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Knowledge modelling for rule-based supervision and control of production facilities

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The technological complexity of modern production facilities and the increasing demands on operation procedures result in new tasks and requirements for automation solutions and operating staff qualification. On the one hand, supervision and control systems must assign tasks which have been carried out by operators—e.g. operative planning of resources, scheduling of maintenance, operation tuning. On the other hand, the operating principles and techniques must become more objective; operating experience and knowledge should be more easily collected, conserved and disseminated. The general objective of this paper is to develop methods and techniques for these issues. The studied approach is based on integrated use of several formalizations of facility operation knowledge—mathematical modelling, data-driven methods, and scenario-oriented supervision and control routines. Here, facility events in the past are classified by means of Data Mining. Cause-and-effect relations between process states and phenomena are expressed by equations. Facility operation routines are modelled in the form of 'if-then' scenarios. The functional chain, which begins with operator knowledge acquisition and moves to knowledge and facility modelling and finally to their integration into a real Supervisory Control and Data Acquisition system, have been implemented and tested for a water treatment and supply plant.

Keywords: Supervisory control; Knowledge modelling; Simulation; Decision support; Water supply network

1. Introduction

The increasing complexity of modern process plants and the demand for energy conservation, product quality, environmental protection, safety and reliability call for new approaches to process automation. As traditional control and supervision technologies are being replaced by complex model-based control procedures (Paiuk *et al*. 2002), system supervision and decision making have become more complex for the operator, who must reflect on the behaviour of the process and the control components as an entire system.

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Extensive knowledge of process technology and facility technique has resulted in sophisticated simulation models which can calculate the facility behaviour in a given environment under certain conditions. Such simulation models are used to train plant operators (Bernhardt and Schreck 2001, Winter and Schmidt 2001) and can also be applied to decision support. Operator training simulators provided as an electronic service (Hohwieler *et al.* 2001, Schreck 2002, Berger and Hohwieler 2003), or even by web-based implementation (Langmann and Hengsbach 2003, Lisounkin *et al.* 2004a, Lisounkin *et al.* 2006), are promising tools for supporting plant operation.

In addition to this, the decision-making process involves analysing actual application contexts, weighting different and partially concurrent targets and objectives and, finally, developing scaling mechanisms for a quantitative comparison of possible behaviour alternatives. Although decision-making procedures have been the focus of many researchers, there is a lack of general modelling concepts and treatment procedures due to the high subjectivity of human decision making (Krüger *et al.* 2005).

Along with decision making and control procedures based on mathematical models and optimization solvers, knowledge-based systems involving the experience of human operators are a promising approach. The aim of the integrated knowledge-based and simulation-based method is to combine available formal information and process data from the facility, e.g. information on plant models and historical operation profiles, with human operation knowledge. This calls for experience-based evaluation and active assessment of operation artefacts through an operator team and further use of this information in a regular manner. The basics for rule-based machine learning concepts with application to facility operation have been developed in Camarinha-Matos and Martinelli (1999).

This paper is devoted to advanced facility supervision and control concepts that simultaneously embrace simulation- and knowledge-based components. Focus is given to the decision-making processes of human operators and the respective modelling of knowledge objects for automatic processing. The aspects of system implementation and the example of their application presented are related to a real industrial environment.

In section 2, the general structure of advanced supervision and control procedures is outlined. Typical control and supervision levels in process industry are presented, and the role and tasks of operators are discussed. Furthermore, requirements concerning the implementation of knowledge-based components are given.

In section 3, the elaborated concepts for the modelling of operation knowledge are presented. Based on an analysis of the decision-making procedure, knowledge levels are introduced and explained. Finally, the data models of the elaborated knowledge objects are presented.

In section 4, aspects of software implementation are discussed. The system architecture of the rule-based supervision system, runtime components and interfaces are presented. A system application and test at a water supply and distribution facility are outlined.

In section 5, conclusions concerning application results, required extension and further research are presented.

2. Advanced facility supervision and control

2.1 *Control levels and degree of automation*

Automation solutions are considered as hierarchical systems, where each level possesses a clearly specified responsibility with respect to automation objectives and a corresponding functionality. Figure 1 shows the typical control and supervision levels for process automation. The two lowest levels are designed for interaction with the real production process. They directly collect information on the process state and trends and implement the impact on the process by means of set up values for functionally active elements—valves, pumps, etc. On the upper levels are located the procedural mechanisms of the process supervision and control. Operation units of the field level are used for the process stabilization and for the automated processing of standard control tasks. Supervisory Control and Data Acquisition (SCADA) systems are usually installed for advanced information management and process regulation. They play an important integrative function in distributed, multilevel control environments and provide an appropriate human–machine interface (HMI). Typical functionalities include the monitoring of process states, the recording of alarms and events, the activation of control actions, optimization of operation points, emergency shutdown, etc. Additionally, SCADA can be equipped by modules with so-called advanced functions such as simulation-based process forecasting and optimization. A high functionality on the upper levels of automation hierarchy reflects a high degree of automation of the facility.

The presented work focuses on the application of simulation- and knowledge-based systems for process supervision and operation. The aggregation of data on the way from the process level to the high-level control is a main aspect to be solved within this approach. Therefore, appropriate abstraction levels must be engineered to provide suitable views on plant conditions and process states for supervisory control and decision making by human operators.

2.2 *Role and tasks of operator*

Even with a high level of automation of process supervision, diagnostics and control, the facility operator's role is continually expanding. Although local

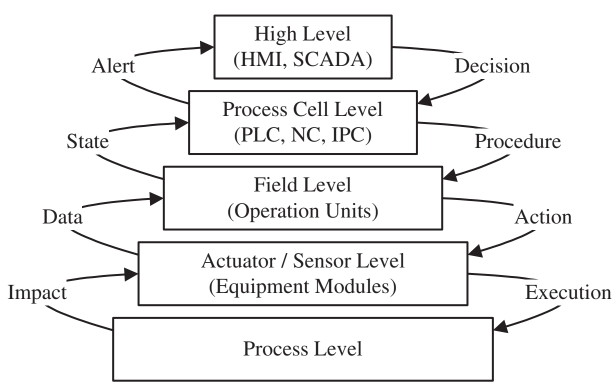

Figure 1. Typical control and supervision levels in a process industry.

automation tasks are covered by an installed control system, the facility operation staff must take precautions with high-level functional, technological, strategic objectives.

The human operator team is responsible for the high-level process management which includes tasks such as

- assessment of process situations;
- selection of operating points;
- consideration of different modes of operation and use of resources;
- reaction to changing requirements/demands; and
- ensuring a continuous and smooth running of the system.

The decisions of human operators are based on their knowledge of process situations, process trends and process control. Here past gained experience, i.e. historical data and knowledge of situations, plays an important role in allowing a high level of performance to be reached (Lisounkin *et al*. 2004b).

In our concept of an advanced supervisory and control system, the provision of support functionalities to the operator team plays an important role. It includes not only tools for decision support, e.g. through integrated simulation functions, but also methods and tools for arranging the automatic execution of favoured process patterns. Here the need for the optimization of system operation and the demand for a high-level supervisory control should be met without compromising the benefits of the flexibility and knowledge of human operators.

2.3 *Requirements on modelling and knowledge processing*

Specific technical realization, technological and administrative requirements, operative performance criteria, as well as long-term planning result in unique supervisory and control schemes for each facility to be controlled. Usually, the design, development and maintenance of such supervisory and control schemes employ a significant amount of human resources for each application. Reasonable methods for modelling a corresponding knowledge base and techniques for its application and maintenance will lead to a high acceptance of such systems and efficiency in use.

Considering that the acceptance by operators is a key aspect, an extensive use case analysis must be foreseen even at the very beginning of the development. Therefore, the system must allow different facility operation modes, such as manual operation, model- and knowledge-based decision support and automatic facility operation. Furthermore, automated functions must provide feedback on decisions in order to establish confidence and also to support the tuning of system behaviour.

From the system integrator's point of view, two classes of requirements can be identified. On the one hand, there are clear technical requirements concerning the functional integration concepts and interfaces with different SCADA systems (Robinson *et al*. 2002, Youngpil *et al*. 2002, Gayet *et al*. 2003). On the other hand, requirements concerning the acquisition and engineering of knowledge, the re-use of models and knowledge components, maintenance and lifecycle support become of increasing importance (Lisounkin *et al*. 2003, Yagüe *et al*. 2004).

3. Operation knowledge modelling

3.1 *Decision making*

An analysis of role-driven staff responsibilities and activities with respect to the commissioning, supervision, control and maintenance of process facilities and power stations has been provided by Rasmussen (1986). His findings continue to influence the development of decision support systems for technical facilities.

Within the context of facility operation, the decision-making procedure consists of the following steps. First, the decision maker must detect the need for intervention by observing actual process data. For this, the operator has features at his disposal—data evaluation functions and criteria—which give him an estimate of the optimality and regularity of the system's operation or of a malfunction in the system. In regular cases, this information can give the direction for subsequent activities. Based on this evaluation, a target state into which the system should be driven will be chosen, and the task that the decision maker should perform will be selected from a review of available resources. Once such a task is identified, the proper execution can be planned and carried out.

If the connection between the data evaluation criteria and the sequence of actions to reach the given goals is clear, the supervision procedure is considered 'skill-based'. A skill-oriented behaviour is an ability to react to known situations with pre-defined actions. This ability can usually be learned and acquired through training.

In cases where decision making involves the evaluation of alternatives, the supervision procedure is considered 'rule-based'. The evaluation of alternatives and the decision are accomplished through simple analysis of the actual process state and additional context information.

A decision-making procedure which involves the comparison of models and analysis of goals and depends on the operator's know-how is considered 'knowledge-based'. In this situation, a deep knowledge of process behaviour is required, and the elaboration of new operation solutions is expected from the facility staff.

These three levels of the decision-making procedure are depicted in figure 2.

3.2 *Knowledge levels*

For integrated knowledge-oriented supervision and control we will consider in parallel three knowledge levels (figure 3) reflecting the origin, the form and use scenarios of facility operational information:

- knowledge of process states and past events;
- knowledge based on formal process modelling; and
- knowledge expressing process operation experience.

In practice these three knowledge models are based on very different modelling paradigms and complement each other. The analysis of historical data provides information on differences in process runs. Using cluster analysis, process runs will be classified and can be used for the recognition of non-usual situations.

The formal mathematical modelling provides a universal and formally interpretable description of the relevant technical and physical phenomena.

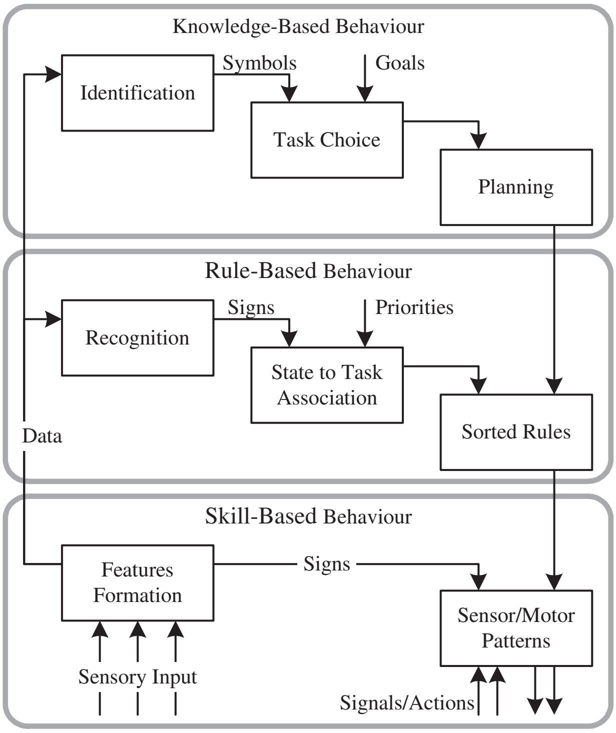

Figure 2. Model of decision-making behaviour according to Rasmussen.

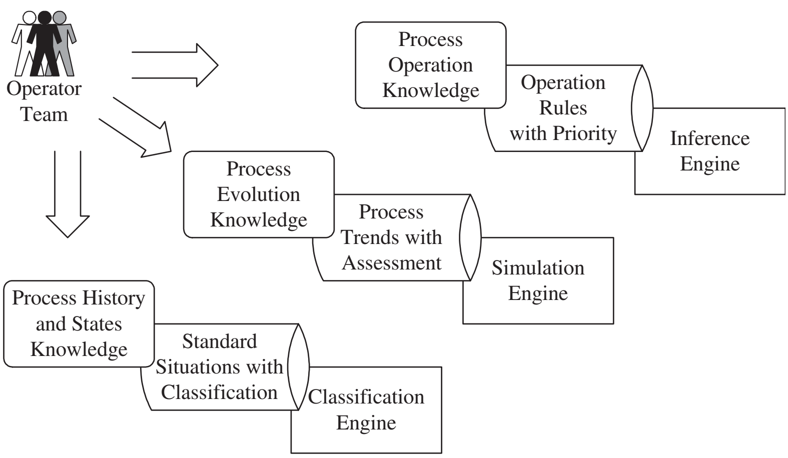

Figure 3. Structuring of operation knowledge and related tools.

Such models allow numeric interpretation in order to compute forecasts and optimal states of process behaviour.

The elaboration of operational rules serves to represent human behaviour in standard situations. Such rules reflect the reaction of facility operators to known process states. For example, the supervision of the fill level of tanks in a water distribution system can be formulated by means of the following rules:

- IF $\exists$ tank, tank.level $\geq$ 0.70 & $\exists$ pump, tank -> pump & pump.state = 'off', THEN pump.state = 'on';
- IF $\exists$ tank, tank.level $\geq$ 0.70 & $\exists$ pump, pump -> tank & pump.state = 'on', THEN pump.state = 'off'.

Figure 3 depicts these knowledge levels with the related application examples. The implementation of these concepts requires the corresponding, indicated engines.

3.2.1 Process states and past events. This type of process knowledge is traditionally exploited by industrial SCADA systems. Usually, events and states of a supervised process are evaluated by mapping them into specified sets or assigning them to defined situations. Here, equipment status, measurement data and events are archived and interpreted by means of signal processing procedures—filtering, approximation, selection, clustering, etc. This provides the background for the identification of correlations and dependencies among process measurements, states and events. This approach is denoted as data-driven. Obviously, within this approach, dependencies and correlations between process phenomena are studied on a generic level. The corresponding routines are covered by the Data Mining concepts (Fayyad *et al*. 1996, Wang 1999, Müller and Lemke 2000, Lisounkin and Schreck 2002).

In earlier applications, this approach focused solely on process and facility data in the scope of real time measurements. More recently, supervision and control applications consider process trends collected over time intervals ('historical data'). Using these applications, steady patterns within the historical data can be identified and can be taken as a characteristic process representation (Lisounkin 2003). During runtime, actual measurements are compared with patterns identified in the past. In the case of a match with a pre-identified pattern, the corresponding past process trend can be expected to recur. With respect to the decision-making model (figure 2), this type of knowledge supports skill-based behaviour (Kouba *et al*. 2002, Lisounkin *et al*. 2004b).

If an actual process trend does not match patterns identified in the past, this approach cannot provide any reliable information on the future evolution of the process. This is the main disadvantage of this approach.

3.2.2 Formal modelling. Generally speaking, mathematical modelling is a universal form of human knowledge representation. This type of technological process and facility modelling—usually in the form of differential equations—finds its absolute eligibility with respect to process simulation (Amsari 2000, Paiuk *et al*. 2002). Dynamical mathematical modelling is the core of almost all behavioural assistance, training and decision support systems (Schreck 2002). Suppliers of industrial SCADA systems often provide their own modelling services and offer an interface for external simulation software. Via the interface, the modelling can be provided by third parties such as research institutes and universities.

Model-based knowledge possesses a high degree of objectiveness and can cover a wide operation area of the facility or process. This form of modelling can facilitate the recognition and identification of tasks on the knowledge-based and rule-based levels of the decision-making procedure (figure 2). However, a large amount of effort—specific to the field of application and even to the respective application—must be dedicated to the elaboration of such models.

3.2.3 Process operation experience. In his daily work, the facility operator is involved in the decision-making process, sometimes with higher and sometimes with lower intensity. Facilities with a high degree of automation require human intervention in critical rather than in the routine situations. In contrast, for facilities with a low degree of automation, the operation staff can be almost permanently involved in the decision-making process. In this context, the human activity consists of mapping planning and maintenance tasks to operation schemes and execution rules (compare with figure 2). Usually, an initial pool of operation rules must be established individually for each facility during its commissioning. Thereafter, the pool of rules can be extended during the entire life-cycle of the facility. These rules can be considered as knowledge based on process operation experience.

The choice of an operation task and the application of execution rules are the responsibility of an involved operating team. Depending on the background, experience and even character of these persons, these decisions may vary. For this reason, the consideration of production objectives and contexts, as well as the analysis and modelling of human behaviour have enormous importance.

There are numerous efforts to formalize this type of knowledge and—by means of systematic within the rule application mechanisms—at least to reduce the subjectivity of this approach (Lisounkin 2006). In order to handle the problem of process operation experience modelling, the authors follow the idea of linking process pattern recognition routines and the equation-based simulation of process trends with execution rules and developed a scenario-oriented procedure.

3.2.4 Decision support procedure. In summary, the integrated knowledge-oriented supervision and control system must consider facility and process elements (resources) when the facility is in operation. The system must supervise the states and events and be able to recognize whether one or several of these would be considered an 'unfavourable' state. Furthermore, the system must be able to transform an unfavourable state to an advantageous one by means of intervention in the process behaviour—i.e. via suitable actions. Transformations from unfavourable states to advantageous ones by means of defined process interventions build a set of executive rules. In the majority of cases, the description of advantageous and unfavourable states can be expressed in the form of inequalities. The violation of one or several inequalities is the condition and, respectively, an initial point for a process correction, which can be organized as scenarios of actions.

All the above-mentioned objects—advantageous and unfavourable states, conditions, actions and executive rules—form the body of process operation knowledge. In the following sub-section, a data model for these objects—knowledge objects—is discussed.

3.3 *Knowledge objects*

For the modelling of the human behaviour in the context of the skill-based facility operation, a set of objects was designed. When the process is running, these objects linked together captured standard situations and corresponding correcting reactions. These objects will be addressed as knowledge objects. The set of knowledge objects must include the following elements: resource, state, condition, rule, action, set point. This system of knowledge objects was modelled by means of XML. The representation of the objects and relations between them are illustrated in figures 4, 5 and 6.

Thus, 'resource' objects represent atomic processes or groups of processes on the corresponding hierarchical level. The entire facility is also a 'resource' object. Objects of this type are the source of information and the operation field for the decision-making procedure (figure 4a). For the decision-making procedure, the principle components of the resource objects are 'state' objects (figure 4b), which collect measurable signals and indicators for the evaluation of facility states and provide an informational starting point for the decision-making process.

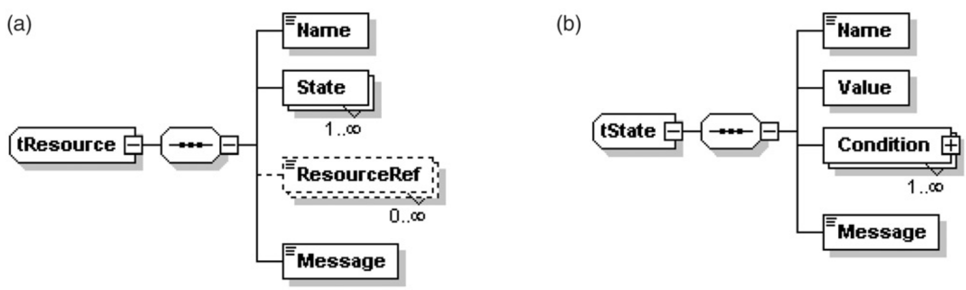

Figure 4. Data model of 'resource' (a) and 'state' (b) objects.

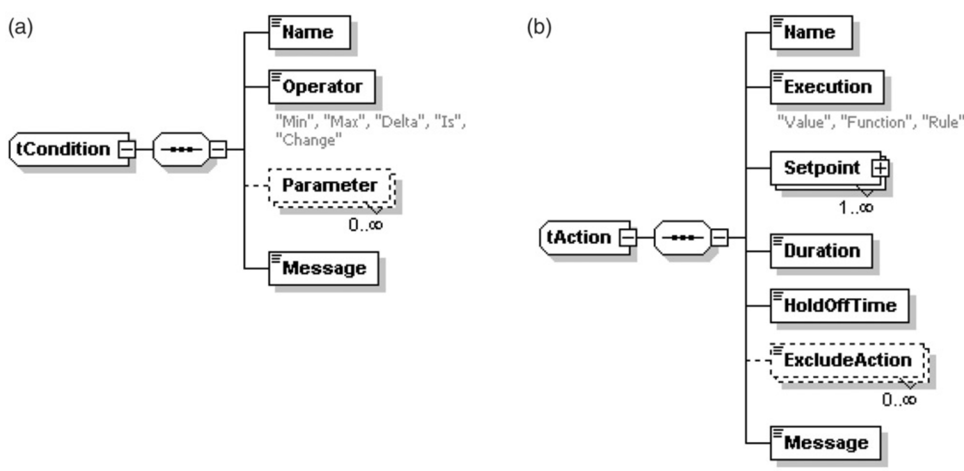

Figure 5. Data model of 'condition' (a) and 'action' (b) objects.

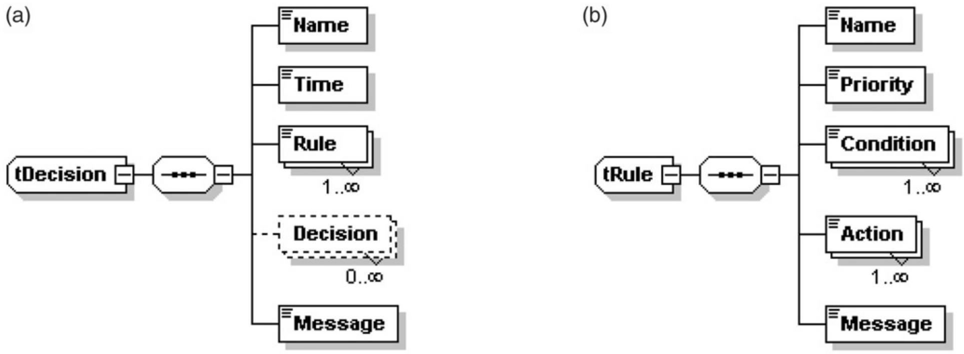

Figure 6. Data model of 'decision' (a) and 'rule' (b) objects.

For the evaluation of process states, 'condition' objects are specified (figure 5a). These objects represent data processing features—operators from a predefined set with 'Boolean'-type result values. The arguments for these operators are the state variables of the resource objects. The supervised system allows impacts which influence the future system evolution. The set of impacts corresponds to the possibilities of the system operator to change the system behaviour in order to achieve desired results. These impacts are modelled by 'action' objects (figure 5b). Action objects include 'setpoint' objects, through which the reference to a corresponding resource object as well as the type of control impact and its parameters are encoded.

Decision scenarios are modelled by 'decision' objects (figure 6a), where 'rule' objects describe elements of the scenario. 'Rule' objects (figure 6b) link 'condition' objects with 'action' objects. If, in the case of some system states, a condition fails to be met, a corresponding 'rule' object provides an automatic reaction. The association of system states with control tasks is defined via the rule objects. In cases where alternative actions can be identified, the rule objects maintain priority over the action objects.

A more detailed description of the knowledge objects by means of an XML scheme is given in Krüger *et al.* (2005).

4. System implementation

4.1 *System architecture*

The approach studied in this paper integrates three rather different modelling formalisms:

- pattern generation and clustering of process runs as a representation of process history and state knowledge (compare with figure 3);
- equation-based simulation for representation of process evolution knowledge; and
- process context analysis and rule-based supervision for representation of process operation knowledge.

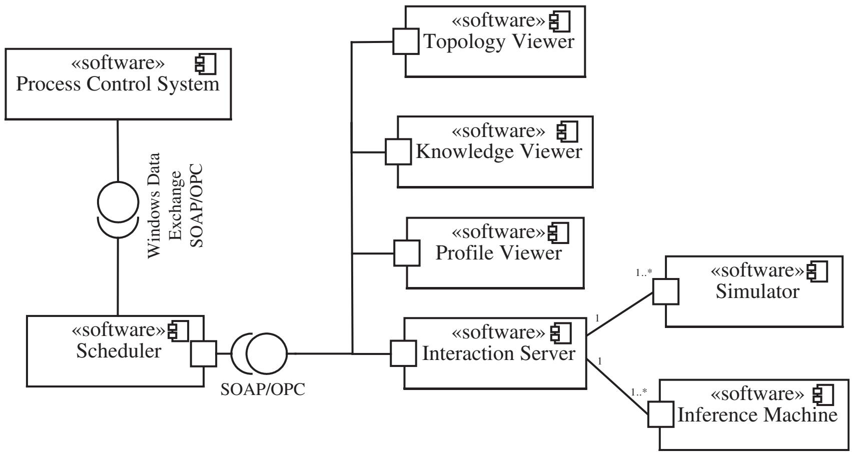

Figure 7. Runtime components of the knowledge-based supervision system.

Several components must be included into the infrastructure of a process control system with regard to each modelling formalism. These components are knowledge modelling, simulation and visualization modules (Pleßow *et al.* 2005). The components can be grouped according to the phase in which they are needed: the development phase or the runtime phase. In this paper we focus on the runtime phase. Its architecture is shown in figure 7. One can see that it is reasonable to develop specialized tools for visualization and editing for each kind of knowledge level. For their interpretation, corresponding engines were used. Thus, for process run analysis and dynamic simulation, a MATLAB-based simulator was developed. For the processing of operation rules, an inference machine was implemented.

The 'scheduler' is the data and task control unit of the system connecting the existing process control system (SCADA) with the knowledge-based supervision. Typical tasks are the initiation, monitoring, timing and data exchange of components. Apart from the process information given by SCADA, the 'topology viewer' provides the processing and visualization of process states relevant for knowledge-based supervision, e.g. intermediate results of the calculations. It also reads in the simulation model and visualizes the dynamic behaviour of the process. The 'knowledge viewer' visualizes the selected and applied rules of the supervision system. This allows the operator to retrace the actions and the reasons for which they were executed. The 'profile viewer' gives the operator an overview of the relevant operation history and actual context. The currently selected as well as all available operation trends are drawn as a diagram on the screen. The 'simulator' forecasts the process values for the supervision components. Based on the current process values, the output values for a defined time frame are computed. This allows the 'inference machine' to take preventive actions based on the knowledge provided. The current process states are checked constantly for violated rules. The 'interaction server' allows the dynamic connection of multiple simulators and inference machines to the system architecture. Simulation and knowledge models can be split into subsystems yet still appear as a single system to the scheduler through an encapsulation of the coordination of the subsystems.

The presented architecture was prototypically implemented and tested within an industrial environment. Further detail on interface generation and task scheduling is given in Schmidt *et al*. (2005).

4.2 *Application example*

A system application and test of the implemented components was performed at a water supply and distribution facility equipped with an advanced SCADA system (Lisounkin and Schmidt 1999) enhanced by model-based components. The main objective of the facility supervision and control was to ensure a proper operation of the system. For this, the following criteria had to be fulfilled:

- allocation of the required quantity of filtered water;
- consideration of the different modes of operation and use of resources;
- compliance with requirements for water quality;
- adherence to a minimal consumption of energy;
- maintenance of the purification cycle of individual water filters;
- a continuous and smooth running of the system; and
- adherence to the prescribed limits of the tanks with a quick reaction to deviations.

Figure 8 shows the user interface for the simulation-based operator support and the main topology of the process plant. Real plant operation profiles (historical data) spanning two years as well as knowledge of the system operation were gathered for the implementation of the knowledge-based supervision and control system.

Here, available simulation models of the facility were extended and the required knowledge objects were implemented. A SCADA module for automatic plant control was used as a reference for the specification and testing of operation rules. The challenge was to show the applicability and flexibility of the proposed approach with respect to the integration and adaptation of the operation knowledge available to facility engineering and operation staff.

The set of operation rules included about 60 items. By means of these rules, the number of possible facility states was reduced from about 10 000 to about 100. During operation, the inference machine had to choose decisions from within this pool of 100 allowed states.

The interaction of the inference machine with the simulator and the functional behaviour were tested. It was possible to show the tuning to the expected operation profile. Furthermore, the overall functionality with respect to the interaction of all functional components and the interface to the process control system was successfully tested. The results show that for large systems the list of operation rules may expand dramatically. This emphasizes the need to focus further research activities on methods for the management and verification of such sets of operation rules. The task of extending rule sets and verifying their consistency as well as techniques for the representation and editing of rule-based operation models are still of high importance.

5. Conclusions and outlook

The developed concept of integrated rule- and simulation-based facility supervision and control was implemented and tested within a SCADA environment for water supply stations. The expected functionality and interaction of the runtime components in response to the process control system were approved. In further investigations, the relevance of this concept to other applications will be tested: in particular, in the scope of gas distribution networks and storage facilities.

In summary, the main supervision algorithm can be formulated as follows. The process context analysis uses the results of the historic data clusters and simulated process trends. If unfavourable process states are identified, correcting actions are executed by the supervisor. The simulation can verify the chosen action with respect to some external operation criteria.

The implementation of the process simulation core together with historic data analysis and clustering was achieved by means of an existing developing environment (MATLAB®). The process context analysis primarily includes the verification of chains of logical conditions.

However, the construction of the system of context and rules should be done at the beginning or at least adopted for any new implementations. For each newly implemented rule system, its completeness and consistency must be verified. The same question must be considered when new rules are to be included or old rules eliminated. The technique for the verification of such rule systems is the topic

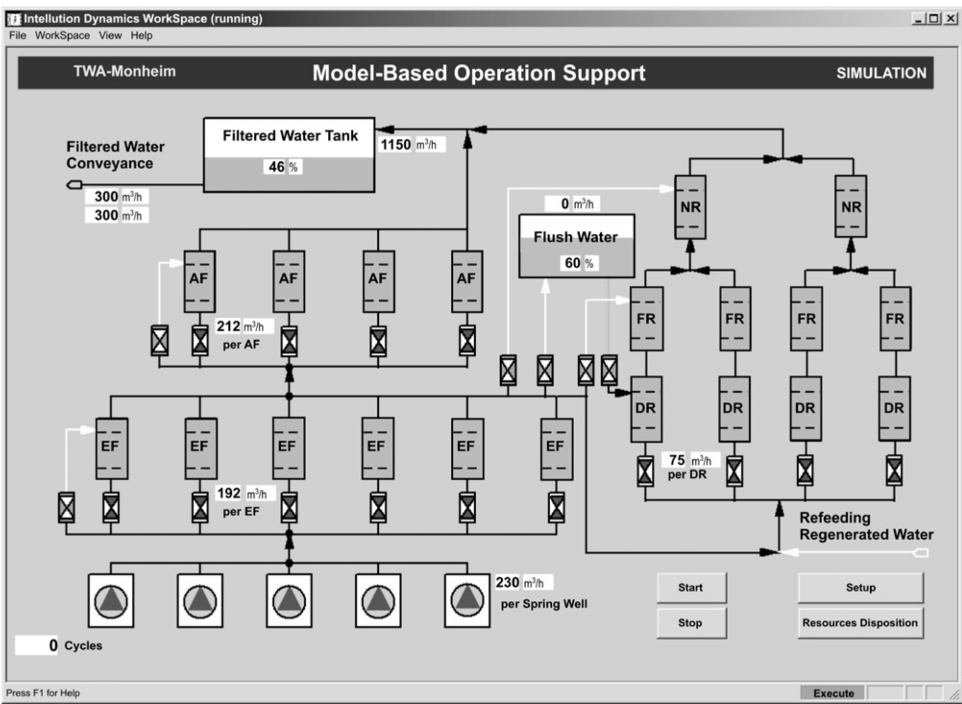

Figure 8. Example of water facility plant operator interface (SCADA GUI).

of current research by the authors (Lisounkin 2004, Lisounkin *et al.* 2004c). Moreover, further research activity is devoted to the generic modelling and engineering tools necessary for process automation solutions.

A second theme for discussion is the real-time behaviour of the supervision system. Obviously, such a system must be able to provide process behaviour forecasts for a rather long horizon. In the tests the forecast period was at least three times as long as the maximal length of the identified data patterns. The approach discussed in the paper must be considered especially for highly dynamic technological processes.

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