

Measuring incineration plants' performance using combined data envelopment analysis, goal programming and mixed integer linear programming

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Abstract Incineration plants produce heat and power from waste, reduce waste disposal to landfills, and discharge harmful emissions and bottom ash. The objective of the incineration plant is to maximize desirable outputs (heat and power) and minimize undesirable outputs (emissions and bottom ash). Therefore, studying the overall impact of incineration plants in a region so as to maximize the benefits and minimize the environmental impact is significant. Majority of prior works focus on plant specific decision making issues including performance analysis. This study proposes a hybrid data envelopment analysis (DEA), goal programming (GP) and mixed integer linear programming (MILP) model to assess the performance of incineration plants, in a specific region, to enhance overall power production, consumption of waste and reduction of emissions. This model not only helps the plant operators to evaluate the effectiveness of incineration but also facilitates the policy makers to plan for overall waste management of the region through decision-making on adding and closing plants on the basis of their efficiency. Majority of prior studies on incineration plants emphasize on how to improve their performance on heat and power production and neglect the waste management aspects. Additionally, optimizing benefits and minimizing negative outputs through fixing targets in order to make decision on shutting down the suboptimal plants has not been modeled in prior research. This research combines both the aspects and addresses the overall performance enhancement of incineration plants within a region from both policy makers and plant operators' perspectives. The proposed combined DEA, GP and MILP model enables to optimize incineration plants performance within a region by deriving efficiency of each plant and identifying plants to close down on the basis of their performance. The

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proposed model has been applied to a group of 22 incineration plants in the UK using secondary data in order to demonstrate the effectiveness of the model.

Keywords Incineration plants · DEA · Goal programming · MILP · Waste to energy

1 Introduction

Energy recovery from waste provide huge scope energy production as well as waste consumption. Accordingly, this has been considered as one of the sustainability measures of urban development. Although there is huge potential for producing energy from Municipal Solid Waste (MSW), the UK has achieved only 18% incineration of MSW (Nixon et al. 2013b) till date. A recent study reveals that the UK needs 170 incineration plants in order to achieve average of EU27 targets of percentage landfill reduction. Currently, the UK has only 32 operating incinerators. Many of them are not as efficient as it should be (Nixon et al. 2013a). A total of 170 million tonnes of waste is produced from households and businesses in England and Wales each year (Sambrook n.d.). There are multiple ways of handling and treating municipal waste. These are: (a) land filling, (b) mass burn with energy/heat recovery, (c) waste recycling and finally (d) waste composting (Daskalopoulos et al. 1998). This waste reduction in the UK over the past years is partly ought to Directive 1999/31/EC which imposed regulations and setting targets regarding biodegradable municipal waste (Environmental Agency annual report and accounts 2013–2014). An alternative way of reducing waste is by incinerating it. With municipal waste incineration, there are benefits (heat and power generation and waste consumption) but also undesirable excipients (harmful gas emissions, bottom ash etc.). However from bottom ash, ferrous and non-ferrous products can be extracted, and the residue could be recycled to cement plant. Concentrating mostly on the hazardous gas emissions from municipal waste incineration, several studies are presented that provide information regarding concentrations of gas emissions. Municipal solid waste incineration however has been reported that can help in greenhouse gas (GHG) emissions reduction, under specific conditions (Papageorgiou et al. 2009). Except for the contribution in GHG reduction, during incineration procedure for heat and power/generation, it has been reported that polychlorinated biphenyls (PCB) and polycyclic aromatic hydrocarbons (PAH) are emitted (Dyke et al. 2003). Life cycle analysis (LCA) is also another tool of assessing environmental impact of wastewater (Gallego et al. 2008) and MSW facilities (Cherubini et al. 2009). Energy recovery from municipal waste through incineration is being used, besides the UK, in EU countries (Pirota et al. 2013) and non-EU countries as well (Tsai and Kuo 2010).

The performance of incineration plants depends on waste quality and quantity, which keeps varying over the time period in a specific location due to variability in waste generation and seasonality. Additionally, waste to energy conversion technology and maintenance policies of operating plants have considerable role to achieve optimum performance of incineration plants. Therefore, it is desired that constant monitoring of incineration plants' performance within a specific region is undertaken in order to make decision on optimal performance of incineration plants by shutting down of a few underperforming plants to achieve overall goal of energy production, waste consumption, and emission reduction within a region. This research addresses this issue through development of an innovative model that enables measuring performance of group of incineration plants' within a region to optimize the outputs in line with the a few targets/goals (e.g. waste consumption, heat and energy production, and

emission reduction). Additionally, the model facilitates making decision on operating and closing down plants in line with their performances.

Prior research on incineration covers issues related to technical, political, social and environmental, and public health. Studies on performance measurement of incineration plants consider incineration as only heat and power generation. Social and environmental aspects of incineration are somewhat ignored. It's worth considering both desirable and undesirable outputs for measuring incineration plants' performance so as to maximize desirable output and minimize undesirable output. Overall performance depends on not only higher heat and power production but also minimum environmental and social impacts. Prior studies on performance analysis of incineration plants using DEA emphasize on improving less performing units. The study by Chen et al. (2010) propose a DEA-based model for incineration plants' performance measurement using waste consumption and energy production as outputs, and come out with suggestions on improving inefficient units' performance. Marques and Simões (2009) compare efficiency of public and private solid waste management services and find no difference. They consider waste amount and cost as criteria for the analysis. Chen and Chen (2012) also consider cost and waste amount as criteria for analysis and reveal that composting and incineration contributes positively to achieve efficiency. Chen et al. (2012) use network DEA to reveal that emission reduction and better resource allocation enhance overall performance of incineration. Benito-Lopez et al. (2011) finds that strong regulatory measures enhance efficiency of incineration. Chang and Yang (2011) derives that build operate transfer contract is more effective to implement incineration projects than any other contracts. Chen et al. (2014) reveals that effort in cost reduction, capacity utilization, ownership and most appropriate location are the critical success factors for enhancing incineration plants' performance. Although the above studies are significant and address specific issue related to incineration plants' performance, these fail to provide an integrated model that analyses performance of both group of incineration plants and individual incineration plant so as to achieve the targets/goals of waste management (e.g. waste consumption, heat and power production, emission and waste reduction) of a specific region. Additionally, in order to achieve the waste management targets the policymakers need to undertake various decisions including shutting down the underperforming plants. Therefore, performance measurement model must have desired capability to facilitate decision-makers with information. The current knowledge on performance measurement of incineration plants is limited to suggesting improvement measures on achieving various goals of incineration using DEA and GP. However, making decision on which plant to keep out of operations due to lower efficiency has not been researched in an integrated way. This is important from policy makers' perspectives so as to keep the region cleaner and enhance overall productivity as the underperforming units could be appropriately maintained during their out of operations period and brought back to operations with full efficiency. This research bridges this knowledge gaps. The objective of this study is to evaluate incineration plants' performance in a region with the consideration of both desirable and undesirable input and outputs, setting a few desired goals and selecting and closing down non-performing incineration plants objectively and an integrated way. This study uses data envelopment analysis (DEA) that is capable of benchmarking decision making units (DMUs) using input and output criteria. The DEA model combines with the Goal Programming (GP) to set targets for DMUs' performance. The combined DEA and GP model integrates with mixed integer linear programming (MILP) to facilitate decision-making on shutting down of the suboptimal plants in order to optimize the overall performance of incineration plants within a region.

Section 2 covers the literature review and identifies knowledge gaps. Section 3 elaborates the research methodology that has been undertaken to develop the proposed performance

measurement model. Section 4 demonstrates the application of the proposed performance measurement model. The theoretical and managerial implications of the proposed model have been discussed in Sects. 5 and 6 concludes the paper.

2 Literature review

Research on incineration addresses various issues such as how to improve energy recovery performance and control pollution (Pai et al. 2008), how to select most appropriate location for incineration plants (Alçada-Almeida et al. 2009; Eiselt and Marianov 2015) and derive compensation package for effected people (Chang et al. 2002), and what extent the recycling volume would change following the introduction of an incineration tax (Sahlin et al. 2007). These facilitate analysing feasibility of incineration plants. Due to the variability of quality and quantity of waste the output of incineration plants (energy and heat, quantities of ferrous and non-ferrous metals and emissions) vary. Also, based on the main ingredients of the waste incinerated, the energy conversion technology is selected (Di Gregorio and Zaccariello 2012). Additionally, quality of waste governs the plant maintenance (predictive, preventive and shut down) requirements. The following paragraphs demonstrate what has been contributed by prior researches on incineration plant performance measurement and the knowledge gaps that need still addressing.

Data envelopment analysis (DEA) is one of the most widely known techniques for measuring units' performance based on a set of inputs that are consumed in order to produce outputs. In their work, Chen and Chen (2012) propose a DEA model to assess the efficiency of Municipal Solid Waste (MSW) incineration services. Application of DEA technique has been demonstrated in 29 MSW incineration plants in Portugal (Simões et al. 2010; Marques and Simões 2009). The environmental performance of large MSW incineration plants has been proposed by Chen et al. (2010). Using power capacity, operation cost, operation time and power consumption as inputs and a plethora of undesirable outputs—such as hazardous emissions, municipal waste suspended, bottom ash, and opacity, environmental efficiency of MSW incineration plants was derived.

Besides assessing MSW incineration plants, DEA has been applied to measure the performance of household refuse collection systems and refuse collection services (Benito-Lopez et al. 2011). Super efficiency and cross efficiency DEA models has also been applied for assessing environmental performance of MSW treatment facilities (Sarkis and Weinrach 2001). The efficiency of waste management systems (generation, sorting of recyclables and collection) has been also examined with a DEA/Analytic Hierarchy Process (AHP) application (Chen 2010). The efficiency of each has been extracted using a conventional input oriented DEA model while weighting factors for each waste management system have been extracted from a panel of experts using the AHP. An aggregated efficiency index is constructed from the two methodologies. In a similar context, managerial preferences are tackled with ANP providing input to DEA for the selection of the best location of solid waste facilities in Iran (Khadivi and Ghomi 2012). The productivity of waste management in Taiwan has been also examined through a non-radial network DEA approach considering different stages and layers (Huang et al. 2014). The packaging waste management system has been examined with Benefit of Doubt (BoD), a DEA like methodology in Belgium; the cost efficiency of 35 Belgian municipal waste joint ventures in 2010 is assessed (De Jaeger and Rogge 2014). Quality of 293 Belgian municipality solid waste collection and processing facilities has been examined with a shared DEA model; the waste cost is treated as a shared input among

treatment efforts of multiple municipal solid waste fractions (Rogge and De Jaeger 2012, 2013). The water treatment is closely related with waste management while reuse of wastewater is achieved through plants. The efficiency of 338 plants has been investigated based on cost factors (inputs) and reused water quality (output) in Valencia, Spain (Hernández-Sancho and Sala-Garrido 2009).

In their work Costi et al. (2004) proposed a Mixed Integer Non-Linear Programming (MINLP) model for the selection of plant waste treatment type and its capacity. A mixed integer linear programming (MILP) model that examines cost minimization has been proposed for landfill location (Fiorucci et al. 2003). Similar mathematical models have been used as decision support system (DSS) for selecting optimal waste treatment facility (Fiorucci et al. 2003; Chang and Chang 1998). Models for treatment type, flows and technology have been proposed using multi-objective programming analysis (Galante et al. 2010; Alumur and Kara 2007). Applications of Goal Programming (GP) in solid waste management (SWM) have been also suggested in the relevant literature for assessing the environmental impact while minimizing operational costs (Galante et al. 2010). The transportation of hazardous waste and location of disposal and recycling centers is important as well to environment and to total population. Samanlioglu (2013) proposed a GP formulation for location-routing of hazardous waste under economic (cost minimization) and risk (total transportation risk related to the population, total risk for the population around treatment and disposal centers) objectives.

The models that have been proposed for measuring incineration plant performance are presented in Table 1. In most of the models demonstrated, Scale Efficiency has been proposed as a measure for performance. The inputs and outputs that are used provide information regarding the operational efficiency (production) leaving out information regarding the quality of each incineration (emissions, opinion of local population towards these plants etc.). This is partially ought to lack of availability of data, as the available data that are used in most of the studies are derived either from national census or from environmental agencies publishing reviews of the performance of each incinerator.

As stated above, majority of the DEA models help assess the operational performance of incineration plants. DEA technique also measures efficiency of incineration plants based on inputs and outputs through benchmarking. An efficient unit would be the one that uses fewer resources to produce energy with fewer emissions. While examining the performance of an energy production unit, additional constraints could be introduced—such as social constraints, or analyzing the demand and supply of each plant. Moreover, as incineration plants contribute to overall power and heat requirements from renewable sources, and also reduces the environmental impact by consuming waste (reducing the landfill) and enhances harmful emissions, one has to study the overall impact of incineration plants in a region so as to maximize the benefits and minimize the emission impact. Chen et al. (2012) propose a network DEA model for incineration plants' efficiency measurement from waste treatment to electricity generation. A directional distance function is used to construct a modified DEA model in accordance with the production characteristics of incineration plants, while allowing for differentiation between desirable (waste disposal and energy production) and undesirable outputs (bottom ashes and pollutants). This helps both policymakers and plant operators to enhance overall performance of incineration in a region. However, as the model doesn't set a goals/targets for desirable and undesirable outputs as per the policymakers' and plant owners' objectives, the outcomes of the model may not very realistic and decision-making on the basis of proposed model's results may not be accurate. Ideally incineration plants consume huge amount of MSW, produce maximum power and heat, and discharge as little emission as possible. However, in reality due to varied quantity and quality of waste within a specific region one has to optimize the outputs through setting up the targets/goals. Additionally,

Table 1 Proposed models for incineration plants performance measurement

Author(s)	Model	Inputs	Outputs	Main conclusions
Chen et al. (2010)	DEA models (CCR, BCC), Scale Efficiency (SE)	Man power (no of workers) Operating costs (NT\$) Installed incineration capacity (Ton/day) Installed electricity generation capacity (KWH/day)	Waste incinerated (ton/yr) Electricity generated (KWH/year)	Analysis of inefficient incinerators and suggestions for improvement.
Marques and Simões (2009)	DEA models (CCR, BCC), SE, Bootstrap	OPEX (€) CAPEX (€)	Treated solid waste (ton) Recycled waste (ton)	No change in efficiency between private and public solid waste services
Chen and Chen (2012)	DEA models (CCR, BCC), SE	OPEX (€) CAPEX (€)	Treated solid waste (ton) Recycled waste (ton)	Composting and incineration contributes positively to efficiency.
Chen et al. (2012)	Activity Network DEA	(SD) Labor (Thousands NT\$) Other costs (Thousands NT\$) Disposal incineration capacity (tm/day) (INT) Refuse incinerated (tn) Level of power generation (KW)	(D) Electricity sold (1000 kWh) (UND) Ash from incineration (tn) (UND) Dioxins (ng TEQ/Nm ³) (EXT) Income (Thousands NT\$)	Overall improvement of performance is achieved by emission reduction and better resource allocation
Benito-Lopez et al. (2011)	Cross efficiency, Monte Carlo simulation	Capital costs Operational costs	Number of low level wastes drums Number of transuranic wastes drums	Strong regulatory model has positive effect to efficiency
Chang and Yang (2011)	TODEA, NS-overall model	Electricity used (1000 Kw/annually) Waste incinerated (Ton/annually)	(D) Electricity power generation (1000 Kw/annually) (UND) ppm/annual average NOx SOx CO HCl	Build-operate-transfer are more efficient, on average, than public-own-operate and build-own-operate
Chen et al. (2014)	4-stage DEA approach, Double bootstrapping	Labor (Thousands NT\$) Other costs (Thousands NT\$)	Refuse (Tonnes) Electricity (1000 Kw)	15% improvement for cost reductions and capacity, ownership, location

there must be provision of withdrawing some facilities if their undesirable outputs are beyond certain limit. This would warrant policy makers and plant owners to run the units optimally and shutting down the suboptimal units for undertaking maintenance and other desirable activities to bring them in full operations in the due course. To authors' knowledge there is no work that has modeled the performance of incineration plants in a region for power and heat production, reduction of waste and harmful emissions with specific targets for both desirable and undesirable outputs. This study proposes a hybrid data envelopment analysis (DEA), Goal Programming (GP) and mixed integer linear programming (MILP) model to assess the performance of incineration plants in a specific region to enhance overall power production, reduction of waste and emissions. This model provides a flexible framework that utilizes the strengths of DEA and GP. Additionally, it enables to make decision on shutting down low performer plants that could be undergone desired maintenance to improve their performance and incorporated into the system again. The proposed model in one hand facilitates policy makers to enhance overall performance of incineration plants within a specific region to achieve desired targets and on the other hand helps individual plant operators to address their issues and challenges related to input and output variables in order to achieve the desired throughput (energy production and waste handling) and undesirable pollutants (reduce bottom ash and emissions)

3 Methodology

This research uses secondary data from literature to formulate the proposed performance measurement model. Information of 22 incineration plants in the UK has been used to demonstrate the effectiveness of the model. The following paragraphs formulate the proposed performance measurement model.

3.1 Model formulation

Incineration plants' performance assessment needs consideration of multiple criteria. DEA derives efficiency scores of decision making units (DMUs) based on pre-determined inputs and outputs. Integrating GP with DEA allows to set goals for multiple objectives (e.g. Operational, economic, environmental, social performance) (Zografidou et al. 2016) In this paper, a hybrid GP/DEA model is presented to measure incineration plants' performance. The model integrates binary variables (0, 1) in order to segregate plants that are performing in line with the desired environmental and operational targets. The proposed model is based on an existing GP/DEA model (Izadikhah et al. 2014) and extends its features by adding binary variables and various scenarios to form a mixed integer linear programming (MILP) model.

Data envelopment analysis (DEA) helps deriving efficiencies of DMUs by comparing the inputs and outputs of each unit against each other. Goal Programming helps to set goals for each criterion and derives decision variables through minimizing the deviations for each goal. Combining DEA and GP into a single framework, helps derive efficiency score of each unit within the desired goals. The use of binary variables facilitates selection of efficient units on the basis of the achievement of the desired goals.

The proposed model has been formulated following a few steps. Figure 1 depicts the flow chart of proposed performance measurement model. Firstly, based on DEA formulation, the units (incineration plants) are identified and the inputs/outputs of each unit are derived from the available data. The GP formulation is used to model operational goals, environmental targets, and capital constraints. The combined DEA and GP model helps derive efficiency

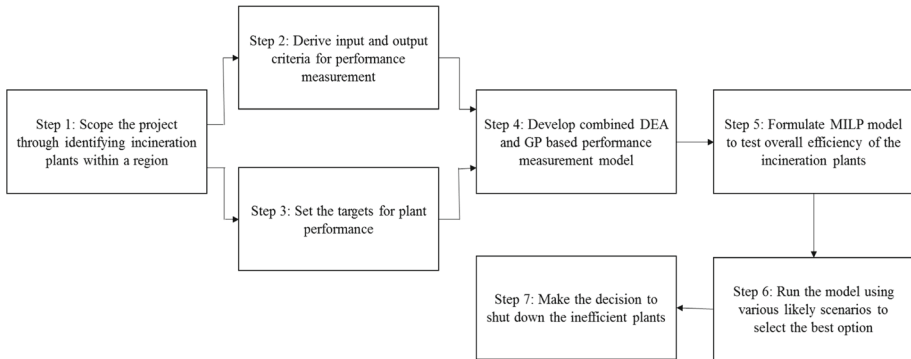


Fig. 1 Flow chart showing the combined DEA, GP, and MILP model for incineration plant performance measurement

of each unit under assessment. In order to identify the plants that need to be closed on the basis of their overall performance in relation to the overall targets, binary variables (0, 1) are introduced within the combined GP/DEA model along with the linearisation constraints. The overall outcome is a MILP model, which identifies the inefficient plants that must be closed in order to keep the overall targets (e.g. MSW consumption, energy and heat production, emissions reduction) of specific zone through analyzing various scenarios. The following paragraphs explained the proposed model mathematically.

3.2 Notation

See Table 2.

Table 2 Indices, variables and parameters of the proposed model

Index	
$j = 1, \dots, n$	DMU (incineration plants)
$r = 1, \dots, s$	Outputs
$i = 1, \dots, m$	Inputs
$\varepsilon = 1, \dots, E$	Scenarios
Variables	
λ_j	Peers of incineration (DMU) j
$\hat{\lambda}_j$	Auxiliary variable for linearization of bilinear term $\lambda_j \cdot \xi_j$
ξ_j	1 if incineration plant is selected, 0 otherwise
η	Auxiliary binary variable for disjunction of constraints
d_r^-	Under achievement of target r
d_r^+	Over achievement of target r
Parameters	
$y_{r,j}^{und}$	Undesirable output r of DMU j
$x_{i,j}$	Input i of DMU j
G_r^{und}	Goal for undesirable output r
PE_j	Power exported of incineration plant (DMU) j (KWh)
AV_j	Annual availability of incineration plant (DMU) j (%)

Table 3 Input (a) and output (b) oriented DEA models

$\min \theta$	$\max \varphi$
$s.t.$	$s.t.$
$\sum_{j=1}^n x_{ij} \cdot \lambda_j \leq x_{io} \cdot \theta, \quad i = 1, \dots, m$	$\sum_{j=1}^n x_{ij} \cdot \lambda_j \leq x_{io} \quad i = 1, \dots, n$
$\sum_{j=1}^n y_{rj} \cdot \lambda_j \geq y_{ro}, \quad r = 1, \dots, s$	$\sum_{j=1}^n y_{rj} \cdot \lambda_j \geq y_{ro} \cdot \varphi, \quad r = 1, \dots, s$
$\lambda_j \geq 0, \quad j = 1, \dots, n$	$\lambda_j \geq 0, \quad j = 1, \dots, n$
$\theta \text{ free}$	$\varphi \text{ free}$
(a)	(b)

3.3 Model description

Economic systems entail production processes; assuming that $i = 1, \dots, m$ inputs are consumed to produce $r = 1, \dots, s$ outputs, then the following DEA models are used in order to assess the efficiency of the entities that are examined (DMUs). Focusing only on envelopment models, the following Linear Programming (LP) formulations are input or output oriented DEA models (Charnes et al. 1981, 1984).

Models presented in Table 3 (a) and (b) are the conventional DEA models. The outputs are treated all as desirable. However, every economic entity may produce undesirable outputs by consuming inputs. In the present study, incineration plants produce, among desirable outputs, undesirable outputs as well. During the incineration procedure, municipal waste is consumed producing power but also harmful gas emissions. The DEA model that assesses a production procedure based on desirable and undesirable outputs is presented with the following LP formulation (Sueyoshi and Goto 2011a, b; Sueyoshi et al. 2010).

$$\begin{aligned}
 &\max \beta \\
 &s.t. \\
 &\sum_{j=1}^n \lambda_j \cdot x_{j,i} \leq x_{o,j}, \quad i = 1, \dots, m \\
 &\sum_{j=1}^n \lambda_j \cdot y_{j,r_1} \geq y_{o,r_1}^{des} \cdot (1 + \beta), \quad r_1 = 1, \dots, s_1 \\
 &\sum_{j=1}^n \lambda_j \cdot y_{j,r_2} = y_{o,r_2}^{undes} \cdot (1 - \beta), \quad r_2 = 1, \dots, s_2 \\
 &\lambda_j \geq 0, \quad j = 1, \dots, n \\
 &\beta \text{ free}
 \end{aligned} \tag{1}$$

In DEA model (1), a DMU is considered efficient if $\beta^* = 0$. However, DEA models assess the production process based on a number of given datasets for inputs and outputs.

Real world problems have more than one objective, based on which criteria are optimized (maximized or minimized). Goal Programming (GP) models are generally used in order to handle such problems. A typical GP model is formulated as follows:

$$\begin{aligned}
 & \min w^1 \cdot \delta^- + w^2 \cdot \delta^+ + w^3 \cdot (\delta^- + \delta^+) \\
 & s.t. \\
 & \sum_{k=1}^K a_k \cdot x_k + \delta^- - \delta^+ = G \\
 & \sum_{k=1}^K a_k \cdot x_k \leq b \\
 & x_k \geq 0, \forall k
 \end{aligned} \tag{2}$$

In formulation (2), slack variables are minimized in the objective function according to the direction of each goal. Extending model (2), then the following model (3) is formulated with the integration of DEA technique (Izadikhah et al. 2014).

$$\begin{aligned}
 & \min \sum_{r=1}^{s_1} \delta_r^- + \sum_{r=1}^{s_2} \delta_r^+ + \sum_{r=1}^{s_3} (\delta_r^- + \delta_r^+) \\
 & s.t. \\
 & \sum_{j=1}^n \lambda_j \cdot y_{rj} + \delta^- - \delta^+ = G_r^1, \quad r = 1, \dots, s_1 \\
 & \sum_{j=1}^n \lambda_j \cdot y_{rj} + \delta^- - \delta^+ = G_r^2, \quad r = 1, \dots, s_2 \\
 & \sum_{j=1}^n \lambda_j \cdot y_{rj} + \delta^- - \delta^+ = G_r^3, \quad r = 1, \dots, s_3 \\
 & \sum_{j=1}^n \lambda_j \cdot x_{ij} \leq x_{io}, \quad i = 1, \dots, m \\
 & \lambda_j \geq 0, \quad j = 1, \dots, n
 \end{aligned} \tag{3}$$

The methodology used in this paper, is a hybrid DEA/GP model. With this combination, the inputs and outputs are utilized, while each combination of incineration plants is examined with the GP approach. The resulting model is a MILP mathematical programming model and is presented in formulation (4). In this model, the aim is to minimize the slack variables that overestimate the goals of undesirable outputs which concern harmful gas emissions. The first set of constraints is introduced to model the goals for undesirable outputs; the second set of constraints, concern the inputs. In both cases, a binary variable is introduced in the model, examining only those DMUs which satisfy constraints third or fourth set of constraints. Binary variable η is introduced to model the disjunction $\sum_{j=1}^n PE_j \cdot \xi_j \geq PE^U \vee \sum_{j=1}^n AV_j \cdot \xi_j \geq AV^U$ (either power exported or annual availability of each incineration plant should be over a specific threshold). Parameters M^1 and M^2 are sufficient upper bounds of each constraint. With disjunctive formulation, incineration plants are selected based on the thresholds set to power exported or annual availability.

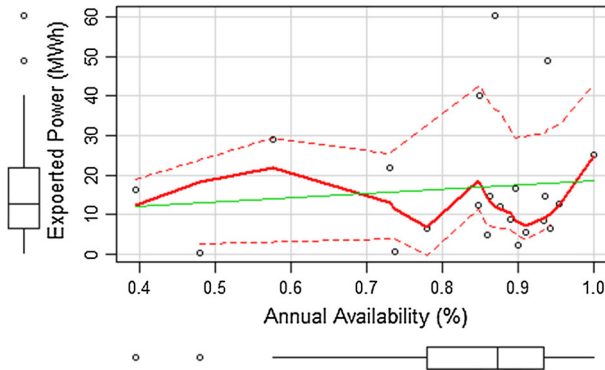


Fig. 2 Scatterplot and boxplot for power exported and annual availability

The power generation of each incineration is more or less steady; however the waste incinerated may vary in type, consistency and power generation value. Thus, the aim is to set constraints on power generation and annual availability. Annual availability could have not been introduced in classical DEA models, as is not part of the production process, however, when considering a centralized model with decisions that concern the selection of a plant, similar to the one proposed in this paper, then this type of information regarding exogenous operations of each plant can be utilized.

As it can be seen from Fig. 2, parameters for power exported and annual availability have very low correlation ($p = 0.10$); thus, DMUs should be selected on one of the two parameters as the more the annual availability does not imply more power exported to the grid.

Fifth constraint guarantees Variable Returns to Scale (VRS) technology for the selected DMUs while sixth and seventh constraints are introduced to bound the number of selected DMUs in the range of $[\mu, K]$.

$$\begin{aligned}
 & \min \sum_{r=1}^s \frac{d_r^+}{G_r^{und}} \\
 & s.t. \\
 & \sum_{j=1}^n \lambda_j \cdot \xi_j \cdot y_{r,j}^{und} + d_r^- - d_r^+ = G_r^{und}, \quad r = 1, \dots, s \\
 & \sum_{j=1}^n \lambda_j \cdot \xi_j \cdot x_{i,j} \leq x_{i,j_0}, \quad i = 1, \dots, m \\
 & \sum_{j=1}^n PE_j \cdot \xi_j \geq PE^U + M^1 \cdot \eta \\
 & \sum_{j=1}^n AV_j \cdot \xi_j \geq AV^U + M^2 \cdot (1 - \eta) \\
 & \sum_{j=1}^n \lambda_j \cdot \xi_j = 1
 \end{aligned}$$

$$\begin{aligned}
\sum_{j=1}^n \xi_j &\leq K \\
\sum_{j=1}^n \xi_j &\geq \mu \\
\xi_j &\in \{0, 1\}, \\
\eta &\in \{0, 1\}, \\
\lambda_j &\geq 0, \quad j = 1, \dots, n
\end{aligned} \tag{4}$$

Due to the existence of bilinear terms (product of binary and continuous variable), model (3) is a Mixed Integer Non – Linear Programming (MINLP) model. In order to avoid any local optima (due to existence of a nonlinear model), the following triplets of constraints (5)–(7) are introduced to linearize bilinear term $(\lambda \cdot \xi)$.

$$\hat{\lambda}_j - M_j \cdot \xi_j \leq 0, \quad j = 1, \dots, n \tag{5}$$

$$\hat{\lambda}_j - \lambda_j \leq 0, \quad j = 1, \dots, n \tag{6}$$

$$\lambda_j - \hat{\lambda}_j + M_j \cdot \xi_j \leq M_j, \quad j = 1, \dots, n \tag{7}$$

In linearization constraints (4), (6) the upper bound of λ value (M_j) is 1. Model (3) is formulated, based on (4)–(6) as follows:

$$\begin{aligned}
\min \quad & \sum_{r=1}^s \frac{d_r^+}{G_r^{und}} \\
s.t. \quad & \\
& \sum_{j=1}^n \hat{\lambda}_j \cdot y_{r,j}^{und} + d_r^- - d_r^+ = G_r^{und}, \quad r = 1, \dots, s \\
& \sum_{j=1}^n \hat{\lambda}_j \cdot x_{i,j} \leq x_{i,j_0}, \quad i = 1, \dots, m \\
& \sum_{j=1}^n PE_j \cdot \xi_j \geq PE^U + M^1 \cdot \eta \\
& \sum_{j=1}^n AV_j \cdot \xi_j \geq AV^U + M^2 \cdot (1 - \eta) \\
& \sum_{j=1}^n \hat{\lambda}_j = 1 \\
& \sum_{j=1}^n \xi_j \leq K \\
& \sum_{j=1}^n \xi_j \geq \mu \\
& \hat{\lambda}_j - \xi_j \leq 0, \quad j = 1, \dots, n
\end{aligned}$$

$$\begin{aligned}
\hat{\lambda}_j - \lambda_j &\leq 0, \quad j = 1, \dots, n \\
\lambda_j - \hat{\lambda}_j + \xi_j &\leq 1, \quad j = 1, \dots, n \\
\eta, \xi_j &\in \{0, 1\}, \quad j = 1, \dots, n \\
\lambda_j, \hat{\lambda}_j &\geq 0, \quad j = 1, \dots, n
\end{aligned} \tag{8}$$

3.4 Introducing scenarios

In order to evaluate how the system will behave if less facilities will be selected, then different scenarios are introduced regarding the number of total facilities to be selected. Thus, scenarios for upper bounds are introduced, leading to formulation (9). With the introduction of scenarios, we are in position to assess the optimal number of facilities that will be selected based on the results. Even if, waste incineration is considered as a safe choice for energy and heat production, there is a lot of dispute especially environmental agencies about the continuation of the operations of several incineration plants. This event is taken into account in this paper in the form of scenarios. In this case, 10 scenarios are introduced for the maximum number of selected DMUs; namely $K^1 = 22, K^2 = 21, \dots, K^9 = 14, K^{10} = 13$. The minimum number of incineration plants (μ) is defined as 13. Thus, for $\varepsilon = 10$ constraints $\sum_{j=1}^n \xi_j \leq K^\varepsilon$ and $\sum_{j=1}^n \xi_j \geq \mu$ lead to $\sum_{j=1}^n \xi_j = 13$.

for $\varepsilon = 1, \dots, E$

$$\min \sum_{r=1}^s \frac{d_r^+}{G_r^{und}}$$

s.t.

$$\sum_{j=1}^n \hat{\lambda}_j \cdot y_{r,j}^{und} + d_r^- - d_r^+ = G_r^{und}, \quad r = 1, \dots, s$$

$$\sum_{j=1}^n \hat{\lambda}_j \cdot x_{i,j} \leq x_{i,j_0}, \quad i = 1, \dots, m$$

$$\sum_{j=1}^n PE_j \cdot \xi_j \geq PE^U + M^1 \cdot \eta$$

$$\sum_{j=1}^n AV_j \cdot \xi_j \geq AV^U + M^2 \cdot (1 - \eta)$$

$$\sum_{j=1}^n \hat{\lambda}_j = 1$$

$$\sum_{j=1}^n \xi_j \leq K^\varepsilon$$

$$\sum_{j=1}^n \xi_j \geq \mu$$

$$\hat{\lambda}_j - \xi_j \leq 0, \quad j = 1, \dots, n$$

$$\hat{\lambda}_j - \lambda_j \leq 0, \quad j = 1, \dots, n$$

$$\begin{aligned}
&\lambda_j - \hat{\lambda}_j + \xi_j \leq 1, \quad j = 1, \dots, n \\
&\eta, \xi_j \in \{0, 1\}, \quad j = 1, \dots, n \\
&\lambda_j, \hat{\lambda}_j \geq 0, \quad j = 1, \dots, n \\
&\text{end for}
\end{aligned} \tag{9}$$

3.5 Extending the model

The proposed combined DEA, GP and MILP model provides a flexible framework for identifying efficient incineration plants through performance measurement. However, in the current state, the model, apart from environmental (reduction of emissions) and operational (energy production, annual availability constraints), does not take into account additional aspects (e.g. social perspectives). Also, the proposed model can incorporate transportation constraints to explicitly examine in detail the supply of MSW and demand for power to grid.

Although incineration plant produces power and heat from MSW, it also discharges undesirable emissions that cause inconvenience to the citizens as incineration plants are located in habitated areas. Assuming that PS_j is the level of satisfaction of citizens about incineration j , and G^{soc} is a goal for overall of incineration plants, then the following goal constraint is introduced to the model. In constraint (10) d_{soc}^- and d_{soc}^+ model the under and over achievement of goal respectively.

$$\sum_{j=1}^n \xi_j \cdot PS_j + d_{soc}^- - d_{soc}^+ = G^{soc} \tag{10}$$

Also, the procedure by which waste is transported to each incineration plant from landfills could be incorporated in the present model. If supply quantities produced in landfill f ($f = 1, \dots, F$) are denoted with S_f and the transported quantities from landfill f to incineration plant j are denoted with $Q_{f,j}$, then constraint (11) implies that the transported quantities should not exceed the ones that are available. Constraint (12) guarantees that the transported quantities from landfill f to incineration plant j must exceed the demand for MSW of incineration plant j . Quantities transported from landfill f to incineration plant j are subjected to upper and lower bound constraints regarding the capacity that can be transported (13), (14). Binary variable $X_{f,j}$ takes value 1 if the corresponding connection between landfill f to incineration plant j exists and 0 otherwise. Finally constraint (15) suggests that the connection between landfill f to incineration plant j exists if – f the corresponding incineration plant j has been selected.

$$\sum_{j=1}^n Q_{f,j} \leq S_f, \quad f = 1, \dots, F \tag{11}$$

$$\sum_{f=1}^F Q_{f,j} \geq D_j, \quad j = 1, \dots, n \tag{12}$$

$$Q_{f,j} \leq Q_{f,j}^U \cdot X_{f,j}, \quad f = 1, \dots, F, \quad j = 1, \dots, n \tag{13}$$

$$Q_{f,j} \geq Q_{f,j}^L \cdot X_{f,j}, \quad f = 1, \dots, F, \quad j = 1, \dots, n \tag{14}$$

$$X_{f,j} \leq \xi_j, \quad f = 1, \dots, F, \quad j = 1, \dots, n \tag{15}$$

In case of high demand, constraint (16) is introduced in order to prevent the model of being infeasible. Also, the following term is introduced in the objective function to penalize any uncovered demand $(\sum_{j=1}^n c^M \cdot \Delta_j)$.

$$\sum_{f=1}^F Q_{f,j} + \Delta_j = D_j, \quad j = 1, \dots, n \tag{16}$$

From the variables introduced above it stands that $Q_{f,j}, \Delta_j \geq 0$ and $X_{f,j} \in \{0, 1\}$.

The addition of transportation model in the proposed DEA/GP model, introduces also another dimension, that of cost. The cost of the model is now computed based on the transported quantities and the connections that are created between landfill f to incineration plant j .

$$\sum_{f=1}^F (c_{f,j}^V \cdot Q_{f,j} + c_{f,j}^F \cdot X_{f,j}) + \text{cost} d_j^- - \text{cost} d_j^+ = G_j^{\text{cost}}, \quad j = 1, \dots, n \tag{17}$$

As the model examines the incineration plants from a holistic centralized perspective, the goal for cost that is considered is set as a means of reducing transportation cost. This cost is incorporated in the price of power and heat production to the grid. Thus, setting individual targets for each incineration plant, the selected incineration plant will not only be selected on the basis of reducing resources used and emissions but also reducing the cost.

The resulting model is based on (9) with constraints (10)–(15), (17).

for $\varepsilon = 1, \dots, E$

$$\min \sum_{r=1}^s \frac{d_r^+}{G_r^{\text{und}}} + \sum_{j=1}^n \frac{\text{cost} d_j^+}{G_j^{\text{cost}}} + \frac{d_{\text{soc}}^-}{G^{\text{soc}}}$$

s.t.

$$\sum_{j=1}^n \hat{\lambda}_j \cdot y_{r,j}^{\text{und}} + d_r^- - d_r^+ = G_r^{\text{und}}, \quad r = 1, \dots, s$$

$$\sum_{f=1}^F (c_{f,j}^V \cdot Q_{f,j} + c_{f,j}^F \cdot X_{f,j}) + \text{cost} d_j^- - \text{cost} d_j^+ = G_j^{\text{cost}}, \quad j = 1, \dots, n$$

$$\sum_{j=1}^n \xi_j \cdot PS_j + d_{\text{soc}}^- - d_{\text{soc}}^+ = G^{\text{soc}}$$

$$\sum_{j=1}^n \hat{\lambda}_j \cdot x_{i,j} \leq x_{i,j_0}, \quad i = 1, \dots, m$$

$$\sum_{j=1}^n PE_j \cdot \xi_j \geq PE^U + M^1 \cdot \eta$$

$$\sum_{j=1}^n AV_j \cdot \xi_j \geq AV^U + M^2 \cdot (1 - \eta)$$

$$\sum_{j=1}^n \hat{\lambda}_j = 1$$

$$\begin{aligned}
& \sum_{j=1}^n \xi_j \leq K^\varepsilon \\
& \sum_{j=1}^n \xi_j \geq \mu \\
& \sum_{j=1}^n Q_{f,j} \leq S_f, \quad f = 1, \dots, F \\
& \sum_{f=1}^F Q_{f,j} \geq D_j, \quad j = 1, \dots, n \\
& Q_{f,j} \leq Q_{f,j}^U \cdot X_{f,j}, \quad f = 1, \dots, F, \quad j = 1, \dots, n \\
& Q_{f,j} \geq Q_{f,j}^L \cdot X_{f,j}, \quad f = 1, \dots, F, \quad j = 1, \dots, n \\
& X_{f,j} \leq \xi_j, \quad f = 1, \dots, F, \quad j = 1, \dots, n \\
& \hat{\lambda}_j - \xi_j \leq 0, \quad j = 1, \dots, n \\
& \hat{\lambda}_j - \lambda_j \leq 0, \quad j = 1, \dots, n \\
& \lambda_j - \hat{\lambda}_j + \xi_j \leq 1, \quad j = 1, \dots, n \\
& \eta, \xi_j \in \{0, 1\}, \quad j = 1, \dots, n \\
& \lambda_j, \hat{\lambda}_j \geq 0, \quad j = 1, \dots, n \\
& \text{end for}
\end{aligned} \tag{18}$$

In (18), the objective function minimizes the deviational variables of three aspects: environmental (undesirable outputs, emissions), financial (cost) and social (citizen's satisfaction). In the presence of preference towards these three aspects, weights can be assigned to each aspect. The objective function becomes as follows:

$$\min w^{env} \cdot \sum_{r=1}^s \frac{d_r^+}{G_r^{und}} + w^{fin} \cdot \sum_{j=1}^n \frac{\text{cost} d_j^+}{G_j^{\text{cost}}} + w^{soc} \cdot \frac{d_{soc}^-}{G_{soc}^-} \tag{19}$$

In the formulation (19), w^{env} , w^{fin} and w^{soc} are the weights towards environmental, financial and social aspects and it stands that $w^{env} + w^{fin} + w^{soc} = 1$. The resulting model is a 0 – 1 Weighted DEA/GP model.

4 Application

4.1 Data description

The study uses information on capacity and harmful emissions of 22 incineration plants in the UK from Department for Environment, Food & Rural Affairs (DEFRA). The thresholds and goals were set based on the basis of regulatory framework; only recent documents (2010–2013) were used for each incineration plant.

The 22 incineration plants that are considered in this analysis are depicted through (INC1 – INC22); data on operational and environmental aspects of each incineration plant were gathered from environmental agencies ("Environment Agency annual report and accounts

Table 4 Inputs and undesirable outputs for each incineration plant

Incineration plant j	Inputs ($x_{i,j}$)		Undesirable outputs ($y_{r,j}^{und}$)				
	Waste capacity (t/a)	Power capacity (MWh)	PM10 (mg/m ³)	HCl (mg/m ³)	CO (mg/m ³)	SO ₂ (mg/m ³)	NO _x (mg/m ³)
INC1	580,000	34.5	6	5	19	6	59
INC2	140,000	10	3.383333	8.733333	6.725	13.45833	155.6667
INC3	102,000	8	1.45	5.66	18.6	13.9	174
INC4	315,000	17.7	2.04	3.68	29.67	23.79	255.2
INC5	105,000	7.4	3	5	9	8	168
INC6	750,000	40	2.8	2.6	44.8	8.4	206.4
INC7	210,000	14	2.385	13.355	21.95	7.575	200.5
INC8	242,000	19.5	20	30	100	200	400
INC9	210,000	14	1.02	6.47	10.1	20.9	211
INC10	52,000	40	2.01	2.44	4.89	3.78	83.72
INC11	210,000	14.2	2.5	6.5	13	18.5	152
INC12	350,000	27	30	60	100	200	400
INC13	110,000	8	1.5	4	17.5	9	177.5
INC14	56,000	3	2.4	2.4	2.1	3	167.8
INC15	150,000	9.5	1.7	4.5666	9.4333	8.5	168.4167
INC16	225,000	19	0.653	7.216	5.896	17.117	143.662
INC17	260,000	20	300	10	100	200	400
INC18	65,000	7	0	44.53333	100	155.7417	211.9583
INC19	65,000	1.7	45	60	100	200	400
INC20	420,000	35	0.25	0.65	0.18	0.28	0.88
INC21	375,000	29	30	60	100	200	400
INC22	29,000	7	0.2317	0.0108	1.063333	5.284167	245.0067

2013 to 2014 - Publications - GOV.UK”) and relevant literature (Nixon et al. 2013a, b). Although there are 32 operating incineration plants in the UK, the study is limited to 22 plants due to data unavailability. In Table 4, inputs and outputs of the DEA based performance measurement model are presented. As it can be seen, inputs of each incineration plant (DMU) are selected, in order to grasp the potential management of waste handled and power generated. On the contrary, the present model considers only undesirable outputs (harmful gas emissions) derived from the incineration procedure. Data for Power Exported and Annual availability, which are used as constraints in the model, are presented in Table 5. Finally, as the presented model is a hybrid GP/DEA model, the goals for undesirable outputs are presented in Tables 6 and 7, thresholds for power exported and annual availability are presented.

4.2 Results

In this section, the results of the analysis are presented, derived by model (9) where the variables for each target are derived for each scenario of total facilities to be installed. The

Table 5 Data for coefficient of power exported and annual availability constraints

Incineration plant j	Power exported (MWh) (PE_j)	Annual availability (%) (AV_j)
INC1	22	0.73
INC2	6.6	0.78
INC3	49.01	0.94
INC4	12.57	0.848333333
INC5	6.5	0.9428
INC6	40	0.85
INC7	14.64283099	0.935502283
INC8	16.5	0.394292237
INC9	12.71908233	0.955365297
INC10	0.461517135	0.4794
INC11	12	0.8759
INC12	25	1
INC13	5.526619499	0.91
INC14	2.32	0.9
INC15	8.9	0.89
INC16	14.60931615	0.863869863
INC17	60.296	0.87
INC18	5	0.86
INC19	0.756322978	0.737642694
INC20	8.5	0.934417808
INC21	29.2	0.575829528
INC22	16.771	0.89760274

Table 6 Targets for undesirable outputs (G_i^{und})

Undesirable output	mg/m ³
PM10	15
HCl	10
CO	25
SO ₂	200
NO _x	100

Table 7 Thresholds for exported power and annual availability

	Threshold
Exported power (PE^U)	300 (MWh)
Availability (AV^U)	75 (%)

formulation and solution of the model has been done using GAMS software (McCarl 2002) and using CPLEX as MILP solver (Rosenthal 2004). In Table 8, optimal decision levels for various scenarios are demonstrated. As it can be seen in Table 8, the first row provides the results of model (3). However, the optimal decisions for over and under achievement of each

Table 8 Results for each scenario of under and over achieving of variables of slack variables ($d_r^{*,-}$, $d_r^{*,+}$)

ε	K	$d_r^{*,-}$				$d_r^{*,+}$
		PM10	HCl	CO	SO ₂	
1	22	14.7683	9.9892	23.93667	194.7158	145.0067
2	21	14.7683	9.9892	23.93667	194.7158	145.0067
3	20	14.7683	9.9892	23.93667	194.7158	145.0067
4	19	14.7683	9.9892	23.93667	194.7158	145.0067
5	18	14.7683	9.9892	23.93667	194.7158	145.0067
6	17	14.7683	9.9892	23.93667	194.7158	145.0067
7	16	14.7683	9.9892	23.93667	194.7158	145.0067
8	15	14.7683	9.9892	23.93667	194.7158	145.0067
9	14	14.7683	9.9892	23.93667	194.7158	145.0067
10	13	14.7683	9.9892	23.93667	194.7158	145.0067

target (presented in Table 6), demonstrate no change over different scenarios. In Table 9, the results of binary variables (ξ_j^*) for each scenario are demonstrated. From Tables 8 and 9, it can be seen that by reducing the upper bound of potentially selected facilities, deviational variables regarding over or under achievement of the goals may not vary, however, the selected incineration plants may vary over time. For example, it can be seen that incineration plant 4 (INC4) is selected for all the possible scenarios (K^ε), while INC1 is selected only for the first scenario $K^{\varepsilon=1} = 22$.

In order to derive a conclusion out of this distribution of selection of each DMU (incineration plant), probability of selection (P_j^*) is calculated based on the following formula:

$$P_j^* = \frac{\sum_{\varepsilon=1}^E \xi_j^{\varepsilon,*}}{|E|} \tag{20}$$

In Eq. (20), the selected DMUs are summed over each scenario, divided by the total number of scenarios.

Results for the probability of occurrence of each DMU, are presented along with scores derived from DEA model (1) in Table 10.

In Table 10, efficiency of each DMU ($1 - \beta^*$) is derived by applying DEA model (1), taking as inputs, the inputs of Table 4, Exported Power from Table 5 as desirable output and gas emissions from Table 4 as undesirable outputs. The rankings of the proposed model and DEA model (1) are presented, and in order to come to a conclusion as to whether the two examined techniques provide equal rankings, Kolmogorov–Smirnov (K–S) and Mann–Whitney (M–W) test non-parametric tests are applied. The hypotheses that are examined in K–S test, is whether the rankings come from the same distribution (null hypothesis), or not from the same distribution (alternative hypothesis). Using M–W test, randomness is checked; null hypothesis states that the two variables (in this case rankings) follow the same pattern, while on the other hand, alternative hypothesis states that two variables are stochastically distributed and do not follow any pattern.

Results for p values for the two aforementioned tests are demonstrated in Table 11, and show that both rankings come from the same distribution and follow the same pattern. Based on this finding, it can be concluded that the presented model keeps all the properties of DEA model (1), but can provide additional information regarding the selection of an incineration

Table 9 Results of allocation of incineration plants for each scenario $\varepsilon (\xi_j^{\varepsilon,*})$

K^ε	INC1	INC2	INC3	INC4	INC5	INC6	INC7	INC8	INC9	INC10	INC11
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1			1	1	1
3	1	1	1	1	1	1			1	1	1
4	1	1	1	1	1	1			1	1	1
5	1	1	1	1	1	1			1	1	1
6	1	1	1	1	1	1			1	1	1
7	1	1	1	1	1	1			1	1	1
8	1	1	1	1	1	1			1	1	1
9	1	1	1	1	1	1			1	1	1
10			1	1						1	2
K^ε	INC12	INC13	INC14	INC15	INC16	INC17	INC18	INC19	INC20	INC21	INC22
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1	1
5	1	1	1	1	1	1	1	1	1	1	1
6	1	1	1	1	1	1	1	1	1	1	1
7	1	1	1	1	1	1	1	1	1	1	1
8	1	1	1	1	1	1	1	1	1	1	1
9	1	1	1	1	1	1	1	1	1	1	1
10	1	1	1	1	1	1	1	1	1	1	1

Table 10 Results for scores of DEA model (1) and proposed GP/DEA model (9) with rankings of incineration plants

	$1 - \beta^*$	P_j^*	Ranking DEA model (1)	Ranking GP/DEA model (9)
INC1	0.997206	0.1	7	19
INC2	0.381189	0.9	15	13
INC3	1	1	1	1
INC4	0.416586	1	13	1
INC5	0.345754	0.9	17	13
INC6	1	0.1	1	19
INC7	0.639598	0.1	9	19
INC8	0.227494	0.1	20	19
INC9	0.49892	0.9	10	13
INC10	0.024401	1	21	1
INC11	0.444879	1	11	1
INC12	0.351652	1	16	1
INC13	0.254815	1	19	1
INC14	0.342015	1	18	1
INC15	0.425952	0.9	12	13
INC16	0.728238	0.7	8	18
INC17	1	1	1	1
INC18	1	0.8	1	17
INC19	0.010188	1	22	1
INC20	1	1	1	1
INC21	0.408029	1	14	1
INC22	1	1	1	1

Table 11 Results of non-parametric tests

Test	p value	Hypothesis accepted
K–S test	0.378	H_0 : The variables come from the same distribution
M–W test	0.242	H_0 : The variables follow the same pattern

plant. Also the proposed formulation is flexible and can incorporate both qualitative (people’s perceptions, social data, preference etc.) and quantitative data.

5 Discussion

Performance measurement of incineration plants is a multiple objective decision-making problem. The incineration plants’ objectives are to consume as much waste as possible, maximizing desirable outputs (e.g. heat and power) and minimizing undesirable outputs (emission and bottom ash). In this study a combined DEA, GP and MILP model is presented to measure incineration plants’ performance that derives plants’ efficiency within the desired

goals. Additionally, identifies sub optimal plants that are candidates for shutting down either permanently or temporarily. This enables deriving improvement measures for each plants and develop business case for improvement projects. The model first identifies the DMUs (incineration plants), input and output criteria for plant performance. Data envelopment analysis (DEA) helps deriving efficiencies of DMUs by comparing the inputs and outputs of each unit against each other. Goal Programming facilitates to set goals for each criterion and derives decision variables through minimizing the deviations from each goal. Combining DEA and GP into a single framework, helps derive efficiency score of each unit within the desired goals. The use of binary variables (0, 1) through mixed integer linear programming (MILP) modeling allows selection of efficient units on the basis of the achievement of the desired goals.

The DEA models for performance measurement of incineration have been extensively used in the literature. Although DEA and GP have been applied separately for optimizing incineration plants performance, according to authors' knowledge there is no research that combines DEA and GP in incineration plants' performance measurement and management. Moreover, in this study we combine DEA/GP model with MILP modelling to incorporate binary variables (0, 1) for scenario building. This enables to model the performance of incineration plants within a region to optimize their combined performance in a multiple objectives scenario (e.g. maximize power and heat production, minimize environmental and social impact). This facilitates to select the most appropriate plants for continuing operations and suggest shutting of a few facilities on the basis of their lower overall performance. The inefficient plants could be further studied to decide to undertake further maintenance to enhance their performance before reintroducing for operations. Additionally, this model is capable of analysing feasibility of adding new plants with a few objective goals (e.g. waste consumption, energy and heat production, emission targets, auxiliary loads, social benefits targets). The proposed model in one hand facilitates individual plant operator to analyse their performance through benchmarking and allows deriving means for improvement and on the other hand helps the policymakers to plan for cleaner environment efficiently. This also facilitates to derive budget allocations for overall improvement of incineration operations across the region. Therefore, this study theoretically contributes a model for performance measurement that enables not only segregating efficient and inefficient DMUs (incineration plants) using series of inputs and outputs but also facilitates making decision on how to achieve desired holistic goals by closing or introducing units. In this paper, the effectiveness of the model has been demonstrated through application in incineration plants' performance measurement. The model could be applied in several similar scenarios (e.g. retails' decision-making on closing down shops, banks' decision on closing of units), which is beyond the scope of this paper but could be considered as further scope of research.

The proposed model can be further extended to incorporate advanced scheduling and time window constraints for the removal of waste and transportation to incineration plants for power and heat production. The ability of DEA technique to consider inputs and outputs is utilized to develop a performance measurement model of each incineration plant. The presented formulation aims at the reduction of the examined facilities that exceed the environmental targets set but satisfy the constraints of power exported and annual availability. The basic idea of not setting power exported and annual availability in GP constraints is that the more each incineration plant works and the more power is exported to the grid, the more emissions are generated. The resulting model is a MILP model, with decision variables providing levels of decisions regarding: (a) which incineration plant satisfies the environmental targets and remains open, (b) the level of achievement of the goals per each scenario, and (c) the peers of that plant. As due to MINLP formulation, local optima may arise, lineariza-

tion constraints are introduced in order to make the model linear and obtain global optimal solution. With this formulation, it is possible to evaluate different combinations of plants and numbers of facilities that will be opened by solving the model for various scenarios of the number of facilities that will be eventually remain opened. Operational constraints on power exported and annual availability of each incineration plant are introduced. Preprocessing of data indicated that these constraints are “either-or” type; constraints regarding the number of incineration plants that will be potentially installed are also taken into account. In this paper a holistic study that examines incineration plants in a centralized way is presented. The objective of the problem is multi-objective as each incineration plant must increase its outputs (power, heat) and to minimize the undesirable outputs (emissions). Thus, the efficiency is examined taking into account the multivariate nature of the problem; the highest power or heat exported to the grid with the lowest harmful emissions. Such model has not been proposed before in the known literature as provides decision levels, not only regarding the “peers” of each incineration plant, but also about whether the incineration plant can be eventually be installed subjected to constraints regarding the power that should be exported and the annual availability. Each incineration plant that does not meet these requirements is not selected and therefore the total overachievement target is minimized. The novelty of the paper lies on the fact that a new type of efficiency is formed using GP and DEA methods. Inefficient units are not selected, thus, the reference set is constructed upon selected DMUs. This is useful in situations where performance needs to consider additional constraints regarding the nature of the problem. Also, decisions regarding selection of the units, adjusts regarding the goals set and disjunctive constraints. This characteristic cannot be addressed using DEA or GP.

The proposed model can be used by policymakers, governmental bodies and public environmental authorities as incineration plants export heat and/or power to the grid, nevertheless, harmful emissions are emitted as well. Therefore, the performance of each incineration plant should be seen on a centralized level. The decisions as to whether an incineration plant should run or shut down have valuable managerial insights. However, by shutting down an incineration plant may cause problems in energy demand satisfaction and not achieving waste reduction target. Therefore, this decision needs to be holistic by taking into consideration of group of plants performance to achieve the overall goals of the region. In this case, shutting down a plant, because is not efficient in the ways described in the analysis, is conducted taking into account the capacity of the remaining plants. Besides the managerial implications, the novelty of the proposed model lies on the fact that it proposes a dynamic and flexible framework for performance measurement based on goals and structural constraints, filling the gap of the incapability of DEA and GP models separately. The proposed model can be further extended to incorporate social (citizen’s satisfaction) and financial (transportation cost and quantities) aspects.

6 Conclusions

Incineration plants consume waste and produce heat and power and contribute in reducing greenhouse gas emission. However, negative environmental impact of incineration is also substantial through emission of gases and bottom ash production. Because of variability of waste quality incineration plants’ outputs (energy, heat, emission and bottom ash) keep varying. Therefore, dynamic measurement of plants’ performance helps achieving overall performance targets incineration in a specific region by shutting down the inefficient plants as and when desired in line with their performance. The proposed combined DEA, GP and MILP

based performance measurement and decision-making model facilitates policy makers and plant operators to operate incineration plants optimally through objectively deriving plants' performance through benchmarking. Additionally, the model allows them to derive desired improvement measures to make the inefficient plants efficient.

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