Transdisciplinary Engineering Methods for Social Innovation of Industry 4.0
M. Peruzzini et al. (Eds.)

doi:10.3233/978-1-61499-898-3-633

Alarm Management According to ISA SP 18.2 Standard Based on Process Mining and Multi-Criteria Decision Making Methods

Cleiton F. dos SANTOS[1] , Rolando J.K. NETTO, Eduardo de F.R. LOURES and Eduardo A.P. SANTOS
Pontifical Catholic University of Paraná (PUC-PR)
Graduate Program in Production and Systems Engineering (PPGEPS)
1155 Imaculada Conceição Street, Curitiba, 80215-901, Brazil

Abstract. Control and supervisory systems have become an important pillar for Automation with the advancement and development of Industry 4.0. These systems are used to reconcile field data with operator analysis, and they are responsible for supporting to the monitoring, analysis, controlling and management of the industrial process. Knowing this, the use of regulations, recommendations and indicators are needed. In this context, Supervisory Control and Data Acquisition (SCADA) systems use factory floor information as an input to alarm management systems in order to control and maintain the plant under operation. The failure event is the consequence of an alarm that has been suppressed or disregarded by the operator, but since the alarm system has been designed in a recommended manner, this occurrence should be displayed and recorded in the event log. Therefore, this record of failures can be analyzed, extracting knowledge of it (quantitative knowledge) and reconciling with the tacit knowledge of the operator (qualitative knowledge) in order to make a better and more clear understanding of the process for an accurate decision making, aiming the reestablishment of the production. However, few systems have the capacity to treat quali-quanti information in parallel and, therefore, the purpose of this paper is to present a model that reconciles such knowledge with a focus on the prioritization of the alarms according to the alarm management regulation ISA SP 18.2. In this context, mining and data analysis tools, and multi-criteria decision making methods are used to elucidate this problematization.

Keywords. alarm management; ISA SP 18.2; multi-criteria decision making (MCDM); process mining; qualitative and quantitative analysis.

Introduction

Nowadays, academia and industry have realized that the amount of data created has grown exponentially and, in order to meet this gap, new fields of study have emerged to meet this need for data and information processing. The "Big Data" era is the unavoidable consequence of our ability to generate, collect and store digital data on an unprecedented scale and our concomitant desire to analyze and extract the value of that

[1] Corresponding author, Mail: ferreira.cleiton@pucpr.edu.br.

data in the making of data-driven decisions [1]. As already mentioned, a big amount of data is generated, but it is still needed to process it in order to convert the raw-data into information and, thereafter, into knowledge. Only after these steps the user is able to understand and interpret the data coming from the industrial process.

Based on this hypothesis, the more knowledge the operator receives about the process inputs', the greater is the assertiveness in decision making. Therefore, it could be observed that one of the challenges faced by managers and decision makers is the ability to unify qualitative and quantitative data in a single system in order to choose the best option in a set of alternatives. According to source [2]:

- Qualitative data: it is concerned with the understanding of human behavior from an information perspective, therefore, it envisions a dynamic and "negotiable" reality; the data are collected through observations and interviews, and they are reported in the same language as the user;
- Quantitative data: it is concerned with the discovery of facts, therefore, it assumes a "fixed" and measurable reality; the data are captured by these measured variables, and they are reported through statistical analysis.

In the attempting to understand this differentiation, it is noticeable the difficulty in performing a qualitative-quantitative analysis of the industrial processes. This effort is related to the qualitative information (i.e. tacit knowledge), since it is not common the SCADA systems captured this kind of data.

Despite this non-triviality in reconciling quali-quanti information, some Multi-Criteria Decision Making (MCDM) methods consider the possibility of these two inputs in their analysis, such as the PROMETHEE (Preference Ranking Organization Method for Enrichment of Evaluations). MCDM refers to decision making in the presence of multiple criteria, in many cases conflicting with each other [3]. Therefore, MCDM methods are formal tools for ranking/sorting or aggregating a set of choices presented to the user [4], which are based on criteria (quali-quanti information) of observation and evaluation.

In this context, the Alarm Management is at focus, because its normative is used to parameterize the systems through the recommendation of decision dimensions and prioritization, however they do not provide guidance on the mechanisms to do so. The standards suggest that an alarm priority must be defined according to the seriousness of the consequences and the response time [5], but alarm management standards and SCADA systems do not guide, for example, which alarm should be prioritized during an alarm flood of the same category/severity. In this scientific and industrial motivational direction, process mining techniques can be used to analyze the event log and extract knowledge of the factory floor, as well as its process metrics (e.g., repeatability, pattern, frequency, etc.), which are used as input for the decision making analysis.

Then, this work aims to exemplify the use of process mining techniques for the extraction of knowledge and its use in multi-criteria evaluation structures to support the qualitative and quantitative decision making based on the alarm management standard ISA SP 18.2. In this view, this paper aims at the ranking and prioritization of the alarms.

The reminder of the paper is structured as follows. Section 1 presents some concepts about Alarm Management and its standards, specially the ISA SP 18.2. In the next section an overview is given about Process Mining. Section 3 is devoted to the presentation of Multi-Criteria Decision Making concerns, with a focus in the PROMETHEE method. The fourth section shows how all these fields interact to each other, and a use case is presented in order to test the proposed approach. Finally, section 5 is dedicated to the conclusion and suggestions of future work.

1. Alarm Management: ISA SP 18.2

An alarm is defined as an audible and/or visible means of indicating to the operator an equipment malfunction, process deviation, or abnormal condition requiring a response [6]. Based on this definition, it is possible to conceptualize the functions of the alarm management, which consist in the design, operation, monitoring and maintenance of the alarm system, aiming at the increasing of the operational safety through better operator interventions [6].

The alarm system is a vital and productive tool for the industrial process control management [7]. It is an effective way to monitor and control factory events in order to alert the operator when a failure occurs, which, by definition, requires a corrective action. Figure 1 shows the alarm management life cycle proposed by ISA SP 18.2.

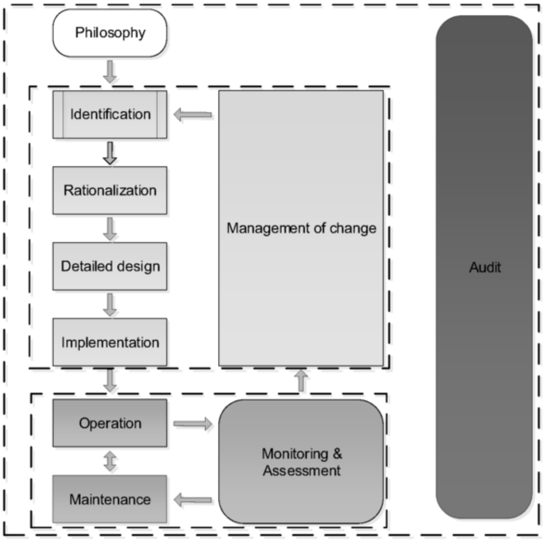

Figure 1. Alarm management life cycle.

Several studies measure efforts to parameterize the alarm system, among them are:

- ISA SP 18.2, published by the International Society of Automation (ISA) in 2009, nevertheless, revised in 2016;
- API RP 1167, published by the American Petroleum Institute (API) in 2016;
- IEC 62682, published by the International Electrotechnical Commission (IEC) in 2014;
- NAMUR NA 102, published by the User Association of Automation Technology in Process Industries (NAMUR) in 2003, however, with a revision made in 2008;
- EEMUA 191, published by the Engineering Equipment and Materials Users' Association (EEMUA) in 1999, but revised in 2007;
- ASM Alarm Management Guidelines, published by Abnormal Situation Management (ASM) Consortium in 2003;

- Among others.

In order to delimit the present paper, the ISA SP 18.2 standard was chosen for a more in-depth study. This standard was designed with the purpose of establishing terminologies and methods for alarm systems in its whole life cycle, i.e., from the development of the alarm philosophy to the management of system performance.

The ISA SP 18.2, which is also a reference to other standards, implements practices and methods that cover an entire alarm system [8]. It addresses the development, design, implementation and management of the alarm system in process' industries. The management of the alarm system includes several procedures defined in the light of regulation that describes the terminology and models for the development of a referential alarm system. Additionally, suggestions on how to maintain the system effectively through the life cycle is made. For reference, the life cycle proposed by ISA SP 18.2 could be viewed in Figure 1.

All phases of the life cycle presented are essential for the commissioning and operation of the alarm system, but one of the most important steps is the Monitoring & Assessment. In this phase, some metrics are presented in order to evaluate the performance of the alarm system according to ISA SP 18.2 – some of them could be visualized in Table 1. These metrics are essential for the evaluation of the alarm system and serve as reference parameters to support the decision making of the alarms recorded in the event log, in terms of sorting and ranking.

Table 1. Alarm performance metrics (ISA SP 18.2).

Metric	**Target Value**	
Annunciated Alarms per Time:	**Acceptable**	**Maximum Manageable**
Day	~150	~300
Hour	~6 (avg.)	~12 (avg.)
10 min.	~1 (avg.)	~2 (avg.)
Percentage of time the alarm system is in a flood condition	~<1%	
Annunciated priority distribution	High (5%) << Medium (15%) << Low (80%)	
Percentage of hours containing more than 30 alarms	~ < 1%	
Percentage of 10-minute periods containing > 10 alarms	~ < 1%	
Maximum number of alarms in a 10 minute period	≤ 10	
Percent contribution top 10 most frequent alarms to overall alarm load	~ < 1% to 5%	
Quantity of chattering and fleeting alarms	Zero	
Stale alarms	< 5 on any day	

2. Process Mining

Process mining is a process management technique that allows analyzing plant procedures from information stored in the event logs [9]. Process mining is a relatively new research discipline that falls between: (i) machine learning and data mining, and (ii) process modeling and analysis [10]. The basic idea is to extract the maximum knowledge of these logs in order to discover or improve the process under analysis [11].

Process mining is useful for at least two reasons: (i) it can be used as a tool to find out how people and/or procedures operate; (ii) it can be used for a Delta analysis, that is, a comparison of the current process with pre-defined and pre-established processes [12].

There are three classifications for mining techniques [13]:

- Discover (model): there is no an *a-priori* model, the construction of this one is made from reading the event log using algorithms (*a-priori* model can be a process model or some business rule [14]);
- Conformance (diagnosis): there is an *a-priori* model, and this model is compared with the event log and the discrepancies between them are analyzed;
- Enhancement (new model): there is an *a-priori* model, and this model is enriched with new aspects or perspectives.

As a result, process mining can give the user a better understanding of the process, allowing the extracted models to be used to support the decision making, since they reflect the reality of the plant operation [14]. Process mining is a powerful tool for an "as-is" analysis of the process, i.e., having an accurate view of the current situation, in order to draw appropriate conclusions [15].

3. Multi-Criteria Decision Making Methods: PROMETHEE

MCDM is a generic acronym for all methods that exist to help people make decisions according to their preferences, in cases where there is more than one criterion conflicting with one another [16]. This implies that, in any decision involving different conflicting criteria, the user must realize trade-offs among the alternatives in order to choose a solution [11].

The use of MCDM methods can be understood as a way to deal with complex problems by breaking them into problems of smaller parts [17]. In general, decision making is carried out by people, because although machine learning techniques contribute to the user, they should never be allowed to replace human decision making [18], because inappropriate or misinterpreted actions taken may rapidly increase the problem dimensions [5]. Besides, critical processes require immediate and effective responses from decision makers under pressures and uncertainties [19]. In this way, decision making in emergency processes is a challenging and time-critical task, since there are risks involved in the process (life, environment, health, and so forth). Therefore, it is essential to provide information and relevant knowledge to the operator about the process, giving him support for inference related to its operation and performance.

In the context of decision making, methods were developed to assist the user in choosing an option among a wide range of alternatives. One method that has been used in several field is the PROMETHEE [20]. The PROMETHEE methods (I, II, III, IV, V, VI, GAIA), compared to the existing one, present greater simplicity and ability to approximate the way that the human mind expresses and synthesizes preferences when faced with multiple contradictory decision perspectives [21]. This is one of the reasons why this technique can deal with uncertain, diffuse and heterogeneous information, including qualitative and quantitative criteria. As observed in other methods, the PROMETHEE method also makes a comparison between pairs with the alternatives showing their performance for a specific criterion [22].

4. Process Mining as a tool for a Decision Making based on the Alarm Management ISA SP 18.2

This paper proposes an association among several fields of study – process mining, decision making (PROMETHEE method) and alarm management (ISA SP 18.2). In order to integrate all these disciplines, a framework is presented aiming to position the interactions and determine what functionalities are within the scope of this research and how to achieve the expected output (ranked alarms). This framework is shown in Figure 2.

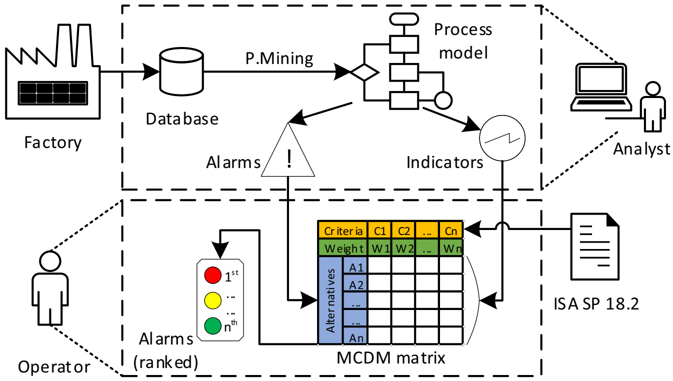

Figure 2. Suggested model.

Looking at this framework, two visions can be identified, which are the analyst's and operator's perspectives. The analyst puts his efforts in extracting knowledge of the plant through the process mining techniques in order to identify the alarms and indicators to be used in the MCDM evaluation matrix. The operator, in turn, only looks at the table for a more punctual and assertive decision making, since for him the most important action is to identify which alarm needs prioritization in a series of incidences.

In order to test the integration that is being proposed, a CPN Tools model was developed simulating the operation of a press machine [8]. This model, shown in Figure 3, considers some possible alarms and the generation of an event log.

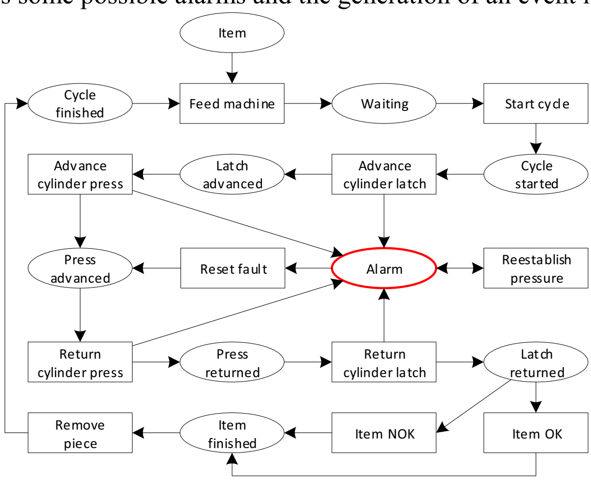

Figure 3. Example in CPN Tools of a press machine.

The log is used to extract process information through the application of process mining techniques. The information will be used to:

- Extract the registered alarms – some filters may be applied;
- Identify actual indicators of the analyzed process (frequency, causes, etc.);
- Collect data to fill out the MCDM matrix.

The data recorded by CPN Tools can be seen in Table 2. In the tests performed, 100 simulations (Case ID) of a piece's production were created related to the press machine, with a total of 747 records (Order #). Specifically, Table 2 shows the events recorded for the case number 67, because it presents the activity 'Reset fault'. Since it is not possible to create a visual signaling to the operator of a malfunctioning condition with CPN Tools, the authors considered, for purposes of validation of the proposed model, creating an activity simulating this functionality, which in this model is represented by the activity 'Reset fault'. To do so, the immediately preceding activity is considered the "alarm" that caused the failure and, thereafter, its reset.

Table 2. Example of failed cycle (cycle #: 6).

Order #	Case ID	Date	Hour	Activity
503	67	24/01/2018	07:13:24	Start cycle
504	67	24/01/2018	07:13:25	Advance cylinder latch
505	67	24/01/2018	07:13:25	Reset fault
506	67	24/01/2018	07:13:26	Return cylinder press
507	67	24/01/2018	07:13:27	Return cylinder latch
508	67	24/01/2018	07:13:28	Item NOK
509	67	24/01/2018	07:13:29	Remove piece

During the execution of this model in CPN Tools, 27 alarms was recorded, which are listed in Table 3 – in descending order of quantity. These data are essential for system analysis and prioritization of alarms. In addition, they can be compared with the reference parameters suggested by ISA SP 18.2 in the Monitoring & Assessment section, such as the information shown in Table 4, where four alarms were recorded in a period of 10 minutes. However, the standard recommends that only one alarm should be recorded at this time interval, even so, the maximum number of alarms that can be managed in 10 minutes are two occurrences (see Table 1).

Table 3. List of events/alarms.

Activity	Qtde.
Alarm 01 – Advance cylinder latch	10
Alarm 02 – Reestablish pressure	7
Alarm 03 – Return cylinder press	6
Alarm 04 – Return cylinder latch	3
Alarm 05 – Advance cylinder press	1

These quantitative data can be used for the prioritization (ranking) of the alarms that need a short-term action. Nevertheless, the production process is too complex to look at only from quantitative data from the factory floor, i.e., operator assessment (qualitative information) is often as important as these measurable indicators. Therefore, it is extremely important to reconcile these data into a more assertive decision making that represents the reality of the operator.

Table 4. Alarms recorded in a range <10min (07:05:01 – 07:15:00).

Order #	Case ID	Date	Hour	Activity
446	59	24/01/2018	07:05:42	*Alarm* 02 – Reestablish pressure
448	59	24/01/2018	07:06:00	*Alarm* 03 – Return cylinder press
504	67	24/01/2018	07:13:25	*Alarm* 01 – Advance cylinder latch
526	70	24/01/2018	07:13:44	*Alarm* 05 – Advance cylinder press

Some MCDM methods use the aggregation quali-quanti for the final decision, among them, the PROMETHEE method. In this way, the Visual PROMETHEE tool was used to develop an evaluation system to prioritize the alarms generated in CPN Tools. Figure 4 shows an extract of the evaluation matrix considering two criteria and five alarms. The criteria used in this system are: alarms generated in a day (quantitative information) and severity (qualitative information). The weights were distributed in such way that the severity of the alarm is four times more important than the total amount of alarms in a day. This option was chosen because studies show that there are a large number of "nuisance" alarms that could be suppressed and/or excluded from the alarm system [7][8].

Alarms	1day	Severity
Unit	unit	impact
Cluster/Group		
Preferences		
Min/Max	min	min
Weight	1,00	1,00
Preference Fn.	Usual	Usual
Thresholds	absolute	absolute
- Q: Indifference	n/a	n/a
- P: Preference	n/a	n/a
- S: Gaussian	n/a	n/a
Statistics		
Evaluations		
Alarm 01	10,00	very high
Alarm 02	7,00	very high
Alarm 03	6,00	moderate
Alarm 04	3,00	low
Alarm 05	1,00	very high

Figure 4. PROMETHEE evaluation matrix for prioritization of alarms generated in CPN Tools.

As already mentioned, the quantitative data were extracted from Table 3. On the other hand, the alarm impact information in the process (qualitative data) was obtained based on the operator's experience on a five-level scale (very high, high, moderate, low and very low). As a complement, in both criteria of the example, the objective is to minimize the variable analyzed under the decision space ("min" function) in order to highlight the more important ones. In the context of alarm classification (ranking), the worst values mean that they are the most critical to the process and, therefore, need prioritization.

Finally, the result of this evaluation is shown in Figure 5, where it is observed that the alarms were prioritized based on the input information and its respective weights for each criterion. As expected, the alarms "01", "02" and "05" show preference over the others because the severity of these ones are considered as 'very high' (weight of criterion 'severity' (80%) >> weight of criterion 'quantity' (20%)). Regarding to the number of alarms generated in a window's operation, alarm "01" registered the most occurrences, suggesting that, among the severe alarms, it has been the most priority. What happens is that the definition of weight performed, under the PROMETHEE method, favors a cracking based on the greater discrepancies (distances) in the evaluation performance of each alternative over the criterion of 'severity' (greater weight). This inference characteristic is attractive in more rigorous decision scenarios in discriminating solutions (alternatives) with performance more convergent to the ideal in terms of decision making.

In short, since the worst values of the alternatives (alarms) are oriented towards the bottom (i.e., -1), it is understood that the highest priority alarms are those closest to this value, which means that critically is related to the worst values. Therefore, as shown in Figure 5, the alarms were ranked using the PROMETHEE II method in the following order of priority for a corrective action: alarm "01", "02", "05", "03" and "04".

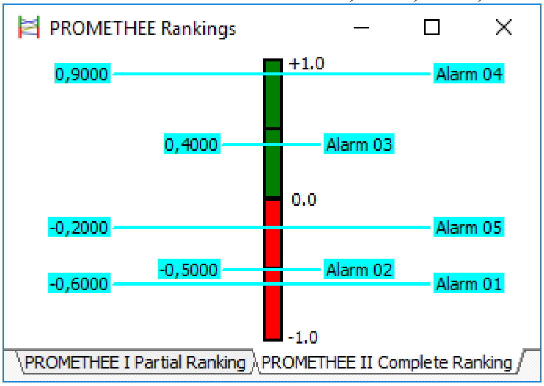

Figure 5. Result of the prioritization (ranking) of the alarms.

5. Conclusion

The purpose of this paper was to present the integration of several fields of study aiming of helping the operator to have a more assertive decision about which alarm needs action considering a series of occurrences, in the use-case, only the severity and quantity of notifications were used as criteria.

Process mining techniques are used to extract knowledge of event logs and, in some cases, to model and compare the generated model with the expected reality. From the data collected, some filters were applied to separate the alternatives (alarms) from the criteria (metrics based on industrial standards). In this context, ISA SP 18.2 is used as a reference for good practices, and its indicators are used as criteria, in the example, severity and number of occurrences in a day. Moreover, the need for an analysis from a qualitative and quantitative perspective of the process is observed, since the knowledge of the operator is as relevant as the measurable data. Finally, in order to reconcile this quali-quanti decision, the PROMETHEE decision-making method presents itself in a very effective way, because it is possible to merge such inputs. Therefore, in order to prioritize the alarms generated in a simulated model, the Visual Promethee tool was used to test the proposed model.

The results obtained were satisfactory and promising, since it is possible to see a gain in productivity by acting assertively on the highest priority alarms in order to put the plant under normal operation.

As future work we suggest: i) using the DEMATEL (Decision Making Trial and Evaluation Laboratory), a MCDM method, to choose the weights for each criterion; ii) applying this methodology with data extracted from real processes.

References

[1] X.L. Dong, Big Data Integration, *IEEE 29th International Conference on Data Engineering (ICDE)*, 2013, pp. 1245-1248.

[2] V. Minichiello, R. Aroni, E. Timewell and L. Alexander, *In-Depth Interviewing: Researching People*, Longman Cheshire, Hong Kong, 1990.

[3] S.H. Zanakis, A. Solomon, N. Wishart and S. Dublish, Multi-attribute decision making: A simulation comparison of select methods, *European Journal of Operational Research*, Vol.107, 1998, No.3, pp. 507-529.

[4] M. Jarke, Knowledge Sharing and Negotiation Support in Multiperson Decision Support Systems, *Decision Support Systems*, Vol. 2, 1986, No.1, pp. 93-102.

[5] R.E. Kondo, E.F.R. Loures and E.A.P. Santos, Process Mining for Alarm Rationalization and Fault Patterns Identification, *IEEE Emerging Technologies and Factory Automation (ETFA)*, 2012, DOI: 10.1109/ETFA.2012.6489695.

[6] ANSI/ISA. *ANSI/ISA-18.2-2009. Management of Alarm Systems for the Process Industries*, 2009.

[7] E.V. Araújo, *Gerenciamento de alarmes em plantas industriais: conceitos, normas e estudo de caso em um forno de reaquecimento de blocos*, Master thesis, UFMG, Belo Horizonte, 2010.

[8] R.E. Kondo, *Mineração de processos para a identificação de padrões comportamentais na racionalização de alarmes em plantas industriais*, Master thesis, PUC-PR, Curitiba, 2013.

[9] W.M.P. van der Aalst, H.A. Reijers, A.J.M.M. Weijters, B.F. van Dongen, A.K. Alves de Medeiros, M.Song and H.M.W. Verbeek, Business process mining: An industrial application, *Information Systems*, Vol. 32, 2007, No. 5, pp. 713-732.

[10] J. Munoz-Gama, *Conformance Checking and Diagnosis in Process Mining*, PhD Thesis, UPC, Catalonia, 2014.

[11] C.F. dos Santos, F. Piechnicki, E.F.R. Loures, E.A.P. Santos, Mapping the Conceptual Relationship among Data Analysis, Knowledge Generation and Decision making in Industrial Processes, *Procedia Manufacturing*, Vol.11, 2017, pp. 1751-1758.

[12] W.M.P. van der Aalst, A.J.M.M. Weijters, L. Maruster, Workflow Mining: Discovering Process Models from Event Logs, *IEEE Transactions on Knowledge and Data Engineering*, Vol.16, No.9, 2004, pp. 1128 - 1142.

[13] W.M.P. van der Aalst, Process mining: Overview and opportunities, *ACM Transactions on Management Information Systems*, Vol. 3, No. 2, 2012, pp. 1-17.

[14] W.M.P. van der Aalst, Decision support based on process mining, In: F. Burstein et al. (eds) *Handbook on Decision Support Systems*, Springer-Verlag, Berlin Heidelberg, 2008, pp. 637-657.

[15] C.W. Günther, *Process mining in flexible environments*, PhD Thesis, TUE, Eindhoven, 2009.

[16] P. Bogetoft and P. Pruzan, *Planning with multiple criteria: investigation, communication and choice*, Handelshøjskolens forlag, København, 1997.

[17] E. Løken, Use of multi-criteria decision analysis methods for energy planning problems, *Renewable and Sustainable Energy Reviews*, Vol. 11, 2007, No.7, pp. 1584-1595.

[18] S. Wang and N.P. Archer, A Neural Network Technique in Modeling Multiple Criteria Multiple Person Decision Making, *Computers & Operations Research*, Vol. 21, 1994, No.2, pp. 127-142.

[19] Y. Peng, Y. Zhang, Y. Tang and S. Li, An incident information management framework based on data integration, data mining, and multi-criteria decision making, *Decision Support Systems*, Vol. 51, No.2, 2011, pp. 316-327.

[20] J-P. Brans, *L'ingénièrie de la décision; Elaboration d'instruments d'aide à la décision. La méthode PROMETHEE*, Instruments et Perspectives d'Avenir, 1982.

[21] D. Bogdanovic, D. Nikolic and I. Ilic, Mining method selection by integrated AHP and PROMETHEE method, *Annals of the Brazilian Academy of Sciences*, Vol. 84(1), 2012, pp. 219-233.

[22] I.M.S. Leite and F.F.T. Freitas, Análise comparativa dos métodos de apoio multicritério a decisão: AHP, ELECTRE e PROMETHEE, *XXXII Encontro Nacional De Engenharia de Produção*, 2012.