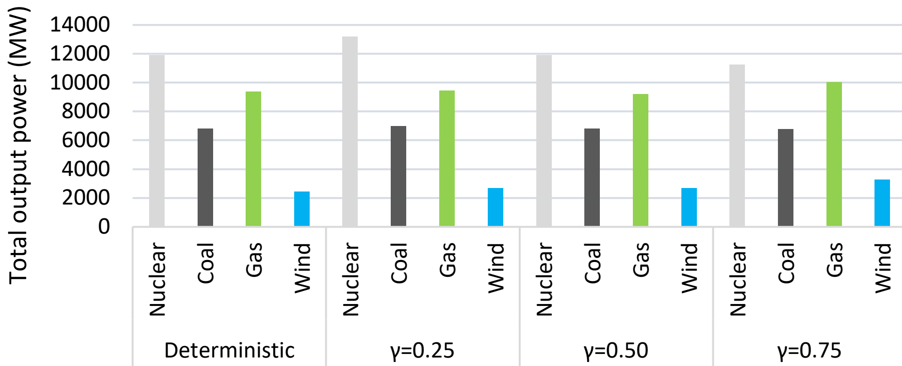

Figure 13. Total output power of the power generation units with and without uncertainty consideration in the second case study.

4.2.3. Cost and resiliency analysis

Table 3 demonstrates the operation costs of gas and power systems with and without resiliency consideration. The results show that implementing the proposed algorithm for a resilient operation of these networks leads to operation cost reduction as well as energy not supplied level decrease in the worst-case scenario (outage of pipeline 8 and transmission line 11-14 base on maximin approach). For example, in normal operation, since there is no outage, the operation cost of these systems is lower compared to when the resiliency algorithm is implemented. However, in the case of outages, by carrying out the resiliency analysis algorithm lower cost and energy not supplied level is achieved. This is due to the fact that in this algorithm, the possibilistic model of these systems are optimized by considering a pessimistic viewpoint. In this algorithm, applying a more pessimistic approach to deal with uncertainty improves the operation of these networks due to the high level of linepack that increase the flexibility of the gas-fired generating units. As a result, wind farms are operating more and hence less wind curtailment happens.

Table 3. Costs of operation and energy not supplied level enhancement through the resiliency analysis in the second case study**.**

	Deterministic		**PCCP (γ=0.25)**		**PCCP (γ=0.50)**		**PCCP (γ=0.75)**	
Resiliency consideration	No	Yes	No	Yes	No	Yes	No	Yes
Energy not supplied (MWh)	-	243.221	-	59.100	-	54.195	-	46.93
Cost of electricity network (m$)	0.185	3.111	0.178	1.862	0.185	1.543	0.198	1.357
Cost of gas network (m$)	3.028	3.566	2.951	5.143	3.028	4.622	3.215	4.637
Total cost (m$)	3.214	6.677	3.129	7.006	3.214	6.156	3.413	5.994

4.2.4. Role of electrical vehicles and demand response

In Figure 14, the aggregated charge and discharge of EV batteries is depicted (possibilistic (γ=0.75)) in which the positive numbers indicate the discharging status, while the negative numbers show the charging status. As depicted, EVs are mainly charged at off-peak hours (e.g. from 04:00 to 07:00) and discharged at peak hours (e.g., from 17:00 to 20:00). In Figure 15, it is demonstrated how EVs flatten output power of generating units, which prevents operating flexible power plants with a higher cost of operation due to their fast ramping rate. In Figure 16, the changes in the output power of different technologies are compared with and without employing EVs. As depicted, the employment of EVs can be used to deal with the intermittency of wind farms, which reduces the wind curtailment.

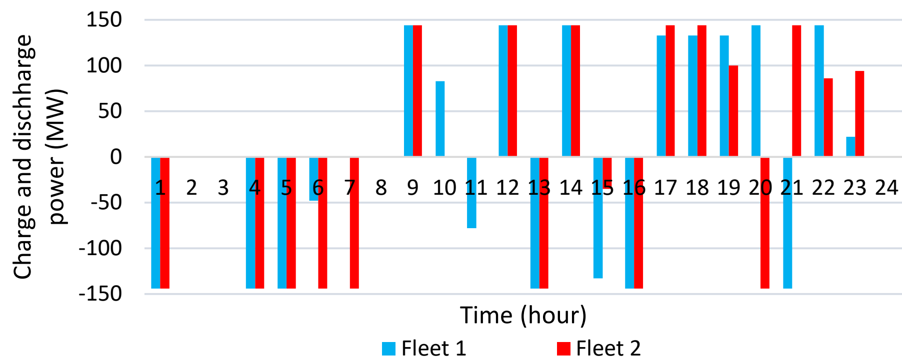

Figure 14. Charge and discharge of electrical vehicles during the operation period (possibilistic (γ=0.75)).

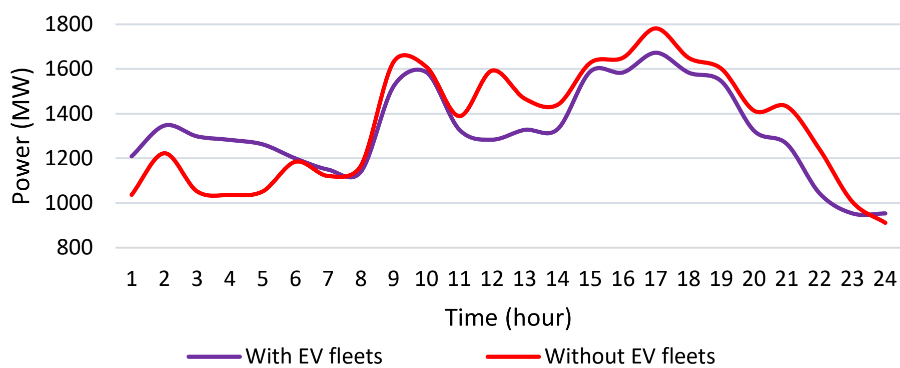

Figure 15. Aggregated output power of different generating technologies with and without electrical vehicles (possibilistic (γ=0.75)).

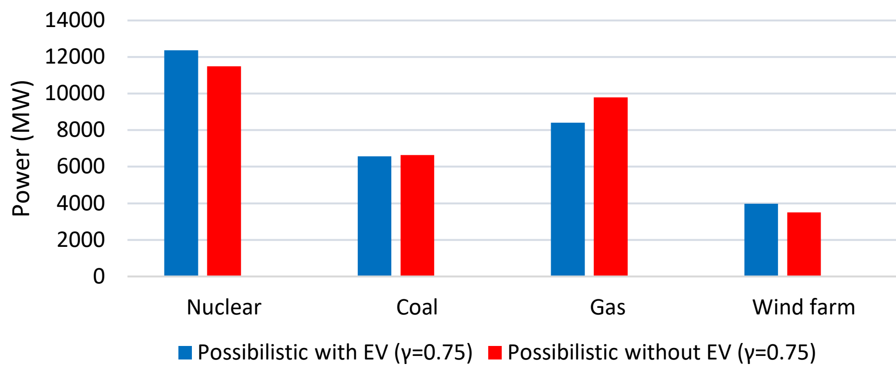

Figure 16. Output power of different technologies with and without demand response consideration (possibilistic (γ=0.75)).

On the other hand, in Figure 17, the impact of demand response in the total output power of generating units is demonstrated (possibilistic (γ=0.75)). Demand response could flatten the output power of generation units, which provides different benefits, such as wind curtailment reduction. The results indicate by increasing the proportion of flexible demand (i.e., the increase in ς by 10%), the cost of operation and wind curtailment is decreased by \$0.17m and 68 MW, respectively. Figure 18 also shows how employing DR can increase the participation of wind farms by flattening the electricity demand.

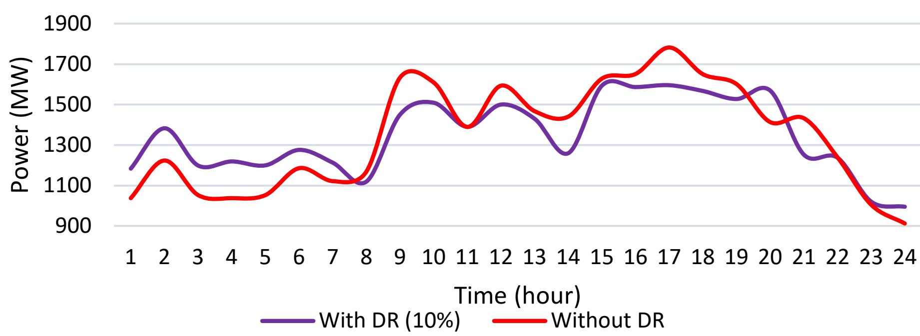

Figure 17. Aggregated output power of different generating technologies with and without demand response consideration.

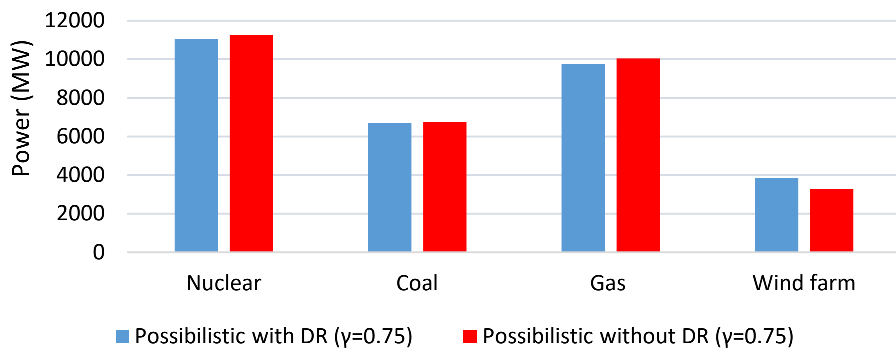

Figure 18. Output power of different generation units with and without demand response.

The resiliency consideration is also implemented in Table 4 with and without employing DR and EVs. As depicted, employing DR and optimal scheduling EVs reduce the energy not supplied level and costs of operation in the case of outages. This is due to the fact that these flexibility options moderate the demand, hence either the less flexible power plants or the wind farms can take part more in providing supply-demand balance. On the other hand, the more flexible power plants, such as gas-fired units, can operate in the case of contingency.

Table 4. Costs of operation and energy not supplied level enhancement through the resiliency analysis considering electrical vehicles and demand response**.**

	PCCP (γ=0.75)		**PCCP with EV and DR consideration (γ=0.75)**	
Resiliency consideration	No	Yes	No	Yes
Energy not supplied (MWh)	-	46.93	-	41.251
Cost of electricity network (m$)	0.198	1.357	0.182	1.343
Cost of gas network (m$)	3.215	4.637	3.210	4.223
Total cost (m$)	3.413	5.994	3.392	5.566

5. Conclusion and future directions

The integrated operation of gas and power systems with and without considering uncertainty was investigated through comparing the proposed possibilistic and deterministic models. The role of flexibility options, including scheduling electrical vehicles and demand response, was quantified in the operation of these systems. Furthermore, the resiliency analysis algorithm was proposed to evaluate and enhance the operation of these systems in the case of probable outages.

Analyzing the obtained results from the possibilistic model (i.e., with uncertainty consideration) demonstrated the better operation of these systems compared to when the deterministic model is used. More precisely, uncertainty consideration through the possibilistic model provided a sufficient gas level within the pipelines (linepack) in every time step. As a result, it allowed system operator to schedule flexible gas-fired power plants more efficiently (658 MWh/day) to deal with the intermittency and variability of wind generation. Furthermore, the results indicated that employing resiliency analysis algorithm in the case of contingency reduced the cost and load shedding up to 12% and 80%, respectively. The impacts of scheduling electrical vehicles and demand response consideration on this problem also indicated operational cost savings up to 17%.

As a future research, the proposed model can be further improved to be implemented at the distribution level. In this case, the model should be extended to take into more details related to distribution level, such as driving hours of electrical vehicles owners during the operation period. To meet this purpose, some factors must be more specifically investigated, such as working hours in the understudy region. Moreover, as some constraints related to distribution level (e.g., AC power flow constraints), increase the complexity of the optimization problem, a decomposition approach can be developed to improve the computational performance as well as increase the chance to reach global optimal solutions.

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Appendix A. Nomenclature

Subscripts	
$\mathcal{Y}$	Set of terminal nodes indexed by y ($y \epsilon \mathcal{Y} \subseteq \mathcal{N}$)
$\mathcal{N}$	Set of nodes indexed by n ($n \epsilon \mathcal{N}$)
$\mathcal{P}$	Set of pipelines indexed by p ($p \epsilon \mathcal{P} \subseteq (\mathcal{N}, \mathcal{N}')$)
$\mathcal{C}$	Set of compressors indexed by c ($c \epsilon \mathcal{C} \subseteq (\mathcal{N}, \mathcal{N}')$)
$\mathcal{T}$	Set of time periods indexed by t ($t \epsilon \mathcal{T}$)
$\mathcal{G}$	Set of thermal units indexed by g (gϵG)
$\mathcal{B}$	Set of busbars indexed by b ($b \epsilon \mathcal{B}$)
$\mathcal{L}$	Set of transmission lines indexed by ℓ ($\ell \epsilon \mathcal{L} \subseteq (\mathcal{B}, \mathcal{B}')$)
$\mathcal{Q}$	Set of gas storages indexed by q ($q \epsilon \mathcal{Q} \subseteq \mathcal{N}$)
$\mathcal{R}$	Set of energy storages indexed by r (rϵR ⊆ B)
$\mathcal{V}$	Set of electrical vehicles indexed by v ($v \epsilon \mathcal{V} \subseteq \mathcal{B}$)

Parameters	
C^{gas}	Cost of gas injection
C^{lp}	Cost of Linepack management
C^{gsh}	Cost of gas shedding

C_{g}^{th}	Fuel Cost of thermal generating units
C_{b}^{lsh}	Cost of load shedding
C_{v}^{ev}	Cost of EV power consumption
Le_{p}	Length of pipelines
η_{p}	Efficiency of pipelines
Di_{p}	Diameter of pipelines
$\pi_{n}^{\mathrm{max/min}}$	Maximum/minimum pressure at nodes
$F_{p}^{\mathrm{pipe.max/min}}$	Maximum/minimum gas flow within pipelines
ϕ^{comp}	Gas turbine fuel rate coefficient of a compressor
η^{comp}	Efficiency of compressors
$\mathrm{PR}^{\mathrm{max}}$	Pressure ratio of compressors
$F_{c}^{\mathrm{comp.min/max}}$	Maximum/minimum gas flow within compressors
$P_{c}^{\mathrm{comp.min/max}}$	Maximum/minimum power consumption of compressors
$GL_{q}^{\mathrm{min/max}}$	Maximum/minimum gas level of gas storages
$F_{q}^{\mathrm{wd.max/min}}$	Maximum/minimum withdrawal gas flow
$F_{q}^{\mathrm{inj.maxmin}}$	Maximum/minimum injected gas flow
$LP_{p,t}^{0}$	Initial linepack of pipelines
V_{p}	Volume of gas
ρ^{nor}	Gas density under standard condition
Z	Compressibility factor for gas
R	Gas constant
π_{p}^{ave}	Average pressure of pipelines
$\mathrm{T}^{\mathrm{nor}}$	Gas temperature under standard condition
K_{g}/J_{g}	Startup/shutdown cost of thermal unit
$T_{g}^{\mathrm{on/off}}$	Minimum up-time/down-time
ς	Flexibility of demand response
$P_{g,t}^{\mathrm{th.max/min}}$	Maximum/minimum output power of thermal generating units
$P_{b,t}^{\mathrm{wind.avail}}$	Available wind power
RU_{g}/RD_{g}	Ramp-up/ramp-down
SUR_{g}/SDR_{g}	Startup/shutdown ramp
X_{ℓ}	Reactance
SRR_{t}	Reserve requirement
η_{v}	Efficiency of EVs
$P_{v,t}^{\mathrm{ev.ch.max/min}}$	Maximum/minimum charging power of EVs
$P_{v,t}^{\mathrm{ev.dch.max/min}}$	Maximum/minimum discharging power of EVs
$E_{v,t}^{\mathrm{ev.ch.max/min}}$	Maximum/minimum net hourly charged energy of EVs
$P_{b,t}^{\mathrm{elec.load}}$	Electricity demand
υ	Thermal efficiency of gas generator
HV	Gas heating value
σ	Standard deviation
μ	Mean value
α/β	Minimum level of confidence to satisfy chance constraints
γ	Weighted coefficient
Γ	Weighted coefficient
$\mathbb{E}$	Possibilistic event
$\mathbb{F}$	Fix costs

$\mathbb{C}$	Variable costs
$\mathbb{L}, \mathbb{T}, \mathbb{H}$ $\mathbb{V}, \mathbb{M}$	Coefficients matrices

Variables

$F_{y,t}^{\text{sup}}$	Gas injection
$\Delta LP_{n,t}$	Changes in linepack within pipelines
$F_{n,t}^{\text{gsh}}$	Gas shedding
$F_{p,t}^{\text{pipe}}$	Gas flow within pipelines
$F_{c,t}^{\text{comp}}$	Gas flow within compressors
$\pi_{n,t}$	Gas pressure at nodes
$P_{c,t}^{\text{comp}}$	Power consumption of compressors
$\pi_{c,t}^{\text{in/out}}$	Input/output pressure of compressors
$GL_{q,t}$	Gas level of gas storages
$F_{q,t}^{\text{wd}}$	Withdrawal gas
$F_{q,t}^{\text{inj}}$	Injected gas
$LP_{p,t}$	Linepack
$F_{p,t}^{\text{pipe.in/out}}$	Input/output gas flow
$P_{g,t}^{\text{th}}$	Output power of thermal generating units
$SU_{g}\,/SD_{g}$	Startup/shutdown cost
$P_{b,t}^{\text{lsh}}$	Load shedding
$P_{v,t}^{\text{ev.ch/dch}}$	Charging/discharging power of EVs
$y_{g,t}$	Commitment status of thermal generating units
$P_{b,t}^{\text{wind}}$	Power output of wind farms
$P_{v,t}^{\text{ev.ch/dch}}$	Charging/discharging power of EVs
$P_{\ell,t}^{\text{line}}$	Power flow through transmission lines
$D_{b,t}^{\text{elec}}$	Flexible electricity demand
$E_{v,t}^{ev.net}$	Net hourly charged energy of EVs
$I_{v,t}^{\text{ev.ch/dch}}$	Charging/discharging status of EVs
$E_{v,t}^{\text{ev.ch/dch}}$	Charging/dischargingenergy of EVs
OF	Objective function
$F_{g,t}^{\text{gen}}$	Gas demand of thermal generating units
X	Vector of continuous variables
Y, U	Vector of binary variables
$\omega_{p}/\omega'_{\ell}$	Outage of pipelines/electrical lines

Appendix B. Possibilistic chance constrained programming

In this model, to represent uncertain data, a quadratic approximation of Gaussian membership function is initially utilized, which is shown in Figure 19 and formulated in (B1).

$$f(x) = \begin{cases} \frac{1}{\sqrt{2.\pi.\sigma}}.\left(\frac{x-\mu+\sigma}{\sigma}\right)^2 & \text{if } \mu-\sigma < x < \mu \\ \frac{1}{\sqrt{2.\pi.\sigma}}.\left(\frac{\mu-x+\sigma}{\sigma}\right)^2 & \text{if } \mu < x < \mu+\sigma \\ 0 & \text{O.W.} \end{cases} \tag{B1}$$

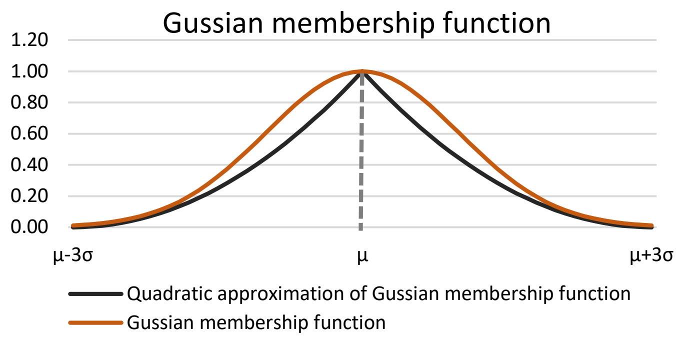

Figure 19. Gaussian possibility distribution of fuzzy parameter to represent an uncertain parameter.

For all values of confidence level, the value of α is greater than or equal to 0.5 [Liu & Liu, 2002]. Therefore, for $\alpha \geq 0.5$, the crisp counterparts are determined in (B2)-(B5).

$$\text{Pos}\,\{\tilde{\tau} \leq x\} \geq \alpha \iff \frac{1}{\sqrt{2.\pi.\sigma}}.\left(\frac{x-\mu+\sigma}{\sigma}\right)^2 \geq \alpha \Leftrightarrow x \geq \sigma\sqrt{\alpha\sqrt{2.\pi.\sigma}} + \mu - \sigma \tag{B2}$$

$$\text{Pos}\,\{\tilde{\tau} \geq x\} \geq \alpha \iff \frac{1}{\sqrt{2.\pi.\sigma}}.\left(\frac{\mu+\sigma-x}{\sigma}\right)^2 \geq \alpha \Leftrightarrow x \leq -\sigma\sqrt{\alpha\sqrt{2.\pi.\sigma}} + \mu + \sigma \tag{B3}$$

$$\text{Nec}\,\{\tilde{\tau} \leq x\} \geq \alpha \iff \frac{1}{\sqrt{2.\pi.\sigma}}.\left(\frac{x-\mu}{\sigma}\right)^2 \geq \alpha \Leftrightarrow \quad x \geq \sigma\sqrt{\alpha\sqrt{2.\pi.\sigma}} + \mu \tag{B4}$$

$$\text{Nec}\,\{\tilde{\tau} \geq x\} \geq \alpha \iff \frac{1}{\sqrt{2.\pi.\sigma}}.\left(\frac{\mu-x}{\sigma}\right)^2 \geq \alpha \Leftrightarrow \quad x \leq -\sigma\sqrt{\alpha\sqrt{2.\pi.\sigma}} + \mu \tag{B5}$$

In a real-world situation, decision makers' opinions may change between the most pessimistic and the most optimistic attitudes. Therefore, the amount of compensatory fuzzy measure is determined in (B6).

$$\text{Me}\{\mathbb{E}\}=(1-\gamma).\,\text{Pos}\{\,\mathbb{E}\,\}+\gamma.\text{Nec}\{\,\mathbb{E}\,\} \tag{B6}$$

By changing γ in [0, 1], decision makers can make a preferable combination [Xu & Zhou, 2013]. The Me is equal to the Nec when the value of γ is equal to zero (i.e., the minimum occurrence possibility level of event) [Liu & Iwamura, 1998]. On the other hand, the Me is equal to the Pos when the value of γ is equal to one (i.e., the maximum occurrence possibility level of event E), For each γ, the Me value is calculated in (B7)-(B10).

$$\text{Me}\{\tilde{\tau} \leq x\} = \frac{1}{\sqrt{2.\pi.\sigma}}.\begin{cases} 0 & \text{if } x < \mu-\sigma \\ \gamma.\left(\frac{x-\mu+\sigma}{\sigma}\right)^2 & \text{if } \mu-\sigma < x < \mu \\ \gamma+(1-\gamma).\left(\frac{x-\mu}{\sigma}\right)^2 & \text{if } \mu < x < \mu+\sigma \\ 1 & \text{if } x > \mu+\sigma \end{cases} \tag{B7}$$

$$\mathrm{Me}\{\tilde{\tau} \le x\} = \frac{1}{\sqrt{2.\pi.\sigma}} \cdot \begin{cases} 0 & \text{if } x < \mu - \sigma \\ \gamma + (1-\gamma).\left(\frac{\mu - x}{\sigma}\right)^2 & \text{if } \mu - \sigma < x < \mu \\ \gamma.\left(\frac{\mu + \sigma - x}{\sigma}\right)^2 & \text{if } \mu < x < \mu + \sigma \\ 1 & \text{if } x > \mu + \sigma \end{cases} \quad \text{(B8)}$$

$$\mathrm{Me}\{\ \tilde{\tau}\ \le x\} \ge\ \alpha \Leftrightarrow \frac{1}{\sqrt{2\pi\sigma}} \cdot \left(\gamma + (1-\ \gamma).\left(\frac{x-\mu}{\sigma}\right)^2\right) \ge\ \alpha \ \Leftrightarrow x \ge \sigma\sqrt{\frac{\alpha\sqrt{2.\pi.\sigma}-\gamma}{1-\gamma}} + \mu \quad \text{(B9)}$$

$$\mathrm{Me}\{\ \tilde{\tau}\ \ge x\} \ge\ \alpha \Leftrightarrow \frac{1}{\sqrt{2\pi\sigma}} \cdot \left(\gamma + (1-\ \gamma).\left(\frac{\mu-x}{\sigma}\right)^2\right) \ge\ \alpha \ \Leftrightarrow x \le \mu - \sigma\sqrt{\frac{\alpha\sqrt{2.\pi.\sigma}-\gamma}{1-\gamma}} \quad \text{(B10)}$$

In (B11), $\mathbb{F}$, $\mathbb{C}$, and $\mathbb{D}$ represent fixed costs, variable costs, and demand, respectively. Besides, the vectors of binary variables are indicated by Y and U, and the vectors of continuous variables are indicated by X. $\mathbb{L}, \mathbb{T}, \mathbb{H}, \mathbb{V}$, and $\mathbb{M}$ also represent the coefficients matrices. In our original model, $\mathbb{L}.X \ge \mathbb{D}$ is the counterpart of power flow balance and gas flow balance, and $\mathbb{H}.X \le \mathbb{V}$ represents maximum output power of wind generators. Moreover, $\mathbb{T}.Y \le 1$ indicates binary-related constraints, such as the minimum uptime/downtime of thermal generating units, and $\mathbb{M}.X \le U$ is counterpart of any other constrains in this problem.

Minimize $W = \mathbb{F}.X + \mathbb{C}.Y$

Subject to

$\mathbb{L}.X \ge \mathbb{D}$ (B11)

$\mathbb{H}.X \le \mathbb{V}$

$\mathbb{T}.Y \le 1$

$\mathbb{M}.X \le U$

Y and $U \epsilon \{0, 1\}$

$X \ge 0$

When the values of V and D are subject to epistemic uncertainty (e.g., the equivalent electricity demand and gas demand which are subject to epistemic uncertainty due to adding EVs and wind farms), in (B12), the PCCP formulation is introduced in which the minimum satisfaction degree of possibilistic chance constraints are represented by α and β.

Minimize $E[W] = \mathbb{C}.\ X + \mathbb{F}.\ Y$

Subject to

$\mathrm{Me}\{\mathbb{L}.X \ge \tilde{\mathbb{D}}\} \ge\ \alpha$

$\mathrm{Me}\{\mathbb{H}.X \le \tilde{\mathbb{V}}\} \ge \beta$ (B12)

$\mathbb{T}.Y \le 1$

$\mathbb{M}.X \le U$

Y and $U \epsilon\ \{0, 1\}$

$X \geq 0$

In (B13), the possibilistic constraints of the model are measured by Me, and the uncertain constraints of the proposed model are consequently reformulated as follows:

$$\mathbb{L}.X \geq \sigma\sqrt{\frac{\alpha\sqrt{2.\pi.\sigma}-\gamma}{1-\gamma}} + D^{mean} \tag{B13}$$

$$\mathbb{H}.X \leq V^{mean} - \sigma\sqrt{\frac{\beta\sqrt{2.\pi.\sigma}-\gamma}{1-\gamma}}$$

Appendix C. 6-node with 6-bus gas and electricity network data

The gas network consists of six nodes, two gas terminals, six pipelines, two gas storage systems. Table 5 indicates the gas demand, limitation of pressure, and maximum/minimum gas injection through each node.

Table 5. The characteristics of 6-node gas network.

Node	Minimum injection (mcm)	Maximum injection (mcm)	Minimum pressure (Bar)	Maximum pressure (Bar)	Gas demand (mcm)
1	0	8.5	50	85	0.55
2	-	-	38	85	0.55
3	-	-	38	85	0.55
4	-	-	38	85	0.55
5	-	-	38	85	0.55
6	-	-	38	85	0.55

The installed capacity of the wind farm is equal to 20 MW, and the characteristics of other generator units are shown in Table 6.

Table 6. Characteristics of generating units in the 6-bus electricity test system.

No.	cost coefficient ($/MW)	Minimum stable output power (MW)	Maximum stable output power (MW)	Ramp-up/down (MW/hour)	Minimum uptime/downtime (hour)	Startup cost ($)	Type
1	13.51	100	220	26	4	100	Coal-fired
2	17.63	10	80	47	1	10	Natural gas-fired
3	27.7	10	20	7	2	50	Biomass-fired

Appendix D. Belgium gas network with IEEE 24-bus electricity network data

Belgium gas network consists of 20 nodes, three gas terminals, 24 pipelines, and four gas storage facilities, which the required data are presented in Table 7, Table 8, and Table 9. The characteristics of the two compressor units located in Berneau and Sinsin are presented in Table 10.

In Belgium, there is no gas well and the required amount of gas is imported from Algeria, Norway, and Netherlands. Algerian gas is piped through the Zeebrugge terminal in the North. The gas from Norway is also delivered through the Gravenvoeren in the East. Through the Popp terminal in the North, a part of the required amount of gas is also delivered to Belgium.

Table 7. The characteristics of Belgium gas network.

Node	Town	$F^{sup.min}$(mcm)	$F^{sup.max}$(mcm)	π^{min}(Bar)	π^{max}(Bar)
1	Zeebrugge	0.0	11.594	50	77.0
2	Dudzele	0.0	8.4	38	77.0
3	Brugge	-	-	38	80.0
4	Zomergem	-	-	38	80.0
5	Loenhout	0.0	4.8	38	77.0
6	Antwerpen	-	-	38	80.0
7	Gent	-	-	38	80.0
8	Voeren	0.0	22.012	50	66.2
9	Berneau	-	-	38	66.2
10	Lieage	-	-	38	66.2
11	Warnand	-	-	38	66.2
12	Namur	-	-	38	66.2
13	Anderlues	0.0	1.2	38	66.2
14	Peronnes	0.0	0.96	38	66.2
15	Mons	-	-	38	66.2
16	Blaregnies	-	-	50	66.2
17	Wanze	-	-	38	66.2
18	Sinsin	-	-	38	63.0
19	Arlon	-	-	38	66.2
20	Petange	-	-	38	66.2

Table 8. Pipelines data in the Belgium gas network.

No.	From	To	Diameter (mm)	Length (km)	No.	From	To	Diameter (mm)
1	Zeebrugge	Dudzele	890	4	13	Berneau	Likeage	395.5
2	Zeebrugge	Dudzele	890	4	14	Lieage	Warnand	890
3	Dudzele	Brugge	890	6	15	Lieage	Warnand	395.5
4	Dudzele	Brugge	890	6	16	Warnand	Namur	890
5	Brugge	Zomergem	890	26	17	Namur	Anderlues	890
6	Loenhout	Antwerpen	590.1	43	18	Anderlues	Peronnes	890
7	Antwerpen	Gent	590.1	29	19	Peronnes	Mons	890
8	Gent	Zomergem	590.1	19	20	Mons	Blaregnies	890

9	Zomergem	Peronnes	890	55	21	Warnand	Wanze	395.5
10	Voeren	Berneau	890	5	22	Wanze	Sinsin	315.5
11	Voeren	Berneau	395.5	5	23	Sinsin	Arlon	315.5
12	Berneau	Likeage	890	20	24	Arlon	Petange	315.5

Table 9. Maximum daily demand in the Belgium gas network.

Node	Town	Demand (mcm)
6	Antwerpen	4.034
19	Arlon	0.222
3	Brugge	3.918
7	Gent	5.256
10	Lieage	6.365
15	Mons	6.848
12	Namur	2.12
-	Total	28.763

Table 10. Characteristics of compressor units in the Belgium gas network.

Polytrophic exponent (MJ/m^3)	Gas turbine fuel rate coefficient (m^3 /MJ)	Pressure ratio of compressor (1.5)	Overall compressor efficiency
4.7	0.084	1.5	80%

In the electricity network, an updated version of the IEEE 24-bus reliability test system is used to test the proposed model. In Belgium, there are projections to supply 20% of energy demand by wind farms in 2050 [Ordoudis et al., 2016]. Therefore, to meet this objective, it is assumed that six wind farms are installed in busbars 3, 5,7 16, 21,23. The share of available wind proportion to maximum available in a 24-hour period is demonstrated in Figure 20 by investigating the statistic of this country [Hand et al. 2012]. The future consumption profile of electricity is also demonstrated for Belgium in Figure 21 [EEA, 2020]. In the prediction, the growth of consumption due to economic growth, population growth, and energy efficiency has been taken into consideration. Furthermore, the development of electrical transportation has been taken into account.

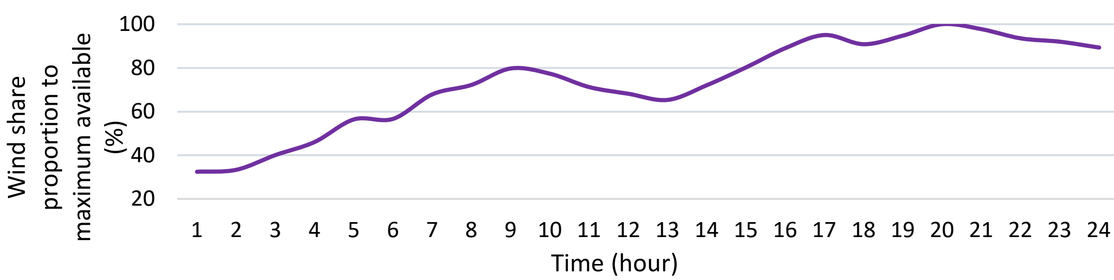

Figure 20. Share of output power of wind generators during operation period.

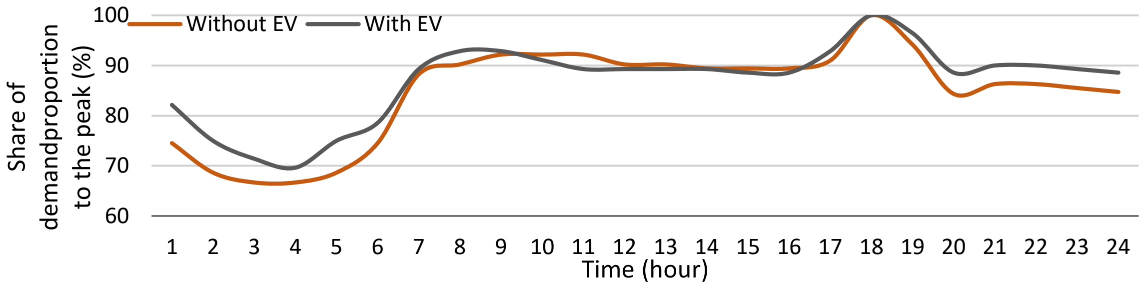

Figure 21. Share of demand in Belgium during three days.

The rapid growth of EV integration is predicted due to the benefits this technology (e.g., cheaper run and being more environmentally-friendly compared to motor vehicles powered by gasoline or diesel) . As there is a great tendency to sustainability in Belgium, and a set of different policy has been introduced to develop EVs, investigating the role of these distributed storages in the future energy system can enable their potential for a low-carbon future [EEA, 2020]. In this case study, it is assumed that two EV fleets are connected on busbars 19 and 21 as distributed energy storage. The characteristic of electric vehicles connected to each fleet is presented considering manufacturers' information in Table 11 (e.g., Mitsubishi [Mitsubishi, 2012], Ford [Ford Motor Company, 2012], and BMW [BMW of North America]).

Table 11. Characteristics of electrical vehicles in IEEE 24-bus electricity network

Average battery size (KWh)	23.75
Battery replacement cost in 2020 ($/kWh)	200
Hourly drive consumption (kWh)	4.2

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