Journal of Electrostatics 71 (2013) 387–391

Contents lists available at SciVerse ScienceDirect

Journal of Electrostatics

journal homepage: www.elsevier.com/locate/elstat

Artificial intelligence in electrostatic risk management

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A R T I C L E I N F O

Article history:
Received 27 September 2012
Received in revised form
5 December 2012
Accepted 6 December 2012
Available online 23 January 2013

Keywords:
Risk management
Hazard management
SCOUT system
Artificial intelligence
Support vector machines

A B S T R A C T

In the last two decades protection against electrostatic hazards became a very important topic. The increase in the range of possible faults fast automated systems and complex fault analysis is required.

The tools of artificial intelligence and expert systems have been applied successfully on this field and this paper aims to take a step further. While giving some insight to the currently used tools, another AI method, the 'support vector machines' are introduced in this paper. Besides a brief review on SVMs they are introduced to the SCOUT system, a novel approach to electrostatic hazard management.

1. Introduction

In electrostatics the proper handling of hazards is one of the key questions. Electrostatic hazards are usually handled as exogenous, they are not considered during planning of industrial processes [1], yet their consequences may be severe. Protection methods may and shall be worked out to decrease the occurring damage, but prevention of the hazardous events is nevertheless important. Moreover these hazards exist not only in a very wide field of industrial applications, but they have to be considered on every possible scale. Generally electrostatics is divided into two fields: industrial and atmospheric electrostatics.

The former refers to the industrial processes during which electrostatic phenomena (electric overstress or arcing) may occur and would cause faults. In this sense the hazards' scale varies from damage of sensitive devices (small sparks), or complications in industrial processes, to – in the worst case – explosion and fire (e.g. electric arcs). Their cause is usually the charge accumulation in a given space or on a surface, not an externally present electric arc. Acknowledging the presence of these hazards led to the application of electrostatic protection measures and the introduction of standardized risk management methods [2–4].

The notion of hazard in atmospheric electricity on the other hand refers to 'externally' present electrostatic hazard, which is the result of electrical phenomena – in most of the cases one refers to the effects of lightning.

The key difference between these fields regarding hazard management is that while in industrial electrostatics one is capable of influencing the industrial processes in order to prevent the development of the hazard (prevent charging), in atmospheric electrostatics the hazard is fully external and the hazardous phenomenon may not be prevented, but should be prepared for. Protection against these hazards is also different: in industrial electrostatics the goal is to minimize the hazards during process planning and work out protection measures, but in atmospheric electrostatics the focus is exclusively on the proper selection of protection devices, as there is no way to influence the development of lightning. [1] Electrostatic risk and hazard management has to cover both fields of course.

The current standards [2–4] provide ample information and guide the experts in planning adequate protection and also describe methods for risk management. While hazard management itself is mostly technical in nature, handling risk properly always raises fundamental questions as well.

In the last decade significant development was done on the field of soft computing methods in general and they have been successfully applied to a wide range of problems including electrostatics. Beside the need to use the most advanced computation methods, novel risk management methodologies also emerged providing a consisting framework for electrostatic hazard handling [1] [6–9]. This paper also contributes to this part of literature focusing on a novel soft computing method from the field of

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[1] One may trigger the lightning artificially, but that is not an option as a protection measure [5].

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http://dx.doi.org/10.1016/j.elstat.2012.12.010

artificial intelligence, the use of the so-called 'support vector machine' (referred to as SVM in the following) [10–13] and its use in electrostatic hazard management.

This paper is structured in the following way: the second section gives a brief review on the use of classifiers and regressors used in electrostatics from the field of artificial intelligence, and the third section focuses on support vector machines themselves. Here their general theoretical background is described (with focus on 'least square' SVMs) and demonstrated through two small examples (for regression). The fourth section deals with the introduction of SVMs into the recently developed SCOUT system, a comprehensive framework for handling electrostatic hazard and risk. The paper concludes with remarks and discussion points in section five.

2. Classifiers and regressors – applications in electrostatics

Artificial intelligence is commonly defined as the study and design of intelligent agents, who perceive then environment and takes actions that maximizes its chance of success [14]. Although only a select few examples will be mentioned here, one can see that AI can and did contribute much to the field of electrostatics already. The tools of AI are used on a broad scale starting from simple classification to physical property regression.

The significance of artificial intelligence in electrostatics is that usually we have to deal with multi-dimensional non-linear problems [1]. Explicit solution of such problems is analytically and computationally difficult, but the advantage of AI tools is that every problem is abstracted to rules, or much simpler mathematic expressions.

A subfield of AI particularly important for electrostatics is called automated reasoning, which means using stored information to react to occurring situation and to obtain new information (or conclusions). This may be realized through storing information via 'learning' and therefore such systems are also referred to as 'learning systems'. Whenever using a learning system it is very important to 'teach it well'. Such a system is taught by providing some examples – referred to as the 'training set' – and is evaluated by testing its acquired knowledge. The latter is achieved through using validation sets during the training and 'test sets' after the training have finished.

Obviously it is crucial to have a good quality training set, but it is useless without an adequate training strategy - it is advised to use n-fold cross-validation or similar methods to improve training accuracy [14].

Classification – or in AI terms 'supervised learning' – means that a given input sample is assigned a 'class' from a set previously known. The input sample refers to a set of input quantities, which refers to multiple dimensions – even nearly infinitely high dimensions. In a classifier the input sample's dimensions are taken into account and the corresponding class (binary or multiple) is determined. In these terms the classification yields a **discrete** output.

Regression on the other hand means that from a set of previous input samples the following input samples are predicted, or that a function is substituted by an approximation – for example when filtering noise. Here again the input samples may be multidimensional, but the output one-dimensional (multivariate regression may be realized as well using multiple regressors of course). In this case the output of the system is **continuous**.

Both classification and regression may be used successfully in electrostatics and the examples for either solution are numerous. Classification solved by neural networks (and fuzzy systems) was presented by Frei and Pommerenke [15], where the authors' goal was to classify electrical transients into ESD, or non-ESD and subclasses within these classes. The authors have used the spectrum of the signal to execute the classify it.

Regression is very often used in electrostatics to approximate physical characteristics of material. It was demonstrated that with ANNs it is possible to estimate quantities from the microscopic [16] to the macroscopic [17] scale. In the former paper the authors used ANNs to approximate the dielectric constant of thin films, while in the latter article the authors used ANNs to predict grounding resistance of buried electrodes.

Regression was also successfully applied in atmospheric electrostatics as well. In [18] the authors attempted to predict a cloud-to-ground lightning location and time using data from field mills, and meteorological systems. A similar solution to the problem was presented in [19], where the authors aimed to use field mill data to determine the thunderstorm zone and used multi-output ANNs for this purpose.

Besides classifiers and regressors, expert systems are used in many cases – as fuzzy systems were mentioned here already. In practice hybrid solutions are quite frequent, where classification and regression is combined with an expert system – for a general overview on this method see [20].

These examples show quite clearly that there are a number of problems in electrostatics where classification and regression is required and that AI tools may be used efficiently for these purposes. However due to the development in the last two decade on the field of AI alternatives to artificial neural networks should be considered as well due to some general problems.

3. Support vector machines

The intrinsic problem of artificial neural networks (regardless of fulfilling a classifier or regressor role) is that the networks' internal structure is arbitrary. The number of hidden layers in an ANN and the number of neurons in the ANN are arbitrary choices upon training the network. Besides this issue there are other drawbacks of training an ANN as well:

- The solution may be sub-optimal (the assumed structure or training function not being optimal itself)
- Optimization may be stuck at local minima (instead of the global minimum)
- Outliers in the training set degrade performance

An alternative solution to ANNs much less prone to these problems is the use of 'support vector machines', which approaches the problem of classification and regression from a different perspective. The aim of using an SVM for classification is to find a hyperplane with the highest margin separating the samples in the different classes (and the lowest classification error for overlapping classes) [12]. The classification rule is the following:

$$f(x) = w^T \varphi(x) + b \tag{1}$$

Here x is a vector of the input dimensions and w and b are the parameters of the support vector machine. The value of this function can be either -1 or 1, which denotes the class a given input sample is classified to. A special feature of the SVM may also be seen in Eq. (1), namely the transformation φ of x inputs. The transformation function φ is called the 'kernel function' and the transformation is done to the so-called 'feature space', which is high (may be even infinite) dimensional transformation of the input space. From this high dimensional space the output is calculated through a simple linear equation. (Note that this input transformation is not mandatory.)The problem to be solved when training the SVM the following, given an arbitrarily selected kernel function: