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A Multi-Expert System for chlorine electrolyzer monitoring

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ABSTRACT

The Chlor-Alkali production is one of the largest industrial scale electro-synthesis in the world. Plants with more than 1000 individual reactors are common, where chlorine and hydrogen are only separated by 0.2 mm thin membranes. Wrong operating conditions can cause explosions and highly toxic gas releases, but also irreversible damages of very expensive cell components with dramatic maintenance costs and production loss. In this paper, a Multi-Expert System based on first-order logic rules and Decision Forests is proposed to detect any abnormal operating conditions of membrane cell electrolyzers and to advice the operator accordingly. Robustness to missing data – which represents an important issue in industrial applications in general – is achieved by means of a Dynamic Selection strategy. Experiments performed with real-world electrolyzer data indicate that the proposed system can significantly detect the different operating modes, even in the presence of high levels of missing data – or "wrong" data, as a consequence of maloperation –, which is essential for precise fault detection and advice generation.

1. Introduction

Due to the increasing demands for greater product quality and variability, short product life-cycles, reduced cost, and global competition, automatic monitoring systems have been gaining importance in the manufacturing industry (Liang, Hecker, & Landers, 2004). These systems allow for a significant reduction in the equipment maintenance costs, and, most importantly, the early detection of potential faults which may lead to catastrophic accidents (Guo, Jack, & Nandi, 2005).

The Chlor-Alkali manufacture – *i.e.*, production of chlorine and caustic soda by electrolysis of aqueous solutions of sodium chloride (or brine) – is one of the largest industrial scale electro-synthesis world-wide (Kaveh, Ashrafizadeh, & Mohammadi, 2008; Kaveh, Mohammadi, & Ashrafizadeh, 2009). The most common accidents associated with the Chlor-Alkali industry are fire, explosion and toxic gas releases. Of these, toxic gas release (*i.e.*, chlorine) is the most damaging due to its potential to cause extensive fatalities and long term health impact on the exposed population (Renjith, Madhu, Nayagam, & Bhasi, 2010). Moreover, wrong operating conditions can cause irreversible damages of very expensive cell components with dramatic maintenance costs and production loss.

A promising way to perform automatic monitoring and fault diagnosis in the manufacturing industry is through expert systems based on well-known Artificial Intelligence (AI) techniques (Liang et al., 2004), such as Artificial Neural Networks (ANNs) (Haykin, 1998) and Support Vector Machines (SVMs) (Burges, 1998; Schölkopf & Smola, 2002). In the particular case of Chlor-Alkali industry, expert systems intended to monitor its production process are not in widespread use. SVM and ANNs have been employed to predict the voltage and the caustic current efficiency (CCE) of membrane cells (Kaveh et al., 2008; Kaveh et al., 2009; Mirzazadeh, Mohammadi, Soltanieh, & Joudaki, 2008); Genetic Algorithms (GA), to find the best operating parameters, such as, anolyte pH, anolyte temperature, anolyte flow rate, brine concentration and current density (Mirzazadeh et al., 2008); and Fuzzy Fault Tree Analysis (FFTA), to detect the root causes of chlorine releases, *e.g.*, flange leak due to gasket failure and pipe rupture due corrosion (Renjith et al., 2010). So far, there has been no attempt to automatically detect and monitor the different operation modes of an electrolyzer (defined later, in Section 2), which may go from IDLED to DRAINING, passing through FILLING, COLDCIRCULATION, HOTCIRCULATION, NORMAL, among others.

In this paper, a Multi-Expert System based on first-order logic rules and Decision Forests (Ho, 1995; Ho, 1998; Ho, 1998) is proposed to deal with three important issues related to the Chlor-Alkali production, that is, (i) to detect the different modes of operation of a membrane cell electrolyzer, (ii) to identify the presence of abnormal operating conditions, and, when applicable, (iii) to generate a set of recommendations to the human operator. Therefore, the proposed expert system (the *Advisory System*) has as main objective the generation of helpful advice to the human operator, in case abnormal operating conditions arise in an electrolyzer. To achieve this purpose, the Advisory System is composed of two

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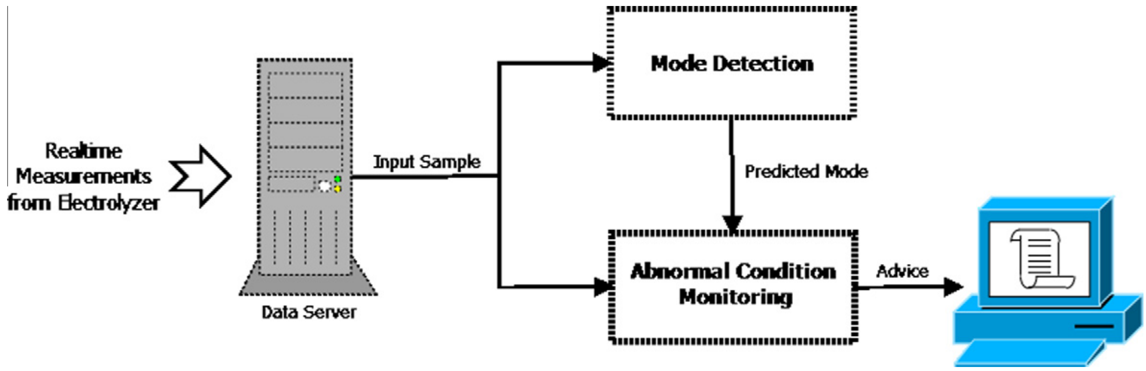

Fig. 1. Block diagram of the Advisory System, showing its main modules.

main modules: the Mode Detection module and the Abnormal Condition Monitoring module.

A simple schema of the proposed system is shown in Fig. 1. The predicted mode is fed to the module that actually generates the advice to the human operators (as we need to know in what state the electrolyzer is functioning in order to detect abnormal operating conditions and recommend a course of action). Robustness to missing data – which represents an important issue in industrial applications in general – is achieved by means of a Dynamic Selection strategy (Polikar, DePasqual, Mohammed, Brown, & Kuncheva, 2010), which chooses only the subset of classifiers (from the Decision Forest) associated with the non-missing features of each input sample. This strategy is particularly interesting for industrial applications, where missing and noisy data are very frequent.

The rest of the paper is organized as follows. Section 2 describes the Mode Detection module, as well as an experimental study performed in order to validate its performance in the presence of different levels of missing data. Then, in Section 3, the Abnormal Condition Monitoring module is detailed. Finally, the paper is concluded in Section 4.

2. Mode detection module

The Mode Detection module identifies, by looking at the different measurements coming from the equipment, the *mode* in which the electrolyzer is functioning. We have defined 8 modes[1] (or states) the electrolyzer can find itself in:

1. **IDLED**: the electrolyzer is not in use;
2. **FILLING**: the electrolyzer is being filled;
3. **COLDCIRCULATION**: the brine is being circulated at a low temperature, the main power supply is off;
4. **HOTCIRCULATION**: the brine is being circulated at a high temperature, the main power supply is off;
5. **STARTUP**: the main power supply is started;
6. **NORMAL**: the electrolyzer current is within the range to achieve the design product qualities (about 20% to 100% load);
7. **LOWLOAD**: the electrolyzer current has been reduced below the lower limit to achieve the design product qualities (about less than 20% load);
8. **DRAINING**: the electrolyzer is being drained;
9. **UNKNOWN**: impossible to determine the actual mode.

The detection of the operating mode is performed by two (2) interacting pieces of intelligent software: a set of **Rules**, encapsulating the knowledge of an expert in the field in the form of simple first-order logic rules, and a **Classifier**, which interprets realtime data and encodes the real behavior of the electrolyzer.

2.1. The rules ($\mathcal{R}$)

The rules $\mathcal{R}$ encapsulate the conditions that, in principle, hold true for any kind of electrolyzer, with any kind of conditions. It constitutes a base case for the functioning of any electrolyzer. An expert in electrochemistry[2] designed these rules based on their experience and their knowledge of the equipment studied (also taking into consideration the "bad" calibration of instruments in industrial scale plants). The set of derived rules is shown in Table 1.

These rules are easily described as natural language expressions. For example, following Table 1, the electrolyzer is in **FILLING** mode when *all* these conditions hold:

1. Current $\leqslant$0.2 kA.
2. Temperature Catholyte Out <40 °C.
3. Brine level $\in(0,100)$%.
4. Catholyte level $\in(0,100)$% .

Slightly more complicated is the description of **COLDCIRCULATION**, that can be reached in 2 ways (differing only in the conditions put on temperature of the catholyte out):

1. Current $\leqslant$0.2 kA.
2. Two conditions on the behavior of Temperature Catholyte Out:
   (a) either Temperature Catholyte Out $\in(40,70)$ °C.
   (b) or Temperature Catholyte Out <40 °C and rate of change of Temperature Catholyte Out >-6 °C/min.
3. Brine container is FULL (*i.e.*, Brine level = 100%).
4. Catholyte container is FULL (*i.e.*, Catholyte level = 100%).

2.2. The classifier ($\mathcal{C}$)

The classifier $\mathcal{C}$ complements the rules $\mathcal{R}$ by adapting to and learning the local conditions of the electrolyzer where the Advisory System is installed. It consists of a predictor that takes as input the measures describing an electrolyzer and outputs the current operating mode. The need for such a predictor arises from the fact that we cannot ensure that $\mathcal{R}$ covers all possible conditions found in any possible electrolyzer installation in the world. For example, observe the conditions previously described for **FILLING** mode:

1. Current $\leqslant$0.2 kA.
2. Temperature Catholyte Out <40 °C.

[1] The definition of these modes is probably not standard or totally in agreement with what can be found in other domains. However, it reflects appropriately the common knowledge in industry.

[2] The rules $\mathcal{R}$ were designed by one of the co-authors of this paper.