Improving automatic control of complex water systems, using AI techniques: design of an expert component for the alarms analysis

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Abstract The aim of this paper is to present an intelligent software tool, using Artificial Intelligence (AI) techniques, which allows the execution of an alarm analysis, during the remote sensing activity of complex plants. The AI component allows to identify all the primary faults of the system, discriminating them from the side effect alarms. In other words this tool shows which alarms are directly connected to primary faults and which alarms are consequential effects of the primary ones. The core of the software is an algorithm which uses a knowledge ontology and a set of alarm propagation rules, which are both based on a Multilevel Flow Modelling (MFM) paradigm. The algorithm has been tested implementing a rule based expert system (RBES) referred to an existing water plant. The main features of the water plant have been identified and all the main components and their possible alarm states have been analyzed to carry out the knowledge base.

Keywords Alarm analysis; expert system; multilevel flow modelling; remote sensing

Introduction

The Supervisory Control and Data Acquisition (SCADA) system represents valid help for the management of complex distributed systems, like water supply networks. The remote sensing activities provided by the SCADA system supply a huge quantity of measures and alarms concerning various parts of the plant. The alarm status, transmitted to the control room, does not provide any explanation of their cause; therefore to manage a complex plant system, specific software components have to be integrated with SCADA. Such software tools must allow: alarm management, the identification and visualization of false or superfluous data and the research of the first cause. This tool must provide information strictly necessary to identify the source of the fault and the actions which are necessary to restore ordinary conditions. A supervisory system, the “alarms management”, can be made up of the following activities (Cauvin et al., 1998):

- Measurement Validation: to check truthfulness of the process data acquired by the SCADA system.
- Alarm Analysis: to separate the primary alarms, connected to the primary sources of error, from the secondary alarms, consequential effects of the primary failures.
- Fault Diagnosis: to define causes which can determine the primary alarm signal.

AI techniques are broadly used to design software tools for alarm management. Expert systems in particular have been designed to fulfil this task. Expert systems use their internal knowledge bases and a inference mechanism to process the set of alarms acquired. In the present work the problem of the Alarm Analysis has been faced by making use of RBES. It is a software tool that analyzes a set of events, in particular alarms and warnings, which are
acquired by the remote sensing system. With the proposed software tool, processing the events, provides the clustering of the primary alarms, and it links each primary alarm with its side effect alarms. With the knowledge of the sequential pattern linking antecedent events to multiple consequences, it constitutes a milestone to implementing an alarm analysis system. The proposed tool has been tested making the analysis of the process data acquired by the remote sensing system of a real water supply network.

The real time control of a regional water transmission main

The proposed AI tool has been designed to address the alarm analysis of supervisory systems that can support the human operator and perform monitoring, control and optimisation tasks of real leading suppliers of water. The test platform has been designed to fulfil this requirement. The proposed software tool has been consequently embedded in a supervisory system that manages the process of a real complex water system.

The selected water system is made up of two main parts. The first one is an interregional raw water transmission mains, and the second one is a regional distribution mains. Both the two parts are hydraulically linked. But each water system has its own information and communication platform to provide remote sensing and control of plants. The two information and communication platforms are based on different technologies, though they meet at the same control room and at the same SCADA software system named Efesto which is developed by Proteo. The primary goals of the Efesto SCADA system are:

- water metering and leak detection
- optimal pump scheduling
- water quality metering
- fault diagnosis of water plant.

The main characteristics of the selected water system are:

- water plants distributed in a wide area (above 100 km)
- high diameter pipelines (ND 1,700 mm, ND 1,800 mm, ND 2,000 mm, ND 2,100 mm)
- water storage caverns
- booster pumping stations
- wells pumping stations, which are located underground
- several types of water sources: groundwater and surface water sources.

The research was carried out to provide the SCADA-user with a better alarm analysis tool. The result achieved was successfully tested on the historical data collected by its Efesto SCADA system.

Figure 1 shows a schematization of the ICT platform that provides the remote sensoring and control of the interregional transmission mains.

Alarm analysis with rule based expert systems and MFM

Alarm analysis

There are several different kinds of causes of faults in complex plant. Many accidents are caused by failures of mechanical or electrical components, by failures in the physical hardware or the control system software, while others are caused by erroneous operation and regulations. Yet another type of accident is caused by human error, which is the kind of accident where the human operators did not manage the plant correctly. The human error is driven by a lack of knowledge about the managed system. The real time control of plant aggravates the needs of knowledge, diagnosis capabilities, and evaluation of alternative scenarios and solutions. The needs of these capabilities are particularly helpful during the management of plants under uncertainty. And water transmission and distribution mains are typical event-driven plant. In this context during a fault too many alarms may be activated,
because the lack of knowledge of the set of activated alarms is incoherent, so that the operators cannot keep up with them, and the alarm system may become useless. This scenario shows that many human errors are partly caused by shortcomings in the design of SCADA systems which would have to present to the operator the process data acquired from the field in a utilizable form (Larsson, 2000).

In consequence of this, several computer-based tools, and in particular expert systems, have been proposed and used for automated sensor fault detection, alarm analysis, and fault diagnosis, to support human operators and to minimize his error.

The aim of these tools is to sort discrete status indicators, such as events and alarms, into primary and consequential. In this way, the main goal of these tools is to identify the root causes of large alarm showers correctly, and they allow for alarm turning off by the operator without risking suppression of the primary cause.

**Rule based expert systems**

RBES are advanced computer programs which emulate the human reasoning and problem solving capabilities, using the same knowledge sources within a particular knowledge domain (Buchanan et al., 1988). RBES always possess certain heuristics that form the static knowledge base, and some inference and search processes. The problems addressed with RBES are very complex and related to specific domains, and they would usually need an expert to solve them.

The main components of RBES are: static knowledge base, working memory, inference engine and user interface. Typically the static knowledge base is encoded in the form of rules and axioms. The rules allow the system to deduce new results from the initial set of data. A rule is basically represented by an antecedent, the condition, and a consequence, the action.

The main problem with such algorithms is that they demand a large effort to build, validate, and especially rebuild when the plant is changed. Knowledge acquisition, usually
extracted from human experts, is in particular the most time consuming and difficult stage in knowledge base development (Hoffman et al., 1995).

The knowledge acquisition task is particularly difficult to carry out if the knowledge is referred to multidisciplinary and no specific domain. And this is the case in industrial plant supervised by a SCADA system. In this case the knowledge base is referred to the specific domain of the plant, as well to the mechanical and electrical domain, and the communication and software domain. It is possible to overcome the problems designing a knowledge ontology to represent the shared understanding of some domain of interest which may be used as an unifying framework to make the communication easier between or among people and/or software systems (Ushold and Gruninger, 1996).

**Multilevel flow modelling**

To support the sharing and reuse of formally represented knowledge among experts, users and software systems which operate on different knowledge domains, we propose the use of an ontology based on MFM. This modelling paradigm provides a good basis for computer-based supervision and diagnosis, especially in real-time applications, where fast execution and guaranteed worst-case response times are essential. The expressive power of MFM is similar to that of traditional rule-based knowledge, while the explicit representation of means–end knowledge and the graphical nature of the models make the knowledge engineering effort less and the execution efficiency higher than that of standard expert systems. Using MFM it is possible to easily model water supply network, as well power supply network, as well communication network.

MFM models are graphical representations of the goals and functions of technical systems (Lind, 1990). The goals describe the purposes of the system, and the functions describe the capabilities of the system. MFM models describe the functional structure of a system by modelling the flow structures in the system. MFM models are built by using three basic concepts, goals, functions, and physical components. MFM describes the functionality of a system by modelling the flows of mass, energy and information. The mass, energy, and information flows are modelled by using six different flow functions. The graphical representation of the MFM functions are shown in Figure 2.

Functions may be connected to each other into flow paths. However, the flow functions may not be connected to each other in an arbitrary manner. The legal MFM connections are shown in Figure 3, in which is shown a portion of the model of the water supply network used as test platform.

**The rule based knowledge**

Each of the MFM functions has a set of alarm states that indicates in which way they have failed (Larsson, 1996). These are described in Table 1.
Each function may only be in some of these states. Besides the alarm states, each function may be in a normal state, that is, working as expected. Alarms can propagate throw flow function in certain ways. This is a consequence of the alarm conditions described above. Thus, primary alarms may cause secondary alarms in other connected functions. This gives a set of rules that point out how an alarm in one flow function may cause consequential alarms in the connected functions, as for example:

- a source locap will force a loflow in the connected transport;
- a transport loflow may cause:
  - a hivol in a storage connected at the inlet of the transport;
  - a lovol in a storage connected at the outlet of the transport;
  - a loflow in another transport connected in the same direction via a balance;
- a storage hivol may cause:
  - a hiflow in an incoming connected transport;
  - a loflow in an outgoing connected transport.

The list of all the consequence propagation rules make up the static knowledge base used by the RBES.

**The MFM alarm analysis algorithm**

The RBES implements the already existing MFM alarm analysis algorithm introduced by Larsson (Larsson, 1998). The implementation of the algorithm has been carried out by using CLIPS language (C Language Integrated Production System), which is a tool for the development of expert systems based on rules and/or objects.

The expert system uses the method of the backward chain to identify the primary alarm. The algorithm analyses two alarms: alarm (a) and the second one (b). In this way it is able to go back to the set A of all the states of alarm which can cause the first alarm (a) and to the set B of all the states of alarm which can cause the second alarm (b).

**Table 1** Description of the MFM alarm state

<table>
<thead>
<tr>
<th>Alarm State</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>locap</td>
<td>The inflow, or outflow, is greater than intended for the function.</td>
</tr>
<tr>
<td>loflow</td>
<td>The flow through the function is lower than intended.</td>
</tr>
<tr>
<td>hiflow</td>
<td>The flow through the function is higher than intended.</td>
</tr>
<tr>
<td>lovol</td>
<td>The stored volume in the function is lower than intended.</td>
</tr>
<tr>
<td>hivol</td>
<td>The stored volume in the function is higher than intended.</td>
</tr>
<tr>
<td>leak</td>
<td>The inflow is greater than the outflow.</td>
</tr>
<tr>
<td>fill</td>
<td>The outflow is greater than the inflow.</td>
</tr>
</tbody>
</table>
In general it is possible to verify the following situations:

- the alarm a is contained in the set B, while the alarm b is not contained in the set A. In this case it results in: the alarm a is a primary alarm, so it can be the cause of the alarm b;
- the alarm a is not contained in the set B, while the alarm b is contained in the set A. In this case it results in: the alarm b is a primary alarm, so it can be the cause of the alarm a;
- the alarm a is not contained in the set B and the alarm b is not contained in the set A or the alarm a is contained in the set B and the alarm b is contained in the set A. In these cases it results in: the alarms are indeterminate;

The expert system with the backward procedure allows us to find out all the possible causes of a state of malfunction or anomaly of a specific component of the plant. This working method may produce a large number of potential causes of a given alarm. The algorithm has been slightly modified. The RBES has been embedded in the Efesto SCADA, so it uses validated process data acquired by the SCADA to reduce the number of analyzed alarms.

![Diagram](https://iwaponline.com/ws/article-pdf/4/5-6/375/477518/375.pdf)

**Figure 4** MFM of the water plant, the arrows represent two alarm acquired by the SCADA

The set A constituted by all the possible alarms causing the alarm a (alarm loflow 60 A):
- alarm hivol storage 70 A;
- alarm fill storage 70 A;
- alarm loflow pipe 80 A;
- alarm fill balance 90 Z;
- alarm loflow pipe 100 Z;
- alarm fill balance 110 Z;
- alarm valve totally closed 120 Z;
- alarm valve choke 120 Z;
- alarm hivol storage 130 Z;
- alarm loflow pipe 140 Z;
- alarm fill storage 130 Z;
- alarm loflow pipe 20 A;
- alarm loflow pipe 140 Z;
- alarm locap source 10 A;

The set B constituted by all the possible alarms causing the alarm b (alarm hivol storage 130 Z):
- alarm fill storage 130 Z;
- alarm loflow pipe 140 Z;
- alarm fill balance 150 Z;
- alarm valve totally closed 160 A;
- alarm valve choke 160 Z;
- alarm hivol storage 170 Z;
- alarm fill balance 110 Z;
- alarm valve totally closed 120 Z;
- alarm valve choke 120 Z;
- alarm hivol storage 130 Z;
- alarm fill storage 130 Z;
- alarm hivol pipe 60 B;
- alarm fill balance 50 A;
- alarm hiflow pipe 20 A;
- alarm fill balance 90 Z;
- alarm hivol pipe 100 A;
- alarm fill balance 50 A;
- alarm hivol pipe 60 A;
- alarm hivol storage 70 A;
- alarm fill storage 70 A;
- alarm loflow pipe 80 A;
- alarm hivol storage 70 A;
- alarm fill storage 70 A;
- alarm hivol storage 130 Z;
- alarm fill storage 130 Z;
- alarm hivol storage 130 Z;
- alarm fill storage 130 Z;
- alarm hivol storage 70 A;
- alarm fill storage 70 A;
- alarm loflow pipe 80 A;
- alarm fill storage 70 A;
- alarm hivol pipe 20 A;
- alarm fill balance 50 A;
- alarm hivol pipe 20 A;
- alarm fill balance 90 Z;
- alarm hivol pipe 20 A;
- alarm fill balance 90 Z;
- alarm hivol storage 130 Z;
- alarm fill storage 130 Z;
- alarm hivol storage 130 Z;
- alarm fill storage 130 Z;
- alarm hivol storage 70 A;
- alarm fill storage 70 A;
- alarm loflow pipe 80 A;
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- alarm loflow pipe 80 A;
- alarm fill storage 70 A;
- alarm hivol storage 70 A;
- alarm fill storage 70 A;
- alarm loflow pipe 80 A;
- alarm fill storage 70 A;
- alarm hivol storage 70 A;
paths of the decision tree. In this way from the whole paths that the traditional backward
analyzes, all those branches that are excluded that describe consequence propagation not
corresponding with the acquired information about the real state of the plant.

Results
The RBES has been tested analyzing the events, as alarms and warnings, which are acquired
by the Efecto SCADA during the remote sensing of the selected water system. It is shown as
an example in Figure 4. Two alarms are analysed and the primary one is fixed.

Conclusions
This work aims to verify the use, the possibility and the effectiveness of the system expert
technique as a support tool for the management and analysis of the alarms of any industrial
plant. A specific application to an existing water plant has been carried out.

It is very important to highlight that ES’s knowledge base has been created not in a
traditional way, but by using the knowledge coming from the modelling of the plant
examined through the methodology of the MFM. The work shows that the realized ES allows
identification of all the possible alarm states that can cause any assumed alarm and allows
highlighting of the existing relation between two alarm states concerning two connected
functions of the physical system. By applying the hybrid backward working way, the ES
allows us to obtain a skimming of the set of all the alarms which can cause an assumed alarm,
providing only those alarm signals compatible with process data acquired by the SCADA
system.

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