# The impact of uncertainties on the Belgian energy system: application of the Polynomial Chaos Expansion to the EnergyScope model.

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**Abstract:**

In an ever-changing world running for overall expansion and facing an unprecedented climate change, the energy transition question remains at the core of today's—and tomorrow's—policies. To address this question, several studies have already looked into optimized energy systems minimizing the greenhouse gas emission and the costs taking into account high renewable energies penetration and energy storage solutions. Such models rely on many parameters to represent as closely as possible the actual behaviour of the system. This paper focuses on the uncertainty of these parameters. To do so, the Polynomial Chaos Expansion method is applied to highlight and rank the parameters that have the highest influence on the model Key Performance Indicator : the total cost of the system. The outcome of this analysis points out that some parameters, as the operational cost of natural gas, have a much bigger impact. In other words, reducing the uncertainty over this cost would drastically improve the robustness of the optimum energy system.

**Keywords:**

Energy modeling, Uncertainty quantification, Global sensitivity analysis, Polynomial chaos expansion, EnergyScope

## 1. Introduction

Climate change as well as ever-growing population development depend on the energy resources usage. In order to ensure the energy supply for a more and more demanding society in a context of environmental crisis, an overall reshape of the energy system is necessary. This change shall be both in terms of primary energy resources usage and technologies used to convert these resources into the end-use demand of the final consumer. To support such a transition, numerical models are able to evaluate the feasibility of different energy system strategies and, via an optimization process, propose an optimal solution given specific constraints (e.g. limited greenhouse gas emissions or limited investment costs). However, defining an energy transition strategy for a large-scale system, such as a country, implies decisions with long-term impacts (20 to 50 years) [1]. Consequently, the optimized energy system strategy that the model generates is highly dependent on uncertain parameters, especially if the strategy relies on economically volatile resources. Therefore, taking into account uncertainty in an energy system model is crucial. Beyond highlighting the most-influencing parameters of the model, this will help to end up the optimization process with a robust and reliable solution.

This works gives the results of an uncertainty analysis performed over a multi-energy model : EnergyScope Typical Days (EnergyScope TD) [2]. The model optimises both the investments and the operation of the entire energy system accounting for all the energy flows within its boundaries, including electricity, heating and mobility. Based on previous works about the Belgium case [3] and uncertainty characterization [4], this paper focuses on the application of the polynomial chaos expansion (PCE) method. PCE is a computationally-efficient surrogate modelling technique which efficiently provides the statistical moments and sensitivity indices (i.e. Sobol' indices) [5]. The results are compared with similar studies [1, 4] that have been performed with the Morris method [6].
The study aims at: (i) verifying the feasibility of applying the PCE method to EnergyScope TD; (ii) identifying the critical parameters that drive the uncertainty and (iii) computing the statistical moments of key performance indicators.
The paper is structured as follows : first, we describe the model used and the case study (Section 2). Then the new methodology is depicted (Section 3). Finally, in Section 4, the critical parameters are identified and different statistical moments are analysed.

## 2. Model used and case study

Through this section, the open source model used and its application are presented.

### 2.1 Model

We use EnergyScope TD [2], an open source energy model suitable for uncertainty analysis. The model represents with the same level of detail the heating, mobility, and electricity sectors. The main features are: (i) satisfying the system end-use demand, accounting for electricity, heat and transport; (ii) optimizing both the design of the system and its operation by minimising its overall cost; (iii) an hourly resolution (time step) which makes the model suitable for analysing the integration of intermittent renewable energies (RE) and storage; (iv) a short computational time (1–5 min) as a result of the use of typical days and a rebuilt method to represent a year with an hourly resolution. The last criteria becomes critical when performing uncertainty analysis. Indeed, a large amount of model evaluations are necessary to estimate the sensitivity.
According to the classification proposed by Codina Gironès et al. [7], the modelling framework belongs to the snapshot category, as it models the energy system in a target year. A specificity of the model is that the demand is imposed in terms of end-use demand (EUD) rather than final energy consumption (FEC). As an example, the passenger mobility is given in passenger kilometers per year (*pass-km/y*) rather than in terms of gasoline needed for cars. The model is open source and fully documented [8].

### 2.2 Case study: the Belgian energy system in 2035

The case study represents the national energy system of Belgium in 2035. The year 2035 appears as a good trade-off between a long-term horizon where policies can be implemented and a horizon short enough to be representative of tomorrow society with a toolbox of technologies already known. In addition, data has been collected for 2035 during previous works [2, 3, 9] and are fully summarised in the code repository [8]. Figure 1 gives an overview of the model operation and the way we performed the global sensitivity analysis (GSA).
The energy system has to supply nine demands regrouped in three categories: electricity, heat and mobility. Each demand is hourly imposed, in an exogenous way. The system relies on 20 different resources which can either be renewable, such as wood, wind or geothermal; or fossil, such as gasoline, coal, uranium or natural gas (NG). These resources are converted into different energy carriers, such as electricity (9 technologies), heat (30 technologies), mobility (19 technologies) or infrastructures (13 technologies). The latter regroups the commonly known infrastructure, such as the grid and district heating networks (DHN), but also technologies that can produce synthetic fuels, such as wood gasification, biomethanisation and methanolation. In addition, the energy can be stored through 21 technologies and under different energy carriers, such as heat, electricity or fuels. These energy

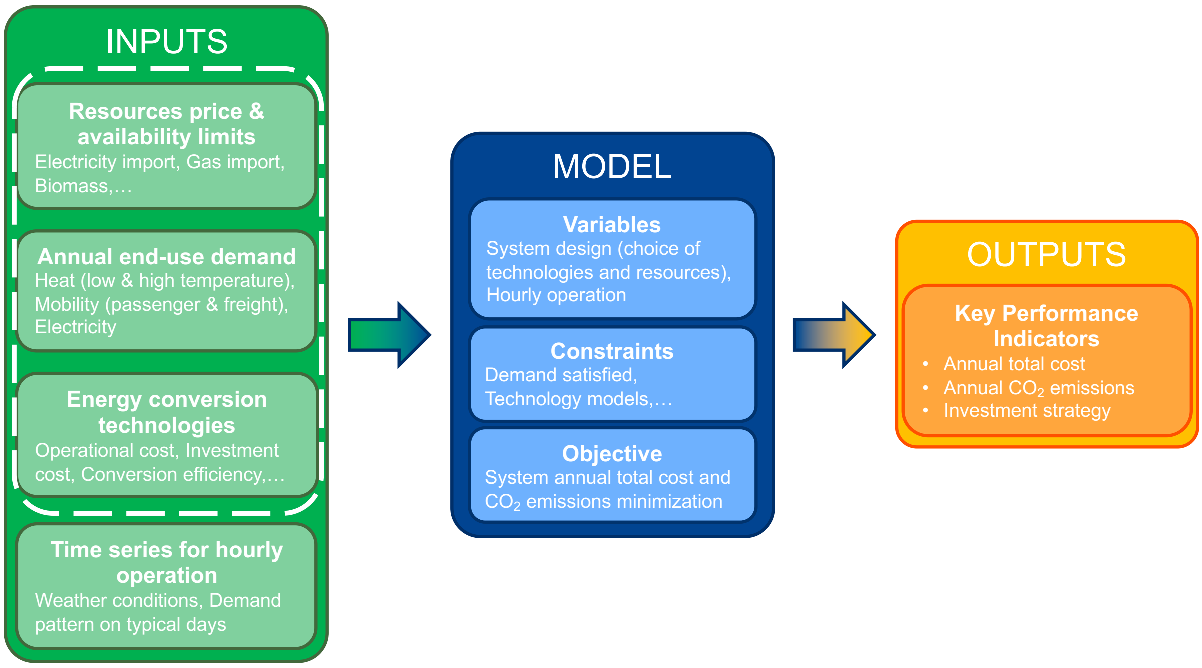



**Figure 1**: Schematic of the EnergyScope TD model. During the GSA, parameters variation ($\xi_1$, $\xi_2$, ..., $\xi_d$) will concern the **dash-boxed inputs** while the key performance indicators will be the **optimized objectives**. Abbreviations: carbon dioxide ($CO_2$).

carriers can either be imported or locally produced. Biogas, hydrogen and synthetic methanol are examples of renewable fuels implemented.
In this work, we use as key performance indicator (KPI) the total annual cost of the energy system ($\mathbf{C_{tot}}$). It is defined as the sum of the annualized investment costs of technologies ($\tau$ $\mathbf{C_{inv}}$), the operating and maintenance costs of technologies ($\mathbf{C_{maint}}$) and the operating costs of the resources ($\mathbf{C_{op}}$):

$$\mathbf{C_{tot}} = \sum_{j \in TECH} \Big( \tau(j) \mathbf{C_{inv}}(j) + \mathbf{C_{maint}}(j) \Big) + \sum_{i \in RES} \mathbf{C_{op}}(i). \tag{1}$$

The annualised factor $\tau$ is calculated based on the interest rate ($i_{rate}$) and the technology lifetime (*lifetime*):

$$\tau(j) = \frac{i_{rate}(i_{rate}+1)^{lifetime(j)}}{(i_{rate}+1)^{lifetime(j)} - 1} \qquad \forall j \in TECH. \tag{2}$$

Based on current policies, the Belgian government plans to phase out nuclear power plants in 2025 and decrease their carbon dioxide ($CO_2$) emissions. In our previous study, we demonstrated that, given the 2035-demand forecast of the European Union Commission [10], Belgium could not achieve less than 73MtCO$_2$ emission per year. To achieve a lower $CO_2$ emissions, additional scenarios (*options*) were investigated. From which, the *Mix* scenario allows the use of non-proven renewable resources (additional offshore wind capacity, geothermal (limited in this paper to 1 GW thermal and 1 GW electric)), nuclear capacity (limited to the existing one (5.92GW)), imports (renewable fuels and electricity up to 9 GW).
As we aim at analysing the sensitivity of the Belgian energy system at low $CO_2$ emissions, we have implemented the *Mix* scenario. This scenario has a cost optimum at around 35 MtCO$_2$.

## 3. Methodology

In this section, we present the different sensitivity analysis methods applied to the case study. First, an uncertainty characterization is required to provide relevant variation ranges to the parameters. Second, we present the two methods used in this study. The first method (see Section 3.2) has been already applied to similar energy systems and will be considered as the reference. The second method (see

Section 3.3) offers similar performances and additional results compared to the first one.

### 3.1 Uncertainty characterization

Moret et al. proposed a range of uncertainties for a previous version of the model [4]. The ranges were defined for the case of Switzerland and were adopted for the case of Belgium. Table 1 gives an illustration of some key ranges for the Belgian case.

| **Parameters**<br>Units | $i_{rate}$<br>[-] | $c_{op}$*(NG)*<br>[€/MWh] | *avail(WOOD)*<br>[TWh] | $c_{inv}$*(photovoltaic (PV))*<br>[€/kW] | ...<br>... |
|---|---|---|---|---|---|
| **reference** | 0.015 | 41.5 | 13.7 | 870 | |
| **min** | -46.2% | -47.3% | -32% | -40% | |
| **max** | 46.2% | 89.9% | 32% | 40% | |

**Table 1**: Illustration of the uncertainty characterisation for different parameters. Abbreviations: natural gas (NG), photovoltaic (PV).

As proposed in [4], after a preliminary screening and grouping of the model reference scenario parameters, 119 parameters are accounted for. With this number of parameters, an accurate global sensitivity analysis (GSA) would require $590\,480$ model evaluations, which is not affordable. In their work, Moret et al. [4] showed that only a limited number of parameters are critical. Hence, we perform the GSA in two steps. First, with a coarse GSA, we identify a shorter list of parameters[1] which have a significant impact. Second, based on this shorter list, we apply two different methods to perform a GSA.

### 3.2 Morris method

The Morris method, as a statistical analysis, relies on individually randomized one-factor-at-a-time designs [6]. Given the $d$ model parameters $\vec{\xi} = (\xi_1, \xi_2, ..., \xi_d)$, the first step of the method consists in generating independent random samples of $\vec{\xi}$ in a standardized and discretized $p$-level *region of experimentation*, $\omega$. In this *region of experimentation*, each $\xi_i$, varying in the interval $[\xi_{i,min},\ \xi_{i,max}]$, can take a random discrete value as follows :

$$\xi_i = \xi_{i,min} + j \cdot \frac{1}{p-1}\left(\xi_{i,max} - \xi_{i,min}\right) \quad \text{with } j \in \{0, 1, ..., p-1\} \tag{3}$$

Then, given these random one-factor-at-a-time samples, Morris method defines, for a given set of $\vec{\xi}$, the elementary effect of the $i$th parameter ($EE_i$) as :

$$EE_i = \frac{M(\xi_1, \xi_2, ..., \xi_i + \Delta, ..., \xi_d) - M(\vec{\xi})}{\Delta} \tag{4}$$

where $M$ is the objective function, $\vec{\xi} \in \omega$, except $\xi_i \leq 1 - \Delta$ and $\Delta$ is a set multiple of $1/(p-1)\,(\xi_{i,max} - \xi_{i,min})$. As in other studies [4, 11, 12], we consider $p$ as even and $\Delta = p/[2(p-1)]\,(\xi_{i,max} - \xi_{i,min})$.

Finally, in order to evaluate the importance of the $i$th parameter over an output, Morris method relies on $F_i$, the distribution of $r$ elementary effects. Computing the mean, $\mu_i = \mu(F_i)$, and the standard deviation, $\sigma_i = \sigma(F_i)$, of the $F_i$ distribution, allows ranking the parameters based on their influence on the concerned output. Usually, in Morris method, $p$ and $r$ respectively get values as follows : $p \in \{4, 6, 8\}$ and $r \in [15; 100]$ depending on, $d$, the number of uncertain parameters. The higher this number is, the higher shall be, simultaneously, $p$ and $r$. In the following comparative analysis, we set

[1] We have verified that the parameters not accounted for have a negligible impact on the total annual cost of the energy system.

$p$ and $r$ to their maximum values, respectively 8 and 100 in order to get the most reliable parameters ranking.

Beyond the original Morris method, we used the standardized elementary effects, $SEE_i$, formulation [11], given by

$$SEE_i = EE_i \cdot \frac{\sigma(\xi_i)}{\sigma(M)}. \tag{5}$$

Among other things, the $SEE$ allows comparing the influence of different inputs on the same output or compare the influence of a same parameter on different outputs, even if these parameters or outputs are significantly different in terms of variation range or average amplitude. Moreover, this standardized analysis does not require any additional model evaluations.
Therefore, in the following results, we rather use

$$\mu_i^* = \mu(|SF_i|) \tag{6}$$

to rank parameters among each other. In (6), $SF_i$ is the distribution formed by the $r$ standardized elementary effects, as done in Moret [12].
In the application of the PCE approach, we compare the Top-14 parameters ranking obtained from this approach with the one provided by the improved Morris method based on $\mu_i^*$.

### 3.3 Polynomial chaos expansion method

The PCE is a method to propagate the uncertainty and quantify the Sobol' indices to perform a GSA [13]. In a previous work, we applied the methodology to other energy systems, including a power-to-ammonia system [14], a micro-gas turbine with carbon capture [15] and a hydrogen-based energy system [16]. The PCE consists of a series of orthogonal polynomials $\Psi_i$ with corresponding coefficients $u_i$:

$$\hat{M}(\vec{\xi}) = \sum_{i=0}^{P} u_i \Psi_i(\vec{\xi}) \approx M(\vec{\xi}), \tag{7}$$

where $\vec{\xi} = (\xi_1, \xi_2, ..., \xi_d)$ represents the vector of independent uncertain parameters and $d$ is the number of uncertain parameters; $M$ and $\hat{M}$ are the EnergyScope TD model and surrogate model, respectively. If the series is infinite (i.e. $P = \infty$), it forms an exact representation of the system model, but its characterization is computationally intractable. Alternatively, a truncated series is defined, where the length of the truncated PCE depends on the complexity of the relation between the stochastic inputs and objective, which is correlated with the order $p$ of the polynomial, and the stochastic dimension $d$:

$$P + 1 = \frac{(p+d)!}{p!d!}. \tag{8}$$

Consequently, $P + 1$ coefficients $u_i$ are present in the PCE. To quantify these coefficients, Least-Square Minimization is applied, based on actual system model evaluations [17]. In order to ensure a well-posed Least-Square Minimization, $2(P+1)$ system model evaluations are usually required [17]. When the coefficients are quantified, the mean $\mu$ (Eq. (9)) and standard deviation $\sigma$ (Eq. (10)) of the objective follow analytically :

$$\mu = u_0 \tag{9}$$

$$\sigma^2 = \sum_{i=1}^{P} u_i^2 \tag{10}$$

In addition to these statistical moments, the contribution of each stochastic parameter to the variance of the objective provides valuable information on the system behavior under uncertainty. Generally, this contribution is quantified through Sobol' indices. PCE provides an analytical solution to quantify these Sobol' indices through post-processing of the PCE coefficients (i.e. no additional model evaluations required). The total-order Sobol' indices ($S_i^{T,\text{PC}}$) are determined as:

$$S_i^{T,\text{PC}} = \sum_{\alpha \in A_i^T} u_\alpha^2 / \sum_{i=1}^{P} u_i^2 \qquad A_i^T = \{\alpha \in A | \alpha_i > 0\}, \tag{11}$$

where $A$ is the set of all the PCE coefficients and $\alpha_i$ represents the coefficient related to uncertain parameter $i$.

## 4. Results

In this part, we first present the reference scenario, then by applying the GSA methodologies presented previously (see Section 3), we depict the critical parameters, compare the Morris and PCE methods and finally analyze the results.

### 4.1 Reference scenario

The Sankey diagram (in Fig. 2) represents the entire energy conversion chain for the reference case (scenario *Mix* in [3]), from primary energy to the final energy consumption. As previously mentioned, the analysed scenario relies on non-proven potentials, such as geothermal or extra-territorial wind concessions. Renewable resources supply 29% of the primary energy (among which are solar (18.2 TWh), wind (57.4 TWh), biomass (8.2 TWh), hydro (0.5 TWh) and geothermal (22.4 TWh)); whereas imported fossil resources take the dominant share (66%) (among which are natural gas (NG) (100.3 TWh), Coal (33.3 TWh) and Uranium (112.6 TWh)). The remaining 6 % are supplied by imported electricity (10.6 TWh) and local non-renewable waste (9.3 TWh). The electricity production sector is diversified and relies on 9 different technologies. The heating sectors rely on fewer technologies. The low temperature heat is mostly supplied by heat pumps. An exception is made for the district heating network which uses also geothermal heat at its full potential. The high temperature heat is supplied by NG combined heat and power (CHP) units, NG boilers, waste boilers and wood boilers. The mobility sectors are supplied by a larger range of technologies, of which, trains, trams, fuel cells cars, gasoline cars, NG trucks, NG boats ...

### 4.2 Critical parameters selection

As mentioned in Section 3.3, performing an accurate GSA over all the parameters is computationally intractable. Hence, we first select a subset of parameters, later called "*critical*" parameters. Out of the evaluated reference scenario, 119 parameters prove to be active (i.e. these parameters have an impact on the system cost). Then, a coarse evaluation with the PCE method is applied (i.e. polynomial of order $p = 1$), in order to define the critical set of parameters that contribute significantly to the variation of the yearly annualised total cost ($\mathbf{C_{tot}}$). To ensure redundancy in the results, five PCE surrogate models have been constructed, each with a different random set of 240 samples.
Figure 3 illustrates the Sobol indices of total yearly cost ($\mathbf{C_{tot}}$) for all the parameters. The trend shows that few parameters are dominating the uncertainties. As a good practice [18], parameters with a Sobol index above the threshold $= 1/d$ (where $d$ is the number of uncertain parameters) are called *critical parameters*. Based on this selection, the computational efficiency is improved significantly ($1360$ evaluations required for order 3 PCE with 14 parameters, as opposed to $590\,480$ evaluations for 119 parameters), while the loss in statistical accuracy is negligible (Top-14 covers 99% of the total variation).

### 4.3 Comparison of the two methods

Based on this shorter list, we apply both methods to quantify the role of each parameter uncertainty and verify the consistency of the PCE method (presented in Section 3.3). The comparison is performed in terms of the critical parameters ranking. As introduced in Section 3.2, based on $\mu_i^*$, Morris

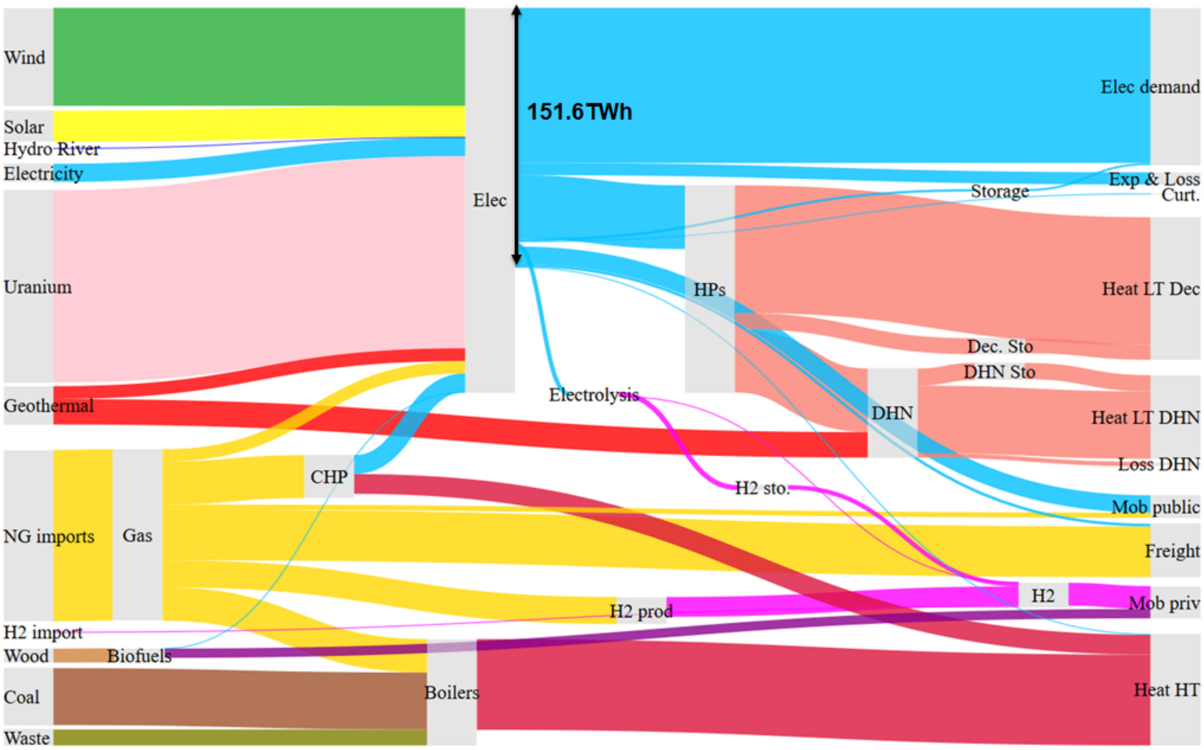



**Figure 2**: Energy flows in the reference scenario representing the Belgian energy system in 2035. Left side gathers all the resources and right side gathers the final energy consumption. In between, the conversion technologies. Abbreviations: natural gas (NG), combined heat and power (CHP), curtailment (Curt.), district heating networks (DHN), di-hydrogen (H2), heat pump (HP), high temperature (HT), low temperature (LT), storage (sto), decentralised (Dec), private and public mobility (Mob priv and Mob public) and exports and losses (Exp & Loss).

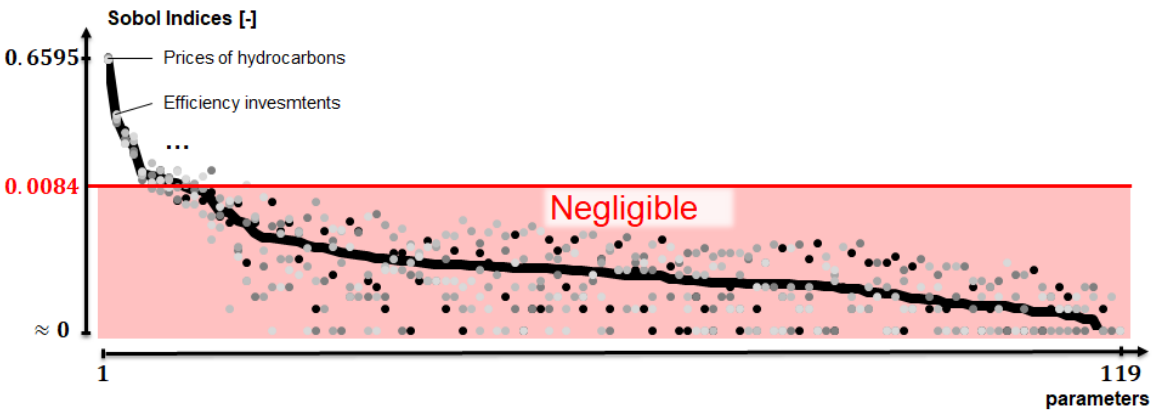



**Figure 3**: Sobol indices of total yearly cost ($\mathbf{C_{tot}}$) for the 119 parameters with 5 different 1st order PCE (grey scales - bullets) and their average (black - curve) in a logarithmic scale. The threshold (red line) represents negligible indices. A total of 14 parameters have at least 1 sobol index above the threshold.

method provides this ranking. Similarly, the PCE approach offers a similar ranking. Both rankings are focused on the optimized objective of the total annual cost (investment, operation and maintenance) of the energy system. Results are summarised in Table 2.

Rankings are very similar and they allow us to verify that using the PCE method is relevant for the case study. Between the two rankings, the different swaps of parameters do not not jeopardize the comparative analysis since the parameters present very close $\mu_i^*$ (or $S_i^T$). It is important to point out that we do not aim to compare the absolute values $\mu_i^*$ with $S_i^T$ as they do not have the same physical meaning.

| Parameter | Morris Ranking ($\mu_i^*$) | PCE Ranking ($S_i^T$) |
|---|---|---|
| Prices of hydrocarbons | 1 (0.7141) | 1 (0.6434) |
| Cost of increased efficiency | 2 (0.3046) | 2 (0.1014) |
| **Cost of maintenance** | **3** (0.2371) | **4** (0.0534) |
| **Interest rate** | **4** (0.2019) | **5** (0.0467) |
| **Price of imported electricity** | **5** (0.1974) | **3** (0.0809) |
| Cost of the grid investment | 6 (0.1498) | 6 (0.0252) |
| Cost of PV investment | 7 (0.1270) | 7 (0.0187) |
| Increase of electricity demand | 8 (0.1168) | 8 (0.0154) |
| Cost of nuclear powerplant investment | 9 (0.0963) | 9 (0.0119) |
| **Increase of space heating demand** | **10** (0.0856) | **11** (0.0088) |
| **Price of coal** | **11** (0.0856) | **12** (0.0087) |
| **Price of renewable fuels** | **12** (0.0794) | **10** (0.0104) |
| Price of uranium | 13 (0.0607) | 13 (0.0047) |
| Annual onshore max wind production | 14 (0.0600) | 14 (0.0046) |

**Table 2**: Comparison of the Top-14 rankings for the improved Morris method (left) and total-order PCE method (right). We used the DTU's implementation of Morris method [19] (with $p = 8$, $r = 100$). The differences in the ranking are in bold.

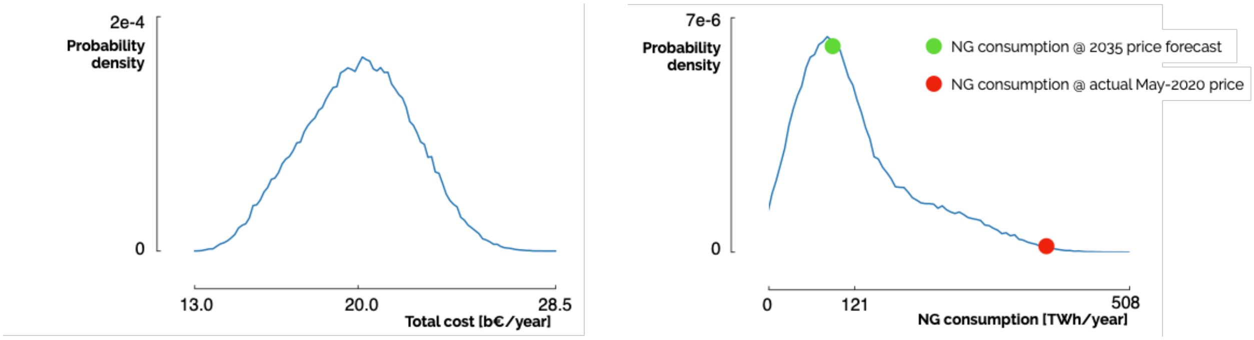
## 4.4 Physical analysis

Table 2 reveals that critical parameters have different impacts over the annual system cost uncertainty. One parameter drives - by far - the uncertainty: the hydrocarbon prices, in this case: NG. Physically, this result can be explained by two facts: (i) in the reference scenario, NG represents 27% of the primary energy consumption and 23% of the annual system cost (including the annualised investments); (ii) NG price is uncertain and ranges between [-46.2%; 89.9%]. The other critical parameters have a smaller impact, but are not negligible. Five parameters have an impact greater than 2% on the total system cost: (i) the cost of implementing energy efficiency measures (10%) that reduce the EUD in 2035 (the budget is estimated around 3.2 b€ [3]); (ii) The price of electricity imported (8%); (iii) the maintenance cost related to cost of labour (5%); (iv) the interest rate (5%); and (v) the investment cost for the grid (3%).
By reducing the uncertainty on the NG price, the uncertainty on the annual total cost of the energy system could be reduced up to 64.3% (see Table 2). Similar measures can be taken to reduce the uncertainty on other parameters, such as international agreements about electricity imports (ii) or policies for energy efficiency (i). The effort should be focused on estimating the prices and cost of the here above parameters instead of the ones which have a lower Sobol' indices, such as the future prices of Uranium.
Based on the two other indicators, which are overall capital expenditure and yearly $CO_2$ equivalent emissions, NG price appears as the key driver of uncertainties. However, the ranking differs based on the indicator. As an example, for the total capital expenditure, the cost of the grid and the nuclear investments are ranked second and third, respectively.
These results are in line with a similar study about Switzerland. In their work, Moret et al. [4] highlight the key impact of the uncertainties on the operating cost of gas on the total annual system cost and investment decisions.

## 4.5 Statistical analysis

In the previous section, the global sensitivity analysis illustrated the contribution of the input uncertainty to the total cost variation. In this section, the total cost variation is quantified and analysed by generating its probability density function (PDF), which is a major added-value to use PCE method. To generate this PDF, the PCE method achieves the highest computational efficiency: a large sample set (i.e. 1e6 samples) is evaluated on the PCE surrogate model, which requires negligible computa-

tional time, as opposed to evaluating these samples on the actual model.
We observe that the PDF of the output is bell-shaped (Figure 4(a)) with a mean of 20.01 b€/year and a standard deviation of 2.37 b€/year. In other words, to be 95% sure to meet the total cost of the system, one should be ready to expend 24.76 b€/year.




(a) Total cost probability density function

(b) Imported primary natural gas (NG) probability density function

**Figure 4**: Probability density functions of the total cost (a) and the primary NG imported (b). Dots represent the reference scenario (green) and the reference scenario with the actual (May 2020) gas price (red).

Figure 4(b) is obtained by applying the same methodology to the primary use of NG. The spread form shows that there is a wide variety of system designs: from fully dependent (up to 95% of primary energy) to NG free solutions. Most solutions are based on moderate use of NG (25%). This share brings flexibility to the energy system, such as in the reference scenario shown in Figure 2. However, assuming an extremely low gas price, the system design may change radically and become totally dependent on NG. Using the actual gas price (May 2020) of 13.35 $€_{2015}$/MWh (this amount includes the European $CO_2$ market price), the system relies mainly on NG (92% of primary energy used).

## 5. Conclusion

Through this work, we applied the polynomial chaos expansion (PCE) method to perform a global sensitivity analysis of the Belgian energy system in 2035 at low $CO_2$ emissions.
First, we have compared the results from the PCE method with the Morris method, which has already been used for similar applications [1, 12]. Even if the output of each method does not have the same physical meaning, both methods can rank the parameters by their impact on the total annual cost of the energy system. Both rankings are very similar.
Based on the PCE, a global sensitivity analysis has been performed. This analysis highlights that the uncertainty of each parameter does not equally affect the total system cost of the energy system. Fourteen parameters have - by far - the strongest influence. Even more, the prices of hydrocarbons dominates the uncertainty. Indeed, it drives 64% of the total cost variation.
Then, we notice that the PCE method offers different advantages. While the total annual cost has a Gaussian distribution shape, the probability density function of the primary use of natural gas (NG) shows different system designs. For example, assuming the gas price in May 2020 ($\approx$13 $€_{2015}$/MWh), the future design is highly gas-dependent (92%) but presents a low probability of occurrence. Instead, taking uncertainty leads to more diversified solutions, which is more resilient to uncertainties.
In future work, we will apply the PCE method to different scenarios and perform robust optimisation on the design of energy system. In addition, the impact of uncertainty on other key performance indicators, such as global warming potential or investment strategies, will be analysed.

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