Modelling, Identification and Control of Constrained Multivariable Industrial Processes Using BrainWave MultiMax

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JM – May, 2003

Outline

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2. The commercial multivariable constrained indirect adaptive predictive controller BrainWave MultiMax
   (a) MIMO Laguerre based identification
   (b) Predictive Control
   (c) Implementation issues
3. Rewarding results of the MIMO control of a fuel blending process
4. Intelligent die casting results and conclusions
5. The context of adaptive control commercial products

The problem motivation

- Process industries need a multivariable predictive controller that:
  1. has low cost
  2. is easy to setup
  3. maintains an adaptive behavior [1] (accounting for plant non-linearities and potential mismodeling).

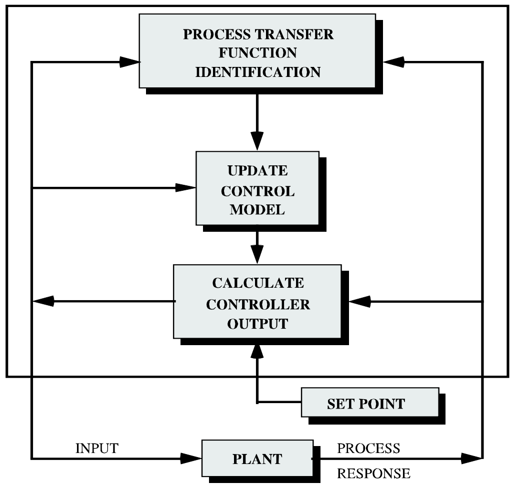
- In answer an indirect adaptive predictive controller Brainwave Multimax is proposed

- To evaluate its performance the control two processes, fuel blending and die casting, is presented

[1] "To adapt = To adjust oneself to particular conditions, in harmony with a particular environment" (Webster)

"A controller is adaptive if it is based on a posteriori information" (Zames)

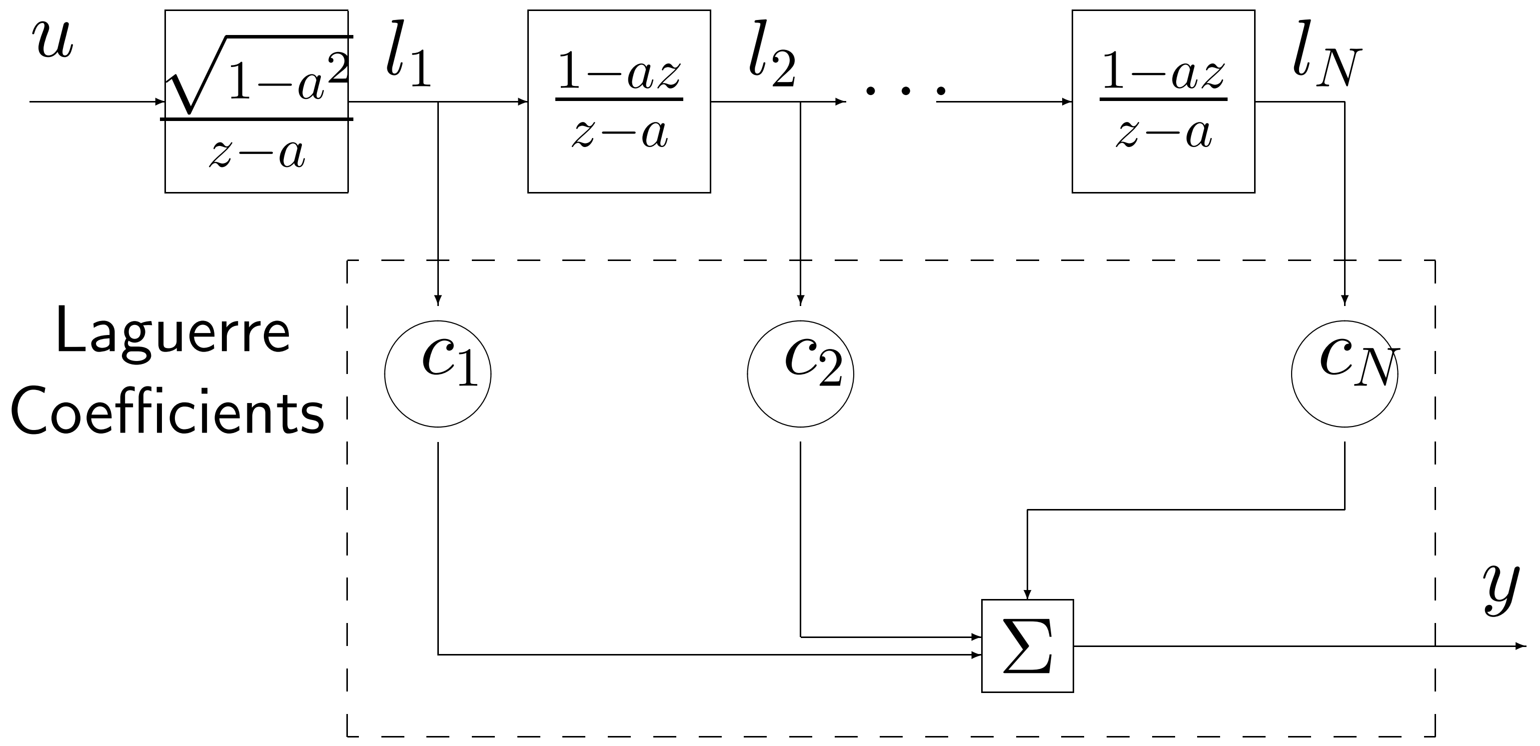
Multivariable indirect adaptive control



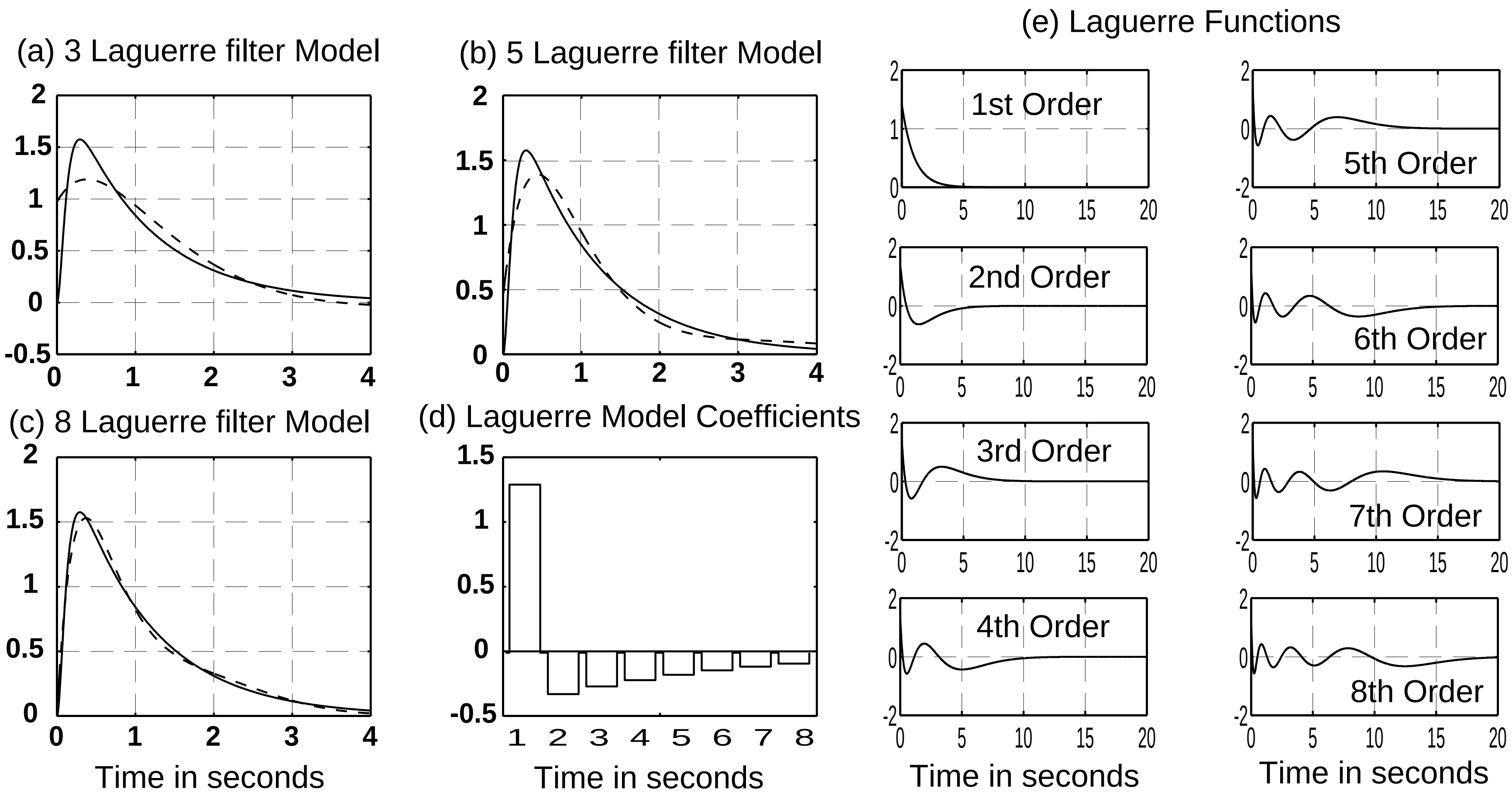
The MIMO indirect adaptive control involves two steps:
1)plant identification and 2)controller (model based) design.

To achieve this a wide variety of identification and controller design methodologies can be used but our choice is:
MIMO Laguerre based identification and **Model Predictive Control**

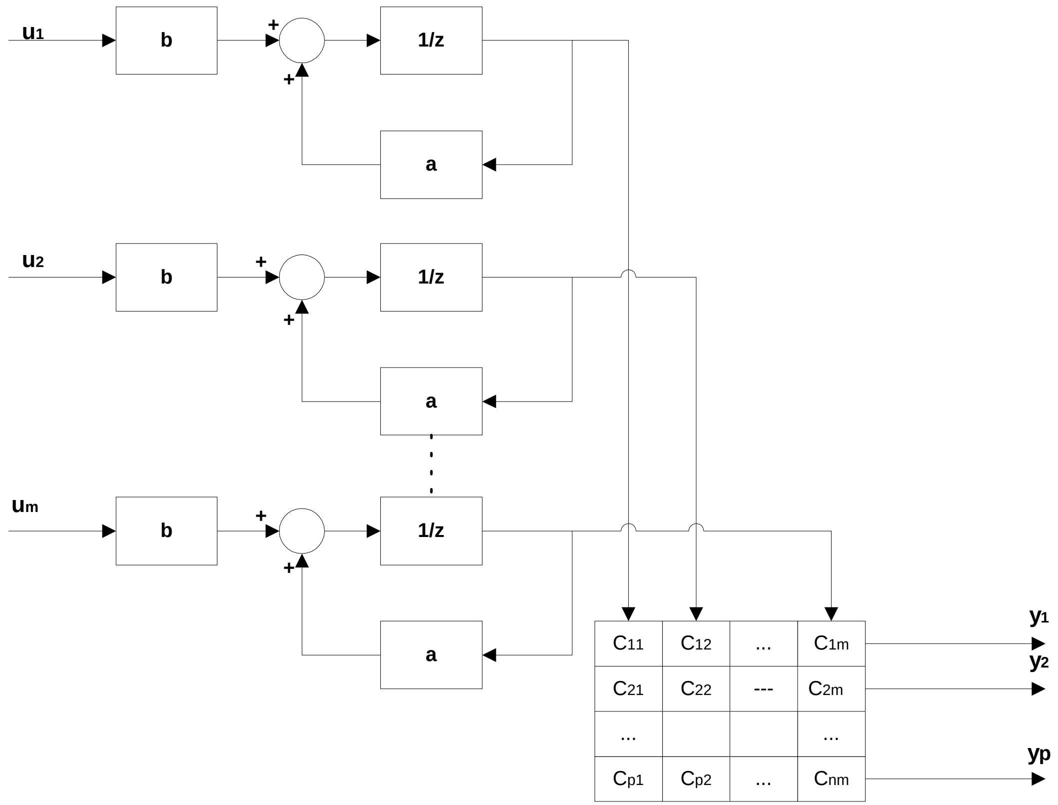
Identification using a bank of discrete Laguerre functions



Example of Laguerre modelling



The multivariable internal model



The identification engine: Recursive Least Squares (RLS)

- A modified RLS - the exponential forgetting and resetting algorithm allows tracking of time-varying parameters while guaranteeing boundedness of the covariance matrix:

$$
\begin{aligned}
\varepsilon(t+1) &= Y(t+1) - L^T(t+1)\hat{C}(t) \\
\hat{C}(t+1) &= \hat{C}^T(t) + \frac{\alpha P(t) L(t+1)}{\lambda + L^T(t+1)P(t)L(k+1)}\varepsilon(t) \\
P(t+1) &= \frac{1}{\lambda}\left[P(t) - \frac{P(t)L(t+1)L^T(t+1)P(t)}{\lambda + L(t+1)^T P(t) L(t+1)}\right] + \beta I - \gamma P(t)^2
\end{aligned}
$$

  I is the identity matrix, and α, β and γ are constants.

- With $\alpha = 0.5$, $\beta = \gamma = 0.005$ and $\lambda = 0.95$, $\sigma_{min} = 0.01$ and $\sigma_{max} = 10$.

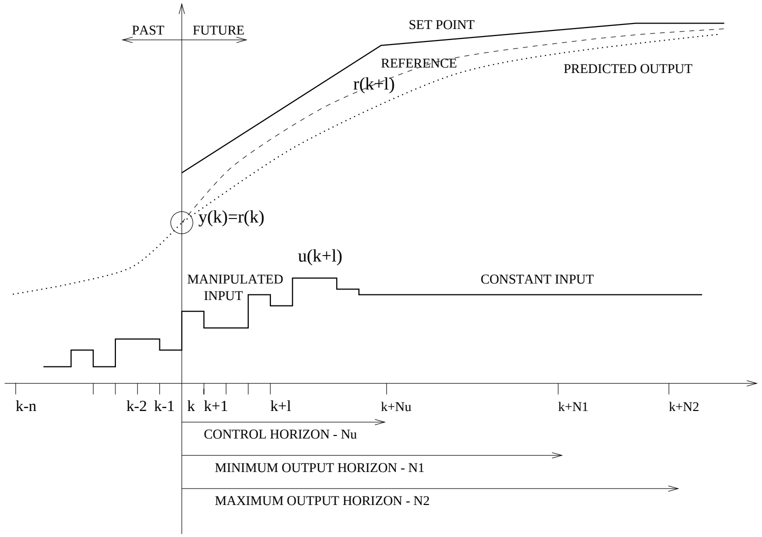
Identification in closed loop

- The identifiability of the process may be problematic hence to guarantee it:

  1. A sufficiently exciting signal independent of the output has to be injected into the loop either at setpoint or at the control input.
  2. Switching, as modelling reveals new dynamics, between different regulators can be an alternative.

- Subtle interactions between identification and control in a closed-loop situation affect the frequency distribution of the estimation variance and bias.

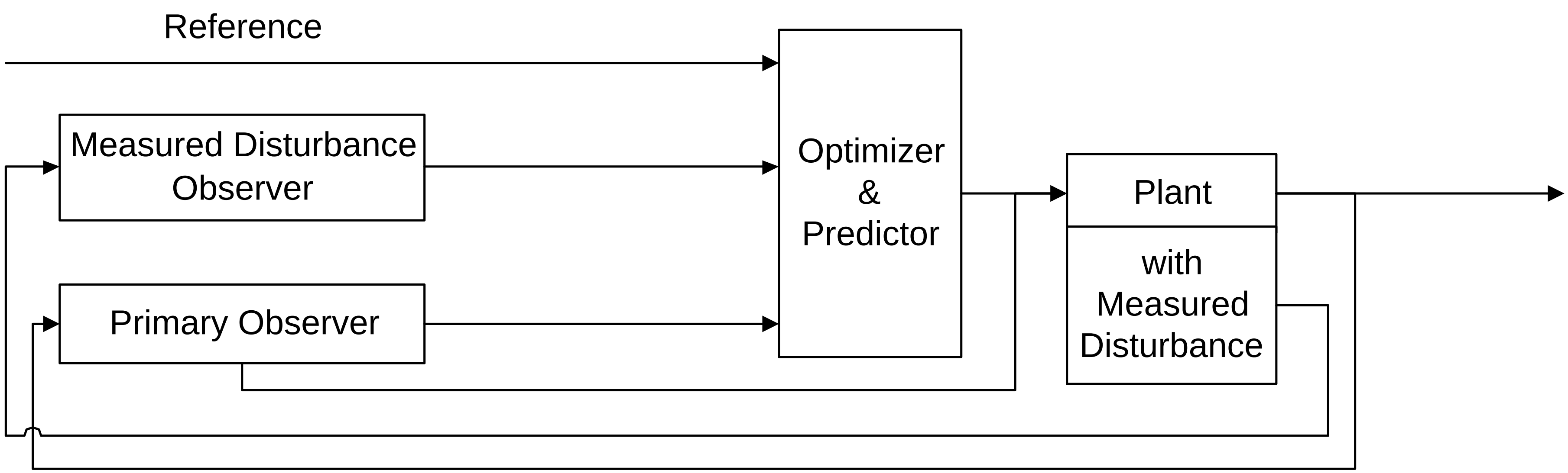
The model predictive control strategy



The cost function employed within the Brainwave Multimax controller is:

$$J(\Delta u) = \sum_{i=N_1}^{N_2} ||\hat{Y}(i) - \hat{S}(i)||_Q^2 + \sum_{i=1}^{Nu} ||\Delta U(i)||_R^2$$

The controller and plant in closed loop

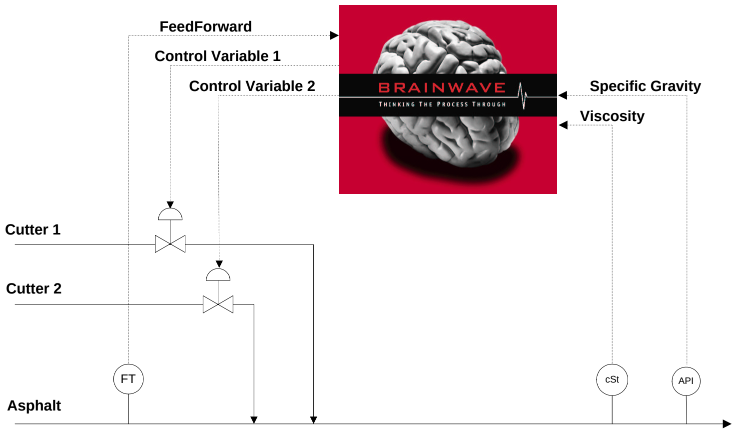


Controller implementation issues

- BrainWave MultiMax was developed for use on multi-input/multi-output MIMO processes with possible integrating responses, exhibiting long delays and time constants.
- A thorough analysis of the parameters involved in the controller provided golden rules for a number of tuning parameters, dramatically reducing the commissioning time.
- Particular attention was paid to the development of the graphic user interface (GUI)
- The real time implementation achieves sample times as low as 0.1 [s] for a medium size 6X6 with 3 measured disturbances per loop MIMO systems.
- The main benefits of this control strategy are:
  1. Easy and systematic tuning procedure;
  2. Reduced cross-couplings between channels;
  3. Minimized closed-loop overshoot and settling time;
  4. Systematic management of input constraints.

The fuel blending process (I)

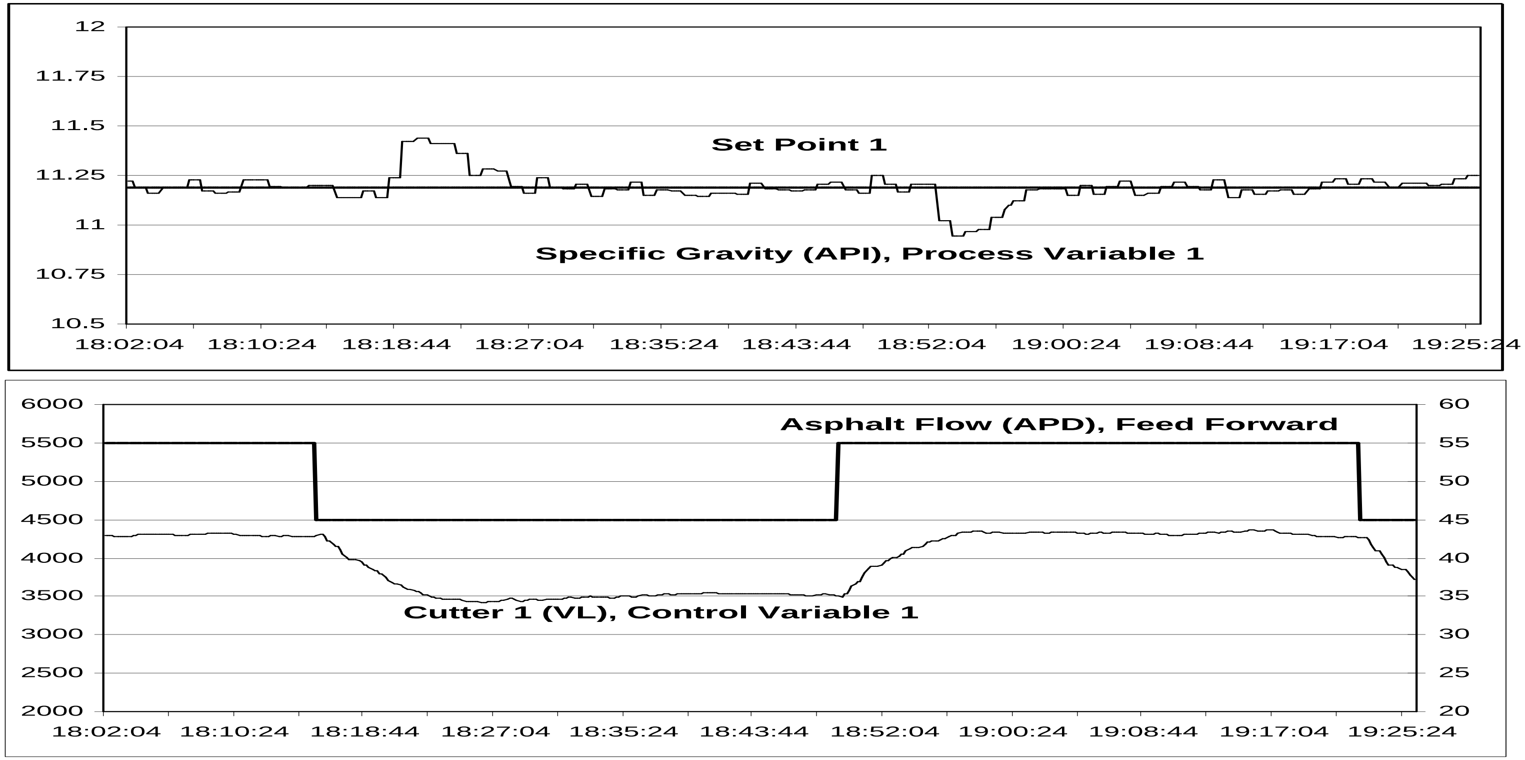
- A by-product of crude oil refining process is asphalt, which can be turned into a low cost fuel for ships and is also used for road construction.
- The process of transforming the asphalt into a low cost fuel requires blending the asphalt with **cutting agents** to meet both **specific gravity** and **viscosity** specifications which are making the asphalt transportable.
- The fuel cutters are expensive and hence the need to minimize the cost of the cutters while maintaining the specific gravity and viscosity of the blended fuel is mandatory.



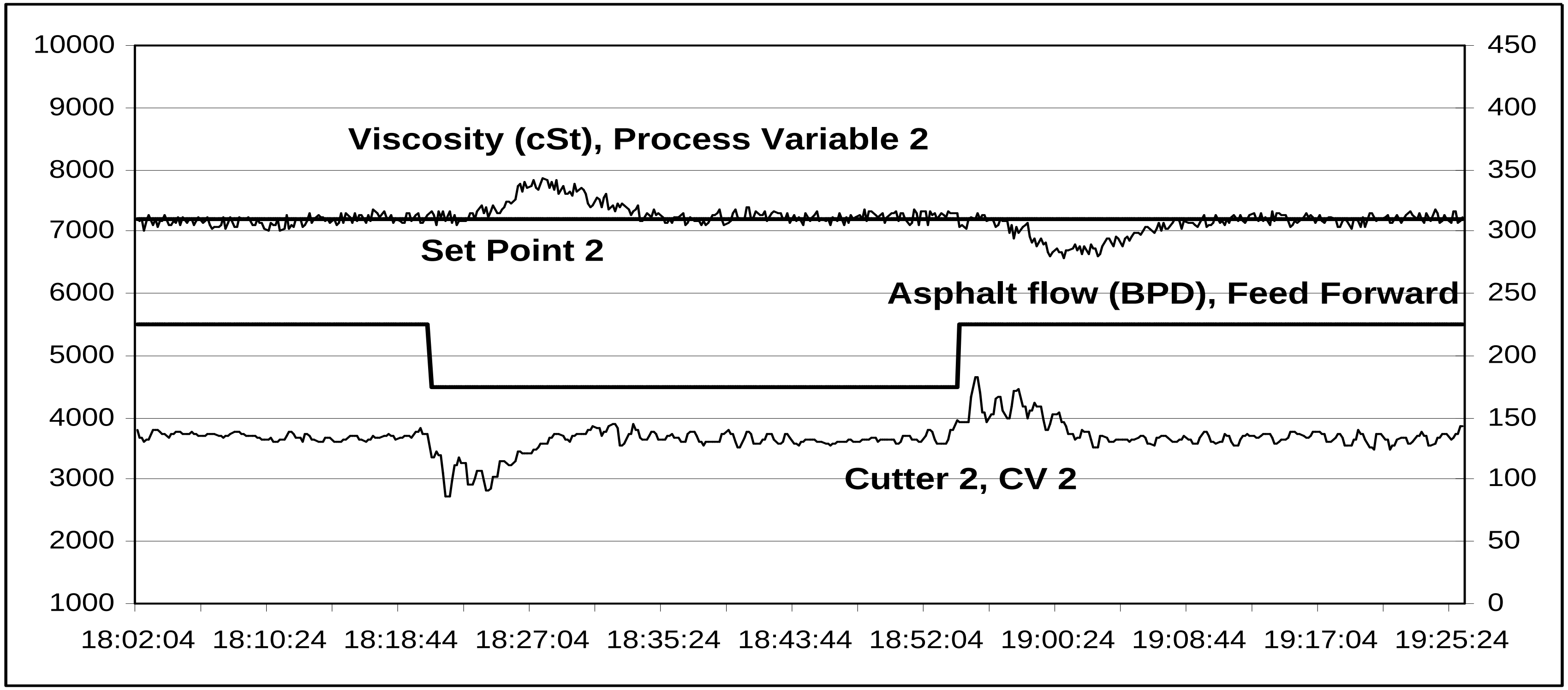
The fuel blending process (II)

- The MIMO plant has two inputs (two different cutter types) and two outputs (specific gravity and viscosity) and a measured disturbance (the flow of asphalt).
- The plant model presented large discrepancies between channels, different dynamics including different gains, time delay and strong cross-coupling.
- The fuel blending control loop had a time constant of 60 seconds and a dead time of 4 minutes.
- The blending of the cutter with the asphalt occurred when the asphalt temperature was 525°F.
- The blended mixture then travels through a series of heat exchangers and the specific gravity is measured when the final mixture is at 75°F.
- The specific gravity must be maintained at 12.3 API (American Petroleum Institute specific gravity units) and the addition of the cutting medium must be minimized.
- The viscosity control loop presented similar dynamics with a negative gain.

Rewarding results: tight control of specific gravity



Rewarding results: adequate control of fuel viscosity [2]



[2] The results exceeded the existing control performance by several orders of magnitude outperforming at the same time the manual control capabilities of the operators.

Implementation details

- BrainWave MultiMax was interfaced to a Siemens Moore Apacs System through a Modbus connection.
- Once the adaptive controller was integrated into the control strategy, bump tests were initiated to determine the initial models for the process response.
- A startup multi-model approach was utilized to take into account the effect different cutters would have on the blended mixture.
- The process of bump tests, model identification and control optimization took 20 hours.

Conclusions of the BrainWave MultiMax application to the fuel blending process

- Reduced cutter addition is saving an estimated $ 150,000 dollars annually, with a return on investment of less than 2 months.

- The possibility for the operators to redirect their attention to more critical loops is greatly appreciated.

- BrainWave MultiMax was implemented quickly and was easily tuned by the company process engineers.

Control of a simulated die casting 2 dimensional finite element model

- A finite element model can be used to predict defect formation in a low pressure die casting process.

- Defects in the cast can be linked to the temperature history of the process.

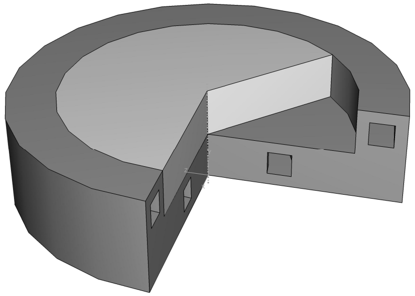
- By controlling certain temperatures in the mold to predefined set-points, defect formation can be minimized.

Control objectives

- Decrease the process startup time.
- Reject disturbances
- Offline evaluation of closed loop performance.
- Optimal instrumentation selection and placement to meet control objectives.
- Educate process operators and designers via an advisory system.

The 2-D axisymmetric finite element ABAQUS process model

- The ABAQUS 2-D axisymmetric finite element model uses 4-node linear temperature elements.
- The casting and mold contain 48 and 72 elements respectively.
- Boundary conditions model the heat transfer.
- The control variables are the cooling channel heat transfer coefficients



The casting process

- Molten aluminum enters the mold at $700°$C.

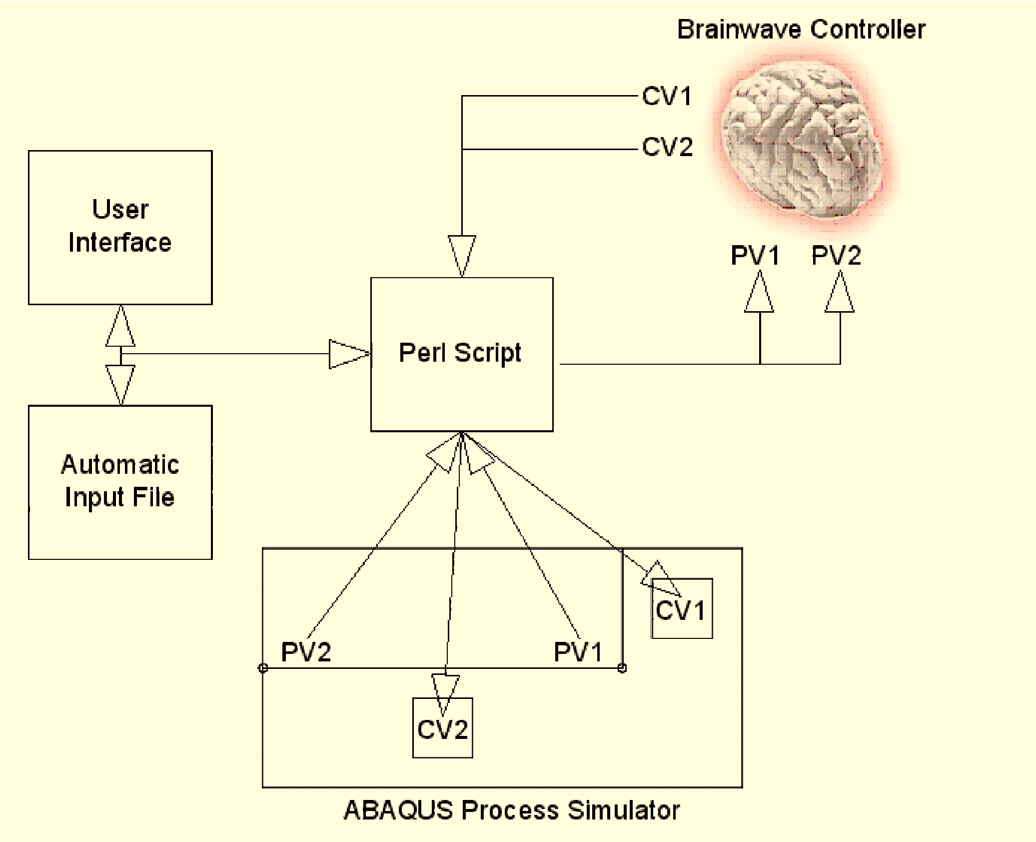
- A single cycle consists of two steps: 15 seconds of cooling with the cast in the mold 10 seconds of cooling with the cast removed from the mold.

- System disturbances:

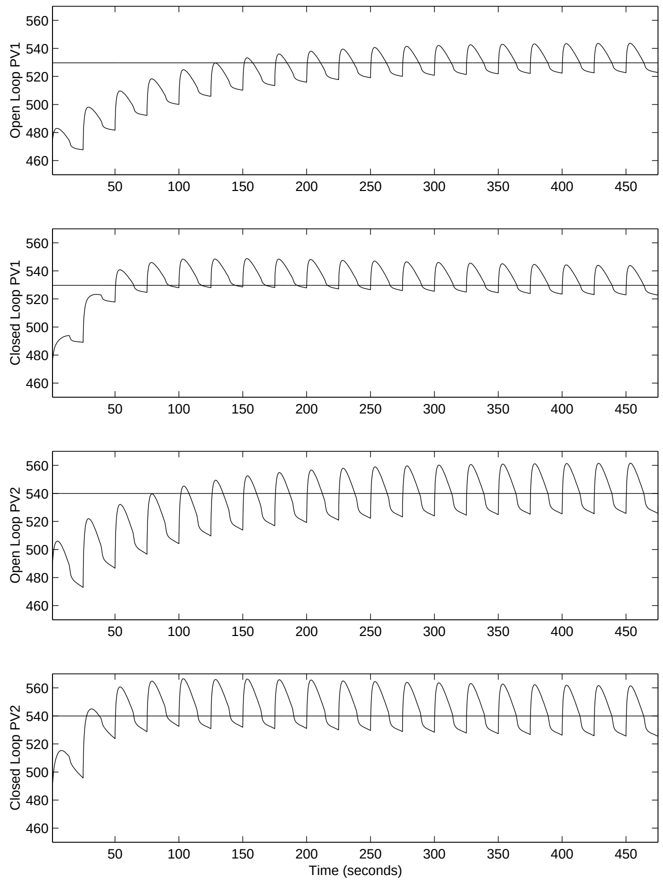
  1. Variations of the incoming metal temperature and
  2. Variations of the length of time the mold cools with the cast removed.

- These disturbances can provide 2 feedforward variables that will be used in controlling the process.

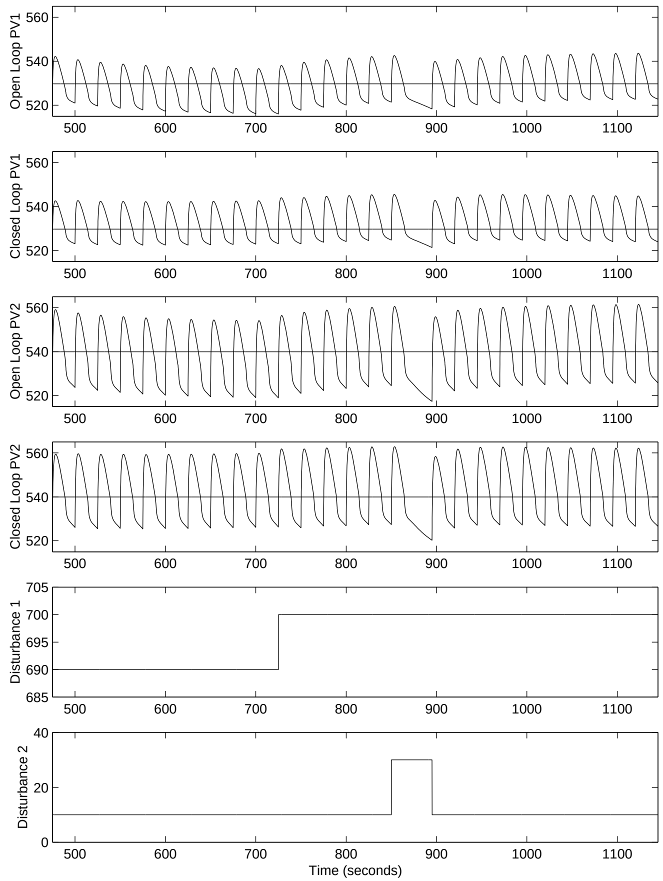
The communication between ABAQUS and BrainWave MultiMax facilitated by the Perl script



The startup time is decreased by 6 Cycles in closed Loop



Very effective disturbance rejection



Conclusions of the BrainWave MultiMax application to the die casting process

- BrainWave MultiMax has been used to control a simulated industrial die casting process using a 2-dimensional finite element model.
- This conduit for the exchange of process and control information can be applied to other similar simulation environments.
- Short startup times and good disturbance rejection encourages the extension to complex die casting processes for aluminum alloy wheels.
- The performance of the scheme enables revisions of current control strategies for better performance with minimum investment and risks.

More commercial controllers are embracing adaptive control ideas

- Adaptive control has a relatively long history and a rich collection of algorithms is available but only few are providing reliable industrial solutions
- Prohibitive costs of predictive control and a low number of commercially available multivariable adaptive controllers prevent industries that operate on small profit margins to take advantage of such technology.
- This is a list of currently available tools:
  - BCI Autopilot www.bciautopilot.com
  - Brainwave www.brainwave.com
  - Connoiseur & Exact www.foxboro.com
  - CyboCon www.cybocon.com
  - Intune www.controlsoftinc.com
  - Knowledgescape www.kscape.com
  - QuickStudy www.adaptiveresources.com
- **With careful engineering, adaptive control can provide significant benefits**