# Artificial Intelligence-Based Modeling and Control of Fluidized Bed Combustion

Enso Ikonen* and Kimmo Leppäkoski

*University of Oulu, Department of Process and Environmental Engineering, Systems Engineering Laboratory, FI-90014 University of Oulu, P.O.Box 4300*

## 1 Introduction

AI-inspired techniques have a lot to offer when developing methods for advanced identification, monitoring, control and optimization of industrial processes, such as power plants. Advanced control methods have been extensively examined in the research of the Power Plant Automation group at the Systems Engineering Laboratory (for an overview, see Ikonen & Kovacs 2007), e.g., in fuel inventory modelling, combustion power control, modelling and control of flue gas oxygen, drum control, modelling and control of superheaters, or in optimization of flue-gas emissions (Ikonen et al. 2000; Benyo et al. 2006; Najim et al 2006).

Most engineering approaches to *artificial intelligence* (AI) are characterized by two fundamental properties: the ability to learn from various sources and the ability to deal with plant complexity. Learning systems that are able to operate in uncertain environments based on incomplete information are commonly referred to as being intelligent. A number of other approaches exist, characterized by these properties, but not easily categorized as AI-systems. Advanced control methods (adaptive, predictive, multivariable, robust, etc.) are based on the availability of a model of the process to be controlled. Hence *identification* of processes becomes a key issue, leading to the use of adaptation and learning techniques. A typical learning control system concerns a selection of learning techniques applied for updating a process model, which in turn is used for the controller design. When design of learning control systems is complemented with concerns for dealing with uncertainties or vagueness's in models, measurements, or even objectives, particularly close connections exist between advanced process control and methods of artificial intelligence and machine learning.

## 2 Objectives of the research

Needs for advanced techniques are typically characterized by the desire to properly handle plant non-linearities, the multivariable nature of the dynamic problems, and the necessity to adapt to changing plant conditions. In the field of fluidized bed combustion (FBC) control, the many promising applications arise from the uncertainties and complexity of the combustion process, and the difficulties in obtaining reliable measurements from the changing furnace conditions. In our works, research on the application of AI techniques on the FBC have been conducted on fields such as modelling of FBC flue gas emissions from data using distributed logic processors, on-line identification of multi-fuel FBC NOx emissions using adaptive prototypes, modelling combustion in FBC using Wiener and Hammerstein models, or multivariable FBC trajectory control using genealogical decision trees. Currently work focuses on applications of controlled finite Markov chains in this area.

*Corresponding author, E-mail: enso.ikonen@oulu.fi

## 3 Results

First, general experiences of applying AI-based approaches are summarized, followed by results on applying controlled finite Markov chains in multivariable FBC control.

### *3.1 AI-based control*

A variety of AI-inspired techniques have been examined in power plant applications, including sigmoid neural networks, Kohonen self-organizing maps, fuzzy relational models, stochastic learning automata, population based optimization schemes, and their hybrid combinations; together with comparisons and combinations with more conventional techniques. From function approximation point of view, many of the AI-inspired model structures can be classified as a modification of a basis function network approach (Ikonen and Najim, 2002). Often, the related learning problems can be efficiently solved using 'conventional' gradient-based techniques. On the other hand, population-based stochastic techniques provide extremely flexible tools for solving efficiently both difficult and also more simple optimization problems, both for 'conventional' and AI-inspired model structures. However, application of techniques of machine learning (etc.) alone is not sufficient. Instead, the fusion of process knowledge with intelligent learning and interpretation are keys to the successful development of feasible techniques and profitable applications.

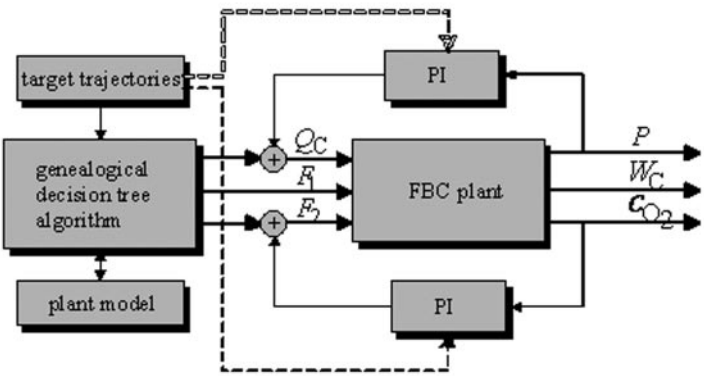



**Figure 1** FBC control with open-loop optimization and two feed-back loops (Ikonen & Kovacs 2007)

### *3.2 Controlled finite Markov chains*

Development of physical plant models typically results in models that do not easily lend themselves for process control design. The finite Markov chains provide a set of techniques which can cope with a large class of nonlinear systems, yet providing straightforward means for developing optimal controllers (Snell & Kemeny 1960, Bertsekas 2007). The basic idea is simple. The system state space is discretized into a finite set of states (cells), and the evolution of system state in time is mapped in a probabilistic manner, by specifying the transition probabilities (counting the observed transitions) from domain cells to image cells. With controlled finite Markov chains (CFMC), the transitions from each domain cell–action pair are mapped. It is straightforward to construct such a model by simulating a physical model, for example. Once equipped with such a CFMC model, a control policy can be obtained by minimizing a cost function defined in a future horizon, based on a specification of immediate costs for each cell–action pair. Immediate costs allow versatile means for characterising the desired control behaviour. Dynamic programming, studied in the field of Markov decision processes (MDP), offers a way to solve various types of expected costs in an optimal control framework. Applications of MDP in process control have been few; instead, the closely related model predictive control paradigm is very popular in the process control community. Whereas not-so-many years ago the computations associated with finite Markov chains were prohibitive, the computing power available today using cheap office-pc's encourages the re-exploration of these techniques.

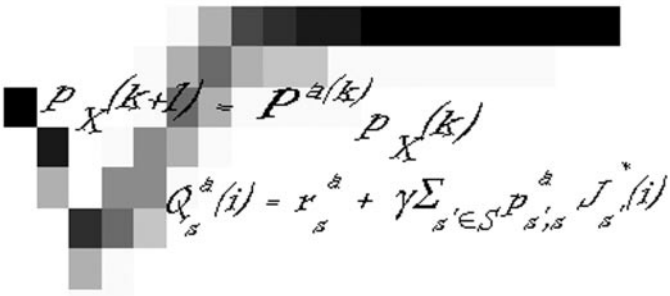



**Figure 2** Controlled finite Markov chains model the evolution of process state as a discrete chain with probabilistic transitions. Control task is formulated as an optimization problem.

In a numerical study, a multivariable control design was constructed for the secondary air system in a fluidized-bed combustor. A four-input four-output system control problem was formulated as a CFMC problem, and solved using dynamic programming. A non-linear Wiener model for the process, developed in earlier studies, was used in this model-based design. The results were compared with those from a gain scheduled system with multiple SISO PI controllers. The interactions between the controllers could be properly handled in the multivariable CFMC scheme. A major problem in the application of CFMC-based approaches is due to the need to discretize the state and control spaces; in a multivariable problem then easily results in an explosion in the memory and computing capacities required for solving the problem numerically. The study indicated, however, that the CFMC modeling and optimal control design approach could be applied in a moderately large control problem, with a commonplace office PC as a computing platform. The many issues related to the exploitation of the tools for handling uncertainties are a central topic to be examined in our future works.

## 4 Relevance of the research

Process control is not just a matter of algorithmic signal manipulation. First of all, the idea of how to control the plant must be physically viable. This requires at least a basic understanding of the characteristics of the process (plant), the physical and chemical phenomena that occur, and which are to be affected by the manipulations. Second, the means for implementation and analysis of the control are to be selected. Plant control can be roughly categorized into three tasks: regulation (automatic control with feedback), control (servo behaviour with at least some degree of supervision by operators), and optimisation (initiated and implemented under supervision, often using complex constrained long-term or steady-state cost functions). Depending on these choices, different requirements are posed on the algorithms.

Issues on nonlinearities, uncertainties, or learning can only be considered after a careful lay-out of the first two stages. In regulation, the inclusion of AI-based techniques is often limited, as the requirements of stability and robustness are essential (robustness – adaptation dilemma). Rather, an effort should be focused in keeping the control structures simple. In servo control, adaptation of simple models (under constraints) can be considered, resulting in adaptive control (auto-tuning, indirect/direct adaptive control, e.g., predictive control.) In a complex system, proper design of servo controls includes taking into account uncertainties, and interactions with other controls, lockings, etc. In optimisation (high level control), 'full scale' AI applications are more viable. At this level a sufficient variety of information is available, time is less critical, and the 'intelligence' in the systems can be exploited by the human users. In two-way interfaces, the interaction can be enhanced with the use of advanced techniques of artificial intelligence, e.g., in improving the explanatory status of models using rule-based representations, or in data mining with applications in process monitoring, in simulation associated with numerical plant optimisation routines, in taking into account the uncertainties related to dynamic optimization tasks, and many more.

**References**

Benyo I, Paloranta M, Kovacs J and Kortela U (2006) Cascade generalized predictive controller: two in one. *International Journal of Control* 79 (8) 866–876.

Bertsekas D (2007) Dynamic Programming and Optimal Control, Athena Scientific.

Ikonen E and Leppäkoski K (2009) Model-Based Multivariable Control of a Secondary Air System Using Controlled Finite Markov Chains. IFAC Symposium on Power Plants and Power Systems Control, 5–9 July, 2009, Tampere, Finland.

Ikonen E and Kovacs J (2007) Learning Control of Fluidized-Bed Combustion Processes for Power Plants. In: Kalogirou S (Ed) Artificial Intelligence in Energy and Renewable Energy Systems, Nova Science Publishers, 395–438.

Ikonen E and Najim K (2002) Advanced Process Identification and Control. Marcel Dekker, New York, 310 p.

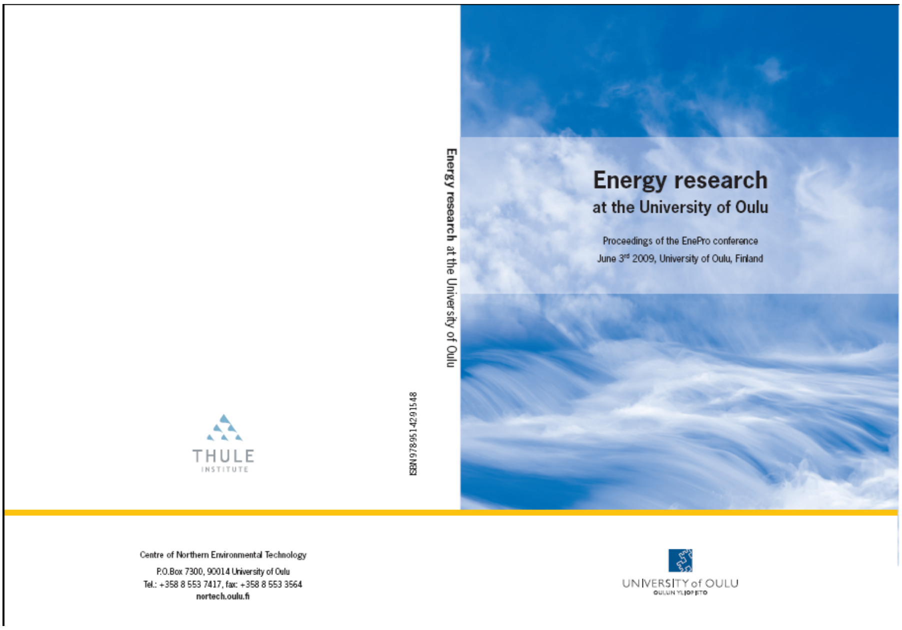
Ikonen E, Najim K and Kortela U (2000) Neuro-fuzzy modelling of power plant flue-gas emissions. *Engineering Applications of Artificial Intelligence* 13 (6), 255–262.

Kemeny J and Snell JL (1960) Finite Markov Chains, van Nostrand, New York.

Najim K, Ikonen E and DelMoral P (2006) Open-loop regulation and tracking control based on a genealogical decision tree. *Neural Computation & Applications* 15, 339–349.

Reference to this article:

Ikonen, E. and Leppäkoski, K. (2009) Artificial Intelligence-Based Modeling and Control of Fluidized Bed Combustion. In: Paukkeri, A.; Ylä-Mella, J. and Pongrácz, E. (eds.) Energy research at the University of Oulu. Proceedings of the EnePro conference, June 3rd, 2009, University of Oulu, Finland. Kalevaprint, Oulu, ISBN 978-951-42-9154-8. pp. 46-49.




EnePro conference: http://nortech.oulu.fi/eng/eneproconf.html

Proceedings: http://nortech.oulu.fi/eneproproc.html