Optimal Technology Selection and Operation of Bio-methane CHP Units for Commercial Buildings

Dagoberto Cedillos

Salvador Acha, PhD
Member ASHRAE

Nilay Shah, PhD
IChemE Member

ABSTRACT

This paper explores the optimal implementation of bio-methane fuelled combined heat and power (CHP) systems to satisfy heat and electricity demands of commercial buildings; with the overarching goal of making cost-effective investments and decarbonizing building operations. The research work consisted in the development of a CHP technology selection and operation (TSO) optimization model. Its results can be utilized to develop a strategy for investment in bio-methane CHP projects for a portfolio of buildings. The TSO model enables a new approach for the selection and operation of CHP units that encompasses whole life costing, carbon emissions as well as real-time energy prices and demands, providing a more comprehensive result than current methods. Utilizing historic metered energy demands, projected energy prices and a portfolio of available CHP technologies, the mathematical model simultaneously solves for an optimal CHP unit selection and operational strategy for a determined building based on a preferred objective: minimizing cost, minimizing GHG emissions, or a mix of both. Results of this model prove that attractive cost and emissions savings are possible through the optimal selection and operation of CHP technologies fuelled by bio-methane.

INTRODUCTION

Energy consumption from commercial buildings is a major contributor of greenhouse gas emissions. Supermarkets alone consume 3% of the country's electricity generation and account for 1% of the country's carbon emissions in the United Kingdom (Tassou et al. 2011). Therefore, decarbonization of the operation of commercial buildings can play an important role in climate change mitigation. This can be accomplished by reducing demands and/or by satisfying these in alternative form. On-site renewable energy systems can provide low-carbon energy to a building, thus avoiding the need to burn fossil fuels or the import of carbon intensive electricity from the grid to satisfy energy demands. Several types of renewable energy systems exist, such as: geothermal, hydro-generation, bioenergy CHP, wind turbines, solar PV, and hybrid PV. However, in considering suitability, reliability, dispatchability, and maturity these can all perform differently. Bioenergy fuelled CHPs are currently suggested as the best alternative to decarbonize the operations of a building upon these elements (Andrianopoulos, Acha, and Shah 2015). The work presented in this paper focuses on the implementation of bio-methane fuelled CHP engines for the provision of heat and electricity in commercial buildings.

On-site energy systems have gained popularity in recent years; energy efficiency, rising energy costs and sustainability (when using renewable fuels) have been motives increasing the attractiveness of their implementation, particularly in buildings. When considering their implementation, decision makers face the task of selecting among a set of options. Different variables such as size, price and performance come into play that can make the search for the best

Dagoberto Cedillos is a postgraduate researcher in the Department of Chemical Engineering, Imperial College, London, UK. **Salvador Acha** is a research fellow in the Department of Chemial Engineering, Imperial College, London, UK. **Nilay Shah** is Director of the Centre for Process Systems Engineering, Imperial College, London, UK.

option a challenging task.

Simulations (Ghadimi, Kara, and Kornfeld 2014; Cardona and Piacentino 2007; Cho et al. 2009; Hueffed and Mago 2010) and mixed-integer mathematical programming (MIP) optimizations (Wang et al. 2015; Fuentes-Cortés et al. 2015; Ren, Gao, and Ruan 2008; Zhang et al. 2015) have assisted decision makers in such task. Diverse features and levels of complexity have been explored; the simplest model approaches consider constant energy demands and fixed energy costs while complex approaches consider fluctuating energy prices, variable energy demands, part-load efficiency integration, a carbon price and the possibility of selling electricity exported to the grid. This paper proposes the use of a comprehensive linear MIP optimization model that can optimize the selection and operation for a given period with the objectives of reducing cost and/or carbon emissions. It considers all the elements of complexity aforementioned and introduces the novel features of fuel flexibility and projections for energy costs, carbon price and grid carbon intensity. The first feature enables the flexibility of selecting from different fuels, renewable fuel (bio-methane for this case) inclusive. Projections, the second feature, provide a higher level of certainty to decision makers when performing the economic analysis of the projects. Additionally, available models define an optimal theoretical unit size while this model selects from a set of available technologies that use technical and economic parameters provided by manufacturers. Therefore, this model can provide the optimal selection from the actual portfolio of options available to the decision maker and not simply a theoretical indicator.

This model has been used for the optimal selection of bio-methane fuelled CHP units for the decarbonization of supermarket buildings. It has been implemented in a sample of stores belonging to a food retailer with more than 1300 stores across the UK. This paper showcases the full extent of capabilities provided by the model through an in-depth case study of a single store.

This paper is structured in four sections. The current section provides an introduction that includes the background, purpose and structure of this paper. The next section provides the methodology which consists of the problem statement, model structure and mathematical formulation of the model. Another section provides sample results and discussion of the model and a case study and the final section provides concluding remarks.

METHODOLOGY

This paper describes a method for the optimal selection and operation of CHP technologies in commercial buildings. The method consists of utilizing a mathematical optimization model that receives several input parameters and provides the optimal result after being solved. Several key indicators are provided with the set of results that enable the economic analysis of a project, such as: costs, resource use, carbon emissions and yearly cash flows. Decision makers can then utilize these results to formulate a decision for the implementation of a project. This section provides the problem statement, structure and mathematical formulation of the model.

Problem Statement

Given: (a) building parameters – heat and electricity demands (i.e. historically metered, assigned per time period), (b) a portfolio comprising different energy technologies available featuring capacities (i.e. electrical and thermal), costs (i.e. capital and operational) and efficiencies (i.e. electrical and thermal; inclusive of part-load efficiencies), and (c) resource parameters (per time interval and including projections for future years)- price of purchased electricity from the grid, price of gas (i.e. fixed per year) , price of electricity sold to the grid (i.e. per time interval, including projections for future years), carbon factors of electricity and fuel (i.e. fixed for fuels, including projections for future years), and carbon tax or cost of carbon allowance as well as any other regulatory surcharges (including projections for future years). **Determine:** the technology selection (if any, based on the objective function and problem formulation) and technology operation (for each interval of the defined time period). **Subject to:** satisfying electricity and heat demands of the building for each time interval considered as well as technical and financial constraints. **In order to:** minimize cost, minimize GHG emissions or minimize a combined function of the two.

Model Structure

The TSO model makes use of the Resource Technology Networks (RTN) methodology (Pantelides 1994) to represent energy resources, conversion technologies and energy transfer networks. A diagram representing the RTN employed for this model is illustrated in **Figure 1**. Electricity demand can be satisfied by on-site generation, the power grid (i.e. electricity import) or a mix of the two. Heat demand can be satisfied through on-site generation (e.g. boiler or CHP). The model can also decide to sell electricity to the grid (i.e. electricity export). Excess heat is simply disposed by releasing it to the environment.

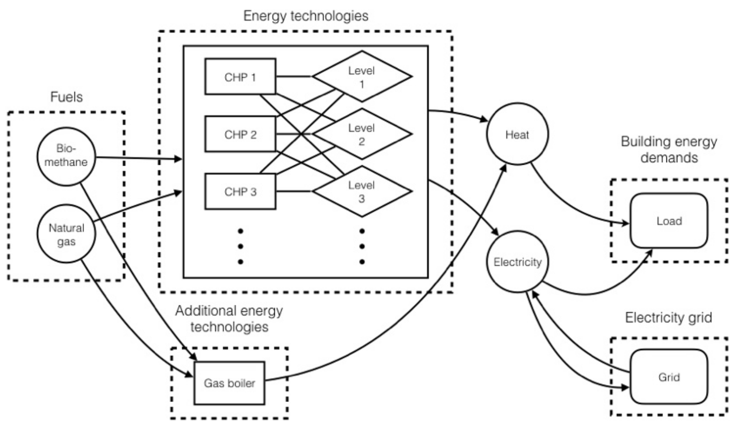

Figure 1. Representation of the resource technology network implemented for the TSO model with circles representing energy resources, rectangles representing energy technologies, rhombi representing operational levels, and rounded rectangles representing end points.

Technologies and levels. The current version of the model database used includes 23 CHP technologies (gas-engine) in its portfolio with capacities ranging from 90 kW to 2 MW. The model can also consider existing gas boilers that may already be installed. Energy technologies are given as a set of technologies *j* that can operate at different levels *l*. The CHP operational levels trialed in this study are: 50%, 75% and 100%. Operational levels can be expanded as desired but this will incur an increase in computational time as the quantity of possible result combinations increases. CHP technologies are generally limited to operate above 50% of their rated capacity. A precise part-load efficiency as indicated by the unit manufacturer is assigned for each level and for each of the units available in the portfolio.

Time. Time is represented in three levels: half-hour intervals, days and years. The TSO model is currently configured for the UK and therefore days consist of half-hour intervals (following UK electricity market structure) and years consist of days. Groups of days are characterized into 'types' of days in order to simplify the solution. The optimization can also consider periods consisting of one or several years, the current configuration is set to optimize for the initial five years of operation. The time level structure allows energy prices and demands to be specific for each time interval of each day type of each year.

Resources. Energy resources are the inputs and outputs of the energy conversion technologies. Resource prices can be applied for each specific time interval if known or generalized into a higher time level. Electricity and fuel prices applied for this model were obtained from Imperial College's real-time energy pricing project (Acha and Bustos-turu 2015). Electricity has a specific price per half-hour interval for both import and export, and is provided characterized into four types of days: summer (March to October) weekday, summer weekend, winter (November to February) weekday and winter weekend. Fuels are considered to have a fixed price per year; the energy pricing project also provides projections on the future prices of these energy resources.

Carbon. Fuels and electricity imports are also assigned a carbon factor which allows for the accounting of the resultant carbon emissions of burning these fuels as well as embodied emissions from electricity imported from the grid.

Mathematical Formulation

A mixed-integer linear programming (MILP) modelling strategy was implemented to represent the problem, thus allowing the use of continuous, discrete and binary variables for the representation of the system. Binary variables, like in (Liu, Pistikopoulos, and Li 2010), were employed in the model to represent the selection (1 value), or not (0 value), of technologies and operational levels.

Energy Balance. Equation (1) states that electricity demand, e^d, at each point in time (t, d, y) has to be equal to import, e^i, minus export, e^e, plus production from a technology (if selected), e^t. Heat demand , h^d, also has to be satisfied by the production of heat through the selected technology, h^t, and the production of heat from the boiler, h^b, as shown in Equation (2). Heat production is allowed to exceed the demand.

$$e^d{}_{tdy} = e^i{}_{tdy} - e^e{}_{tdy} + e^t{}_{tdy} \quad (1)$$

$$h^d{}_{tdy} \leq h^t{}_{tdy} + h^b{}_{tdy} \quad (2)$$

Electricity and heat production from the technologies are the result of the multiplication of variable β and the parameters power output, O^p, or heat output, O^h, respectively, shown in Equations (3) and (4). Variable β represents the state at which both a technology has been selected and a level for that technology is active; it will only have a value of 1 for a single combination of technology *j* and level *l* in each point in time (t, d, y).

$$e^t{}_{tdy} = \sum_j \sum_l \beta_{jltdy} \, O^p{}_{jl} \quad (3)$$

$$h^t{}_{tdy} = \sum_j \sum_l \beta_{jltdy} \, O^h{}_{jl} \quad (4)$$

Technology and active level constraints. A technology constraint was used to restrict the selection technologies, τ, to a maximum of 1 for this study as shown in Equation (5) . It is unfeasible to have more than one active level of operation at a specific point in time. Therefore, a constraint is applied for this restriction as shown in Equation (6).

$$\sum_j \tau_j \leq 1 \quad (5)$$

$$\sum_l \alpha_{ltdy} \leq 1 \quad (6)$$

Nonlinearity circumvention. The status represented by variable β at which one technology is selected and an operational level is active at a certain point in time could possibly be obtained by the product of the two binary variables τ and α. However, this results in non-linearity, unsuitable for MILP. A common MILP technique allows maintaining linearity while providing the intended output for variable β and is achieved through a set of equations (7 – 9):

$$\beta_{jltdy} \geq \tau_j + \alpha_{ltdy} - 1 \quad (7)$$

$$\beta_{jltdy} \leq \tau_j \quad (8)$$

$$\beta_{jltdy} \leq \alpha_{ltdy} \quad (9)$$

Resource use. The rate of gas use at a certain point in time (*t, d, y*) is the sum of gas use from the selected technology and the gas boiler. The gas used by the technology is calculated through the division of electricity production at that point in time by the efficiency of that technology *j* and operational level *l*. The gas used by the boiler is simply the division of the heat production from the boiler by the efficiency of the same. The gas use can consist of a mix of bio-methane and natural gas.

$$G_{tdy} = \sum_{j}\sum_{l}\left(\frac{\beta_{jltdy}\, O^{p}{}_{jl}}{\eta^{t}_{(e)jl}}\right) + \left(\frac{h^{b}{}_{tdy}}{\eta^{b}}\right) \tag{10}$$

$$G_{tdy} = BM_{tdy} + NG_{tdy} \tag{11}$$

Emissions. The carbon factors of natural gas, bio-methane and electricity are used in order to calculate the carbon emissions for each time interval. Fuel and electricity consumption rates (kW) are multiplied by the duration of the time interval, σ, in order to represent the total quantity of resource used (kWh). Carbon emissions, GHG (tCO_2e), can then be obtained by the multiplication of each energy resource use with its corresponding carbon factor, F(tCO_2e/kWh).

$$GHG_{tdy} = \left(NG_{tdy}\, F^{NG} + BM_{tdy}\, F^{BM} + e^{i}{}_{tdy}\, F^{E}{}_{y}\right)\sigma \tag{12}$$

Costs. The TSO model considers capital, carbon, operating and maintenance costs when performing the optimization. Costs are individually brought by summation to the highest time level (years) from the level at which they initially exist. Then, using a present value multiplier, PVM, they are again individually summated to provide the cost for the entire period of analysis. Finally, they are added together to provide the grand total cost for the objective function. A multiplier, dt, is included as shown in Equations (15 - 16) to account for the number of days each day-type occurs in a year. A duration multiplier, σ, is used to transform rates of use into total resource used each time interval.

$$C^{c} = \sum_{y}\sum_{j} AC^{c}{}_{j}\, \tau_{j}\, PVM_{y} \tag{13}$$

$$C^{m} = \sum_{y}\sum_{j} AC^{m}{}_{j}\, \tau_{j}\, PVM_{y} \tag{14}$$

$$C^{o} = \sum_{y}\sum_{d}\sum_{t}\Big(NG_{tdy}\, p^{NG}{}_{y} + BM_{tdy}\, p^{BM}{}_{y} + e^{i}{}_{tdy}\, p^{e,import}{}_{tdy} - e^{e}{}_{tdy}\, p^{e,export}{}_{tdy}\Big)\, dt_{d}\, PVM_{y}\, \sigma \tag{15}$$

$$C^{GHG} = \sum_{y}\sum_{d}\sum_{t} GHG_{tdy}\, dt_{d}\, PVM_{y}\, p^{c}{}_{y} \tag{16}$$

$$C^{t} = C^{c} + C^{m} + C^{o} + C^{GHG} \tag{17}$$

Objective Functions. Three objective functions can be solved by the model. For all three, the objective is to minimize the value of the function. f_1 is equivalent to the total cost for the period, f_2 is equivalent to the total carbon emissions of the period and f_3 is a weighed sum of total cost and total emissions. ω_1 and ω_2 are user defined parameters that give weight to total cost and total emissions respectively.

$$f_1 = C^{t} = C^{c} + C^{m} + C^{o} + C^{GHG} \tag{18}$$

$$f_2 = GHG^{total} = \sum_{y}\sum_{d}\sum_{t} GHG_{tdy}\, dt_{d} \tag{19}$$

$$f_3 = \omega_1\, C^{t} + \omega_2\, GHG^{total} \tag{20}$$

RESULTS

This section provides in-depth results for a single building to demonstrate the capabilities of the model. The characteristics for the building studied were the following: peak demand – 524 kW (electricity) and 314 kW [1.071 MBTU/hr] (heat), average demand – 419 kW (electricity) and 181 kW [0.618 MBTU/hr] (heat). Table 1 presents the key results of the optimizations for the store. Both optimizations provide a cost reduction for the period of analysis as well as significant emission reductions which translate to an attractive investment.

Table 1. Key Indicators for Case Study Optimizations

Objective (unit size)	Cost Reduction	GHG Reduction	Capital Investment	NPV Benefit (lifetime)	Yearly emissions reduction (tCO2eq.)	Abatement Cost (£/tCO2 eq.)	ROI	Payback Time (yrs.)
Cost (400 kw)	-14.6%	-87.9%	-£233,333	£589,430	1,732	-31.23	281%	3
Emissions (530 kW)	-10.1%	-99.8%	-£316,940	£426,848	1,967	-19.13	153%	5

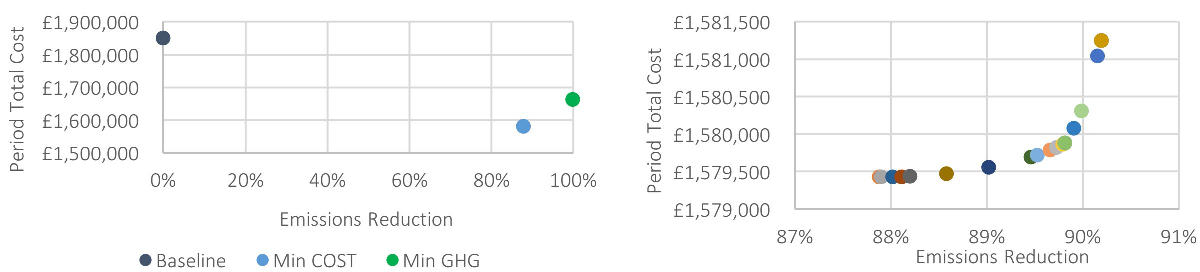

Figure 2. (left) Cost and emission reduction indicators for minimum cost and emissions optimizations as well as baseline indicator, (right) Pareto-optimal set of results for sequence of multi-objective optimizations.

Figure 2 provides a visualization of the cost and emission reductions obtained from each optimization against the base case. It can be observed that for higher emission reductions, a higher capacity unit able to satisfy energy demands also during peak periods is required, elevating the cost. On the right side of the figure, results are presented for the multi-objective optimization. A sequence of optimizations shifting weight from one objective to the other provide the Pareto-optimal set that demonstrates the trade-off between objectives, how cost rises while achieving higher emission reductions. The optimal operating schedule defined by the model is provided below in **Figure 3**. This output is generated for each year of the period being analyzed. It can be observed that the unit might be operated differently depending on day-time, season and weekday.

Figure 3. Example operational strategy for the first year of the minimum cost optimization.

The model was implemented on a sample of 35 out of 1500 stores. 31 out of the 35 minimum cost optimizations resulted in emission reductions above 70%, while 22 of them provided a return on investment (ROI) higher than 100%.

CONCLUSION

It was demonstrated that the TSO model can provide results which guide decision makers in the implementation of decentralized energy systems. A case study of a commercial building in the UK showcased the functionality of the model. Results were obtained and summarized as key indicators such as cost, emission reductions, investment returns among others. The TSO model proves to be a suitable and comprehensive tool for guiding decision makers. It was identified that the majority of buildings assessed could reduce their operational emissions more than 70% while providing returns on investment above 100% by installing low-carbon co-generation units. Results of this model prove that attractive cost and emissions savings are possible through the optimal selection and operation of CHP technologies fuelled by bio-methane.

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NOMENCLATURE

Indices and sets

j = energy technologies
l = operational levels
t = intervals
d = days
y = years

Parameters

$e^{d}{}_{tdy}$ = electricity demand at time interval t of day d and year y (kW)
$h^{d}{}_{tdy}$ = heat demand at time interval t of day d and year y (kW)
$O^{p}{}_{jl}$ = power output of technology j at operating level l (kW)
$O^{h}{}_{jl}$ = heat output of technology j at operating level l (kW)
$\eta^{t}_{(e)}{}_{jl}$ = electrical efficiency of technology j at operating level l
η^{b} = thermal efficiency of the gas boiler
η^{g} = electrical efficiency of the generator
σ = time duration of intervals (hr)
dt_{d} = number of days of type d in a year
F^{NG} = carbon factor of natural gas (tCO_2e/kWh)
F^{BM} = carbon factor of bio-methane (tCO_2e/kWh)
$F^{E}{}_{y}$ = carbon factor of electricity (tCO_2e/kWh) at year
$AC^{c}{}_{j}$ = annualized capital cost of technology j
$AC^{m}{}_{j}$ = annual maintenance cost of technology j
$p^{NG}{}_{y}$ = price of natural gas at year y
$p^{BM}{}_{y}$ = price of biomethane at year y
$p^{e,import}{}_{tdy}$ = price of electricity import at time interval t of day d and year y
$p^{e,export}{}_{tdy}$ = price of electricity export at time interval t of day d and year y
$p^{c}{}_{y}$ = Carbon price at year y
PVM_{y} = Present value multiplier for year y
ω_{1} = Weight coefficient for cost
ω_{2} = Weight coefficient for carbon emissions

Binary Variables

τ_{j} = Defines the selection of technology j
α_{ltdy} = Defines the active status of operational level l at time interval t of day d and year y
β_{jltdy} = Defines the status at which both a technology j has been selected and operational level l is active at time interval t of day d and year y

Positive Variables

$e^{i}{}_{tdy}$ = Electricity import at time interval t of day d and year y (kW)

$e^{e}{}_{tdy}$ = Electricity export at time interval t of day d and year y (kW)

$e^{t}{}_{tdy}$ = Electricity generated by the selected technologie(s) at time interval t of day d and year y (kW)

$h^{t}{}_{tdy}$ = Heat generated by the selected technology(s) at time interval t of day d and year y (kW)

$h^{b}{}_{tdy}$ = Heat generated by the gas boiler at time interval t of day d and year y (kW)

G_{tdy} = Rate of gas use at time interval t of day d and year y (kW)

BM_{tdy} = Rate of bio-methane use at time interval t of day d and year y (kW)

NG_{tdy} = Rate of natural gas use at time interval t of day d and year y (kW)

Free variables

GHG_{tdy} = Greenhouse gas emissions for time interval t of day d and year y (tCO2e)

C^{c} = Total capital cost for the period (£)

C^{m} = Total maintenance cost for the period (£)

C^{o} = Total operating cost for the period (£)

C^{GHG} = Total cost incurred from carbon emissions for the period (£)

C^{t} = Grand total cost for the period (£)

GHG^{total}= Total GHG emissions for period (tCO2e)

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