Computational intelligence technologies in the design of hierarchical control architecture of glass melting furnaces

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Manuscript received 19 December 2001
Revision received 23 August 2002
Accepted 30 August 2002

The present paper overviews the benefit of advanced model based control strategies considering the increased emphasis placed on the operation of industrial glass melting furnaces in a safe and profitable way, while improving the glass quality and preserving a clean environment without equipment degradation. Several research studies explore methodologies in order to execute a transition from the manual control of glass furnaces and the use of off-line modelling tools to the automated, on-line model based strategies that can control glass furnaces. The present study explains the potential applications of model based expert systems such as supervisory control applicable to fault diagnosis, thermal and emission efficiencies and operator training. There is a review of methodologies used for the integration of the computational intelligence and conventional mathematical modelling technologies in the design of hierarchical control architecture of glass melting furnaces.

The glass industry is expecting to meet future challenges set by the alternative ecologically sustainable materials and global competition in terms of the price and quality of the products. The industry demands new methodologies and technologies for the operation of glass melting furnaces in a safe and profitable way while satisfying the glass quality specifications and environmental regulations without equipment degradation.

Recent developments in mathematical and artificial intelligence modelling, sensors and computer technology lead to the development of new control strategies for glass making process control. This paper is concerned with the use of mathematical and artificial intelligence modelling (Experts System, ES, Fuzzy Logic, FL, Neural Network, NN and Genetic Algorithms, GA) tools in a hierarchical control structure of a process. The ES seems to be the next step following conventional control systems, advanced control (model predictive control, MPC) and optimisation tools. The ES can be used to compile and analyse real time data, CFD (computational fluid dynamics) results, operator observations and laboratory analysis, to draw inferences and to issue recommendations for optimal operating of glass making processes.

The present study describes the need and potential applications of the ES which allows for the combination of mathematical and artificial intelligence models for on-line control optimisation. The architecture of the ES that can be applicable to a glass furnace is described. The capabilities of commercial ES software packages are given to help development engineers during the technology transfer from other industries. Finally, previous studies in the field of control and supervision for glass processes are reviewed.

Current state and needs of control of glass furnaces

In the glass industry, the current control systems require significant advances to achieve energy and cost reductions as well as a better product control. Because unnecessary extra energy is used for glass making processes due to insufficient and incorrect measurements and manual control over the furnaces.

The conventional PID (proportional integral derivative) controllers cannot meet all modern requirements of glass melting furnaces control, namely because PID controllers are not easily adaptable to new operating conditions and under the exclusive supervision and control of human operators. In the PID based control, if the process characteristics change because of

Paper presented at XIX ICG, 1–6 July 2001
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Table 1. *Components of hierarchical control structure of a process with implementation tools*

Hierarchy of control tasks		*Advanced technology*	*Level of intelligence*
Lower (controller) level	Data acquisition and reconciliation	DCS/PLC/SCADA/ES	
• Firing and air flow rate	Regulatory control (PID)	DCS/PLC	Sense of the environment
• Glass level	Advanced control (MPC, FL, NN, GA)	PC	
Intermediate (supervisory) level	Sensor validation	ES	
• Glass quality	Process monitoring	SCADA/ES	Learning
• Thermal and emission (NOx) efficiencies	Alarming and trends	SCADA/ES	Adaptation
• Optimum operating conditions	Fault diagnostics	ES	Reasoning
	Optimisation and quality	ES	
	Supervisory control (Set point changes)	SCADA/ES	
Higher level	Strategic decision	SCADA/ES	Planning
• Glass type	Planning and scheduling	SCADA/ES	
• Fuel type			
• Pull changes			

MPC: Model predictive control, FL: fuzzy logic; NN: neural network; GA: genetic algorithms; DCS: distributed control system; PLC: programmable logic control; SCADA: supervisory control and data acquisition; ES: expert systems

new operating conditions (change of colour, pull rate) the parameters of PID controllers (gain, time constants or dead time) must be adjusted or retuned. Despite tuning tools (Ziegler-Nichols, Brodia, process reaction curve methods) calculation of optimum PID tuning values for different operations is not straightforward due to lack of understanding of PID tuning techniques and the difficulties in obtaining an accurate transfer function for glass processes having long time delays and changing characteristics. Therefore, the process is controlled manually by the operator's acceptable but not optimal control actions. Manual control affects production rate and glass quality. For example, it takes a long time stabilise the process because of incorrect control actions.

Existing temperature sensors (thermocouples and optical pyrometers) used in the glass industry are very unreliable after a while. They decay due to corrosive environment and estimate temperature inaccurately. In manual control, operators verify and correct the temperature reading coming from the sensors. Incorrect estimation of the temperature causes wrong adjustment of heat input to the process.

There exists a very real need to assist operators in their decision making especially for problems related to glass quality. This is mainly due to the lack of precise knowledge about both the steady state and dynamic behaviour of the glass processes. The typical characteristics of the glass melting furnaces are the broad residence time distribution, sensitivity to small fluctuations, especially in batch composition, flame coverage and heat transfer, the batch pile movements and changes in thickness of the refractory walls over time. These complexities of glass melting processes require extensive modelling activities and corresponding sensor development efforts such as on line determination of melt constituents, oxygen activity measurements and flame visualisation for further improvements.

Hierarchical control structure of glass furnaces

The task of the control systems of glass furnaces is to keep the process variables (temperature, pressure, level, etc.) at their set points and effectively handle the essential problems of the glass industry such as energy saving, glass production with fewer defects (bubbles, chords, stones, etc.) and the reduction of changeover times and pull changes.

Hierarchical control structure is a functional architecture where the basic control activities such as regulatory control, supervision of each control unit, data storage and analysis, and man-machine interface are inserted in a hierarchical manner in order to cope with the complexity. The concepts of intelligence and control are closely related. Since a control system is an intelligent system, the characterisation of an intelligent system may provide a good understanding of the complex control problems.[1]

The multilevel concept of the hierarchical control structure is displayed in Table 1 which describes the components of the hierarchical control structure of a process with the implementation tools. The hierarchical control structure of a process is categorised into three levels as follows.

1. The lower (controller) level includes data acquisition (I/O processing), logging and reconciliation, instrumentation and basic regulatory control (PID). This execution level is also called low level of intelligence in terms of the characterisation of an intelligent system. At a minimum, intelligence requires the ability to sense the environment, to make decisions and to control the actions. For example, I/O processing typically refers to the measurements with a minimal 'intelligence' at the I/O point. The 'Smart' I/O, with at least a minimal local memory and processing capabilities keeps the output at a fixed level when communications are lost.
2. The intermediate level is also called supervisory level. The local controllers are evaluated in order to confirm whether they satisfy the prescribed performance criteria or not. The optimisation tools specify the set points of the controllers. The diagnostic system, which detects and predicts faults and failures, requires complex reasoning activities that call for computational intelligence, including the ES and soft computing (FL, NN and GA[2]).
3. The higher level includes management, planning and scheduling. Higher level intelligence may include the ability to learn how to cope with the changing circumstances, to act appropriately in an uncertain environment and to reason about and plan the future.

In glass furnaces, at a lower level, the short term control variables are firing rate, air flow rate and batch feed rate. Intermediate and higher levels deal with long term controlling parameters such as batch preparation, fuel type and quality and furnace condition.

The flow of knowledge and data between these levels requires an advanced hardware and software technology. The conventional control systems in glass furnaces are based on the DCS (distributed control system) and the PLC (programmable logic controllers).[3] The data is transmitted from the instruments to the PLC through the SCADA (supervisory control and data acquisition). SCADA systems provide a complete computer interaction with the controlled process. The whole process is viewed and monitored by graphical user interfaces. The operator may interact and supervise it from a control station. The ES may be considered as a SCADA system enhanced with mathematical and intelligent modules that may infer knowledge from relevant data.

Expert systems

The modelling, in an expert knowledge environment, is classified into three categories.

1. Knowledge based guidance in modelling: ES may provide support for a CFD application during the grid generation, input data generation and selection of relaxation parameters. Consultative ES may be used to cultivate inexperienced engineers and computer specialists into CFD engineers.
2. Combining modelling and knowledge based systems: the ES is a dynamic tool. The performance of a process may be tested periodically. It allows the use of CFD models for on-line control by employing predefined simulation results which work as reference optimal operating conditions.[4]
3. Representing knowledge in models: the rule based representation of a nonprocedural knowledge may be used as a qualitative model in case a validated numerical model does not exist, for example, the interaction between glass currents and refractories.

Basic principals of expert systems

Figure 1 shows a hybrid system that couples a rule-based expert system with different numerical modelling tools in order to execute an on-line control optimisation. The system consists of:

1. a monitoring system which converts a huge amount of process data (sensor readings), coming from each section of the process, into useful values that can be processed by the ES;
2. a model library that contains various models (CFD models, soft computing, simple models, optimisation tools) which produce reference data for inference mechanisms and information for process evaluation; and
3. an ES shell that performs a decision making activity by compiling the available knowledge from process data, model library and operator experience.

The on-line implementation of the transient CFD models on the control systems is limited due to the excessive computation time but the ES provides the use of steady state CFD codes at the supervisory level. CFD codes are used to generate a database covering the range of process operations and simplified models or functions for the model library.

The ES can be used either on-line or off-line. In the former the ES gives recommendations, which specify the best control strategy to follow in predefined situations, to the operator. Most currently implemented ES runs in tandem with existing control strategies, which allows plant operators to select which control action to follow.[2] In the latter, operators enter into a dialogue with the ES supplying answers to the questions. What-if analysis provided from the off-line use of CFD models in the ES can be used for training of inexperienced or new operators.[4] The open architecture shown in Figure 1 allows on-line access to relevant data and information but is limited to the memory and CPU of computers.

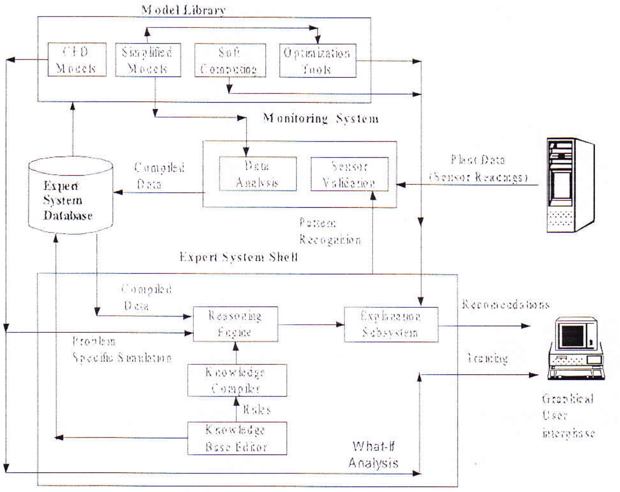

Figure 1. *A configuration of the ES*

The successful application of the ES depends on the overcoming of the knowledge acquisition bottleneck, the knowledge base maintenance, the integration within existing systems and the transparency of the inference mechanisms. Besides the above implementation problems, the expert systems are not good at recognising in case no answer exists or when the problem is outside their area of expertise.

Expert system building tools

The ES tool or shell is a software development environment.[2] As shown in Figure 1 it typically consists of four basic components:

1. a knowledge base which contains knowledge that is represented as IF-THEN rules, frames or logical statements;
2. a reasoning engine which works with an inference mechanism such as the backward chaining IF-THEN rules and the object oriented, case base and model based reasoning;
3. a database that contains knowledge that was entered by a user or concluded by the system itself; and
4. a user interface with which the expert system communicates with the user.

ES shells (G2, EUREKA) have come to the market recently.[5] These tools are usually equipped with ready-to-use knowledge representation schemes, inference engines, databases and user interfaces, a knowledge editor and only the knowledge base needs to be implemented. The rules in the knowledge base are classified according to their usage area, such as fault knowledge base, emission and efficiency knowledge base.[4]

Fault diagnosis by expert systems

Fault diagnosis is one of the potential applications of the ES. The malfunctions of a process are expressed as either a failure, which means an operational breakdown, or a fault, which are deviations from the normal operational conditions.[6] The fault diagnosis includes fault isolation (i.e. location of the fault) and identification (i.e. magnitude of fault) tasks. The ES can be designed for diagnoses including equipment failures, process abnormalities and defects. The diagnosis includes pattern recognition and reasoning activities. The basic steps of the diagnosis are as follows:

1. Sensor validation: the analysis of the malfunctions' root cause starts with the interpretation of the sensor readings. Some sort of faults may be easily detected by checking the limits. However, identification of sensor bias or deterioration prerequisite compilation of knowledge from process models, qualitative process relationships, empirical correlation, history of sensor and data from other sensors, etc.[7]
2. Trend analysis: a data analysis technique may be used to determine the rate of change of the process condition.
3. Generation of malfunction hypotheses: a troubleshooting or decision tree is formed for the diagnostic search. This approach is a process oriented approach that is based on structural decomposition of the process in terms of functionality of the sub processes and the general fault categories.[8] The hypotheses are hierarchically arranged. For example, the hierarchical arrangement of hypotheses for the glass melting process—melting, refining, conditioning and glass quality— may form the nodes of the hierarchy at the upper level of the decomposition. More specific malfunctions, such as specific modes of failure and improper operating conditions, would be the nodes of the lower levels.
4. Evaluation of hypotheses: the decision tree is searched recursively by applying an inference mechanism to evaluate the fault or failure hypotheses from the symptom condition, which is represented in the form of rule. In case multiple hypotheses are identified by the diagnostic search, the consequences of the symptoms are used to determine a possible interaction between the malfunctions.

A rule based knowledge is more transparent and may be verified by the domain expert. If NN is used for the diagnostic search, the ES is not able to tell the operator how a specific fault situation is defined.

Advanced control applications in the glass industry

In recent years much attention has been paid to computational intelligence in order to make controllers autonomous and intelligent. Some of the recent studies about glass furnace control at the supervisory and regulatory control levels of the hierarchical control architecture are displayed in Table 2. In these studies[9-24] different models, having different levels of complexity and usefulness that depend on different approaches, are used.

Table 2. *Advanced control applications in the glass industry*

Advanced control	*Application*	*References*
ES	Optimisation	Farmer *et al*[9]
	Optimisation and glass quality	Carvalho & Nogiera[10,11]
	Glass quality	Chmelar *et al*[12]
MPC	Temperature control	Schill *et al*[13]
	Temperature control	Chmelar *et al*[14]
	Temperature control	Huisman *et al*[15]
Flame image processing system	Optimisation	Correia *et al*[16]
NN and FL	Colour change	Bauer *et al*[17]
	A gas hearth control	Pirovolou *et al*[18]
FL	Temperature control	Malik[19]
	Glass tubing process	Zuo & Yi[20]
	Temperature control	Nakagama & Kimura[21]
GA	Optimisation	Pina & Lima[22]

Table 2 indicates that artificial intelligent techniques are used for the control and diagnosis of glass melting furnaces. The ES acts as a knowledge manager at supervisory control. Application of transient CFD models for on-line control of glass furnaces is limited by the computational requirements involved. The ES provides the use of steady state CFD models at the supervisory level for the on-line evaluation of the indirect control parameters such as the pollutant emissions, thermal efficiency and glass quality.[9-11] Due to the large amount of computational time required for calculation of bubbles from the batch, a knowledge base that represents furnace operation, behaviour of defects and blister chemistry is used to analyse chemical composition of bubbles.[12] Another point of interest is the training of new operators to control glass furnaces and refreshing old operator's knowledge are important, time and money consuming. The ES allows the off-line use of CFD models for optimum control decisions as well as the knowledge of experienced operators for acceptable control decisions under typical operating conditions simulated during the training of operators, Figure 1.

As an alternative to PID-based control MPC refers to a class of algorithms that compute a sequence of manipulated variable adjustments in order to optimise the future behaviour of a process. Due to the solution of contained optimisation problem in its algorithm, MPC can handle supervisory control problems, e.g. glass quality. The performance of MPC on glass furnaces depends on the accuracy of dynamic model capturing highly nonlinearity of the process. CFD results are used for the derivation of a step response model in MPC for temperature control.[13] The MPC which use a linear dynamic model identified from test data, is used for temperature control[14] but the use of a simplified nonlinear model, derived from simplified mathematical description of the glass melting process (melting redox, fining, foam formation, homogenising) for MPC is investigated.[15]

As can be seen from Table 2, the application of soft computing (FL, NN, GA) to nonlinear control[17-22] is another alternative when the accuracy of nonlinear mathematical model is unsatisfactory. Dynamic testing during the process is necessary to create the knowledge base for the construction of input output model (NN)[18] or rules (FL).[19] Due to limitations of measurements in furnaces for the construction of dynamic models, operator's knowledge and CFD results are integrated in a feed forward adaptive Neuro-Fuzzy control.[17]

Some technical advances have not yet been incorporated into the glass production control. Computational intelligence for example FL modelling is not incorporated into MPC for glass furnace control. In most applications advanced controllers run in tandem with existing PID controllers which needs retuning frequently. For PID controllers a tuning knowledge base can be developed by using computational intelligence techniques and ES can supply PID parameters for different operating conditions at execution level. The tuning knowledge base can also be used for training of new operators on a control scenario.

Difficulties in the accurate monitoring due to physical restriction or high temperature and hostile environment cause missing vital information and hence make control of the furnace inherently difficult. The status of the sensor technology for the glass making is available elsewhere.[23] As development in sensor technology continues control strategies will be modified accordingly. For float furnaces, hierarchical glass production control based on integrated control system, which combines product sensors and numerical models and NN, is outlined by Huber.[24] On-line characterisation of the flame geometry can be correlated with air/fuel ratio, level of nitrogen oxide emissions and flame temperature. A model based control strategy for optimal control of fuel efficiency in glass furnaces is developed[9] and a flame viewing system is used for the control of atomisation air, with the conventional control which uses crown temperature to control air/fuel ratio.[16] A new application area of NN in a glass furnace is recognition of the flame patterns as a function of operational condition.[25]

Conclusion

The present study is concentrated on the state of the art in the field of advanced model based control strategies to be used in the glass industry. Comments on recent methodologies for the integration of modelling and computational intelligence technologies in the design of hierarchical control architecture of glass melting furnaces are given. The importance of improved process control with model based expert systems is emphasised. Expert systems as a knowledge manager at a supervisory level provide better process control by using CFD, artificial intelligence modelling tools and verbal process experience from the industry.

Acknowledgement

This research is financially supported by FCT (Fundação para a Ciência e Tecnologia, PRAXIS XXI / BPD / 22023 / 99) in Portugal.

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