A DISTRIBUTED AUTOMATION FRAMEWORK FOR PLANT-WIDE CONTROL, OPTIMISATION, SCHEDULING AND PLANNING

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Abstract: The objective of the talk will be to identify current open problems and trends in plant wide control and demonstrate a solution based on distributed, solution component based architecture for integrated process management, embracing the layers of Advanced Process Control, Real Time Optimisation and Planning & Scheduling, in selected application areas. The problems and outlined solutions are intended to stimulate discussion as well as attract more research interest.

Keywords: Advanced Process Control, Real Time Optimisation, Planning, Scheduling.

1. INTRODUCTION

The potential of a seamlessly integrated solution covering process control, optimisation, planning and scheduling as well as plant asset management is generally accepted. It is expected that this integration will result in better responsiveness of the whole plant to the varying economic environment, removing expensive storages, buffers and margins and improving operational safety on one side, but will also yield dramatic reduction of integration and customisation costs.

Current developments in control and optimisation theory, together with the enormous increase in computational power together with new component based software technology open immense possibilities for a continuing development in this area.

Model predictive control (MPC) is one of a few advanced control approaches that have made a substantial impact in the industry (Mayne, 2001). The reason for such success of this concept is its ability to deal with hard constraints imposed on manipulated and process variables. These days, MPC is an active research area intensively developed by leading process control suppliers and academic teams. However, the predecessor of today's MPC – the 'Dynamic Matrix Control' algorithm (Cutler and Ramaker, 1980) – was developed by practitioners from the industry in the 70's and had been neglected by the academic community for a relatively long time.

The area of decentralized control and optimisation for large-scale systems has a similar genesis. These topics were extensively studied in the years when popularity of the new science – cybernetics – culminated in the 60‘ and 70‘ (Mesarovic *et al.*, 1970; Findejsen *et al.*, 1980). After this early period, the interest of research community faded out, partly because of the inherent complexity and difficulty of the problem and partly because of limited implementation possibilities. However, practitioners in the field – motivated by the increasing requirements of processing industries as well as capabilities of control systems – have continually developed more and more complex distributed control and optimisation solutions (Shinskey, 1996), often relying on heuristics, simulation and experience rather than rigorous theoretical research.

With increasing scope of advanced process control solutions, emerging solutions bring together process control and optimisation functions based on both technical/technological and economic knowledge and criteria.

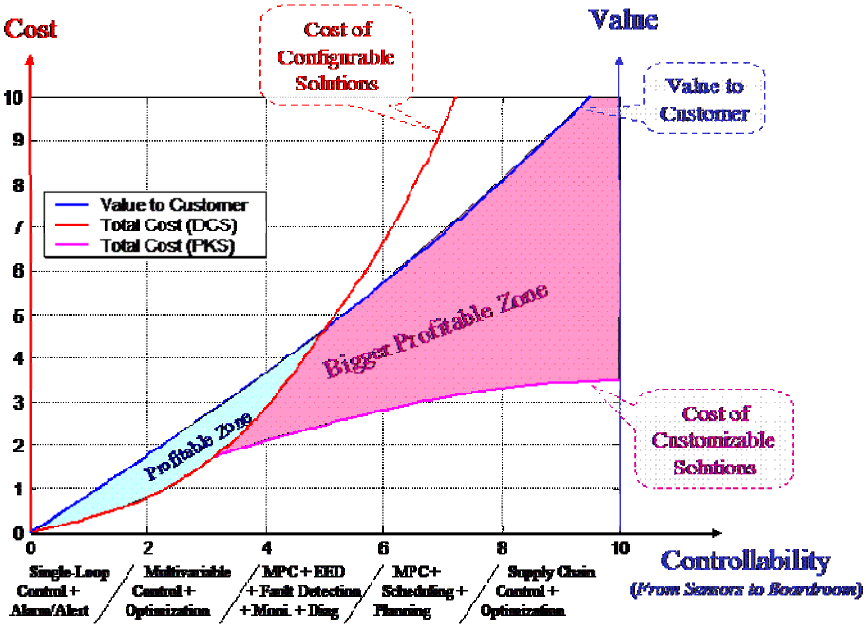

Fig. 1. Cost of solution vs. value to customer for traditional and solution component based solutions.

However, without efficient tools for cross-functional integration provided by the latest software technologies, the scalability of the traditional "configurable" solution – where the pre-built knowledge is being configured by selecting different options during the configuration process – is reaching its limits: the cost of adding some new knowledge in an integrated way is prohibitive to extend the "controllability"[1] of the process from the traditional layers of single-loop regulatory control, multivariable control and optimisation to higher layers of planning, scheduling and supply chain management (see Figure 1).

Solutions that can bring additional benefits will have to be built from customisable *solution components* with high domain specific process knowledge content that is an inherent part of the delivered solution.

Mathematical programming (optimisation) is the basic enabling technology for this effort. Optimisation-based control can absorb – in real-time – the economics-related information as a part of its internal criteria. The "optimisation-based" paradigm can be naturally extended to other areas, for example the problems of asset management/predictive maintenance, fault detection and active fault accommodation (fault recovery) can be formulated as optimisation problems – find the best achievable performance under the detected faults by finding optimal control configurations under a modified set of constraints.

In spite of the efficiency and performance of modern optimisation methods, it is not viable to formulate complex process control and optimisation problems as single huge, "all-or-nothing" black box optimisation tasks. The limiting issues – human effort required to set-up, maintain and run/monitor such a solution, as well as its flexibility and operability – force us to implement solutions of complex, large scale problems in a well structured, decentralised and hierarchical way. This is one of the many design challenges we see; compromising between the needs that support decentralised approach and the need of solving global economic optimisation problem.

Presented concepts of Integrated Process Management based on modern software tools and solution components will facilitate

- Tight coupling between economic decisions and process/technology-related decisions. This will improve responsiveness to the varying economic environment (e.g. real-time pricing of gas and electricity) while eliminating additional safety margins, buffers, etc., with positive impact on process economy.

- Flexible integration scheme for consistent decision making on individual hierarchical levels with different optimisation horizons and different time granularity (the users prefer a multi-tier system where the higher layer you go, the more abstracted the physical process becomes – or more aggregated in time and in details), based on "self-maintaining" models derived from plant topology reference model with real-time responsiveness to technology changes (unit configuration/commitment) and information (incl. uncertainty) propagation between the levels.

- Full exploitation of modern information and software technologies for component-based

[1] In this paper, the term "controllability" is not used in its narrow, rigorous control theoretical meaning

solution of complex enterprise-wide instrumentation, data acquisition, process control, optimisation and planning problems.

- Extensive cross-functional integration between the on-line control and optimisation functions and (traditionally) off-line functions like asset health monitoring/fault detection, model-based what-if analysis.

The objective of the talk will be to identify current problems and trends and demonstrate some concepts for distributed, solution component based architecture for integrated process management, embracing the layers of Advanced Process Control (APC), Real Time Optimisation (RTO) and Planning & Scheduling (P&S).

The concepts will be illustrated by the coordinated control and optimisation of the process side and the utility side, covered, respectively, by Honeywell Profit Suite and Unified Energy Solutions with the objective to operate the plant with maximum achievable profit (maximum efficiency) under the constraints imposed by technology and environmental impacts.

2. CONTROL TECHNOLOGY USED IN SOLUTION COMPONENTS

2.1 Process Models for Control and Optimisation

Design of decentralized control of complex systems results usually in a highly structured system (Mesarovic et al., 1970; Singh, 1977). As there is no appropriate theory supporting the design, an intuitive treatment is generally employed. This heuristic approach cannot produce optimal results (Mesarovic, 1975).

Recently, new system theory based on a consistently chosen set of paradigms was proposed (Žampa, 1996; 1999). This theory redefines main system-theoretical notions without ambiguities and inconsistencies from which standard theories suffer as pointed out e.g. by Willems (1991).

Control synthesis for complex systems based on successive designs of simple feedback loops often fails, because of significant interactions among the loops (Shinskey, 1996) that deteriorate the resulting performance and may even bring the closed loop system into instability. The use of formal design techniques for Multi-Input-Multi Output (MIMO) plants like H_2 or H_∞, that are popular e.g. in the aerospace industry, is not a viable solution for process control, because they do not exploit the structure of the problem and fail even for medium-size problems (several tens of input and output variables). To treat this design problem rigorously, a theory linking system structure and achievable control performance is still missing.

Another fundamental challenge in system modelling is the extraction and propagation of information (including the uncertainty representation) that is compatible with the functionality, granularity and objectives of each layer. For integrated plant management, the ultimate objective is to achieve self-maintaining models based on propagation of information from the process control level (dynamic models for MPC control) to higher levels (optimisation/planning/scheduling). A built-in mechanism is needed for reducing complexity, which will keep the models manageable. This mechanism should filter out high and middle frequency behaviour, which is important for efficient process control but unnecessary for longer-term optimisation. This approach will eliminate the burden of building and maintaining separate models for the process control and real-time optimisation levels. Real time responsiveness of hierarchical plant model to plant topology and parameter changes will resolve the critical issue of model adaptation preserving consistency of individual abstraction layers.

2.2 Advanced Process Control

Model predictive control (MPC) has become a standard multivariable control solution in continuous process industry covering over 90% of industrial implementations of multivariable control (Qin *et al.*, 1996). For multivariable controllers, the traditional controller objective – *regulatory control* (minimize variance of controlled variables around their set-points, track set-point changes and reject disturbances) – can be extended by *constraint handling* (prevent another set of variables from exceeding their limits) and *transition control* (find the trajectory for moving set-point from *A* to *B* optimally).

Standard approach exploited in large scale process control applications is the decomposition of the original large model into several smaller subsystems and control of each subsystem. Theoretically the whole plant can be treated by a single MPC but this solution is not practicable. An optimal decomposition of a large model should minimize the interactions among the subsystems. The principal remaining interactions can be modelled as additional measured disturbances.

For regulatory and constraint control MPC appears to be a well-suited candidate for decentralized design; the individual controllers can take full advantage of the information on the disturbances at current time and their future predictions computed by adjacent units in the previous step. However, to provide additional space for absorbing the disturbances locally, classical MPC formulation has to be extended from multivariable set-point based regulatory control to *range control* providing additional degrees of freedom for disturbance absorption, rejection and optimisation.

With range control, the QP optimisation problem in the standard MPC engine

$$u^* = \arg\min_{u} \|Su + \tilde{y} - r\|_Q^2 + \|\Delta u\|_R^2 ,$$

where S is the dynamic sensitivity matrix and $\tilde{y}$ is the response to initial conditions and measured disturbance, is replaced by

$$u^* = \arg\min_{u,z} \|Su + \tilde{y} - z\|_Q^2 + \|\Delta u\|_R^2 \ ; \ \ y_{LO} \le z \le y_{HI} .$$

The auxiliary variable z constrained by lower and upper set range y_{LO}, y_{HI} instead of the reference trajectory r provides zero error penalty for controlled variables within the funnel defined by the lower and upper set range trajectory (see Fig 2a).

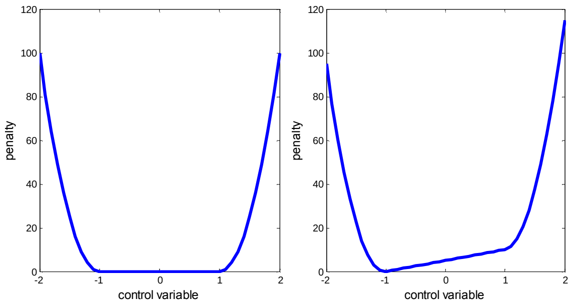

Fig. 2: a) – penalty function for range control with y_{LO} = -1, y_{HI} =1 (left). b) – modified penalty function for range control with simultaneous minimization of controlled variable (right)

Additional steady-state optimisation (minimisation or maximisation of selected controlled variables) can be implemented by adding a linear term to the range definition as depicted in Fig 2b.

An alternative approach – to optimise the target values of selected manipulated variables – will be discussed later. In the case of decentralized transition control, interaction between target value optimisation and dynamic coordination of several multivariable controllers may require a more complex three-tier structure – the top tier provides optimisation-based targets, the bottom tier is a layer of MPC controllers and the additional middle tier is a coordination "collar" for preventing each MPC controller in the bottom tier from receiving a locally infeasible transition trajectory (Lu, 2001).

Analysis and design of *robust MPC* based on Maximal Output Admissible Sets (Kolmanovsky and Gilbert, 1995), (Kothare et al., 1996) can be extended to predictive control schemes based on the range control (Pekar and Havlena, 2005).

For decentralized solutions, the concept of robustness as "tolerance to model uncertainty" has to be extended to complex, hierarchical and networked systems. In the multi-tier structure of plant-wide process control and optimisation, each layer reduces the degrees of freedom available for optimisation at upper levels. As a result, individual units are not able to localize the impact of local disturbances and uncertainties that propagate through adjacent units, resulting in poor robustness of the interconnected solution. The range control based MPC will enhance robust performance, both at the classical "loop level" and in the newly introduced "integrated/networked" sense.

Replacing set-points by set-ranges provides not only the necessary degrees of freedom for the superior levels in the hierarchy, but increases the robustness of the integrated solution – if the control variable trajectory fall into the funnel, the control law provides transient with minimum control effort

$$u^* = \arg\min_{u} \|\Delta u\|_R^2 \ ; \ \ y_{LO} \le Su + \tilde{y} \le y_{HI} ,$$

efficiently removing high-frequency excitation in the advanced control level.

Other advantageous properties of range control can be demonstrated using *stochastic constraint control* formulation. Consider plant model with time domain uncertainty described by step response

$$y(t) = \sum_{\tau=0}^{N} g(\tau)u(t-\tau); \ \ h(t) = \sum_{\tau=0}^{t} g(\tau) \approx N\left(0, \sigma_h^2(t)\right).$$

Typically, this class of models can capture the difference between the high uncertainty of transient response and known steady-state gain. Then the output uncertainty excitation

$$\mathrm{var}\{y(t)\} = \sum_{\tau=0}^{N} \sigma_h^2(\tau)\Delta u^2(t-\tau)$$

is minimized (in an average sense) by the minimum norm control that minimises the $\Delta u^2(t)$ term.

This "minimum norm" control property of range control MPC can be used in *cautious optimisation strategy* (taking the uncertainty explicitly into account). The control and optimisation criterion 'maximise uncertain output under given high limit y_{HI}' can then be formulated in probabilistic terms as

find control u such that

$$P\left\{Su + \tilde{y} < y_{HI}\right\} \ge 1 - \varepsilon .$$

Minimisation of the output variation by minimum norm control results in getting the maximum achievable performance under given (time varying, input dependent) uncertainty (Havlena *et al.*, 2002). Similar stochastic approach to MPC is reported in (Kouvaritakis *et al.*, 2004).

We have demonstrated that range control provides a unified framework for the versatile control needs – regulatory, constraint, and transition controls, where the role of the same controlled variable can change over different time/operations. Another contribution of range control approach is separation of closed-loop time response tuning from open loop model – which is particularly useful in connection with local model switching. Recall that in the case of standard LQ control, the closed loop response depends on the tuning parameters Q, R as well as on the open loop dynamics.

Upper and lower range bound funnel can be generated as a response of a dynamic system to the changes of the reference as well as disturbance inputs to provide additional space for disturbance rejection – see Figure 3. In this way, range control provides robust, minimum control effort model matching – without attacking the open loop dynamics by providing extra space during the transient and independent tuning of transient and disturbance rejection dynamics (Baramov, 2005).

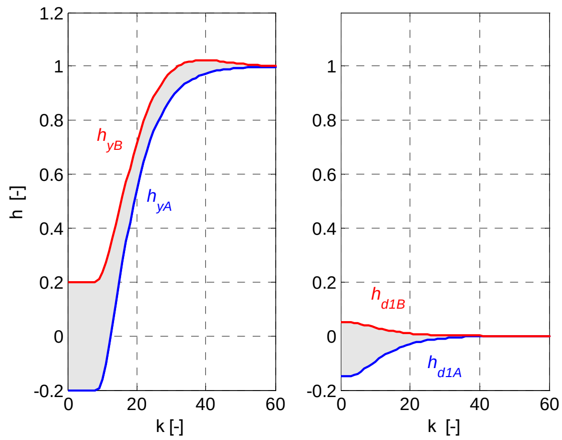

Fig. 3. Normalized range responses to step change in the set-range (left) and disturbance (right).

Another extension of the MPC with range control is ratio control. With hard fixed ratio constraint, the optimisation problem is non-linear. However, the hard constraint on the ratio of process variables $y_i(k)/y_j(k) = c_{ij}$ can be replaced by a soft constraint added to the criterion. For a process with two outputs, the penalty corresponding to a soft constraint on the ratio

$$\sum_{k=1}^{N} q_k \left(y_1(k) - c_{12}(k) y_2(k)\right)^2 = \|y_1 - Cy_2\|_Q^2$$

can be written in matrix form as

$$\left\| \begin{bmatrix} I & -C \end{bmatrix} \begin{bmatrix} \tilde{y}_1 + S_1 u \\ \tilde{y}_2 + S_2 u \end{bmatrix} \right\|_Q^2 = \left\| \begin{matrix} \tilde{y}_1 + S_1 u \\ \tilde{y}_2 + S_2 u \end{matrix} \right\|^2_{\begin{bmatrix} Q & -QC \\ -C^T Q & C^T QC \end{bmatrix}},$$

i.e. resulting optimisation problem is a standard quadratic programming. Moreover, the soft constraints on the ratio do not increase the dimension of the original optimisation problem.

2.3 Real Time Optimisation

A standard way of dealing with high dimensionality in processing industries is solving the problem in two separate layers: the Advanced Process Control (APC) layer performing dynamic optimisation (typically on linearised models), and the Real Time Optimisation (RTO) layer performing static optimisation (usually non-linear). Most of the RTO packages try to detect a steady state condition and then optimise the costs of operations by optimising the steady state via set points. To operate in this fashion, RTO have to wait for transient responses to settle. However, for processes with slow dynamics and/or high levels of disturbances, the dependence of RTO on steady state detection substantially deteriorates the performance of the overall system. Clearly, there is a need for RTO to operate during transients with a tight interaction with the APC layer.

In a typical optimal load allocation for a number of units operating in parallel, the performance index like boiler efficiency or heat rate is well defined only for steady state operations. Note that optimal allocation is based on equal incremental costs of parallel units. If the master controller for the set of parallel units is implemented as MPC, the optimisation layer can dynamically respond to the predicted steady state that is obtained as the target values of manipulated variables at the end of the prediction horizon (provided the prediction horizon length is correct) resulting in fast tracking of the optimal allocations.

On the APC layer, all the three common tasks – regulatory control, constraint control and economic optimisation – are unified in a single range control formulation using an additional term forcing the manipulated variable u at the end of the control horizon T to follow the target u_{TARG}

$$u^* = \arg\min_{u,z} \|Su + \tilde{y} - z\|_Q^2 + \|\Delta u\|_R^2 + \|u(T) - u_{\mathrm{TARG}}\|_{R_{\mathrm{TARG}}}^2$$

$$y_{LO} \le z \le y_{HI}, \quad u_{LO} \le u \le u_{HI}.$$

In this way, economic optimisation is implemented as *transition control* that utilizes the additional degrees of freedom resulting from the range control.

In the case of decentralized control, without global coordination, composition of local optima achieved by each predictive range controller and local optimiser may provide significantly worse performance than the globally optimal solution. One approach is to use more centralized optimisation layer and add some mechanism how to reach globally optimal targets by local controllers without a conflict. An alternative approach is to use decentralized optimisation with additional coordination layer to guarantee convergence to globally optimal solution.

As an example of the first approach, a three tier APC/RTO integration method was proposed (Lu, 2001).

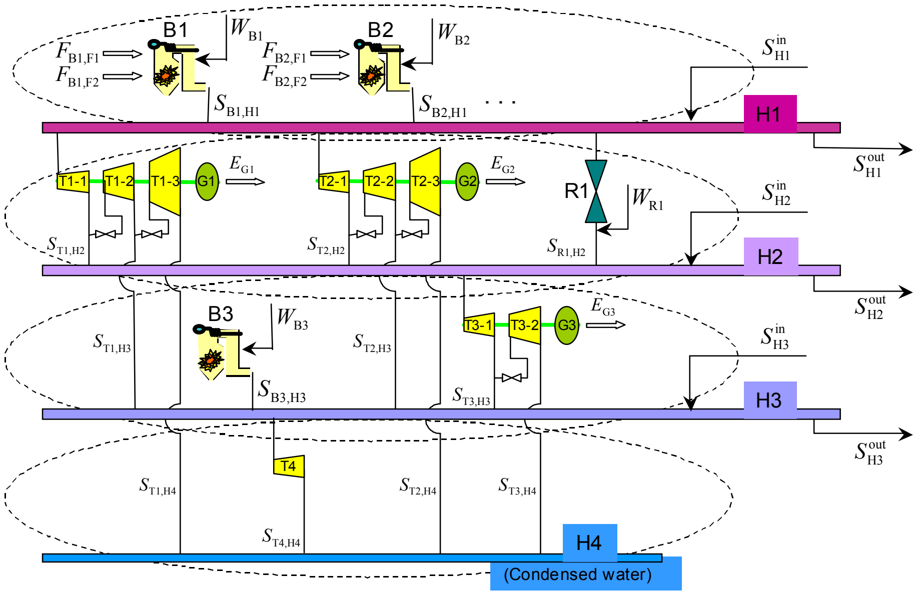

Fig. 4. Example of industrial energy steam plant topology.

The top tier finds global optimum u_G based on projected future constraints

$$\min_{u_G} f(u_G)$$
$$y_{LO} \le G u_G \le y_{HI}, \quad u_{LO} \le u_G \le u_{HI}$$

where G, the global gain matrix, and the two sets of constraints are composed from local gains and constraints of individual controllers. Then set of locally feasible targets u_{TARG} closest to the global solution u_G for (i)-th controller can be obtained as

$$\min_{u_{TARG}^{(i)}} \sum_i \left(u_{TARG}^{(i)} - u_G^{(i)} \right),$$
$$y_{LO}^{(i)} \le G^{(i)} u_{TARG}^{(i)} + y_D^{(i)} \le y_{HI}^{(i)}, \quad u_{LO}^{(i)} \le u_{TARG}^{(i)} \le u_{HI}^{(i)}.$$

The two sets of constraints correspond to the constraints of the (i)-th controller at the end of its prediction horizon. This step is a "coordination collar" that protects local controllers from obtaining locally infeasible target destination. While the global optimum is based on the full gain matrix, the locally feasible targets are based on the (i)-th diagonal block of the gain matrix and local estimate of the impact of disturbances y_D that may result from interaction with the other controllers.

The locally feasible target is then passed to the corresponding (i)-th controller

$$u^{(i)*} = \arg \min_{u^{(i)}, z^{(i)}} \left\| S^{(i)} u^{(i)} + \tilde{y}^{(i)} - z^{(i)} \right\|_Q^2 + \left\| \Delta u^{(i)} \right\|_R^2 + \\ + \left\| u^{(i)}(T) - u_{TARG}^{(i)} \right\|_{R_{TARG}}^2,$$
$$y_{LO}^{(i)} \le z^{(i)} \le y_{HI}^{(i)}, \quad u_{LO}^{(i)} \le u^{(i)} \le u_{HI}^{(i)}.$$

This integration approach has been successfully commercialised and deployed in both refineries and ethylene plants with significant benefits (Verne, 1998), Nath and Alzein (1999) describe application of this technology to an entire ethylene facility. The optimiser coordinating 10 RMPCT controllers is executed every minute while a comparable "classical" RTO solution runs every 2-4 hours. The acceptance test for the project demonstrated 10% increase in average production.

To illustrate an alternative approach to interaction between the APC and RTO layers, consider the industrial utility as in Figure 4. Unit's resource flows, R_i, and product flows, P_j, are functions of a chosen set of optimisation variables, x, and a set of parameters p (measured variables not subjected to optimisation, slowly varying with respect to control and optimisation execution period)

$$R_i = R_i(x, p) \quad , \quad i = 1, \ldots, n_r$$
$$P_j = P_j(x, p) \quad , \quad j = 1, \ldots, n_p$$

It is assumed that all resource flow functions are convex, and all product flow functions are concave. The cost criterion is a linear combination of resource and product flow functions

$$f(x|p) = \sum_{i=1}^{n_r} c_i^r R_i(x, p) - \sum_{i=1}^{n_p} c_i^p P_i(x, p)$$
$$\text{all} \quad c_i^r \ge 0 \quad \text{and} \quad c_i^p \ge 0$$

The price coefficients c may vary in time and depend on parameters.

In the case of parallel units with fixed total flow, the optimal allocation problem results in well-known *incremental cost* based allocation (Šomvárský *et al.*, 2002). For more complex set-ups, general optimisation problem

$$\text{minimize} \quad f(x)$$
$$\text{subject to} \quad h(x) = 0$$

has to be solved (additional inequality constraints will be considered later). Introducing the *Lagrangian function*

$$L(x,\lambda) = f(x) + \lambda^T h(x),$$

necessary conditions for minimum are given by

$$\nabla L(x,\lambda) = 0$$

and using Newton's method to solve this non-linear equation, iterations $x^{k+1} = x^k + \Delta x^k$, $\lambda^{k+1} = \lambda^k + \Delta\lambda^k$ can be obtained by solving the system of equations

$$\begin{pmatrix} L_{xx}(x_k) & h(x^k) \\ h^T(x^k) & 0 \end{pmatrix} \begin{pmatrix} \Delta x^k \\ \Delta\lambda^k \end{pmatrix} = -\begin{pmatrix} f_x(x^k) + h_x(x^k)\lambda^k \\ h(x^k) \end{pmatrix}.$$

which – after a simple rearrangement – are the necessary conditions for $(\Delta x^k, \lambda^{k+1})$ to be the solution of a quadratic program

$$\begin{array}{ll} \text{minimize} & {f_x^k}^T \Delta x + \tfrac{1}{2}\Delta x^T L_{xx}^k \,\Delta x \\ \text{subject to} & h^k + {h_x^k}^T \Delta x = 0 \end{array}.$$

This algorithm can be extended for problems with inequality constraints resulting in well known local SQP (Sequential Quadratic Programming) method (Nocedal and Wright, 1999).

For real-time optimisation applications, the SQP can be implemented with *iterations spread-in-time* (IST), with the limits and rate-of-change constraints providing natural "trust region" in each iteration. In real-time applications, feasibility of successive iterations should be enforced (Panier and Tits, 1993). Also, objective function may not be well-defined outside the feasible set. IST approach results in fast tracking of optimal trajectory. The problem with feasibility of trust region based methods (empty intersection of the feasible set and trust region for a general starting point) is avoided, as the iterations are started from currently applied set-point that is always feasible.

The concept of incremental cost, used for load allocation to parallel units (boiler, that supply steam to a common header, or turbines, that operate between the same headers) can be generalized to a more complex multi header topology. Consider a problem of production cost minimization under given steam and generation demand. Let $f(x)$ represent the cost function of the steam from the boilers. The linear equality constraints define steam balance conditions for flows x in individual headers

$$h(x) = Bx - d = 0$$

where the balance matrix has non zero elements $B_{ij}=\pm 1$ for flow x_j entering/ leaving i-th header and d_i is the demand for process/heating steam from header i and the total generation balance

$$g(x) = [1,\ldots,1]\,G(x) - d_{\mathrm{G}} = 0$$

where $G(x)$ is the generation on individual turbines as a function of steam extraction/condensation flows and d_{G} is the total generation demand. Row i of the first order optimality condition

$$L_x(x,\lambda) = f_x(x) + B^T\lambda + g_x(x)\mu$$

can be interpreted as a transformation of the incremental costs related to flow x_i from header j to header k

$$\lambda_j = \lambda_k + \partial g(x)/\partial x_i \;\mu$$

i.e. incremental cost of steam from header k is the incremental cost of steam from header j reduced by the incremental cost of generation. If the *equilibrium prices* are known, the optimal allocation between parallel extraction flows $x_{i_1},\ldots,x_{i_n}$ from headers $j_1,\ldots,j_n$ to header k can be found locally based on modified *equal incremental generation* condition

$$\frac{\partial g(x)}{\partial x_{i_s}} \propto \lambda_{j_s} - \lambda_k .$$

For the equilibrium price, the global minimum cost benefit will be obtained as a sum of individual local cost (resulting in maximum generation from available steam).

$$f^k(x) = \sum_s \lambda_{j_s} x_{i_s} - \lambda_k d_k^{TOT} - \mu \sum_s \Delta G(x_{i_s})$$

Moreover, the balance between internal interaction flows as well as global demand will be achieved.

The optimal (equilibrium) price can be obtained by solution of the dual problem. When the duality gap occurs, the set of interconnection flow prices, such that each system can minimise its local costs and achieve global optimisation, does not exist. The conditions under which the duality gap does not occur are rather restrictive – convex cost function $f(.)$, convex feasible set defined by the inequality constraints and linear equality conditions (Simmons and White, 1977) – but are fully satisfied e.g. for a class of load allocation problems.

Decomposition theory appeared in the 1970's and 80's in the works of Mesarovic et al. (1970). Singh (1977, 1978), Findeisen et al. (1980, 1982), Jamshidi (1996) and recently Michelena et al. (1998, 2002) analyse different method of coordination. The complementary approach is aggregation. Its principal idea is that a subsystem is replaced by a simpler model with the characteristic behaviour of the original system almost unchanged. Several aggregation techniques were presented lately by Tsurkov (2000; 2001).

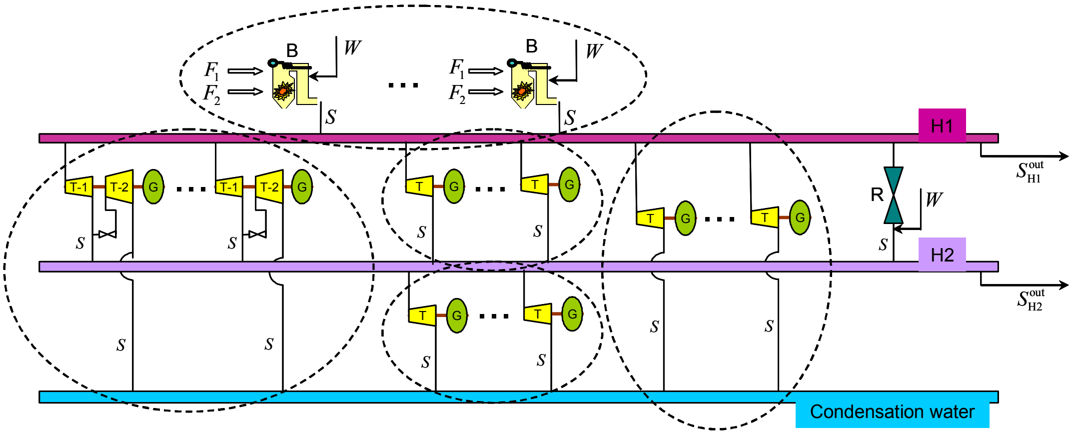

Fig. 5. Industrial energy steam plant topology with aggregation of parallel units.

Also the load allocation problem can be formulated using the aggregation. For parallel units operating between the same headers (in a more general setting, using the same resources and turning out the same product), optimal load allocation problem can be solved locally and the group of parallel units can be described as a single unit characterised by resulting optimised cost curve (see Fig. 5). Then, the global optimisation problem uses the aggregated models, i.e. there is a single aggregated flow between each couple of interconnected headers represented by a single (locally optimal) cost curve.

Using aggregation and hierarchical solution of the global allocation problem, convergence of the global problem calculating the aggregated cumulative flows is drastically improved. The optimal allocation of cumulative flows to parallel units is handled by local allocation algorithms. However, the aggregation necessarily results in conservative treatment of internal constraints between the extraction and condensing flows within a single turbine. The trade-off depends on turbine/header topology – whereas in the case of the topology depicted in Figure 4 aggregation will not provide major benefits, for the topology depicted in Figure 5 the convergence and stability of the allocations will be significantly improved.

2.4 Asset management

The impact of asset management elements in Integrated Process Management have been limited. We will use examples from power generation domain to illustrate how the same solution component – economic optimisation based on incremental costs – can be reused asset related problems and how the asset management can be integrated with advanced process control layer.

A typical dependence of losses resulting from technology ageing/degradation resulting in diminishing productivity and average cost of maintenance is depicted in Figure 6. The optimal maintenance period depends on the rate of process degradation.

Beside long term process degradation, when manual performance monitoring and manual evaluation may be practicable, for short term degradation, also the decision about the maintenance has to be automated. An example is Soot Blowing Optimisation, where the fouling of boiler surfaces results in reduced heat transfer, increased losses in the flue gas and reduced efficiency.

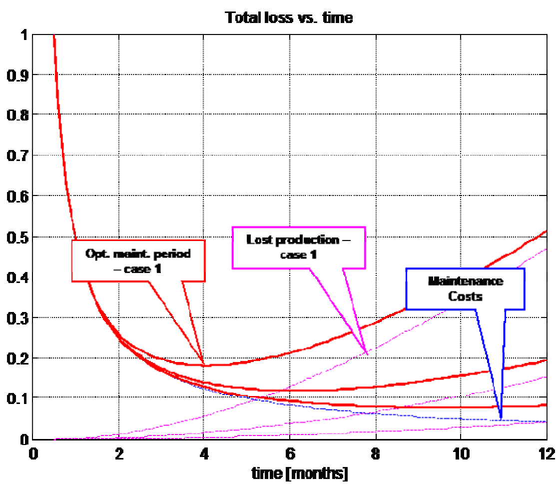

Fig. 6 – Typical maintenance economy – different rates of process degradations and corresponding optimal maintenance periods.

Beside a global approach – scheduling a fixed soot blowing sequence based on global performance index degradation – more detailed optimisation targeting individual surfaces is required. The optimum depicted in Fig. 6 can be also interpreted as equal incremental costs of soot blowing steam and incremental losses from reduced efficiency. The incremental cost based approach can be extended to multivariable optimisation problems.

While the impact of fouling can be evaluated by real time performance monitoring components, the incremental benefits from cleaning can not be simply evaluated – change in cleanliness of any surface results in redistribution of heat flux, different fuel consumption and cooling water redistribution. Cumulative impact on global performance can be evaluated only using a steady-state boiler heat balance model.

Another area for dramatic improvement of the return on asset is extension of asset life. Classical methods of life time estimation based on accumulated creep and cycling stress damage calculated by thermal stress monitoring packages as defined by ASME or TRD industry standards are overly conservative and provide extensive space for asset life time extension based on modern computational methods like Finite Element Method for thermal and stress field evaluation.

Beside the benefits from improved monitoring methodology, information about the current values of thermal stress can be used in real-time – defining an auxiliary output to unit master controller, reflecting the impact of load and fuel changes to thermal stress at the critical point of the boiler. This auxiliary output will be used to introduce real-time feedback constraint control as introduced in Section 2.2 based on maximum allowable stress. This approach provides maximum unit responsiveness and optimal utilisation of boiler storage capacity during the transients under given constraint on asset life time consumption rate.

3. APPLICATION FRAMEWORK

Currently, commercially available computers and operating systems play more and more significant role in hosting level 3 and level 4 applications (advanced control, real time optimisation, performance monitoring, planning, scheduling). However, control applications have many requirements not provided by commercial operating systems. Honeywell Advanced Process Control group undertook the implementation of a platform to run on MS Windows 2000 and successors that would provide execution services, data exposure, process data access, configuration, and other application needs in as general and flexible way as possible. The solution is based on software components (Szyperski, 1999) using Windows standard Component Object Model (COM) and Distributed COM (DCOM) technology (Grimes, 1997). The resultant platform is called *Unified Real Time (URT)*.

Control applications typically need to expose data to operators and engineers, pass data between modular pieces of an application, or between applications. Advanced applications may need to expose large amounts of data, which implies that flexible containers and structures are needed for organization of data. To meet these needs, data values that need to be exposed are encapsulated in component objects called data items and organized in a tree structure. The generality of the data tree provides the flexibility needed for large applications to organize their data in a simple way.

Scheduler blocks perform execution. A scheduler block typically heads a branch that contains the function blocks and data items for an application instance. Each scheduler block exposes child data items that hold scheduling information such as desired execution interval, interval offset, demand trigger, execution priority, and active/inactive status.

Details on *Unified Real Time (URT)* platform and architecture of a typical advanced control application depicted in Figure 7 will be presented in Invited Session "Variability Management for Control System Software" (Horn et al., 2005).

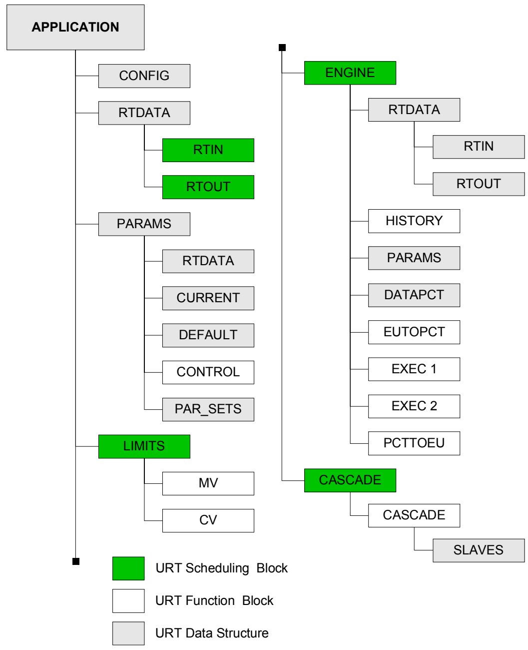

Fig. 7 – Architecture of an application built from software components.

Even with software component based applications, there is still a number of barriers to extension of "controllability" of the process – starting from additional costs, difficult integration of knowledge in different forms, lack of solution collaboration to limited action space. A cost effective way to *higher controllability* is to increase *solution customisability*. Customisable solutions can be built from plug-in *solution components*, that use common base infrastructure (transparent and scalable system services). The "plug-and-play" content of the solution components will expand the traditional scope of control and optimisation to performance monitoring/diagnostics, forecasting, planning, scheduling and supply chain management. Unified Authoring Environment will provide language, algorithms and specific process knowledge.

The solution component – basic building block for customisable solutions (smallest customisable module that offers independent functionality) is different from *software components* – typically it is one or more software component, but while software components are containers designed to encapsulate with respect to reusability, scalability etc., the solution components encapsulate with respect to

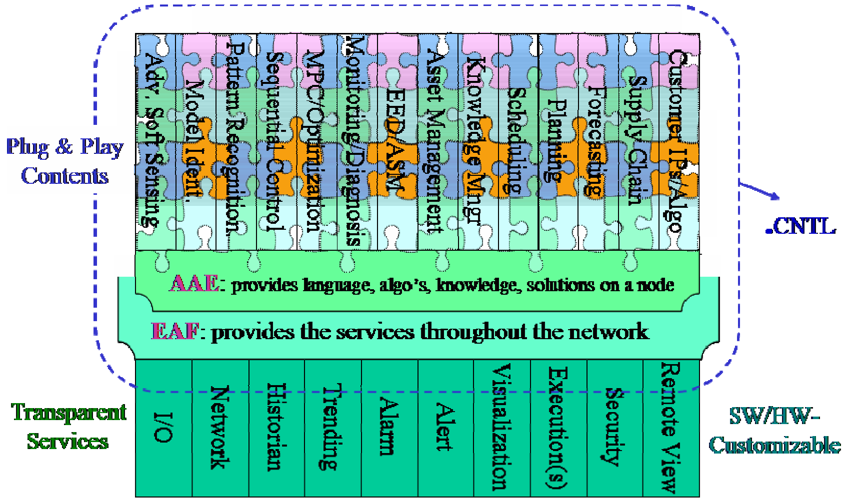

Fig. 8 – Automation Authoring Environment for customisable solution components.

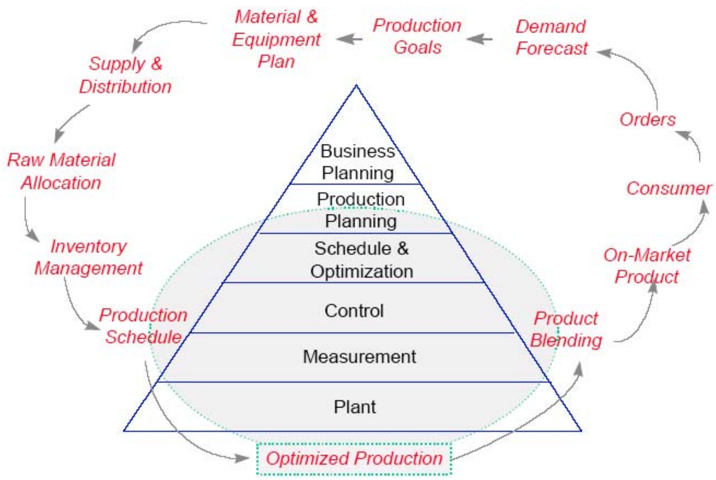

Fig. 9 – Example of enterprise wide optimization in a refinery.

algorithmic content or domain knowledge. Built-in solution components encompass at least the common control/optimisation subspace and can work together with externally coded plug-in components.

The next generation .NET based software platform for Automation Authoring Environment for solution components called .CNTL is depicted in Figure 8.

4. DEMO APPLICATION

Although the presented concepts are applicable across the processing industries, in the talk we shall particularly concentrate on problems arising in power generation and chemical/refining industries.

The reasons for choosing these domains are as follows:

- Power generation is leading other industries in its need for real-time responsiveness. External conditions are dictated by real-time cost and price fluctuations in the energy market, by stringent environmental constraints and by demands for stability of the distribution system. Moreover, different time scales must consistently be considered: medium to long-term production plans (months-years) and short-term schedules (down to fractions of seconds) for power contract execution and ancillary services (frequency control). Other industries are likely to face similar challenges of the demand driven real-time economy in the near future.

- Chemical/refining industries provide the most complex control problems. A refinery example of enterprise wide optimisation is depicted in Figure 9. To date, the largest implementation of coordinated RMPCT controllers coordinates 40 controllers with total number of controlled variables and additional constraints exceeding 1000 (Nath and Alzein, 2001).

5. CONCLUSIONS

The paper summarized some of the challenges resulting from increasing scope of integrated process management solutions that bring together technical/technological and economic knowledge and criteria. Current control technologies and their implementation based on software components was reviewed. Solution components were introduced as basic building blocks and efficient tools for cross-functional integration that will enable extension of the "controllability" of the process from the traditional layers of single-loop regulatory control, multivariable control and optimisation to higher layers of planning, scheduling and supply chain management.

The talk covered work that several research teams in Honeywell have done as a pioneer attempt at solving those challenging problems – mostly in the advanced control and real time optimisation tiers. There is still much work left to be done – starting with the design challenge between the need of decentralized solution and the need of solving global economic optimisation on enterprise wide level and continuing with incorporating flexible planning and scheduling layers into an essentially decentralized control system, with adequate levels of abstraction of the physical process and different time granularity at different layers.

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