Computational Intelligence Methods for the Optimisation of Thermal Waste Treatment

Dr. Hubert B. Keller, Dipl.-Inf. Andreas Fick, Dipl.-Ing. Eugen Kugele, Dipl.-Inf. Bernd Müller
Forschungszentrum Karlsruhe, Institut für Angewandte Informatik,
Postfach 3640, D-76021 Karlsruhe,
Phone: ++49-7247-825756, Fax: ++49-7247-825730
email: keller@iai.fzk.de

ABSTRACT: The paper presents several approaches to the optimisation of grate furnaces used for thermal waste treatment. Improvements are achieved by application of methods from fuzzy control, neural networks, infrared image processing, and machine learning.

KEYWORDS: thermal waste treatment, fuzzy control, neural networks, infrared image processing, machine learning, machine modelling.

1 INTRODUCTION

Thermal waste treatment [Keller (1996b)] serves to exploit the energy contained in waste not fit for recycling, and to convert solid constituents into inert, reusable slag. The objectives of optimising the design and operation of solid waste incineration plants lie in the **continuous generation of steam and heat, in minimum pollutant emissions, and optimum burnout.** Most materials are very heterogeneous with respect to their calorific value, composition, and component size. This gives rise to pronounced fluctuations in the ignition and combustion behavior of solid waste, in furnace temperature, heat release, steam generation, and in pollutant concentrations in the untreated flue gas. The composition of the material to be incinerated cannot be measured. Consequently, control based on a detailed combustion technology model is not feasible, and the standard measurements obtained don't allow optimum control. The use of innovative information technologies of computational intelligence as described below, such as fuzzy control, neural networks, imaging processes, and machine learning, in controlling solid waste incineration plants greatly improve process management.

2 FUZZY CONTROL OF BURNOUT

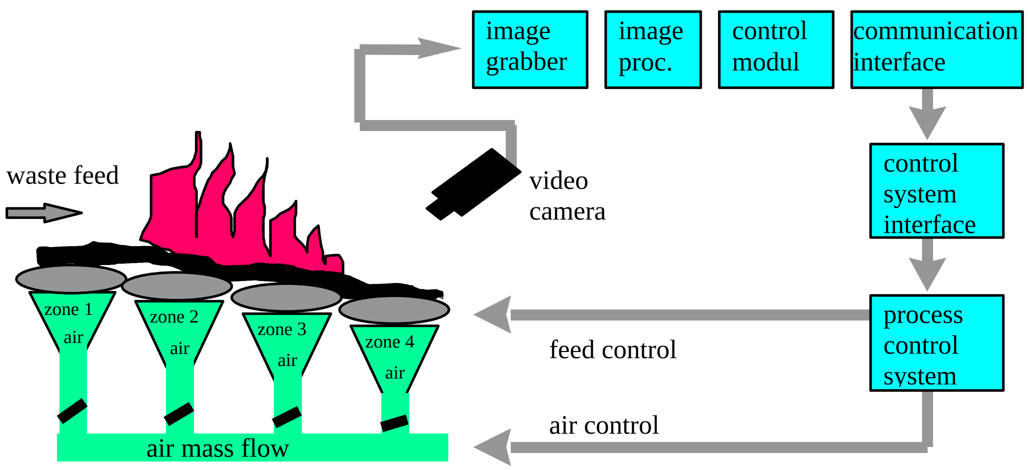

Figure 1 : Structure of the camera based burn out control system.

Solid municipal waste incineration plants mainly use grate furnaces. Again and again, this gives rise to situations in which unburned waste components move from the main combustion area into the burnout area. To prevent this from happening, a **fuzzy control system** [Figure 1, Müller (1998)] was developed for visual processing of perspective images of the burnout zones and for appropriate control of air supply and feed. The fuzzy controller recognises unburned material from the burning surface and the intensity related to that surface, and accordingly changes the air supplied to the grate. In the current version, also feed in the last zone is controlled depending on the situation. The system has been found to work excellently in the on-line closed-loop mode of an industrial-scale solid municipal waste incineration plant.

3 NEURAL NETWORKS FOR CONTROLLING FURNACE PERFORMANCE

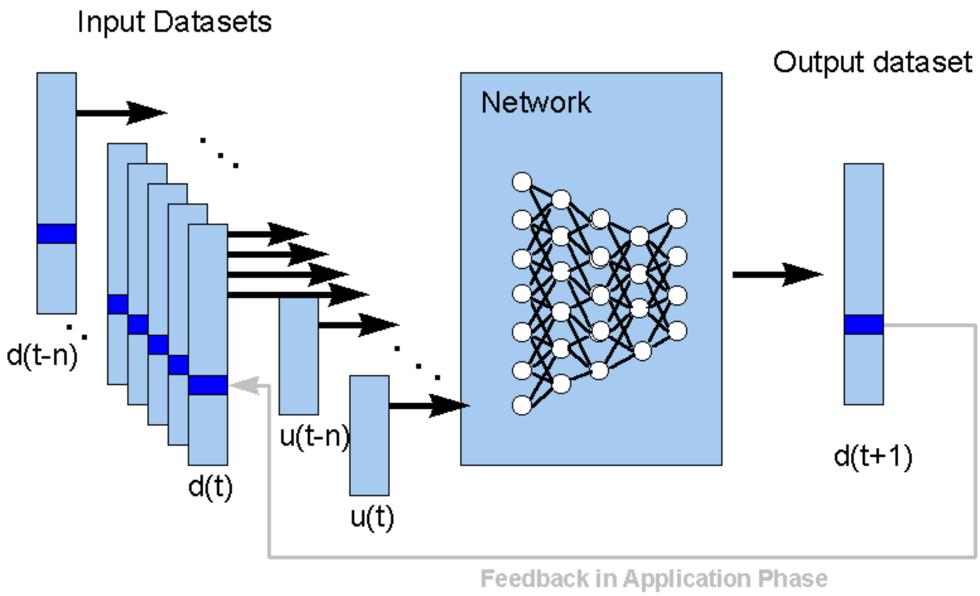

Figure 2 : Using a neural network for simulation (input variables “u”, state/output variables “d”, time steps “t”).

To improve the combustion process and, hence, reduce pollutant emissions from solid waste incineration plants, it is also possible to model and simulate the process by **neural networks**. A high-level control algorithm uses a neural network as a simulator [Figure 2, Keller (1996a)] to calculate input variables which produce a desired process state with respect to the set points of certain reference variables. In this case, the only reference variable is the steam output.
In this case, a correction term is calculated from the difference between the network output as the forecast value and the set value, and this correction term is propagated back to the input variables applied to the network. New input variables are calculated in analogy with learning new weights in the back propagation algorithm. The parameters so determined comprise the feed rate of the grate, the amount of waste fed, and the amount of air supplied.
Multiple applications of the manipulated variables to the simulation process build up an intervention sequence. A quality function determines whether this sequence is meaningful, and the temporary setpoint is modified. This iterative process continues until a satisfactory sequence of actions has been found. Only then the input variables determined will be transferred to the operator as control proposals by means of a user interface. An on-line open-loop test installation has shown this control approach to succeed. Work still needs to be done on a multi-model with the ability to switch between different models (neural nets) according to process states in order to determine an optimal control strategy – depending on the situation (Figure 3).

4 INFRARED IMAGE PROCESSING FOR GENERATING VISUAL MEASURED QUANTITIES

Other work relates to deriving additional visual quantities and to their partial integration into the neural model. **Additional visual quantities**, which can be used just like directly measured quantities, are derived to characterise the furnace condition and the intensity of combustion. For this purpose, object recognition algorithms etc. must be used. Sub-areas are combined by means of dilatation and erosion. Subsequent control then can be achieved by means of controllers existing in the process instrumentation and control system or by using an additional fuzzy controller.

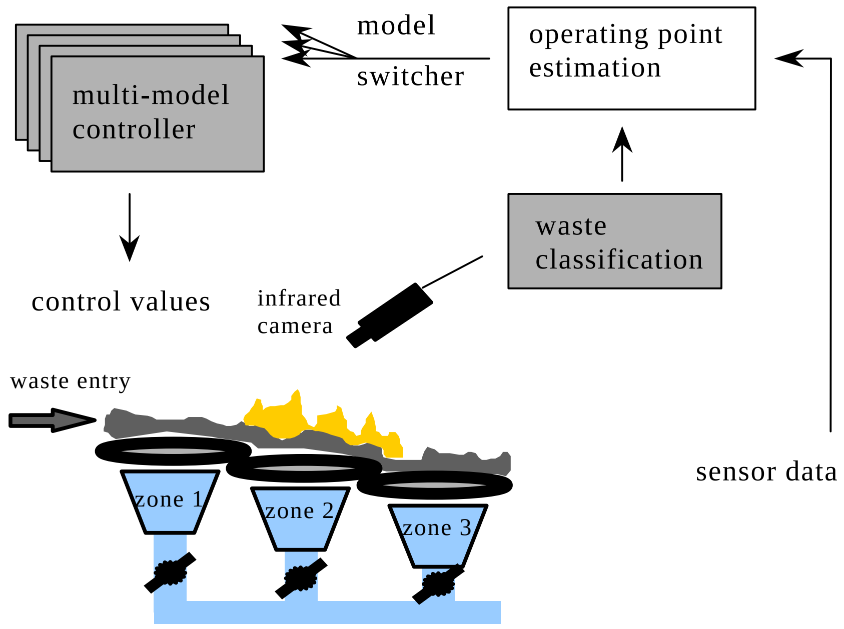

Figure 3 : Neural Process control with waste classifier and multiple models.

Deviations in simulation of the combustion process because of the unknown variable "change in type of waste" (calorific value, moisture, and size) are to be corrected by integrating image information (detection of systems status). Infrared images or video images are decomposed into tiles of equal size. A neural network is trained with these tiles; subsequent classification results in class lists of the sample images and representatives of the classes found. The class lists serve to **characterise image contents** in the form of additional **image-based measured values**. This information resolves existing ambiguities in the standard measured quantities, allowing more precise simulation and, hence, control of the process.

5 MACHINE MODELING

The C^3R system [Figure 4, Weinberger (1995), Keller (1995)] has been developed for machine modelling of process dependencies. It is characterised by a combination of symbolic (machine learning), subsymbolic (analogous to neural networks), and purely numerical (clustering) processes.

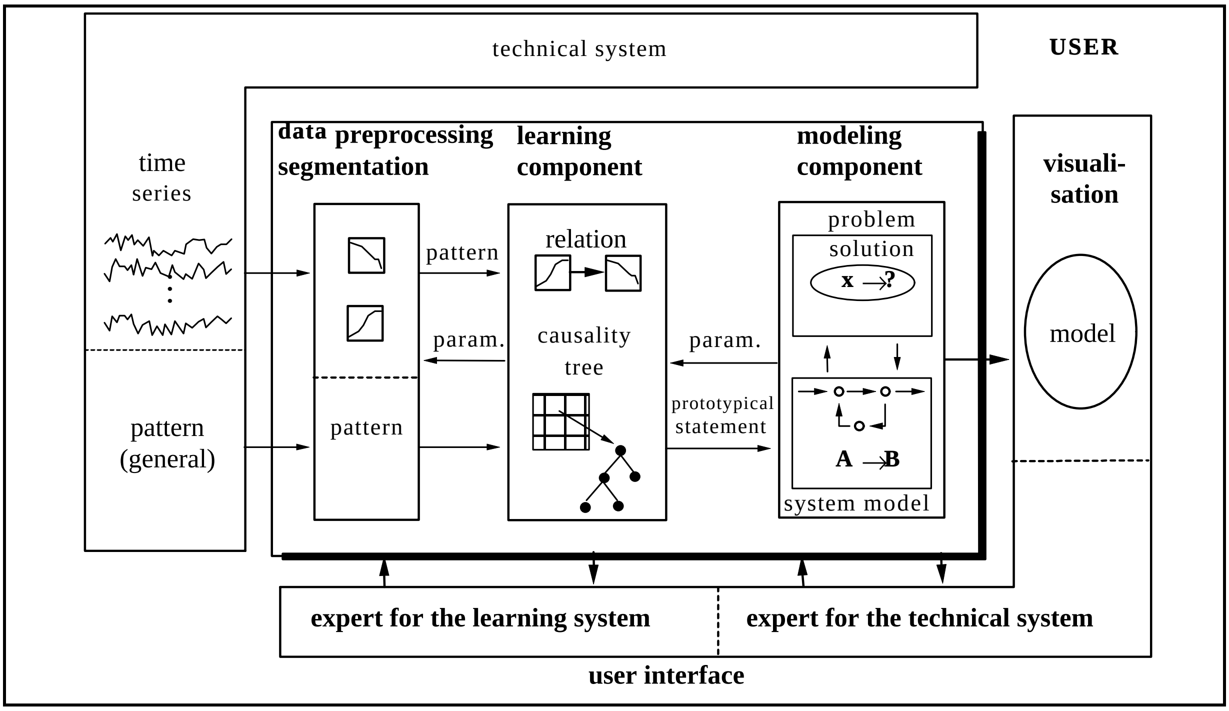

Figure 4 : C^3R system structure.

The inputs into the C^3R system are time series of the quantities measured or direct samples of observable quantities from the (technical) system. The system has several adaptive dynamic parameters for which initialisation values can be entered. The output of the C^3R system is a visualisation of the cause-effect relationships recognised in the form of a (directed) causality graph (Figure 5) and a representation of the functional dependencies by a set of approximate local rules (fuzzy rules).

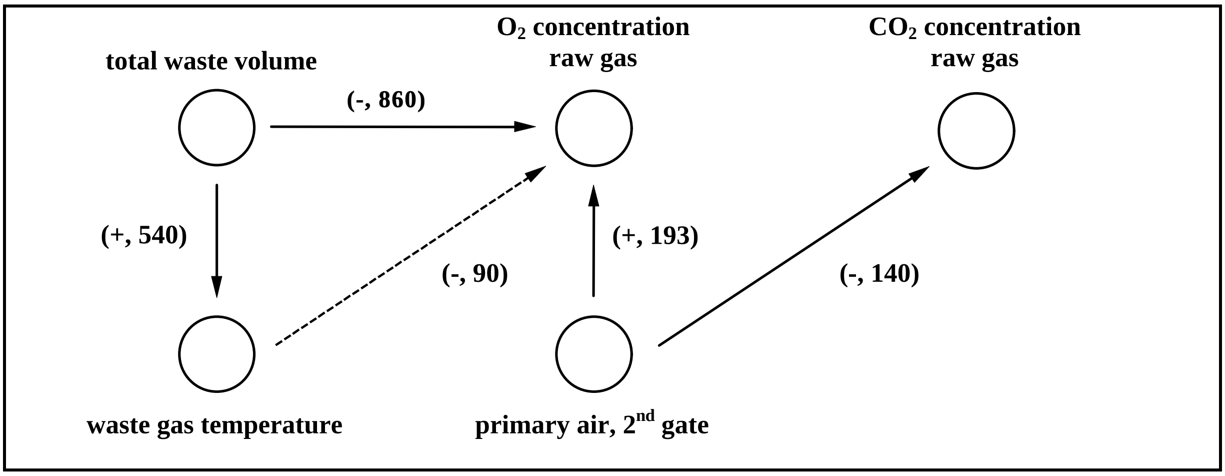

Figure 5 : Causality graph of the TAMARA experiment. (“+” and “-“ indicate positive or negative direction of influence (parallel / opposite), numbers indicate average time delay.)

6 CONCLUSION

The application of Computational Intelligence methods offers a very promising way to optimise thermal waste treatment. While this has already been proved for single methods, the next step will consist of the combination of different methods together with advanced data analysing techniques like image processing.

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