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An Interoperable Workflow-Based Framework for the Automation of Building Intelligent Process Control Systems

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Abstract: One of the major problems to design and implement a control/supervision system for a process lies in the need to establish an *ad-ho*c system for each process installation. On the other side, an open challenge related to the deployment of Intelligent Decision Support Systems (IDSSs) is the *interoperability* of the different methods used, in order to allow interaction and reuse of different data mining methods and the use of methods based on a model or an expert. Thus, this paper proposes the use of *visual workflows*, to enable the *automation* of the design task and the implementation of Intelligent Process Control Systems (IPCSs). The framework will allow the user to specify the design and control of a concrete process as well as the required data-driven and expert models using a graphical workflow environment. The framework is based on a three-layer architecture: first, a comprehensive data science flow description layer (dataflow layer) to produce/discover data-driven models from process data; second, a flowchart of the different components of the process (process-design flow layer) to obtain a simulation model from the design. Finally, the on-line IPCS (process control workflow layer), where the different data-driven models, expert-based models and intelligent reasoning methods interoperate to control and supervise the process. Thus, the resulting system can automatically generate both simulation models of the process and programming code to control and supervise the process, using workflows designed for each particular installation. The case study is focused on the supervision of a Wastewater Treatment Plant (WWTP) located in the Barcelona region.

Keywords*:* Intelligent Process Control System; Wastewater Treatment Plant; Interoperability; Visual workflow; Data Mining; Energy Sustainability.

1 INTRODUCTION

Environmental Decision Support Systems (EDSS) field has been trying to use models of the real world to get insight of the behaviour and evolution of the corresponding real systems modelled. Historically, former EDSSs were using only *mechanistic models*. Notwithstanding, usually huge amounts of data gathered from the system being managed were available, hence new empirical models started to be used. *Empirical models* are based on direct observation, measurement and extensive data records. The first empirical models used were mathematical and statistical methods e.g. Multiple Linear Regression (MLR) models. The success of several inductive *machine learning techniques* within the Artificial Intelligence (AI) area led to their application in EDSSs. Some instances of this usage are e.g. the Association Rules (AR) models, Classification Rules (CR) models, Decision Tree (DT) models or Bayesian Network (BN) models. Since the 80s, both the former mathematical/statistical empirical models and the later machine learning empirical models have been named *data mining methods*, because they result from a mining process using these data. With the use of *data mining models* within the AI framework, the EDSS have evolved to Intelligent Environmental Decision Support Systems (IEDSSs) (Sànchez-Marrè *et al*., 2006). IEDSSs may be built using a single AI model or integrating several AI models in order to be more powerful, together with system components geographical information, mathematical or statistical models, environmental/health ontologies or some extra economic information. IEDSSs integrate knowledge/data stored by human experts through years of experience in a certain environmental process operation and management. In addition, knowledge/data can be mined through the intelligent analysis of available large databases coming from historical operation of this environmental process. Thus, *knowledge/data mining model production*, as well as *reasoning* and *interoperation* among the models produced, are key steps to build reliable IEDSSs. In this context, single AI models provide a solid basis for construction of reliable and real applications, and *interoperability* between AI and Numerical models is one of the main current open challenges in this field. In addition, the building of IEDSSs is currently performed in a very *artisanal* way, hence for each different type or instance of Environmental system the IEDSS must be deployed in an *ad-hoc* basis. To the knowledge of the authors, there is currently no general framework available for the automation of the deployment of IEDSSs, which makes the study of this matter an issue of great interest. Hence, this paper proposes the design of an Intelligent Process Control System (IPCS) using *visual workflows* and providing *interoperability* of models among the different layers of the obtained IPCS. The suggested design aims to overcome the need to establish *ad-hoc* approaches for each installation, providing deployment *automation* of the IEDSS by means of visual workflows. The case study is focused on a Wastewater Treatment Plant (WWTP) located in the Barcelona region, although the framework is considered in a general fashion allowing its use with systems of different nature as the one considered in this work.

2 RELATED WORK

On the one hand, *Interoperability* is defined as “the ability of two or more systems or components to exchange information and to use the information that has been exchanged” (IEEE, 1990). Additionally, *semantic interoperability* is achieved when the components share a common understanding of the information model behind the data being interchanged (Manguinhas, 2010; Ouksel and Sheth, 1999). Semantic integration and interoperation have been the focus of some research works in the environmental modelling field, e.g. pioneer work in semantic integration of Environmental models for application to global information systems and decision making, specially related to GIS components and models (Mackay, 1999; Wesseling et al., 1996). In addition, some work related with model and data integration and reuse in EDSS may be found in (Rizzoli et al., 1998), and an overview of model integration is presented in (Argent, 2004). An interesting work in this area is also presented in (Sottara et al., 2012), where the Drools Rule-based integration platform is used as a unified data model and execution environment, and in (Sànchez-Marrè, 2014), where a general framework for the development of interoperable IEDSSs was proposed. In the information systems field several recent works are done in semantic integration of business components (Elasri and Sekkaki, 2013; Kzaz et al., 2010). Further works are focused on the semantic interoperability through service-oriented architectures (Vetere and Lenzerini, 2005). Several works have been also developed in the medical domain e.g. (Komatsoulis et al., 2008), where service-oriented architectures were used, or in (Dolin and Alschuler 2011), aiming at data interoperability on Health Level Seven’s standard (HL7, http://www.HL7.org). Regarding this issue, one of the most effective ways to interchange information between several software components and share the corresponding information semantics is via XML (eXtensible Markup Language). XML is a meta-language intended to supplement HTML’s presentation features with the ability to describe the nature of the information being presented (Erl, 2004). XML adds a layer of intelligence to the information being interchanged, providing meta-information, which is encoded and embedded as self-descriptive labels for each piece of text in the document. XML is implemented as a set of elements, which can be customized to

represent data in unique contexts. A set of related XML elements can be classified as a vocabulary. An instance of a vocabulary is an XML document. Vocabularies can be formally defined using a schema definition language like Document Type Definition (DTD) or XML Schema Definition Language (XSD). Furthermore, the Data Mining Group (DMG, 2014) is an independent, vendor led consortium that develops data mining standards, such as the Predictive Model Markup (PMML) Language. PMML is a standard for statistical and data mining models, supported by over 20 vendors and organizations. PMML uses XML to represent data mining models. The structure of the models is described by an XML schema. One or more mining models can be contained in a PMML document. A PMML document is an XML document with a root element of type PMML. A PMML document can contain more than one model, and most common data mining models are supported, e.g. AssociationModel, RegressionModel, TreeModel, RuleSetModel, NeuralNetwork, ClusteringModel.
On the other hand, *Visual workflow* building and execution can be a very useful tool for specifying the workflow involving the raw data, the models produced, the model executors, and the auxiliary processes. Workflows are graphical notations, which were first introduced to model and describe Business Processes (ter Hofstede et al., 2010). They let the design and specification of a workflow involving several elements —e.g. data, interchange PMML models, model producers, model executors, solution combiners, current problem specification—. The idea of using workflows for the control of a process e.g. in organisations has been pointed in the literature (zur Muehlen, 2004). In the approach presented here the use of several tools will be assessed, e.g. jBPM —java for Business Process Management (jBPM, 2017)—, which is an open source business process engine supporting the Business Process Model and Notation standard (BPMN 2.0) and provides a graphical workflow editor (BPMN, 2011), or YAWL (Yet Another Workflow Language), a powerful language based on the well-known workflow patterns which includes an open-source support environment. BPMN concepts and constructs can be mapped into YAWL (ter Hofstede et al., 2010). The main idea here is to describe the IEDSS solving process —through its different tasks and layers — using workflows, which may be directly executed or, alternatively, used to generate the corresponding software code for the IEDSS. Although there are some architecture proposals in the literature to combine some of these models, there is no common framework to deploy Interoperable IEDSS, which would provide an easy way to integrate and (re)use different AI or statistical/numerical models in a whole IEDSS. Until now, most of the interoperability of the models is achieved by *ad-hoc* model interaction, which may be considerably improved. Hence, the aim of this research work is to provide a useful and *systematic approach* to *interoperate* different models at different stages of the IEDSS design, and to automate the building of the IEDSS by means of workflow-based solutions.

3 METHODOLOGY

3.1 Development environments

In order to develop the framework introduced here, the use of visual workflows is proposed. To this end, the use of graphical programming environments provide some advantages in relation to traditional languages like C or Java (Johnston et al., 2004), e.g. reusability and understandability of the code, modularity and flexibility, intrinsic parallelism, easy debugging or faster prototyping and development. To choose a valid developing environment is necessary to define the desired specifications. Here, graphical programming languages will be used, aiming to create standard and reusable toolboxes. The idea of using open-source languages and tools is also explored. Methods and algorithms needed are all related to data mining: Table 1 shows a non-exhaustive list of useful data science techniques and algorithms that can be useful for this development. In Gibert et al. (2010) an overview of different data mining techniques and choosing criteria are presented. Most programming languages have available libraries for data science, for example *scikit-learn* for python or *JDMP* (*Java Data Mining Package*) for Java. Although they are not designed for graphical programming, we can find the Flow Based Programming (FBP) paradigm described in Morrison (2010), which allows the programmer to create applications as a set of black boxes or interconnected processes or some programming environments like NoFlo for JavaScript, based on the FBP concept. On the other hand, there are some programming environments and languages that make the development process easier because are oriented to graphical programming, e.g. Matlab/Simulink and LabVIEW or open source equivalent options like Scilab and MyOpenLab respectively. These environments also have available data science libraries, as well as other specialized useful tools, for example database connection and reading data or data acquisition, among others, so they would be a better choice for implementation. Another advantage of these graphical environments is that they can be complemented with libraries from other programming languages —like C or Java— by creating new user defined blocks or tools, or using developed ones, e.g. Drools, a rules inference engine, developed in Java.

Table 1 Data mining techniques and reasoning methods

Data Filtering/Data Selection
Feature Selection techniques
Feature Weighting techniques
Clustering techniques
k-means method
g-means method
Nearest neighbour method
Association Models
Association Rules: A-priori algorithm
Discriminative/classification models
Decision trees induction: ID3 algorithm, C4.5 algorithm, CART algorithm
Classification rues induction: RULES algorithm, PRISM algorithm, CN2 algorithm, RISE algorithm
k-NN classifier
Predictive models
ANN
k-NN predictor
Rule-Based Reasoning module (rule inference engine o expert system shell)
Case-Based Reasoning module (case-based reasoning shell)

In order to provide standardization and reuse of models in different installations, the use of a standard to define them is considered. Concretely, PMML format is studied. For models generation in Layer 1 a visual workflow data science platform can be used. Different payment (e.g. Rapid Miner) or open-source (e.g. KNIME) options are studied.

3.2 System architecture

The main aim of the IPCS presented here is to generate the set-points for the local controllers and the decision support system. The architecture of the whole system is shown in Figure 1. The tool developed here is based on a three-layer architecture (Figure 2). The data science flow layer (Layer 1) is used to generate models obtained from process data. It is an off-line procedure that takes historical available data from each system with the aim of generating valid data-driven models to supervise and control the process. In Figure 3 an example of a possible data science flow is shown. The input is a standardized and properly formatted raw database containing all available data for each system: sensor measurements, equipment states and alarms, plant set-points or other data derived from them. First, different data validation and reconstruction methods (Cugueró-Escofet et al., 2016) can be applied to obtain a new filtered and valid database. Then, some of the proposed data mining methods can be applied to the complete dataset to find relations among variables, behavioural patterns and so on to obtain valid models that can be used in Layer 3. These models can be e.g. rule models induced from decision trees or case databases. Both interoperate in Layer 3 to supervise the system by discriminating between abnormal situations and normal operation and to control the process by generating actuator set-points based on knowledge obtained from data. Rule models can also include human expert knowledge of the system, so it is interesting to include in this layer an easy user interface to integrate such human-based knowledge. In the Process Design flow layer (Layer 2) the layout of the plant is designed, including all processes to be supervised or controlled and the corresponding signals. Finally, the Process Control workflow layer (Layer 3) is the application core. The plant defined in layer 2 is supervised and controlled using the models generated in layer 1 with the workflow designed in this layer, so it is directly connected with both off-line previous layers. The graphical nature of this development allows using the workflow itself as a graphical user interface (GUI). In spite of this, the design in layer 2 can be used in this stage to generate a GUI adding all possible configurable parameters of the control system and showing useful Key Performance Indices (KPIs) for decision support. Figure 4 shows an example of a possible workflow for Layer 3.

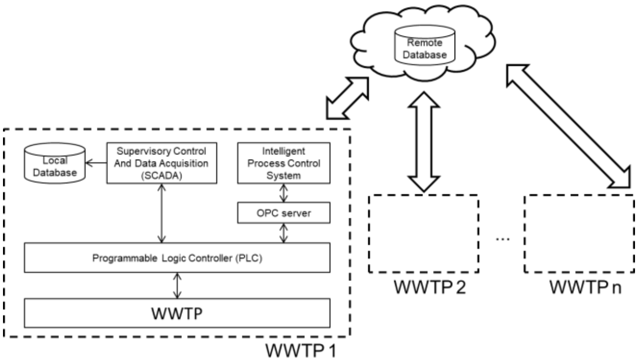

Figure 1 System architecture

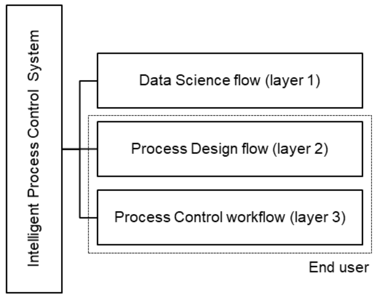

Figure 2 Intelligent Process control architecture

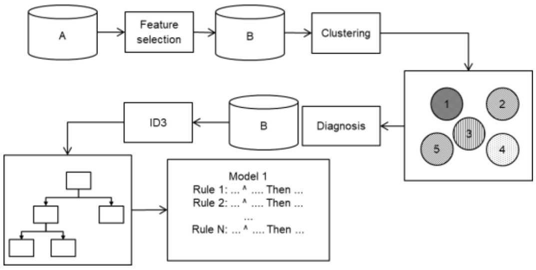

Figure 3 Layer 1 data science flow

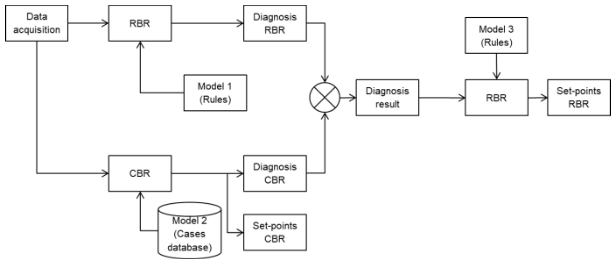

Figure 4 Layer 3 Process Control workflow

As it can be seen in Figure 4, the proposed approach is to combine Case-Based Reasoning (CBR) and Rule-Based Reasoning (RBR) algorithms, obtaining redundancy in diagnosis and/or set-points generation. CBR and RBR modules inputs are correctly formatted with online data gathered from the process and the corresponding models generated in Layer 1. Using both methods and different models obtained with the same data, diagnosis results and set-points obtained can be compared in order to provide a more reliable diagnosis and set-point generation. Hence, this diagnosis and set-point generation redundancy helps on relying on the outcome of the tool presented. Also, the human expert knowledge –provided e.g. by the plant manager– should be considered in order to validate the tool outcome and also to feed the database with human-based knowledge.

4 CASE STUDY: Consorci Besòs Tordera water sanitation systems

4.1 Description

Consorci Besòs Tordera (CBT) is a local water administration composed of 64 municipalities in four different regions of Catalonia with a population of about 470.000 inhabitants. CBT is the responsible for the sanitation facilities from the very beginning in project and building stages to the final facilities operation and maintenance —including 300 km of sewers and 22 WWTPs— with the main objective of preserving and improving the good health of the rivers in its area —*Ripoll* river, *Besòs* river, *Riera de Caldes*, *Tenes* river, *Congost* river and *Mogent* river—. All WWTPs within CBT ambit are based on the activated sludge process for the wastewater treatment. Plants capacity range from 1000 m^3/day to over 40000 m^3/day, or expressed in other terms, from some hundreds of population equivalent (PE) to over 300000 PE. However, the general schema in most cases is similar. The waste water coming from urban and industrial areas in the CBT ambit is conducted through a sewer system to the corresponding CBT WWTP. Each WWTP includes water and sludge lines, and in some cases, a biogas line, as it is shown in Figure 5. Even though all the WWTPs layout are similar, there are some particularities that imply a custom-made control system, e.g. number and type of actuators and sensors or the influent characteristics. The most important and critical part to be controlled and supervised is the biologic reactor, which also involves the process with electrical consumption due to aeration. The aim of this process is to remove organic matter (organic carbon) and nutrients (nitrogen and phosphorus) from the sewage water. To make this biological process feasible oxygen is necessary. Oxygen is usually introduced from the environment to the biological reactors by using aeration blowers. The process of removing nutrients and organic matter requires periods with oxygen and periods without oxygen, so the adequate management of the aeration blowers is very important. Internal and external recirculation flows are also involved in the biological process: the external recirculation is used to maintain an adequate ratio of sludge microorganisms in the biological reactor, whilst the internal recirculation is used to control the nitrates concentration, involved in the nitrification – denitrification process used to remove nitrogen and biological phosphorous. In a first stage, nitrogen is oxidized to nitrates in presence of oxygen (nitrification). This process is done by some autotroph bacteria, which consume dissolved oxygen. Then, in a second stage, nitrates are reduced to gaseous state nitrogen (denitrification) by some kind of heterotroph bacteria. In an anoxic situation, these bacteria use nitrates instead of dissolved oxygen and consume carbon obtained from organic matter. Other controlled processes are e.g. phosphorus removal by chemical dosing or bypass flow in case of overload situations.

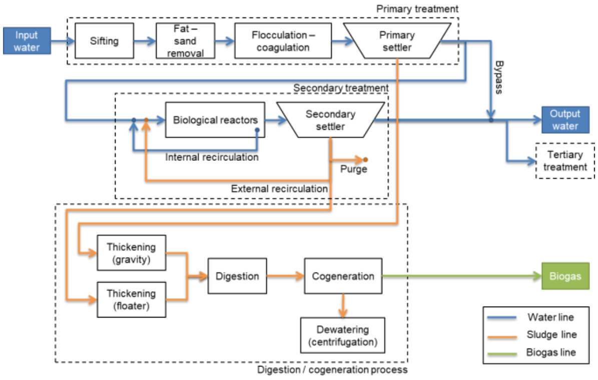

Figure 5 WWTP generic schema

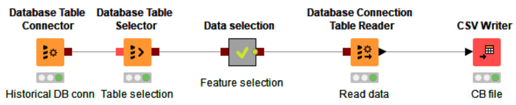

Figure 6 Case database model generation using a visual workflow data science platform

Almost all WWTPs within CBT are provided with some kind of automatic process control system in order to optimize the performance of the sub-processes involved in the water sanitation of these installations. Despite all these WWTPs have similarities to some extent, they have features e.g. plant capacity, instrumentation, layout which are characteristic of each WWTP and must be taken into account in the process control system design. Here we propose the use of data mining techniques to extract the knowledge available in the historical data and to produce useful data-driven models for the process control and supervision. Generated models are not system-dependent, i.e. they just rely on the data at a first stage. These data-driven models are going to be used to control and supervise the process. Additionally, the interoperability of all methods and tools that are part of the Process Control System environment is an important issue to be tackled. Thus, here we suggest the standardization from the data acquisition to the plant interaction, including all data mining techniques, in order to allow reuse of the developed workflows in any installation.

4.2 Results

The approach presented in this work is addressed at the current stage for a real CBT WWTP process using CBR. The set-point generation for this real case is proposed. Historical data gathered from the CBT WWTP considered is used. This WWTP is formed by two primary settlers, three independent biological reactors and two secondary settlers. The prototype is focused in one of the set-points in the biological process, concretely the on-off signal of the blower in one of the two reactors. Blowers operation straightforward: they are turned on during the nitrification process and turned off during the denitrification. Figure 6 shows a simple data science flow generated using a visual tool. It is composed of a connection to the historical database in order to extract the raw data, a feature selection phase and a case database file generation. Available online measurements from this WWTP are ammonium and nitrates concentrations, as well as redox at each biological reactor and output flow. Other offline and analytical measurements with variable periodicity are suspended solids concentration (SS), Chemical Oxygen Demand (COD), Biological Oxygen Demand (BOD), ammonium, nitrogen dioxide, nitrates, total nitrogen and phosphorus at the plant input and output, respectively. In the prototype developed here, only sensor raw data and derived variables are considered, e.g. the trend of each measurement, which is calculated in order to add important information related to the nitrification-denitrification process. Then, a feature selection based on the correlation with the blower set-point is performed. The case database obtained is used in Layer 3 as an input of the CBR block. Figure 7 shows the block diagram in Layer 3.

At this first testing stage, Layer 3 is not using real-time data gathered from the WWTP, but using historical data instead. Figure 8 shows the obtained results for a 24 hour simulation, comparing the set-point generated by the current control system running in the WWTP with the set-point obtained by the CBR algorithm for a 24h scenario. The first 12 hours of the scenario have been used in order to obtain the CBR database (Layer 1), and data from hours 12 to 24 have been used for testing the set-point generation. As may be observed in Figure 8, the CBR set-point generator achieves similar results as the actual set-point generation for the test dataset considered. Due to the generality of the method presented, this may be extended to further environmental applications following the same approach detailed here. The visual platform introduced, based on the use of data-based interoperable methods, aims to facilitate this process as long as there is enough data —in terms of measured variables and historical records— in order to properly model the process under study.

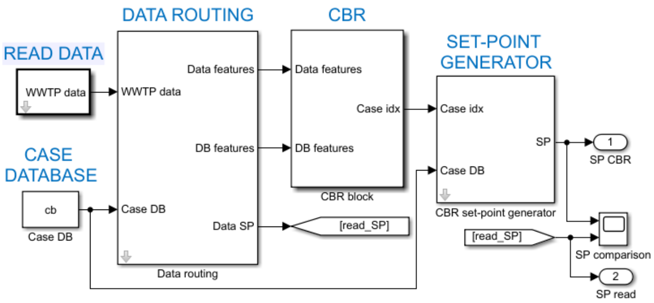

Figure 7 CBR prototype implementation using Matlab/Simulink

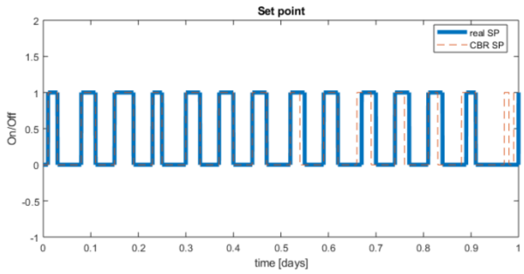

Figure 8 On/off set-point generation results

5 DISCUSSION AND CONCLUSIONS

In this paper, an interoperable workflow-based framework proposal for the automation of building IEDSSs, and specifically IPCSs, has been described. The framework relies upon the use of *visual workflows* and the *interoperability* of data mining models in order to enable the automation of both the design and control stages of a certain process. The framework is based on a three-layer architecture: the Data Mining workflow layer, the Process Design workflow layer, and the Process Control workflow layer. The framework proposal aims to overcome the *ad-hoc* nature of the design of most of the IEDSSs, and specifically Environmental Control systems, according to the specific characteristics of each particular Environmental system. This framework provides an automated way of generating the Intelligent Environmental Control System from the visual workflows designed at the third layer of the approach presented. The proposed framework has been preliminary tested in a case study focused on the supervision of a WWTP. A prototype has been implemented mainly relying on the available data, and using a CBR method to predict the set points of the blower in a WWTP aeration tank using a Matlab/Simulink environment. The preliminary experimental results with real operational data are very promising, and suggest the viability of the framework for deploying a data-driven IEDSS in a WWTP. Further work includes the development for more complex systems in order to assess the viability and performance of the proposal in real processes. This include further WWTP in the CBT ambit with higher sanitation capacity, taking advantage of the generality of the method in order to use the data-based approach presented to minimise the design effort in these new installations.

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