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Multi-Objective Optimization of Operational Variables in a Waste Incineration Plant

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Abstract

One of the primary objectives of the operation of an incineration plant is to maximise throughput. However, increasing throughput can intensify the loading on the gas-clean-up system and also cause a violation of operational constraints. This may result in penalty costs due to excessive pollution emissions and the need for increased maintenance. Therefore a multi-objective strategy is required to optimize plant operation in terms of economic goals and environmental and operational constraints.

This paper discusses an supervisory level optimization scheme, using Multi-Objective Genetic Algorithms (MOGA), for a waste incineration plant, which will allow certain parameters to be adjusted for maximum throughput, whilst keeping within emission and operational constraints. The optimization procedure is independent of plant construction and waste stream input and is applied in this case to the model of a municipal solid waste incineration plant, incorporating a moving grate.

Key words: Waste Incineration, Multi-Objective Optimization, Genetic Algorithms, Computational Fluid Dynamic Modelling

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1 Introduction

Incineration is increasingly being used to dispose of various waste streams including municipal, hazardous and clinical waste. Benefits can be found from the reduction in waste volume, destruction of hazardous constituents and the energy that is recovered from the process (Swithenbank et al., 2000). The higher level supervisory control of a waste incineration plant is typically left to the the decisions of a human operator. This is a distinct task from the automatic low-level control loops that regulate dynamic behaviour and provide dynamic disturbance rejection (see for instance Chen et al. (2002)). Decisions by the operator are based on experience and often rely on limited knowledge of the process (about the usual operating points). Decision support tools, which aid the operator, have been shown to be beneficial (particularly in related systems such as coal-fired power stations (Kalogirou, 2003)). However, a methodology for effective decision support is currently lacking in waste incineration plant performance optimization.

The objectives that must be considered to assure optimal performance may be grouped by three categories: the maximization of economic performance (e.g. throughput), minimization of products of environmental concern (e.g. NOx, dioxins and carbon-in-ash) and to ensure that operational constraints are not violated (e.g. regarding temperature levels and oxygen concentration within the combustion chamber). The task of optimizing waste incineration plant performance is complicated by the trade-off that must occur when attempting to improve conflicting objectives. For instance maximizing throughput conflicts with minimizing emissions and performing within operational constraints. Such a multi-objective problem has no single solution that optimizes performance across all objectives. Rather a range of solutions will be obtained according to the specified optimization criteria, each with a unique trade-off.

Multi-Objective Evolutionary Algorithms (MOEAs) (Fonseca and Fleming, 1995; Coello, 1999) are highly suited to problems where a range of optimal solutions are available. The use of genetic algorithms in combustion plant performance optimization (with a single objective) has been promoted in Chu et al. (2003). The advantage of using a multi-objective approach is that an optimal trade-off can be found in terms of all objectives of importance. The MOEA uses a population of potential solutions which can spread along the multi-objective trade-off surface. This gives high flexibility to the incineration plant operator: the benefits and penalties associated with all potential decisions can be transparently assessed. This allows the operator to make an informed choice based on current operational rquirements.

It is possible to use an approach that combines mulitple objectives into a single cost function with appropriate weights for each objective (see for instance

Canning et al. (1998)). However, the selection of weights is not necessarily intuitive and more importantly limits the operator to a single solution with no knowledge of decision consequences for any other operational conditions. Therefore MOEA has been selected in this investigation as a tool that has advantages in application to waste incineration plant optimization. In particular, a well-known MOEA, the Multi-Objective Genetic Algorithm (MOGA) (Fonseca and Fleming, 1993), with the ability to handle varying levels of constrained objectives, is applied to the problem.

The MOEA requires information on the effects of different operational conditions in order to direct the search. This means that a model of the plant must be available to test each set of input conditions. Combustion plant modelling has been successfully accomplished using neural networks (Stopford et al., 1998; Chang and Chen, 2000; Hao et al., 2001). Data driven methods are well suited to incineration plant modelling because whilst the underlying physical functions governing behaviour are constant across all plants, each plant behaves in a unique way. Therefore operational data, which can be routinely collected at all plants, is ideally suited to describe such individual behaviour. The relationships that need to be captured are often non-linear, which particularly motivates modelling using neural networks. In the case of this investigation Radial Basis Function networks (Broomhead and Lowe, 1988; Liu and Kadirkamanathan, 1999) are used to model the incineration plant.

In order to design and demonstrate the method, data was obtained from a physical model: Fluid dynamic Incinerator Code (FLIC) (Yang et al., 2002), developed in the Sheffield University Waste Incineration Centre (SUWIC). This model provided a well-understood, controlled test problem where the design and analysis of the optimization tool could be effectively accomplished without the additional complications and expense of using and collecting real-world data.

This paper aims to show the suitability of using MOEAs in optimizing waste incineration plant operation and to provide a decision support tool for plant operators where trade-offs in plant performance objectives may be transparently perceived. The use of MOGA in solving this problem is illustrated on a model of a Municipal Solid Waste (MSW) incinerator, with a set of typical optimization decision variables and objectives.

Section 2 provides a brief review of MOGA. Section 3 explains the RBF modelling procedure used and section 4 explains the FLIC model. The application of MOGA is presented in section 5 and finally the investigation is concluded in section 6.

2 The Multi-Objective Genetic Algorithm (MOGA) with constraint handling

The consideration of multiple objectives in evolutionary based search algorithms has received much interest, with a number of algorithms having been proposed including MOGA, Niched Pareto Genetic Algorithm (NPGA) (Horn and Nafpliotis, 1993), Nondominated Sorting Genetic Algorithm (NSGA) (Srinivas and Deb, 1994) and Strength Pareto Evolutionary Algorithm (SPEA) (Zitzler and Thiele, 1999). These algorithms and variations thereof comprise the basis of the most popular MOEAs currently in use. For a review and comparison, which is beyond the scope of this paper see (Coello, 1999; Purshouse and Fleming, 2001).

The commonality that links these methods is the use of Pareto-optimal ranking strategies and the use of techniques such as niching that aids in spreading the solutions along the Pareto-optimal front. The method that is utilized in this paper is a modification of MOGA that incorporates a methodology to handle constraint information (Fonseca and Fleming, 1998) and hence is particulary well suited to the case of waste incineration. MOGA has been often utilized in the area of control engineering (Fleming and Purshouse, 2002) and in particular has been applied in the combustion-related area of gas turbine engine performance optimization (Chipperfield and Fleming, 1996).

Multi-objective optimization methods are required to be used when there is a problem that incorporates objectives that conflict and hence require a trade-off in the solution. The solution or decision variable vector, $\mathbf{x}$ will often be comprised of a number, m of adjustable parameters:

$$\mathbf{x} = [x_1, x_2, \ldots, x_m] \tag{1}$$

The cost of one solution over another can be assessed by an objective function, which in the multi-objective case will be comprised of n evaluation functions, each related to a single objective:

$$\mathbf{f}(\mathbf{x}) = [f_1(\mathbf{x}_1), f_2(\mathbf{x}_2), \ldots, f_n(\mathbf{x}_n)] \tag{2}$$

where $\mathbf{x}_j \subseteq \mathbf{x}$ for $j = 1, \ldots, n$: each objective may only be dependent on a subset of the full range of decision variables.

The task in a multi-objective optimization is to find the set of decision variables that minimizes (2) according to some criteria. This is most often accomplished in MOEAs by comparing solutions in terms of Pareto-optimality: a solution is said to be part of the Pareto-optimal set if it not dominated (or out-performed) by any other solutions in terms of one or more objectives. A solution $\mathbf{x}^*$ can be said to be Pareto-optimal if:

$$f_i(\mathbf{x}^*) < f_i(\mathbf{x}) \quad \forall \quad \mathbf{x} \in \mathcal{X} \quad \text{for at least one } i \in \{1, \ldots, n\} \tag{3}$$

where $\mathcal{X}$ comprises the full set of all possible decision variables. Solutions can be ranked relative to each other using the concept of Pareto-dominance (Goldberg, 1989):

(1) The dominant solutions are selected (in terms of Pareto-optimality).
(2) This dominant set of solutions is ranked highest and then removed from the full solution set.
(3) The procedure is repeated until all solutions have been ranked.

The MOGA is a method of search that can be used to solve (3), which is based on the Darwinian principle of 'survival of the fittest'. A random initialization of solutions within the search-space leads to a multi-objective ranking, stochastic selection and crossover process that produces new individuals. These individuals can be thought of as the offspring of their predecessors. The fitter individuals within a population will have a higher chance of reproducing leading to their desirable characteristics being propagated through the search. The steps involved in the MOGA algorithm can be stated as (for more details see (Goldberg, 1989; Fonseca and Fleming, 1998)):

(1) Initialise candidate solutions.
(2) Evaluate candidate solution performance using the objective function.
(3) Rank solutions according to the given multi-objective ranking procedure.
(4) Perform fitness sharing between individuals to prevent dominance by one group of solutions.
(5) Select solutions for reproduction using a stochastic sampling method that is weighted by their fitness (e.g. stochastic universal sampling) to form the Parent set.
(6) Apply mating restriction to the Parent set to prevent the occurence of lethals.
(7) Recombine Parent solutions to produce the Offspring solution set.
(8) Select the new candidate solution set from some combination of the Parent and Offspring set.
(9) Return to Step 2 and repeat until the termination criteria is satisfied.

Ranking that is solely based on Pareto-optimality gives equal weighting to each objective. In real-world problems certain objectives may be more important to satisfy than others. For instance many process plants will have hard constraints, violation of which will result in an emergency shutdown. A feature of the MOGA approach used in this investigation is the multi-objective ranking procedure, which gives the user the ability to articulate a preference for solutions beyond mere Pareto-optimality. Goal values, g are used to specify desired levels of performance (utilizing *a priori* knowledge), which the optimization must seek to satisfy:

$$\mathbf{g} = [g_1, g_2, \ldots, g_n] \tag{4}$$

where there is a goal value for all n evaluation functions and

$$\mathbf{f}(\mathbf{x}) < \mathbf{g} \tag{5}$$

Additionally, integer priority levels, p can be assigned to each individual objective to specify which are most important to satisfy.

$$\mathbf{p} = [p_1, p_2, \ldots, p_n] \tag{6}$$

Objectives that have hard constraints are assigned the highest priority level. Softer constraints can be assigned lower priorities according to operational requirements. This goal and priority information can be used to perform a relative ranking of the solution set. This ranking procedure can be explained by the comparison of two candidate solutions, $\mathbf{x}_1$ and $\mathbf{x}_2$:

(1) Initially the performance of $\mathbf{x}_1$ is compared to $\mathbf{x}_2$ in terms of the highest priority objectives where goals values (for $\mathbf{x}_1$) are *not* met.
(2) If the solution $\mathbf{x}_1$ out-performs $\mathbf{x}_2$ in terms of unsatisfied goals then it is said that $\mathbf{x}_1$ dominates $\mathbf{x}_2$ and is ranked relatively higher.
(3) If all goals are satisfied at the current priority level (or are violated to the same degree) then the next lower level priority objectives are considered and step 2 is repeated.
(4) Finally, if all goals at all priority levels are found to be satisfied and therefore the dominance of $\mathbf{x}_1$ over $\mathbf{x}_2$ cannot be decided using this information, then the lowest priority level objectives are compared in terms of Pareto-optimality.

Each solution can be compared to all other solutions in this way leading to a relative ranking of the entire population. This comparison basis is referred to as *preferability* and more details can be found in (Fonseca and Fleming, 1998). The significance of this ranking procedure is that solutions that most closely satisfy higher level priority objectives have a greater chance of propogating through the search.

3 Evaluating Plant Performance using Radial Basis Function Networks

An optimization study requires a way of testing and hence comparing potential solutions to find the best set according to the defined criteria. In this case a Radial Basis Function (RBF) network (Broomhead and Lowe, 1988) is used to evaluate the performance of the plant under different operational conditions. RBF networks are two-layer feed forward networks that are able to approximate any continuous non-linear function to an arbitrary accuracy (Bishop, 1995).

Given a set of of multi-input, multi-output data with m inputs, n outputs and N pairs of input and output training data vectors:

$$\mathbf{x}_t = \left\{x_1^{(t)}, x_2^{(t)}, \ldots, x_m^{(t)}\right\}, \quad t = 1, \ldots, N \tag{7}$$

$$\mathbf{y}_t = \left\{y_1^{(t)}, y_2^{(t)}, \ldots, y_n^{(t)}\right\}, \quad t = 1, \ldots, N \tag{8}$$

where $\mathbf{x}_t$ is an input vector and $\mathbf{y}_t$ is an output data vector. Output data can be transformed so that predictions are made more robust by ensuring that they are made within limits that are physically possible. In this case a sigmoidal transformation is used:

$$z_i^{(t)} = -\ln\left(\frac{1}{y_i^{(t)}} - 1\right), \quad i = 1, \ldots, n \tag{9}$$

If $\mathbf{z}_t$ can be said to be dependent on $\mathbf{x}_t$ then they can be related by a fixed functional mapping:

$$\mathbf{z}_t = f(\mathbf{x}_t) \tag{10}$$

In the case of an RBF network the input data set undergoes a non-linear transformation before mapping to the output via a set of weights. Specifically, a Gaussian RBF was used in this investigation of the form:

$$\phi_j(\mathbf{x}_t) = \exp\left(-\frac{\|\mathbf{x}_t - \mathbf{c}_j\|^2}{2\sigma^2}\right), \quad j = 1, \ldots, p \tag{11}$$

where σ is the width of each RBF, $\mathbf{c}_j$ is the centre of the j^{th} RBF. There will be p basis functions in total:

$$\Phi(\mathbf{x}_t) = [\phi_1(\mathbf{x}_t), \phi_2(\mathbf{x}_t), \ldots, \phi_p(\mathbf{x}_t)] \tag{12}$$

The expression relating inputs and outputs can therefore be stated as follows:

$$f(\mathbf{x}_t) = W^T \Phi(\mathbf{x}_t) \tag{13}$$

where W is the set of weights. The optimum set of weights, W^* can be found analytically from the least squares solution (due to the linear relationship between $\mathbf{z}$ and W):

$$W^* = (\Phi^T \Phi)^{-1} \Phi^T \mathbf{z}_t \tag{14}$$

The user must define the structure of the network such as the number of RBFs, location of centres and widths of RBFs. A computational search may be performed to assist in the network structure selection (see for instance (Billings and Zheng, 1995; Liu and Kadirkamanathan, 1999)).

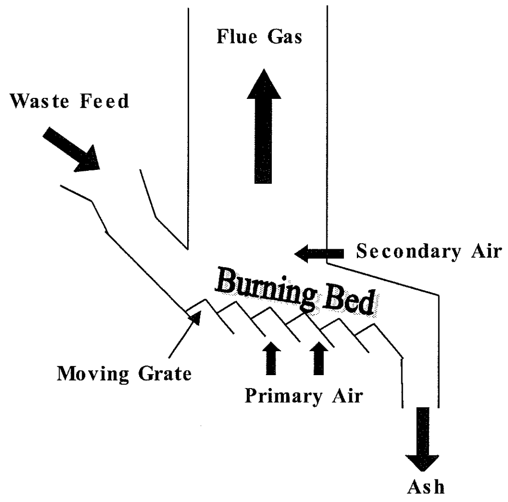

Fig. 1. Diagram of a typical municipal solid waste incinerator

4 Physical Model of a MSW Incineration Plant: FLIC

An MSW incinerator is required to thermally treat usual household waste such as cardboard, wood, glass, food wastes and tin cans etc. The operation of a typical moving grate, MSW incinerator is a simple process: mixed waste is picked up from a storage bin by a grabber and dropped down a chute that leads onto the burning bed. The waste is agitated along by a moving grate system (or by rollers). Primary air is fed from underneath the bed and secondary air into the region above the burning bed to further aid in combustion of particles carried up in the gas stream (see figure 1). The general process can be described as:

$$\begin{aligned} \text{Waste} \longrightarrow\ & \text{Volatile}(C_mH_n, CO_2, H_2O, O_2, CO,\ \text{etc.}) \\ & + \text{Char} \end{aligned} \tag{15}$$

FLIC (Yang et al., 2002) provides a comprehensive model of all variables (both input and output) of significance concerning the operation of the burning bed in a moving grate incinerator. FLIC utilizes transport equations governing flow, heat transfer and combustion of the solid and gas phases to describe the burning bed region. The individual equations governing the reactions are too numerous to list here and require detail beyond the scope of this paper, however, the interested reader may refer to (Yang et al., 2002) for more information. The combustion process can be summarized as follows (with appropriate mathematical model for each stage):

(1) Evaporation of moisture from the solid waste
(2) Waste devolatilization

Table 1
Set of input-output variables that can be set/predicted within the FLIC model

Inputs	**Outputs**
Moisture content of waste	Carbon-in-ash
Calorific value of waste	Carbon Monoxide
Waste feed rate	Nitrous Oxides
Residence time	Sulfurous Oxides
Primary air flow rate	Solids' temperature
Grate speed distribution	Gas temperature
Bulk density of waste	Hydrogen Chloride
Primary air distribution	Oxygen
Secondary air flow rate	Heavy metals

(3) Combustion of volatiles
(4) Gasification of char

with further models governing:

(1) Turbulent fluid flow
(2) Heat transfer in the gas-phase
(3) Heat transfer in the solid phase
(4) Radiation heat transfer in the bed

The differential equations contained within the models listed above are solved by iterative numerical methods, where the representation of the space of the burning bed is divided in many small sections forming a grid. The variables of interest are solved across this grid at the discrete points of intersection, where grid lines cross (also known as nodes). The only requirement for the solution of the model is that the boundary conditions at the input side of the grid are known, such as initial temperatures and waste composition.

A range of input and output variables can be described in the model and a typical selection of interest are shown in table 1. It should be noted that any of the variables listed in table 1 can be used in the optimization; the inputs comprise the decision variables, which must be adjusted for optimum operation. Objectives that define performance of the plant can be taken from both inputs and outputs, for instance minimization of emissions such as NO_x and SO_x (output variables) and maximization of waste feed rate (an input variable).

5 Performance Optimization of an Industrial MSW Incinerator

This performance optimization study investigates the use of MOGA applied to the model of an industrial MSW incineration plant. The following sections report on the problem definition, plant modelling and performance optimization.

5.1 Problem definition

The task was defined as follows; To find the set of parameter values for the operational input variables:

(1) Waste feed rate, x_f
(2) Residence time, x_r

that give optimal performance in terms of the following objectives:

(1) Maximising waste feed rate, $f_1(\mathbf{x}_1)$
(2) Minimising carbon-in-ash, $f_2(\mathbf{x}_2)$
(3) Performing within temperature constraints, $f_3(\mathbf{x}_3)$

where $\mathbf{x}_1 = [x_f]$ and $\mathbf{x}_2 = \mathbf{x}_3 = [x_f, x_r]$.

The decision variables and objectives chosen to illustrate the optimization method comprise only a small subset of possible objectives that impact on plant performance. Each objective is chosen as a representative of the the three objective categories of concern outlined in the introduction: economic, environmental and operational.

The maximization of waste feed rate is necessary to ensure profitability. Minimization of unburnt carbon in the combustion ash (carbon-in-ash) gives a measure of the reactivity of the bottom ash collected from the incinerator: high values of carbon-in-ash engender penalty costs when sent to landfill (if over certain limits), conversely nonreactive ash may be used in the construction industry, thereby creating a positive economic return. Temperature is chosen as an operational variable to constrain, which is a typical consideration in the operation of all waste incineration plants: excessively high temperatures may cause damage to the combustion chamber increasing maintenance costs; too low temperatures are undesirable for thorough burn-out of the waste. Peak solids' temperature was chosen as an indicator of the trend of temperature throughout the bed for different operating conditions.

Table 2
FLIC model parameters

Input Variable	Value
Moisture content (of waste)	41%
Fixed Carbon	7.7%
Volatiles	44.8%
Lower calorific value	12049kJ/kg
Bed length	7.4m
Grate speed distribution	Uniform
Number of primary air inlets	13
Primary air flow rate (per inlet)	31.3Nm^3/min

5.2 Incineration Plant Modelling

The FLIC model was initially set up to the physical specification and usual waste content of a particular Japanese MSW incinerator; a selection of values can be seen in table 2. All input variables were set to realistic values for a certain point of operation. The two decision variables investigated here (waste feed rate and residence time) were then varied within fixed limits about this point while other inputs were kept constant.

In the usual operation of an incineration plant primary air flow rate, as well as other variables, would be adjusted by the plant operator based upon factors such as maintaining the best fuel/air ratio. However, such variables were left to a constant value in this investigation as they are decision variables that are not included within the model and are not significant as regards illustrating the method of search. The important thing to note is that in a plant-wide optimization all variables of significance should be included to ascertain the best performance conditions.

A set of output data comprising carbon-in-ash, and peak solids' temperature was generated for a range of input data comprising waste feed rate and residence time from the FLIC model. The particular training and validation sets used are shown in figure 2. RBFs were centred on each training data point (appropriate in this case because of the approximately regular grid of data points (Powell, 1987)).

Two separate networks were trained (on normalised data) to predict values of carbon-in-ash and peak solids' temperature separately, which simplified the modelling procedure (widths of the basis function were adjusted to 0.4 and 3 respectively). The prediction surface was tested on the validation data with root-mean-squared-error (RMSE) = 0.45% for the carbon-in-ash prediction values and RMSE = 2.70 Kelvin (K) (5.86%) for temperature prediction

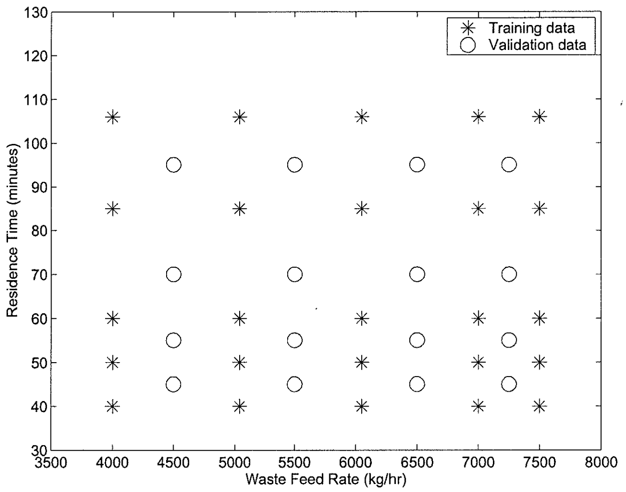

Fig. 2. RBF model training and validation data

values.

Figure 3 shows that carbon-in-ash varies in an approximately quadratic way at low residence time across all values of feed rate. This relationship changes as residence time increases to one that is approximately linear, with a slight increase in carbon-in-ash towards increased feed rate. The peak solids' temperature appears to have a more complex relationship with residence time and feed rate. The major trends can be explained by examining different relative combinations of these input conditions and consideration of further simulation parameters:

(1) Low residence time and low waste feed rate: low residence time means that waste quickly passes through the burning bed and in conjunction with low feed rates this implies that there is only a thin layer of waste (and therefore fuel) on the bed. The volume of primary air is kept constant for all conditions throughout this investigation and therefore there is an excess of air (in this region), which leads to a damping effect on temperature and reduced burnout of the waste, hence high carbon-in-ash and a fall in peak solids' temperature.
(2) Low residence time and high waste feed rate: under such conditions there is a large volume of waste passing quickly through the bed which has a direct negative impact on the efficiency of combustion, e.g. the depth of the bed is large therefore radiation through the bed is poor and there would be a relative lack of primary air for the amount of waste. This leads to poor burn-out of the waste and high carbon-in-ash. The extra fuel that is available (resulting from higher feed rate) compared to the lower feed rate values is able to utilize what was previously excess air therefore higher temperatures result. However, this amount of air is not sufficient for perfect combustion conditions, in which case you would expect to see

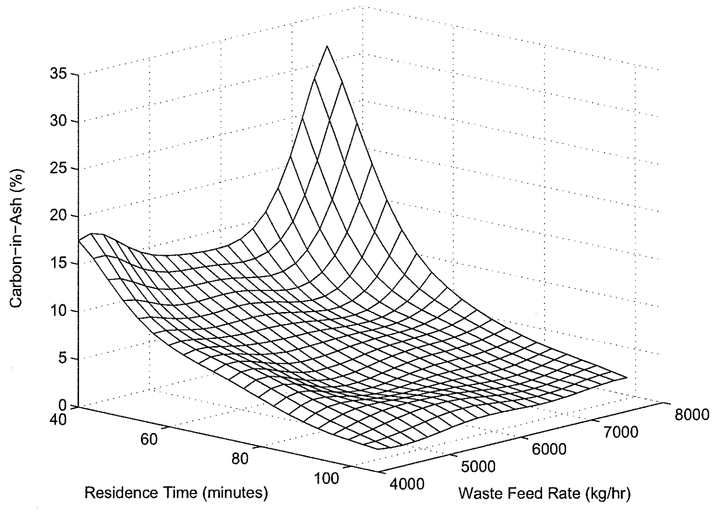

Fig. 3. RBF model of relationship between waste feed rate, residence time and carbon-in-ash

even higher temperatures.

(3) High to low residence time: figure 3 shows that carbon-in-ash falls with increasing residence time. This is simply explained as the waste has longer time to burn on the bed. The main trend in figure 4 shows that there is a rise then fall in temperature as the residence time increases. The drop in temperature at low residence times can be attributed to excess primary air. The fall in temperature towards higher residence time can be attributed to the increasing depth of the burning bed; heat energy must be radiated through a larger volume of waste and therefore temperature drops.

(4) High residence time and low to high waste feed rate: waste spends a long time on the burning bed allowing thorough combustion of the waste, hence low carbon-in-ash. The quadratic relationship appearing at lower residence time gradually shifts to a linear relationship with the increase in residence time. It appears therefore that residence time dominates the relationship with burn-out of the waste; in the limit as residence time is increased the waste will undergo thorough burn-out regardless of the feed rate, resulting in low carbon-in-ash.

5.3 Optimization results

The significant MOGA parameter values set in this investigation are shown in table 3; the MOGA was implemented using a multi-objective ranking modification of a Genetic Algorithm tool box for MATLAB (Chipperfield et al., 1994). A large population size was used in an attempt to fully cover the op-

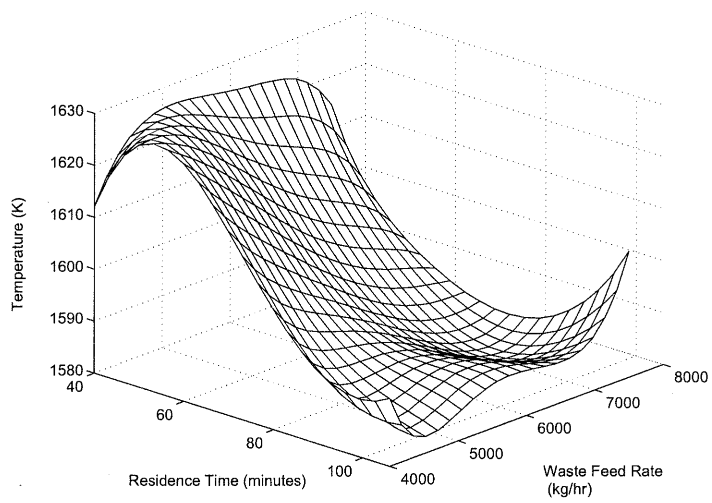

Fig. 4. RBF model of relationship between waste feed rate, residence time and peak solids' temperature

Table 3
MOGA search parameters

Parameter	Value
Number of generations	100
Population size	200
Crossover rate	0.7
Crossover function	Intermediate recombination
Generation gap	1.0
Selection function	Stochastic universal sampling
Population encoding	Real-valued
Selective pressure	2.0
Mutation probability	0.1

timal front. The number of generations was set to 100 as a robust cut-off after a preliminary analysis of the apparent convergence rate: Figure 5 shows a comparison of the Pareto-front (in terms of minimizing carbon-in-ash and maximising feed rate) found after the initialization of solutions, 10^{th} and 100^{th} generations (note that the figure is zoomed for clarity and therefore certain intial solutions are not shown, which come outside the figure limits). It is apparent from this figure that there is little difference between the solutions at the 10^{th} and 100^{th} iteration implying swift convergence. It should be noted that the true Pareto-optimal front is unknown in this problem and therefore only a relative assessment of convergence can be made as opposed to an absolute comparison. Further parameters such as cross-over rate were heuristically adjusted with experimentation.

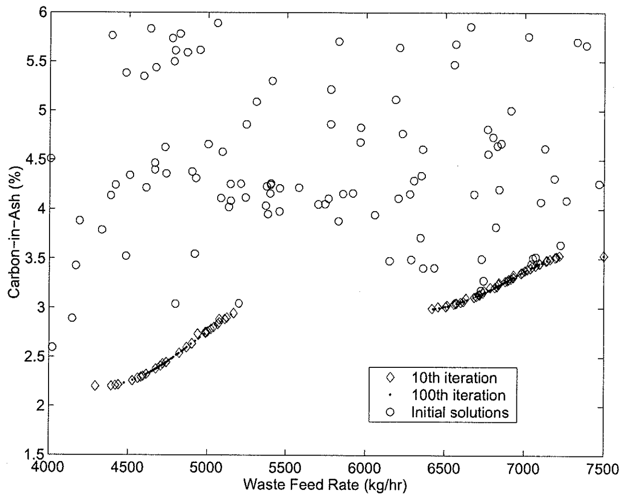

Fig. 5. Pareto-optimal solutions based on maximising waste feed rate and minimizing carbon-in-ash at various iterations throughout the search

5.3.1 Maximising Waste Feed Rate and Minimizing Carbon-in-Ash

Initially waste feed rate and carbon-in-ash were investigated in the optimization procedure, using Pareto-optimal ranking. The solution converged as expected to values of high residence time and a range of feed rate values (see figure 6). Figure 5 clearly shows the trade-off that is experienced between attempting to maximise feed rate and minimize carbon-in-ash.

The secondary significance of figure 5 is in the gap between regions of the solution: this shows that there is a region where feed rate can be increased (between 5200kg/hr and 6300kg/hr) and no significant degradation in performance is suffered in terms of carbon-in-ash. This can be attributed to the fact that the central region of operation, where there is a gap in solutions, coincides with pre-tuned values of other operational parameters, which were kept constant during the investigation. The implication is that in the region of tuned operating points carbon-in-ash is burnt out to a constant level. As the feed rate increases the carbon-in-ash level rises, due to poor combustion resulting from the lack of air. As the feed rate decreases it is seen that carbon-in-ash also falls. This may be attributed to the stoichiometric point shifting: at mid-feed rate and mid-residence time (the pre-tuned operating point) there is the same amount of fuel on the bed as at low feed rate and high residence time. At a constant air supply the stoichiometric point will shift with these changing conditions, improving burn-out to the region in which it moves to.

In waste incineration plant operation, *a priori* knowledge is usually available concerning desired levels of performance. Therefore it is helpful to include this in the search procedure in the way discussed previously via solution ranking using goal and priority information. Therefore goal values were set for feed

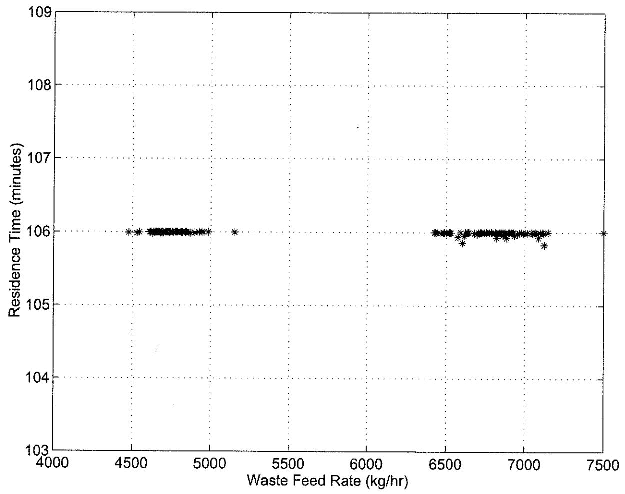

Fig. 6. Location of decision variables for Pareto-optimal solutions based on maximising waste feed rate and minimizing carbon-in-ash

rate to maximize beyond, g_1 and carbon-in-ash, g_2 to minimize below.

$$g_1 = 7000\text{kg/hr}$$
$$g_2 = 6\%$$

Priority levels for feed rate, p_1 and carbon-in-ash, p_2 were kept equal as both variables are arguably equally desirable to optimize ($p_1 = p_2 = 0$). The optimization was then repeated using ranking based on the *preferability* method (Fonseca and Fleming, 1998).

The results of the search are shown in figure 7. It is apparent that the region of the optimal front shown in figure 5 has been reduced to lie only in the area above the feed rate goal. There is a significant gap in the solution between 7200kg/hr and 7500kg/hr. With reference to figure 4 this can be explained as follows: there is a temperature rise towards the region of highest feed rate and highest residence time. This accounts for the lack of rise in carbon-in-ash (higher temperatures imply improved combustion therefore improved burn-out of waste).

5.3.2 The effect of operational constraints on optimization decisions: peak solids' temperature

The optimization for finding maximum feed rate and minimal carbon-in-ash was repeated with the addition of upper and lower temperature limits. Such limits in plant operation are often classed as hard constraints where violation results in a plant shut-down. The satisfaction of temperature limits was therefore classed as a higher priority objective, p_3 over feed rate and carbon-in-ash

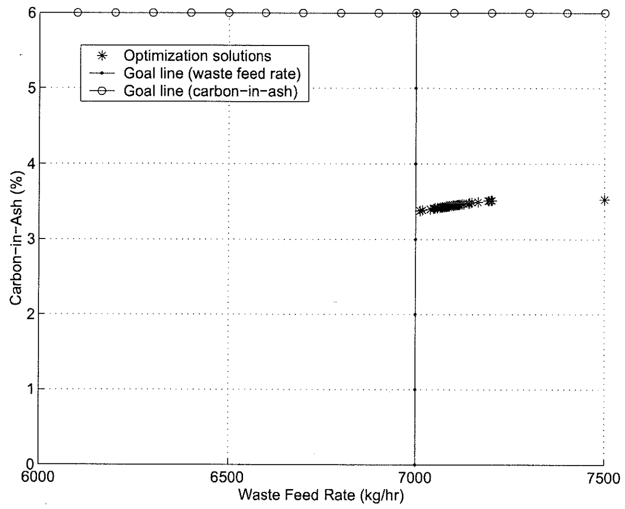

Fig. 7. Preferred optimization solutions (based on goal and priority information) for maximising waste feed rate and minimizing carbon-in-ash

($p_1 = p_2 = 0$ and $p_3 = 1$). The upper, g_{3u} and lower, g_{3l} temperature limits were defined to lie in the central region of operation (usually plants are required to operate away from extremes) and were specifically chosen as:

$$g_{3u} = 1615K$$
$$g_{3l} = 1605K$$

The results from the optimization show that all preferred solutions lie within the temperature goal bounds (figure 8) and the carbon-in-ash and waste feed rate solutions are shifted from the initial study (section 5.3.1) accordingly (figure 9). It is apparent from figure 9 that the optimal front is attempting to find the region in the lower right portion of the graph where both carbon-in-ash and feed rate goals are satisfied. However, the front does not cross into this preferred region (due to the temperature being too low in that area of operation) and therefore the solutions are strung across from low feed rate and high carbon-in-ash, to high feed rate and high carbon-in-ash.

There is a steep increase in the carbon-in-ash at feed rates between 6500kg/hr and 7000kg/hr. This corresponds to the constrained temperature band entering the region of low residence time and high feed rate (the resulting increase in carbon-in-ash for these conditions can be seen in figure 3 and is explained in section 5.2).

A feature of the results between feed rates of 4000kg/hr and 6500kg/hr is the gap in solutions; these show regions where increases in feed rate can be made with only a small penalty in increasing carbon-in-ash and occur mainly in two sections: either side of the mid-region of operation from 4200kg/hr

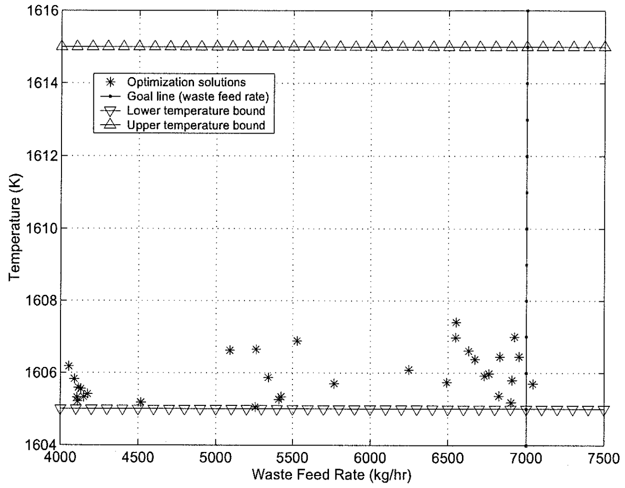

Fig. 8. Preferred optimization solutions (based on goal and priority information) for maximising waste feed rate, minimizing carbon-in-ash and constraining peak solids' temperature: in terms of waste feed rate and peak solids' temperature

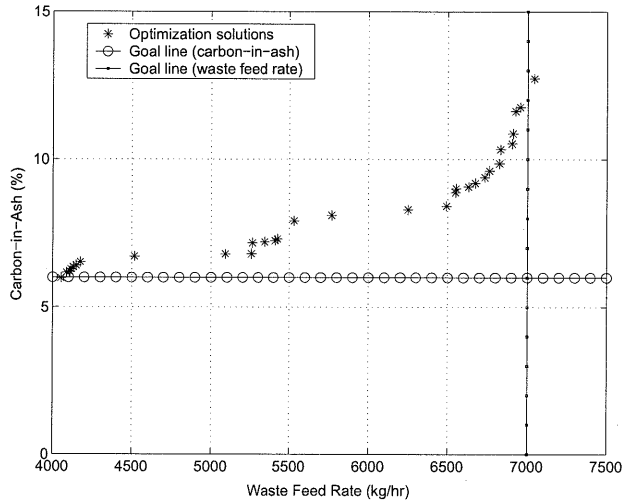

Fig. 9. Preferred optimization solutions (based on goal and priority information) for maximising waste feed rate, minimizing carbon-in-ash and constraining peak solids' temperature: in terms of waste feed rate and carbon-in-ash

5250Kg/hr and from 5500kg/hr to 6500kg/hr. The mid-region, where a swifter increase in carbon-in-ash is seen (relative to feed rate change), may appear to contradict the results in figure 5 where it was assumed that a small deviation about the 'tuned' operating point causes only a small change in the output. However, it is actually because of this insensitivity (of carbon-in-ash variation) to changes in feed rate about the mid-point that this occurs: figure 10 shows that temperature contours coincide with carbon-in-ash contours immediately above and below the mid-region of feed rate operation (note that the residence time scale is inverted to provide easy comparison with figures 3 and 4). This

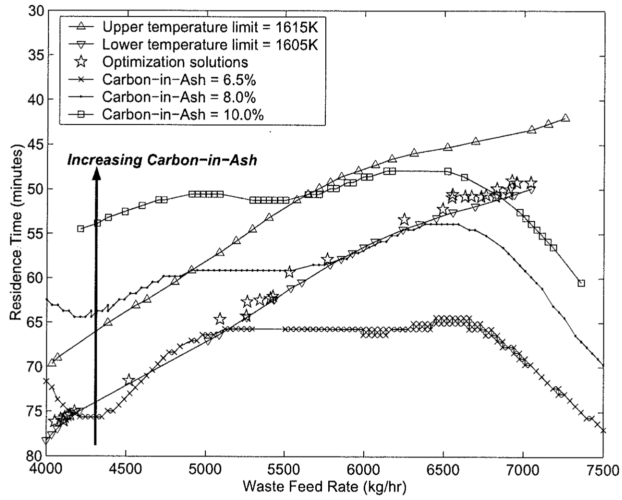

Fig. 10. Preferred optimization solutions in terms of waste feed rate and residence time, showing contours of temperature constraints and contours of carbon-in-ash

shows why there are gaps in the solution: solutions are able to move along temperature contours in the direction of increasing feed rate without suffering a penalty in increasing carbon-in-ash. However, in the central region (between feed rate values of 5000kg/hr and 5500kg/hr) the carbon-in-ash contours do not coincide with the temperature contours. Therefore solutions are forced by the temperature constraints across increasing levels of carbon-in-ash.

The implication of these results is that the relationship between feed rate, residence time and temperature is approximately constant (in the region of the optimization solutions) and can be explained as follows: a decrease in residence time results in waste leaving the bed faster and therefore an increase in feed rate is required to maintain the same amount of fuel on the bed and hence a certain temperature. The further implication is that the relationship between feed rate, residence time and carbon-in-ash varies in a more complex way: as stated earlier the reason for a central carbon-in-ash region that does not vary with changes in feed rate is probably due to the fact that conditions for optimum combustion (in terms of fuel/air ratio) are met in this region and slight deviations about this point still produce good burn out of the waste.

6 Conclusion

An optimization scheme for improving the operation of a generic waste incineration plant has been designed using a multi-objective evolutionary algorithm (specifically MOGA). The method was illustrated on the model of a MSW incineration plant (where the modelling was accomplished using radial basis functions). In this investigation a subset of typical important operational parameters and objectives were utilized to demonstrate the method. The approach will allow for extension to any further variables deemed useful to include (such as minimization of NO_x and SO_x), providing a potential plant-wide optimization procedure. It may also be applied, given suitable data, to any type of waste incineration facility.

Results from the simulation studies have demonstrated how the inclusion of additional constraints or objectives may lead to a different solution region; this often appears to take the form of distinct regions. The technique of Pareto-optimal ranking combined with goal and priority information has been shown to be ideally suited to this type of problem where a number of conflicting operational considerations must be taken into account by the plant operator. In conclusion, the use of MOGA to improve waste incinerator operation facilitates a robust plant-wide optimization procedure, across a non-linear search space linking multiple decision variables, objectives and constraints that can be easily interpreted by a plant operator and used to improve performance.

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