Intelligent Control of Waste Incineration Plants

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Introduction

Incineration is currently 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. Pollution may effectively be controlled to within acceptable limits, although improvements are constantly being sought.

Gas clean-up technologies and the control systems that they interface with are continuously undergoing improvements to meet ever more stringent regulations. Inefficient control at the incineration stage can place a strain on the gas clean-up and effluent treatment systems, which inevitably leads to a degradation in overall performance. This can result in excursions over emission constraints and higher maintenance costs as the system is more frequently operated to its limit.

Multi-Objective Optimisation of an MSW Incinerator

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 optimise plant operation in terms of economic goals and environmental and operational constraints.

This section presents an off-line optimisation scheme, using a Multi-Objective Genetic Algorithm (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 optimisation procedure is independent of both 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.

FLIC Modelling

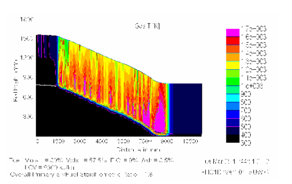


Figure 1 – Typical FLIC output graph, showing gas temperature throughout the bed

- Fluid dynamic Incinerator Code (FLIC) is an incinerator burning bed software simulation package, based on a fundamental mathematical model.
- A wide range of different real-world incineration plants can be represented in the model.
- FLIC can generate prediction values for a range of output variables.
- Computational time is too long (40-60 minutes for one set of solutions) for direct use in a search.
- A range of data can be generated for use in a further modelling approach that can interpolate between the data points.

Neural Network Modelling

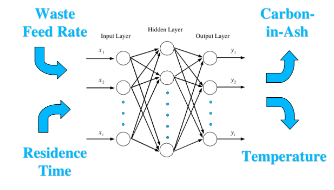


Figure 2 – Representation of the multi-input multi output neural network model

- Artificial Neural Networks (ANNs) are a non-linear function approximation tool that can be used to interpolate between discrete data points.

$$y = f(x)$$
$$f(x) = W^T \Phi(x)$$

- A Radial Basis Function (RBF) network is a 2-layer ANN that transforms the input data using an RBF such as a Gaussian in the hidden layer.

$$\phi(x) = \exp\left(-\frac{\|x-c\|}{2\sigma^2}\right)$$

- The training procedure, to calculate the network weights, is equivalent to minimising the least-squared error cost function.

$$W = (\Phi^T \Phi)^{-1} \Phi^T y$$

MOGA Optimisation

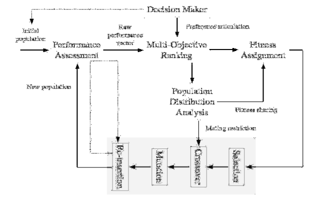


Figure 3 – The MOGA algorithm

- The MOGA is a directed evolutionary search algorithm, which is based on the Darwinian principle of 'survival of the fittest'.
- A population of points are propagated, which allows the problem domain to be searched in parallel.
- An objective function, F(X) is used to evaluate the performance of candidate solutions, which may be comprised of multiple decision variables, X seeking to satisfy multiple objectives.

$$X = (x_1, x_2, \ldots, x_i)$$
$$F(X) = (f_1(X_1), f_2(X_2), \ldots, f_j(X_j)) \quad X_j \subseteq X$$

- The technique of Pareto-optimal ranking ensures the survival of individuals, X* that are fit in all objective categories.

$$X^* = \arg\min F(X)$$

Neural Network Modelling Results

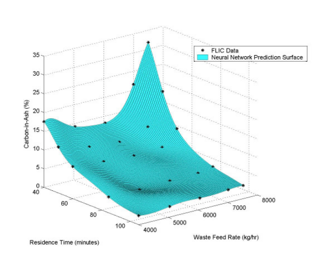


Figure 4 – Neural network model relating input variables Residence Time and Waste Feed Rate with output Carbon-in-Ash

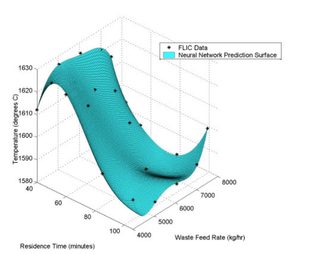


Figure 5 – Neural network model relating input variables Residence Time and Waste Feed Rate with output Peak Solids' Temperature

Unconstrained Optimisation

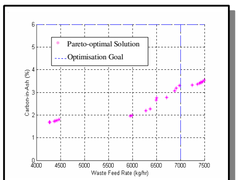


Figure 6 – Set of Pareto-optimal solutions for Waste Feed Rate and Carbon-in-Ash

- An unconstrained optimisation has been carried out to find plant settings that both minimise carbon-in-ash and maximise waste feed rate.
- A range of Pareto-optimal decisions have been found that a human operator may choose between based on current desired performance.

Constrained Optimisation

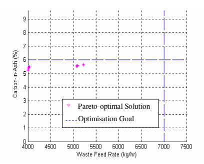


Figure 7 – Set of Pareto-optimal solutions for Waste Feed Rate and Carbon-in-Ash

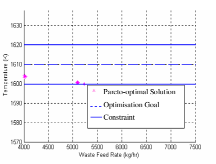


Figure 8 – Set of Pareto-optimal solutions for Waste Feed Rate and Temperature

- A constrained optimisation has been carried out to find plant settings that minimise carbon-in-ash, maximise waste feed rate and ensure that solutions exist in a suitable temperature range.
- The solution has altered dramatically in terms of the carbon-in-ash and feed rate objectives. This emphasises the potential necessity of including all constraint information in the optimisation, to minimise the risk of damaging excursions during operation.

Dynamic Modelling of a Hazardous Waste Thermal Treatment Plant

A hazardous waste thermal treatment facility must be operated within tightly controlled constraints to ensure Environment Agency compliance for safe operation. Data collected from a plant can be used in a dynamic modelling procedure to derive specific knowledge of the process. This can then be used to improve performance whilst keeping within operational constraints. Data from a UK hazardous waste thermal treatment plant has been collected to enable such a modelling procedure.

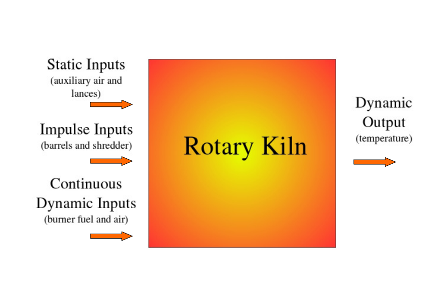
This section presents results from using linear dynamic modelling techniques. The inputs have been sub-divided on the basis of steady-state effects, discrete impulse-like transients and continuous-time transients. A single input-single output model has been extracted from the available data coupling burner fuel flow and air flow. The resulting model is suitable for use in a control system design application.

Linear Dynamic Modelling

- A black box procedure can be used to model the dynamics of a system.
- A common structure is that of ARX (Auto-Regressive with eXogenous inputs).
- The ARX model assumes that future outputs of the system can be described by a linear combination of past inputs and outputs.

Auto-Regressive (Output description e.g. temperature) with eXogenous Inputs (e.g. fuel and combustion air)

$$y(t) + a_1 y(t-1) + \ldots + a_{n_a} y(t-n_a) = b_1 u(t-1) + \ldots + b_{n_b} u(t-n_b) + e(t)$$



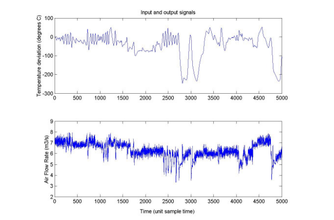


Figure 10 – Set of data for single input-single output modelling with Air Flow Rate as the input and Temperature Deviation as the output (sample time = 5s)

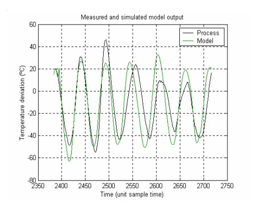


Figure 11 – Model predicted output using training data (sample time = 5s)

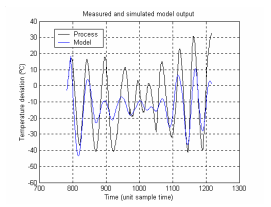


Figure 12 – Model predicted output using validation data (sample time = 5s)

Conclusions

- A static optimisation method, using multi-objective genetic algorithms, has been developed that gives the human operator a wide choice of Pareto-optimal decisions for running the plant.
- Linear dynamic models have been developed that can be utilised in a preliminary control system design.
- Future work has been motivated in the area of non-linear dynamic modelling, due to the seeming inability of linear models to cope with certain aspects of the plant dynamics.

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