Using data mining and support vector machines to optimize cooling effectiveness in a gas turbine blade leading edge

Uso de minería de datos y máquinas de vectores de soporte para la optimización del enfriamiento de álabes de turbina de gas

Omar Dávalos,[1] Alberto Ochoa,[2]* Juan Carlos García,[1] Gustavo Urquiza[1]

[1] Centro de Investigación en Ingeniería y Ciencias Aplicadas, Universidad Autónoma del Estado de Morelos.
Av. Universidad 1001, Chamilpa. Cuernavaca, Morelos, México. CP 62210
[2] Juarez City University. México
* E-mail: alberto.ochoa@uacj.mx

KEYWORDS:

data mining, support vector machine, pattern recognition, decision support system

ABSTRACT

This paper discusses a research related with the innovative use of a decision support system based on data mining (to evaluate historical information) and the support vector machine method to determine the optimal values related with the cooling efficiency of a gas turbine blade and to determine the adequate selection of components to build scenarios under uncertainty. This research allows the selection of a specific number of optimal values for components, in a time horizon of a power energy installation (approximately four hours). These components are evaluated with data from an information repository of a successful energy system. The intent of this research is to apply the computational properties of an established model of intelligent optimization. The case study allowed the analysis of the individual features of each component with the emulation from set matching features (optimal values reached by our hybrid algorithm). This way it is possible to predict a better functionality in this kind of system.

PALABRAS CLAVE:

minería de datos, máquinas de vectores de soporte, reconocimiento de patrones, sistemas de soportes de decisión

RESUMEN

En este artículo se discute el uso de sistemas de decisión de soporte basados en minería de datos (para la evaluación histórica) y máquinas de vectores de soporte, con la finalidad de obtener los valores óptimos relacionados con la eficiencia de enfriamiento en un álabe de turbina de gas para determinar la adecuada selección de componentes y construir escenarios bajo incertidumbre. Esta investigación permite seleccionar un número específico de componentes, los cuales son evaluados a partir de un depósito de información con datos de otro sistema de energía. La intención de la presente investigación es aplicar propiedades computacionales, en este caso un modelo de optimización inteligente. El caso de estudio permite analizar las características individuales de cada componente con la emulación de una serie de características correspondientes (valores óptimos alcanzados por el algoritmo híbrido). De esta manera es posible predecir una mejor funcionalidad en un sistema de este tipo.

Recibido: 7 de septiembre de 2012 • **Aceptado:** 12 de noviembre de 2012 • **Publicado en línea:** febrero de 2014

1 INTRODUCTION

The high gas temperatures registered at first stages in a gas turbine can cause serious damages in blades. This is a critical situation if we consider that in today's turbines temperatures at inlet are up to 1400°C. Higher thermal stresses, material corrosion and creep are typical situations when the machine is operated under these conditions and a considerable reduction in remnant life of the blades occurs [1]. Techniques like film cooling are used to avoid these damages. This technique consists in ejecting air through holes placed in the leading edge. The interaction between the air and the main flow generates a film cooling in the leading edge surface, keeping it at temperatures that don't affect the blade's integrity. Several investigations have been done about parameters of fluid dynamics, such as blowing ratio, variations in density ratios and momentum flux ratios, but a simpler model to predict cooling effectiveness is still needed. Geometrical factors can increase or reduce the cooling effectiveness of holes and help to avoid damages in turbine blades. Diameters, ejection angles and separation between them can be used to predict cooling effectiveness and other factors, like penetration of cooling flow into main flow, which can lead in turn to higher levels of turbulence in the interaction zone of main flow and cooling flow. Several investigations have been performed about blade turbines using intelligent systems for optimization. Verstraete *et al.* improved a method to design and optimize the cooling channels on a high pressure gas turbine [8]. They showed that combining evolutionary algorithms with metamodels like artificial neural networks and radial basis function it is possible to optimize turbine components. Pierret and Van den Braembussche used simulated annealing to design blade turbines [9]. They found that there is a better performance in turbines with blades designed with the proposed methodology. Chunting *et al.* made a fault detection system for hydraulic turbines based on the support vector machine (SVM) method [10]. They concluded that SVM is more efficient for classification and robust performance. Sosa Coeto *et al.* optimized the impeller and diffuser of an hydraulic submersible pump using computational fluid dynamics (CFD) and neural networks [11].

In this work, decision support systems (DSS) based on data mining (DM) and SVM are used to improve a thermal analysis of a gas turbine blade in order to know its cooling effectiveness. The database for the above algorithm was obtained using CFD and design of experiments method (DoE) was employed to reduce the computational cost of CFD. The database set includes cooling efficiency and heat transfer in a gas turbine blade.

2 PROPOSED METHODOLOGY

2.1 Support vector machine

Classifying data is a common task in machine learning. Suppose some given data points in which each point belongs to one of two classes, and the goal is to decide which class a new data point will be in. In the case of SVMs, a data point is viewed as a p-dimensional vector (a list of p numbers), and we want to know whether we can separate such points with a *(p−1)*-dimensional hyperplane. This is called a linear classifier. There are many hyperplanes that might classify the data. One reasonable choice as the best hyperplane is the one that represents the largest separation, or margin, between the two classes. So we choose the hyperplane in which the distance to the nearest data point on each side is maximized. If such a hyperplane exists, it is known as the maximum-margin hyperplane and the linear classifier it defines is known as a maximum margin classifier; or equivalently, the perceptron of optimal stability.

2.2 Linear SVM

Given some training data D and a set of n points of the form: $D = \left\{(x_i, y_i) \middle| x_i \in R^p, y_i \in \{-1,1\}\right\}_{i=1}^{n}$
where y_i is either 1 or –1, indicating the class to which the point x_i belongs, and each x_i is a p-dimensional real vector, we want to find the maximum-margin hyperplane that divides the points having $y_i=1$ from those having $y_i=-1$. Any hyperplane can be written as the set of points x satisfying $w \cdot x - b = 0$, where · denotes the dot product and w the normal vector to the hyperplane. The parameter $\frac{b}{\|w\|}$ determines the offset of the hyperplane from the origin along the normal vector w.

We want to choose w and b so as to maximize the distance between the parallel hyperplanes; that they be as far apart as possible while still separating the data. These hyperplanes can be described by the equations $w \cdot x - b = 1$ and $w \cdot x - b = -1$.

Note that if the training data are linearly separable, we can select the two hyperplanes of the margin in a way that there are no points between them and then try to maximize their distance. By using geometry, we find the distance between these two hyperplanes is $\frac{2}{\|w\|}$, so we want to minimize $\|w\|$. As we also have to prevent data points from falling into the margin, we add the following constraint: for each i either $w \cdot x_i - b \geq 1$ for x_i of the first class or $w \cdot x_i - b \leq 1$ for x_i of the second.

This can be rewritten as:

$$y_i(w \cdot x_i - b) \geq 1 \text{ for all } 1 \leq i \geq n \quad (1)$$

We can put this together to get the optimization problem:

Minimize (in w, b) $\|w\|$ subject to (for any $i= 1,.....,n$)

$$y_i(w \cdot x_i - b) \geq 1 \ .$$

2.3 Primal form

The optimization problem presented in the preceding section is difficult to solve because it depends on $\|w\|$, the norm of w, which involves a square root. Fortunately it is possible to alter the equation by substituting w with $\frac{1}{2}\|w\|^2$ (the factor of 1/2, being used for mathematical convenience) without changing the solution (the minimum of the original and the modified equation have the same w and b). This is a quadratic programming optimization problem. More clearly:

Minimize (in w,b) $\frac{1}{2}\|w\|^2$ subject to (for any $i=1,...,n$) $y_i(w \cdot x_i - b) \geq 1$.

By introducing Lagrange multipliers α, the previous constrained problem can be expressed as

$$\min_{w,b} \max_{\alpha \geq 0} \left\{ \frac{1}{2}\|w\|^2 - \sum_{i=1}^{n} \alpha_i [y_i(w \cdot x_i - b) - 1] \right\}$$

that is, we look for a saddle point. In doing so all the points which can be separated as $y_i(w \cdot x_i - b) - 1 > 0$ do not matter, since we must set the corresponding α_i to zero.

This problem can now be solved by standard quadratric programming techniques and programs. The "stationary" Karush–Kuhn–Tucker condition implies that the solution can be expressed as a linear combination of the training vectors $w = \sum_{i=1}^{n} \alpha_i y_i x_i$.

Only a few α_i will be greater than zero. The corresponding x_i are exactly the support vectors, which lie on the margin and satisfy $y_i(w \cdot x_i - b) = 1$. From this, one can derive that the support vectors also satisfy $w \cdot x_i - b = 1 / y_i = y_i \Leftrightarrow b = w \cdot x_i - y_i$,which allows one to define the offset b. In practice, it is more robust to average over all N_{SV} support vectors:

$$b = \frac{1}{N_{SV}} \sum_{i=1}^{N_{SV}} (w \cdot x_i - y_i) \quad (2)$$

2.4 Dual form

Writing the classification rule in its unconstrained dual form reveals that the maximum margin hyperplane, and therefore the classification task, is only a function of the support vectors, the training data that lie on the margin.

Using the fact that $\|w\|^2 = w \cdot w$ and substituting, $w = \sum_{i=1}^{n} \alpha_i y_i x_i$ one can show that the dual of the SVM reduces to the following optimization problem:

Maximize (in α_i)

$$\tilde{L}(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i^T x_j = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j k(x_i, x_j) \quad (3)$$

subject to (for any $i = 1,\ldots,n$) $\alpha_i \geq 0$, and to the constraint from the minimization in $b = \sum_{i=1}^{n} \alpha_i y_i = 0$.

Here the kernel is defined by $k(x_i, x_j) = x_i \cdot x_j$, and w can be computed thanks to the α terms:

$$w = \sum_{i} \alpha_i y_i x_i$$

2.5 Biased and unbiased hyperplanes

For simplicity reasons, sometimes it is required that the hyperplane passes through the origin of the coordinate system. Such hyperplanes are called unbiased, whereas general hyperplanes not necessarily passing through the origin are called biased. An unbiased hyperplane can be enforced by setting $b=0$ in the primal optimization problem. The corresponding dual is identical to the dual given above without the equality constraint (figures 1, 2).

3 CHARACTERIZATION OF THE PROBLEM

The fluid domain is represented by a section of a gas turbine blade at midspan corresponding to a 150 MW gas turbine with 72 blades in blade wheel (figure 3).

Cooling efficiency is dependent on the heat transfer in the leading edge. Due to this it is necessary to solve a conjugate heat transfer analysis to know the temperature distributions in the leading edge. The flow field in the domain is determined by the continuity and the Navier-Stokes equations and the heat transfer

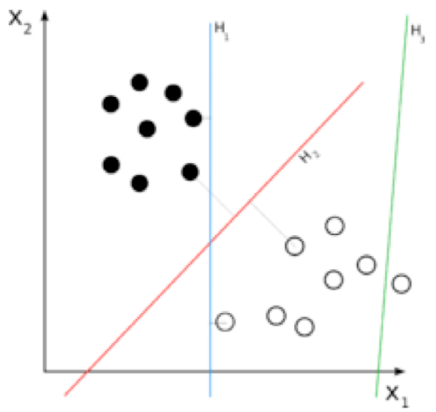

Figure 1. H3 (green) does not separate the two classes. H1 (blue) does, with a small margin and H2 (red) with the maximum margin

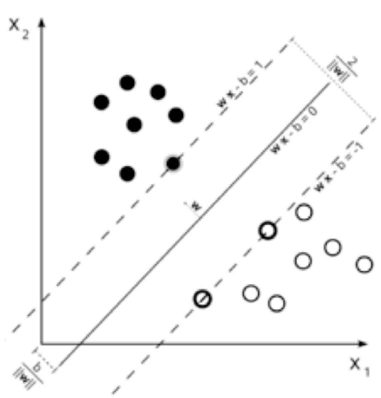

Figure 2. Maximum-margin hyperplane and margins for an SVM trained with samples from two classes. Samples on the margin are called the support vectors

is governed by the energy equation. In order to solve those equations a CFD commercial code was used. The turbulence was solved using the k-ε model.

$$\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x_i}(\rho u_i) = 0 \tag{4}$$

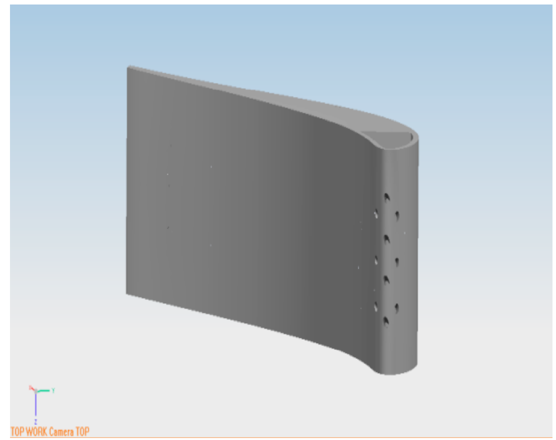

Figure 3. Gas turbine blade

$$\frac{\partial}{\partial t}(\rho u_i) + \frac{\partial}{\partial x_j}(\rho u_i u_j) = -\frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_j}\left(\mu \frac{\partial u_i}{\partial x_j}\right) + \frac{1}{3}\frac{\partial}{\partial x_i}\left(\mu \frac{\partial u_j}{\partial x_j}\right) \tag{5}$$

$$\frac{\partial}{\partial t}(\rho E) + \nabla \bullet \left(\vec{v}(\rho E + p)\right) = \nabla \bullet \left(k_{eff} \nabla T\right) + S_h \tag{6}$$

4 MULTIPLE MATCHING

Multiple matching is a series of many evaluations according to different combinations of optimal values associated with the components and a batch of 50 runs under different scenarios. In the evaluation phase, thermomechanical specifications with more similarities will be given a preference, and then these aspects will be selected to compete. Components must be ranked according to their customers' preferences after tournaments end, once the final list of multiple matching is evaluated. The hybrid algorithm will be scheduled to set the timing for the comparison of different similarities using a round of multiple matching analyses based on the optimization assigned to a component. Then, components that qualify for selection in a model will be chosen on the following prioritized basis. Given the organization for each component and the matches for each round in the algorithm, components are assigned to state their participation for its evaluation in each of the series. To ensure an active participation in the future, a minimum of twenty-five comparatives are recommended for the four included rating lists and before the main rating list. When a component does not accept to participate

Table 1. The orthogonal array test

Turbulent kinetic energy	Number of revolutions	Radius	Temperature	Expansion coefficient	Kronecker	Delta	Rate energy disipation	Deformation vector	Volumetric module	Lame constant	Diameter	Mass flow rate
1	2	2	3	5	3	5	2	2	4	2	4	4
1	2	2	3	3	4	4	7	4	5	3	5	3
1	3	2	4	1	2	2	5	5	3	4	6	2
1	3	2	5	4	5	5	4	3	2	2	5	5

into a multiple matching series, then the selection process uses the average rating plus number of games played during the rating period. The algorithm repeats this process until reaching the required qualifiers of the multiple matching series.

5 EXPERIMENTATION

In order to obtain the most efficient arrangement of components, we developed a cluster for storing the data of each representative individual for each component. The narrative guide is made with the purpose of distributing an optimal form for each evaluated component. The main experiment consisted in implementing components with our hybrid algorithm, with 500 issues and 200 epochs. The stop condition was reached after 50 iterations; this allowed the generation of the best selection for each component. An optimal value was evaluated using the multiple matching model, as in Yang, Tao and Yu [10]. The vector of weights employed for the fitness function was Wi= [0.6, 0.7, 0.8, 0.5, 0.6, 0.9, 0.8, 0.7, 0.6, 0.9, 0.5, 0.8, 0.7], which represents the importance of each component. Then, the hybrid algorithm would select the specific value of each component based on the similarity of attributes. Each attribute was represented by a discrete value from 0 to 7, where 0 means absence and 7 the highest value of the attribute. The experiment design consisted of an orthogonal array test with interactions among variable components; these variables were studied within a location range (1 to 400) specific to coordinates x and y. The orthogonal array was L-N(2**7), in other words, 7 times the N executions. The value of N is defined by the combination of the 7 possible values of the variables with the values in the location range. In table 1 we list some possible scenarios as the result of combining the values of the attributes. The results allowed us to analyze the effect of all possible combinations of values.

6 CONCLUSIONS

The use of the orthogonal array test facilitates the reorganization of the different attributes. Aditionally, the array aids to specify the best possibilities to adequate correct solutions for each component. Different attributes were used to identify the real possibilities of improving a component set in a particular environment, and to specify its correlations with others. A CFD analysis was realized to find out the temperature distribution *and efficiency in the leading edge of a gas turbine blade. After* the classification of data based on relationships that keep their attributes, these changes can help to reduce thermal stress, thus ensuring the structural integrity of the blade. Therefore, we realize that the concept of "optimization under uncertainty" exists based on determining the acceptance function to propose an alternative optimization for the rest of the components. For further implementations we intend to analyze the level and degree of cognitive knowledge for each component. Additionally, this may help us to understand true similarities that share different components based on the characteristics to be clustered while keeping their own mechanical identity. In a related work [7], it has been demonstrated that small variations go beyond phenotypic characteristics and are mainly associated to tastes and related characteristics developed through time.

REFERENCES

1. Min Kim, K. *et al*. (2011). Analysis of conjugated heat transfer, stress and failure in a gas turbine blade with circular cooling passages. *Engineering Failure Analysis*.
2. Campos, A. *et al*. (2008). Thermo-mechanical analysis and conceptual optimization of a first stage bucket. *Procedings of ASME Turbo Expo 2008: Power for Land, Sea and Air*. Berlin, Germany.
3. Han, J. C., Ekkad, S. (2001). Recent development in turbine blade film cooling. *International Journal of Rotating Machinery*, vol. 7, 21-40.
4. Ronggang, J., Yongmei, L., Gaozhao C., Xuening F. (2012). Parallel predicting algorithm based on support vector regression machine. *ACIS-ICIS*, 488-493.
5. Patil, S. G., Mandal, S. A., Hegde, V. (2012). Genetic algorithm based support vector machine regression in predicting wave transmission of horizontally interlaced multi-layer moored floating pipe breakwater. *Advances in Engineering Software*, 45(1), 203-212.
6. Lee, L.H., Wan, C. H., Rajkumar, R., Isa, D. (2012). An enhanced support vector machine classification framework by using Euclidean distance function for text document categorization. *Appl. Intell.*, 37(1), 80-99.
7. Diosan, L., Rogozan, A., Pécuchet, J. P. (2012). Improving classification performance of support vector machine by genetically optimising kernel shape and hyper-parameters. *Appl. Intell.*, 36(2), 280-294.
8. Verstraete, T., Amaral, S., Van den Braembussche, R., Arts, T. (2008). Design and optimization of the internal cooling channels of a hp turbine blade-Part II: Optimization. *Proceedings of ASME Turbo Expo 2008*.
9. Pierret, S., Van den Braembussche, R. Turbomachinery blade design using a navier-stokes solver and artificial neural network.
10. Yang, C., Tao, J., Yu, J. (2009). Fault diagnosis of a hydro turbine generating set based on support vector machine. *Intelligent Systems, GCIS '09. WRI Global Congress on*, vol.3, 415-418.
11. Sosa, B., Urquiza, G., Garcia, JC., Castro, L. Optimization of the impeller and diffuser of hydraulic submersible pump using computational fluid dynamics and artificial neural networks.

About the authors

José Omar Dávalos Ramírez is PhD candidate at the Research Center for Applied Sciences and Engineering (CIICAp), at Universidad Autónoma del Estado de Morelos. His thesis research is about the design and optimization of cooling systems in gas turbine blades using evolutionary algorithms, artificial neural networks, computational fluid dynamics and finite element method.

Juan Carlos García Castrejón is PhD professor at the Research Center for Applied Sciences and Engineering (CIICAp) at Universidad Autónoma del Estado de Morelos. He is member of the turbomachinery research group at CIICAp. He has been involved in research related to failure diagnosis, optimization, measurement of flow and vibration of turbomachines. He is coauthor in more than 17 conference or journal papers related to CFD or FEA applied to turbomachinery.

Alberto Ochoa Ortiz-Zezzatti (BS, ’94, Eng. Master, ’00, PhD, ’04, Postdoctoral Researcher, ’06, and Industrial Postdoctoral Research, ’09). He joined Juarez City University in 2008. He has published 1 book and 7 chapters in books related to AI. He has supervised 17 PhD theses, 27 MSc theses and 29 undergraduate theses. He participated in the organization of COMCEV’07, COMCEV’08, HAIS’07, HAIS’08, HAIS’09, HAIS’10, HAIS’11, HAIS’12, ENC’06, ENC’07, ENC’08, MICAI’08, MICAI’09, MICAI’10 and MICAI’11. His research interests include evolutionary computation, natural processing language, anthropometrics characterization and social data mining. In his second postdoctoral research participated in an internship in ISTC-CNR in Rome, Italy.

PhD Gustavo Urquiza Beltrán is professor at the Research Center for Applied Sciences and Engineering (CIICAp) at Universidad Autónoma del Estado de Morelos. His main research areas focus on turbomachinery, heat exchangers and termohydraulics. He has worked at Instituto de Investigaciones Eléctricas and Centro Nacional de Innovación y Desarrollo Tecnológico. He is author in more than 30 journal and conference papers and member of Sistema Nacional de Investigadores, level 1.