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A Novel Optimisation Framework to Support Increased Uptake of Low Carbon Industrial Energy Systems

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Combustion of fossil fuels in industrial energy systems (IES) is responsible for over 45 % of CO_2 emissions. Low Carbon IES will go a long way in achieving the climate goal of the Paris Agreement; yet, uptake of concepts to deliver low carbon IES is slow. Cost and emissions minimisation based optimisation frameworks applied to design and assess IES, though important, are not able to directly quantify the uptake of new technologies to deliver low carbon IES in a country or region. This work presents a novel MINLP framework capable of directly maximing the adoption of low carbon IES within a country and region whilst determining the optimal energy flows and associate costs. The method is applied to a case stufy of 6,181 energy systems in wastewater treatment plants (WWTP) in 27 EU countries to support increased adoption of technology switching (from combustion to electrochemistry), and fuel switching (from natural gas to biogas). Results show that without policy interventions uptake of these measures is only in 0.2 % of the plants located in Denmark, with policy intervention uptake increases to 60 % in more countries. The novel framework shows how the uptake of a new cleaner technology in a country or region can be accelerated.

1. Introduction

Achieving the climate goals of the Paris Agreement – to hold the increase in the global average temperature to well below 2 °C above pre-industrial levels while pursuing efforts to limit the temperature increase to 1.5 °C, and the EU plan for a climate-neutral economy by 2050 requires accelerated adoption of concepts to deliver low carbon energy systems in hard to abate sectors such as industry today. Example of concepts include minimising energy demand using Pinch Analysis and Total Site Analysis, maximising energy supply efficiency via waste heat recovery and Process Integration, fuel switching (for example to biogas, electricity, hydrogen), technology switching (from combustion to electrochemistry), and carbon capture utilitisation and storage (CCUS). Accelerared adoption is possible if these concepts are economically viable. The size of an industrial sector within a country or region can be leveraged together with policy interventions to accelerate uptake.

Previous research apply cost and/or emissions minimisation based optimisation frameworks to design, and retrofit clean energy systems (Klemeš et al., 2019). For example in Zhang et al. (2019), a multi-objective framework based on minimising total annual cost and life cycle greenhouse gas emissions is applied via an MILP model to CCUS supply chains,. A bi-objective model to allocate funds to innovation projects using the technology readiness level, system readiness levels, and return on investment is developed in Tan et al. (2019), and annualised cost reduction applied in the MILP framework developed in Oluleye et al. (2019). Optimization frameworks select objective functions in the design stage to find the optimal energy sources, prime movers, storage system, energy demand and system configuration (Gao et al., 2019). There is a lack of studies that directly address uptake of new technologies within a country or a region, whilst determining optimal design conditions within a plant. Of the 232 papers reviewed in Gao et al. (2019) none of them directly focus on increasing uptake of clean IES concepts. Shen et al. (2020) proposed a deterministic and robust optimization framework formulated as MINLP problems for energy systems optimization under uncertainty, their focus was reduction in energy cost within a plant. The framework in Hofmann et al. (2019) considers simultaneous operation and retrofit design characteristics in the identification of cost-efficient heat integration options for an IES. Ershadi and Karimipour (2018) present a multi-criteria modelling framework with an objective function defined by taking into account thermodynamic, economic, and environmental aspects in industrial Combined Cooling Heat and Power generation systems, and in Hasanbeigi et al. (2016) a steam system energy efficiency cost curve is proposed to quantify the energy saving potential and associated costs of implementing steam system optimization measures on coal-fired boilers in China's industrial sector. Again, the uptake of measure to support clean IES transition is not investigated directly. Other research focusing on optimisation techniques include the use of a material flow cost accounting concept to reduce costs in Ho et al. (2019); however, these techniques have not been modified to address uptake of concepts to support clean IES. There is a need to build on previous research and show how the uptake of a new technology which is cleaner and more efficient can increase by leveraging on the number of industrial sites within a country and a region defined as a market. This is particularly important to shorten the time between research and adoption of a technology, thereby seeing many more Process Integration concepts adopted worldwide and informing policy creation. This is also necessary as a high uptake of cleaner technologies would accelerate achieving climate targets within the industrial sector. A major barrier to effective policy interventions, and to global adoption of low carbon concepts in industry is the lack of systematic methods for quantifying and assessing the market uptake of these concepts. Accordingly, to our knowledge, there is no previous work focused on direcltly maximising uptake of a technology, whilst determining the optimal energy flows and cost. Therefore, the main goal of this paper is to systematically increase the uptake of new technologies and fuels by means of mathematical formulation of a MINLP optimization problem, considering its market share as an objective function. The novel framework is applied to assess fuel switching from natural gas to biogas, and technology switching from combustion to electrochemistry using Solid Oxide Fuel Cells (SOFC) in 6,181 WWTP in 27 EU countries. The method is this paper can also be applied to assess the impact of policy interventions and business models in increasing uptake of sustainable solutions in industry.

2. Methodology

A novel mixed integer non linear problem (MINLP) is defined to maximise the uptake of clean technologies in industrial energy systems within a country or region. The MINLP model also performs an economic assessment of the energy system taking into account the business as usual technology, determines the optimal energy flows, and the impact of various policy interventions on increasing the market uptake of a new cleaner technology. A broader analysis within a country or a region that builds on detailed optimization of a plant is relevant to accelerate uptake of clean industrial energy systems in order to satisfy the goals of the Paris Agreement, and EU emissions targets. The objective function maximises the market share (ꚍ) of a new technology (i) in a existing plant (j) within a country (k) (Eq(1)). The market share is a product of the market fraction for the plant (θ) and a binary variable (β) defined for when the total annualized cost of integrating the new technology is less than the total annualized cost (TAC) of the business as usual (BAU) technology (Eq(2) to Eq(5)). The market fraction of a plant takes into account the number of plants in a country (N_k^{plants}), the optimal number of units of the new technology required in each plant ($N_{i,j,k}^{units}$), and the size of the technology ($Size_{i,j,k}$) as shown in Eq(5). Whilst the technology size is an input, the number of units is determined optimally. The number of plants in a country is available in public databases.

$$Maximise \quad \sum_{j,k} \tau_{i,j,k} \tag{1}$$

$$\tau_{i,j,k} = \theta_{i,j,k} \times \beta_{i,j,k} \tag{2}$$

$$\beta_{i,j,k} - \Delta T_{i,j,k} \geq 0 \tag{3}$$

$$\Delta T_{i,j,k} = TAC_{i,j,k} - TAC_{BAU,j,k} \tag{4}$$

$$\theta_{i,j,k} = \frac{N_k^{plants} \times N_{i,j,k}^{units} \times Size_{i,j,k}}{\sum_{i,j,k}\left(N_k^{plants} \times N_{i,j,k}^{units} \times Size_{i,j,k}\right)} \tag{5}$$

The TAC is a sum of the technology capital cost (CC), operating cost (OC) and maintenance cost (MC). The CC is annualized using the annualisation factor (AF) in Eq(7), where DR is the discount rate, and n the lifetime of the new technology.

$$TAC_{i,j,k} = \left(CC_{i,j,k} \times AF\right) + OC_{i,j,k} + MC_{i,j,k} \tag{6}$$

$$AF = \frac{DR \times (1+DR)^n}{(1+DR)^n - 1} \tag{7}$$

$TAC_{BAU,j,k}$ would be dominated by the operating and maintenance cost since the capital has already been incurred in an existing energy system. A breakdown of the capital and operating costs is provided in Eq(8) and Eq(9). Where IC is the installed capital of technology (i), $f_{i,j,k}^{BOP}$ is a factor for the balance of plant (BOP), Q^{fuel} is the quantity of fuel consumed, W is the quantity of electricity flow, NGP and GEP are the natural gas prices and grid electricity prices.

$$CC_{i,j,k} = \left(IC_i \times f_{i,j,k}^{BOP}\right) \times Size_{i,j,k} \times N_{i,j,k}^{units} \tag{8}$$

$$OC_{i,j,k} = \left(Q_{i,j,k}^{fuel} \times NGP_{j,k}\right) + \left(W_{imported,j,k} \times GEP_{j,k}\right) - \left(W_{exported,j,k} \times GEP_{j,k}\right) \tag{9}$$

If the fuel is a clean energy vector generated on site for example biogas: the operating cost is defined based on the residual fuel and electricity required if energy from biogas is not enough (Eq(10)). The residual fuel demand is estimated using Eq(11) and the residual electricity demand using Eq(12). Eq(11) and Eq(12) take into account the efficiency of the business as usual system and the grid. . Where the demand for heat and electricity is represented as Q_{demand} and W_{demand}, heat and electricity produced from the new technology Q and W, and ɳ represents efficiency.

$$OC_{i,j,k} = \left(\Delta Q_{i,j,k}^{fuel} \times NGP_{j,k}\right) + \left(\Delta W_{i,j,k}^{grid} \times GEP_{j,k}\right) \tag{10}$$

$$\Delta Q_{i,j,k}^{fuel} = \left(Q_{demand,j,k} - Q_{i,j,k}\right)/\eta_{BAU} \tag{11}$$

$$\Delta W_{i,j,k}^{grid} = \left(W_{demand,j,k} - W_{i,j,k}\right)/\eta_{grid} \tag{12}$$

In most cases, new technologies with lower carbon emissions are more expensive than the BAU. The novel method in this paper, can be modified to quantify the impact of various schemes to increase the market uptake by adjusting the TAC in Eq(6). In this work we exploit the benefits of a more efficient clean technology in increasing it's market uptake. A more efficient technology's operating cost would be lower than the BAU, even though the capital cost is higher. Here we design a new policy intervention where the plant receives an incentive (I_k) for each unit of electricity produced if savings in operating costs for the lifetime of the technology is ploughed back to offset it's capital investment. The savings is discounted every year for the technology lifetime in Eq(13). Eq(14) shows how the income from the incentive is estimated taking into account the duration of the incentive, m, in years. Eq(15) is the adjusted TAC, where Z is the income from the incentive offered in each country (I_k). The model was solved in GAMS on an Intel(R) core(TM) i7-6700 CPU.

$$\Delta OC_{i,j,k} = \left(OC_{i,j,k} - OC_{BAU,j,k}\right) \times \left(\frac{1}{(1+DR)^1} + \frac{1}{(1+DR)^2} + \frac{1}{(1+DR)^3} + \cdots + \frac{1}{(1+DR)^n}\right) \times AF \tag{13}$$

$$Z_{i,j,k} = I_k \times W_{i,j,k} \times m \times AF \tag{14}$$

$$TAC_{i,j,k} = \left(CC_{i,j,k} \times AF\right) + OC_{i,j,k} + MC_{i,j,k} - \Delta OC_{i,j,k} - Z_{i,j,k} \tag{15}$$

3. Industrial Case Study

The case study is designed to support technology switching (from combustion to electrochemistry), and fuel switching (from natural gas to biogas) in the energy system of wastewater treatment plants (WWTP) in Europe. There are 6,181 WWTP's in the EU with suitability for anaerobic digestion to produce biogas (Waterbase, 2014), plant distribution by country is shown in Figure 1, and energy demand in Table 1. The new technology is the Solid Oxide Fuel Cell (SOFC) with economic inputs in Table 2, and the BAU system consists of a biogas boiler for heat provision, and importation of electricity from the grid. A natural gas boiler is available for back-up heating. The market conditions i.e. natural gas and electricity price for the twelve countries considered are obtained from Natural gas prices Eurostat (2017a), and electricity price Euostat (2017b). The methodology in section 2 is applied to support technology switching to SOFCs and fuel switching to biogas in EU WWTP's.

Table 1: Number of EU-wide plants, energy demand and biogas produced for all plants

Number of Plants in each category	Total biogas (GWh/y)	Total heat demand (GWh/y)	Total electricity demand (GWh/y)
6,181	9,995	9,673	23,036

Table 2: Economic inputs of the SOFC (Ammermann et al., 2015)

SOFC	Unit	Value
Stack lifetime	y	3-3-4-4
Module CAPEX	€/kW	15,700
Stack replacement	€/kW	1,223
Maintenance	€/kW-y	72
Gas clean-up CAPEX	€/kW	917
Gas clean-up OPEX	€/kW-y	76

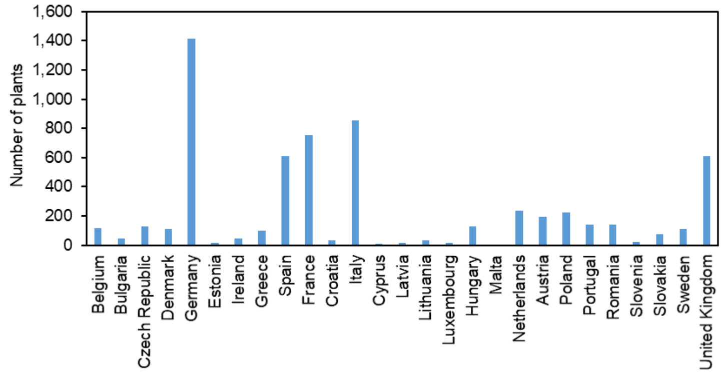


Figure 1: Plant distribution by country

4. Results and discussion of results

The optimal energy flows, total number of SOFC installed in all 6,181 plants are provided in Table 3. Heat and electricity produced from the SOFC satisfies about 23 % of the plants energy demand, the limiting factor is the biogas produced, which is 31 % of the demand for heat and electricity (Table 1). Figure 2 shows the TAC for a sample plant in all countries. The TAC for the SOFC system is higher than the BAU system, except in 9 plants located in Denmark. The optimal market share without the policy intervention described in section 2 is 0.002, this is too low to support the transition to low carbon energy systems in WWTP. Since satisfying the energy demand via the SOFC has a higher efficiency than the BAU system, it's operating cost is lower (Figure 3). Overall the market share increases with the incentive value, its duration and a reduction in the discount rate. With a high incentive value in Figure 4d, a market share of 0.4 is possible even with a high discount rate. When the lowest value of the incentive is offered (Figure 4a) the TAC of the SOFC is lower than the BAU system in plants located in Denmark and Italy. When 20 Eurocents/kWh is offered for 4 y with a 9 % discount rate the market share is 0.016, increasing to 0.1 for 7 yand 0.4 for 20 y. At 20 y incentive duration, the TAC of the SOFC becomes lower than the BAU in more countries such as Belgium, Bulgaria, Czech Republic, Denmark, Germany, Estonia, Ireland, Greece, Spain, Croatia, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Netherlands, Austria, Poland, Portugal, Romania, Slovakia, Sweden, and the UK. A new body of research in this remit could help promote accelerated adoption of strategies from Process Integration. The presented results are sensitive to the assumptions on cost metrics, such as energy prices and capital costs, and the data for the WWTP plants. It is acknowledged that variations in these assumptions can result in different outcomes; however, a detailed analysis of these impacts is outside the current scope. The methology can be applied to different new technologies and plants in another region.

Table 3: Total energy flow, number of technologies units in all 6,181 plants

W_{SOFC} (GWh/y)	Q_{SOFC}(GWh/y)	N_{units}	$Size_{SOFC}$ (kW)	ΔW (GWh/y)	ΔQ (GWh/y)
5062	2,572	13,282	58	17,974	7,100

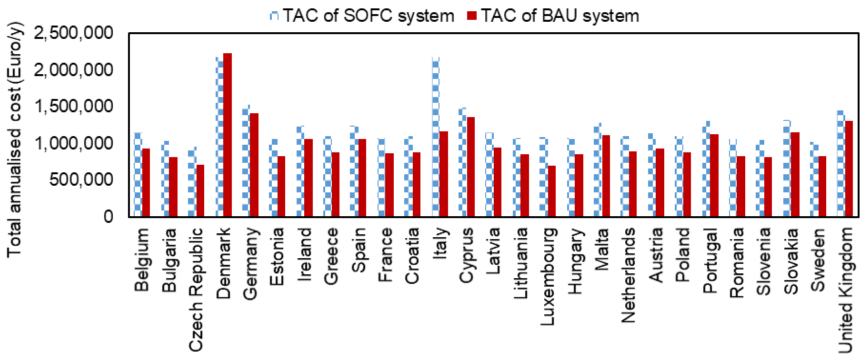


Figure 2: Total annualised cost for a sample plant in all countries

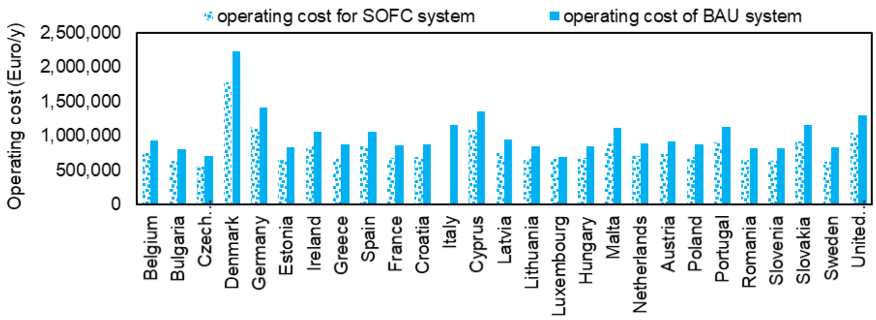
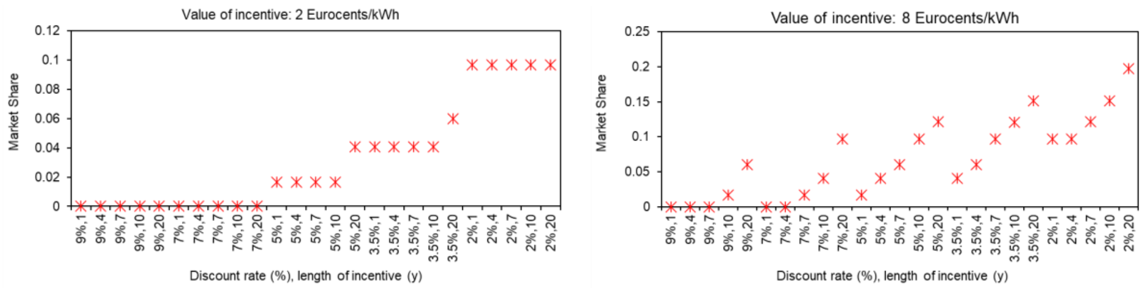
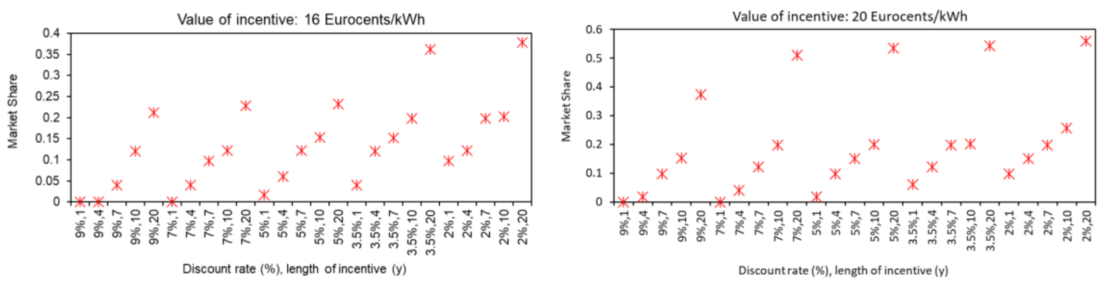


Figure 3: Operating cost for a sample plant in all countries



(a) *(b)*



(c) *(d)*

Figure 4: Model output: EU-wide market share under different conditions: (a) 2 Eurocents/kWh incentive, (b) 8 Eurocents/kWh incentive, (c) 16 Eurocents/kWh incentive, (d) 20 Eurocents/kWh incentive.

5. Conclusions

Switching to more efficient cleaner technologies and fuels support the transition to low carbon industrial energy systems. However, the uptatke of these technologies and fuels are low due to their high costs. The economic viability of technology and fuel switching can be increased if the market share increases, and in most cases policy interventions may be required. This work presented a novel MINLP framework which directly address uptake of technologies within a country and region by maximising its market share whilst determining its optimal energy flows and costs within a plant. The novel method is able to quantify the impact of policy inerventions. The methodology is applied to support technology and fuel switching in wastewater industrial sector, specifically using biogas fuelled SOFC in 6,181 WWTP in the EU. Results shows that heat and electricity produced can satisfy 23 % of energy demand, and the market share without policy interventions is 0.2 % – too low to support transition to clean industrial energy system. At 0.2 % market share, all 6,181 plants were at minimum costs; hence minimising cost even though relevant within a plant does not provide information on the market uptake of new technologies. A higher market share of over 50 % can be achieved today if an incentive is provided per unit of electricity produced from a more efficient technology. The quantified market share is relevant for assessing technology cost reduction based on increased demand and associated manufacturing volume, and also relevant for policy creation to support transitioning to clean industry. Future work would account for uncertainty in the modelling assumptions, and apply the methods to other technologies and industrial sectors.

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